Learning from Law Enforcement

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How do agents respond to experiencing law enforcement ('being punished')?

- Assume no change in p and F (Becker 1968)
- No increase in expected price of future offense/crime
- No scope for **general deterrence**
- Rational, *perfectly informed* agent would not respond

Conflicts w/ notion of offenders 'learning their lesson'

- Experiencing punishment $\Rightarrow$ future behavior
  specific deterrence
- Imperfectly informed agents update priors about enforcement process and respond accordingly
  $\rightarrow$ *learning from law enforcement*

Objective: identifying deterrence effects mediated by learning

- Tricky to separate learning from other channels
  1. Past offenses ⇒ expected future 'prices'
  2. Punishment typically 'compound treatment'
     - *Prison:* incapacitation, peer/criminogenic effects, labor market effects, etc; (high) *fines:* income effects

Our approach: speeding tickets (fines) → speeding

- Large administrative data from speed camera systems
  - Track >1 mio cars in suburbs of Prague, CZ
  - Speed for *every* ride (26 mio)
- No incapacitation, no general deterrence
  - Fines independent of past offenses; no demerit points
  - No impact on insurance rates

Main research questions:

- Does speeding ticket influence subsequent driving behavior?
  (*extensive margin variation in punishment*)
- Does the level of fines matter for behavioral responses?
  (*intensive margin variation*)
- Which learning process best explains data?

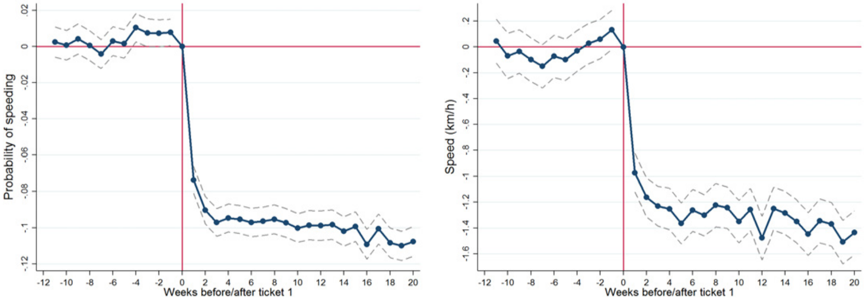
Empirical strategies:

1. RDD exploiting two speed cutoffs
   - Enforcement cutoff – ticket: yes/no
   - Cutoff for ticket with lower/higher fine
2. Event study design
   - Makes use of high frequency nature of data

Preview of results (1): RD, response to ticket (extensive margin)

- $\approx$ 32% drop in speeding rate; $\approx$ 3% drop in *average* speed
  - van Benthen (2017): 10mph speed limit variation
  - Bauernschuster & Rekers (2020): publicized crackdowns
- $\approx$ 70% drop in offenses; strong shift in speed distribution
- No evidence on bunching
  - No learning about cutoff

Preview of results (2): Event study estimates



- Immediate and persistent responses
- ATE (event) $\simeq$ LATE (RDD)

Preview of results (3): Higher fines tend to induce larger responses, but: imprecisely estimated (intensive margin)

- Higher fines clearly amplify effect in theory motivated subsample

Evidence consistent with learning framework:

- Rejects case of 'fine-grained' updating
  - Would imply small, fine-tuned speed adjustment, small/no drop in speeding, heaping below cutoffs
- Supports 'coarse' updating
  - Larger adjustment of priors and behavior
- Potential policy implications: optimal ambiguity (of, e.g., enforcement cutoffs)

Contribution to Literature:

1. Learning about law enforcement
   - Perceptional deterrence (Sah 1991; Lochner 2007; Hjalmarsson 2008)
   - *Between* peers: Rincke & Traxler 2011; Drago et al. 2020
   - This paper: (*within*) learning from own experience
   - Most closely related: learning from trials (Philippe 2020) or police crackdowns (Banerjee et al. 2019)

2. Specific deterrence
   - Mixed evidence on imprisonment (e.g., Bhuller et al. 2020, Chen & Shapiro 2007, DiTella & Shargrodsky 2013, Drago et al. 2011, ...)
     - Compound treatments
     - Isolation of 'pure' learning channel is FUQ
   - Mixed evidence on tax enforcement (e.g., Kleven et al 2011, DeBacker et al. 2015)
     - But: income effects, complex strategic game

Contributions: (cont'd)

3. Traffic law enforcement & deterrence
   - Drunk Driving (Hansen 2015)
   - Speeding (Gehrsitz 2019, Studdert et al. 2015)

   Differences to/innovations from our study:
   - Identifying pure learning channel
   - No general deterrence, incapacitation, etc.
   - Outcome measures beyond re-offending (we observe illegal *and* legal behavior)
   - 'Automated' enforcement vs discretion by police officers (Makowsky & Stratmann 2009, Goncalves & Mello 2021)

Background & Data

Speed cameras

- Říčany - suburban town outside Prague, population 16,000
- 5 speed camera zones, starting 2014
- Measures speed over a zone of *several hundred meters*
- Speed limit is 50km/h (one camera w/ 40km/h limit)
- Costly (time) to circumnavigate

map

Speed cameras (cont'd):

- Cameras are visible; no warning traffic sign
- No 'flash' or any other immediate feedback

Two relevant levels of **fines**:

1. 900 CZK $\simeq$ \$40 $\simeq$ average daily wage
   - speed $>$ enforcement cutoff
   - enforcement cutoff: 14km/h above speed limit
     - Ad-hoc (set by local police), no public info
2. 1900 CZK $\simeq$ \$83
   - speed $>$ 23km/h above speed limit (& $<$ 43km/h)
     - Cutoff defined by law

No general deterrence mechanisms:

- No reporting to car insurer
- Fines independent of past offenses

Speed Camera Data:

- 26mio recorded rides (full universe)
  - Focus on tickets from 2014/10 – 2017/06
- Exact time, location (camera zone) and measured speed
- Identifier of number plate
  - Driving history of 1.3 mio cars, for rides above **and below** speed limit

Enforcement Data:

- Administrative database used in processing tickets
- Information includes:
  - Day ticket sent, received, date fine paid, etc.
  - Little car (owner) information, only for ticketed cars

summary statistics

Main outcome variables:

- **Speed**
  := measured speed (relative to speed limit), km/h
- **Speeding**
  := driving above the speed limit
  - 13.52% of all rides
- **Offending**
  := driving above the enforcement cutoff
  - 0.23% → ticket w/ low fine
  - 0.04% → ticket w/ high fine

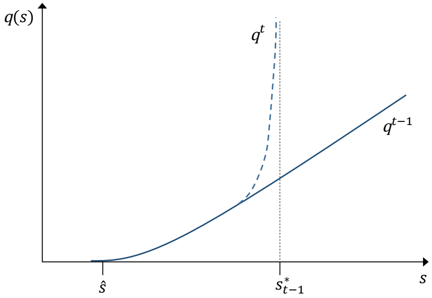
Theoretical Framework

Theoretical Framework

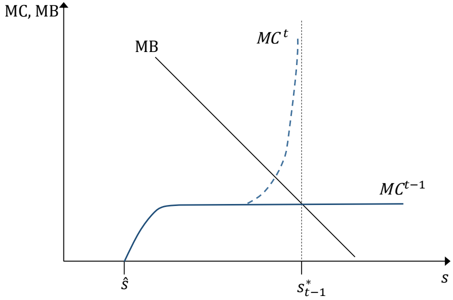
- Simple model of optimal speeding choice ▸ model details
  - Not full dynamic (Bandit) problem
- Drivers trade off *MB* w/ expected *MC* from speed s
  - Note: expected costs based on probability & severity
  - Denoted $q^t(s)$, with $q^t(s) = p^t(s) \times \phi^t(s)$
- After (not) receiving a ticket for past rides in $\tau < t$ with s^τ, drivers may update prior $q^t(s)$
- Alternative modes of updating...
  - No updating (e.g., know 'true' $q(s)$)
  - 'Fine-grained' updating
  - 'Coarse' updating
- ...different, testable implications

‘Fine-grained’ updating:

Expected costs

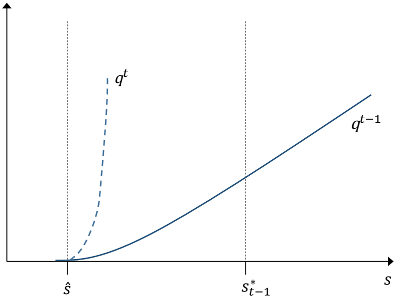


Optimal choice

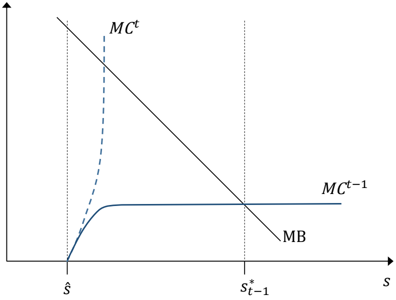


‘Coarse’ updating:

Expected costs



Optimal choice



Testable predictions

	No updating	Fine-grained upd.	Coarse updating
Behavioral response to speeding ticket	no response	(small) drop in speed, continued speeding	(large) drop in speed, drop in speeding
Bunching/1st cutoff (enforcement)	yes (correct prior) no (incorrect prior)	yes (evolving over time)	no
Bunching/2nd cutoff (higher fine)	yes$^{(a)}$ (correct prior) no (incorrect prior)	yes$^{(a)}$ (evolving over time)	no$^{(b)}$
Behavioral response to high- vs low-fine speeding tickets	no (no responses to either)	scope for differential effect	limited scope for differential effect

Note: framework offers Econ 'translation' of (one channel of) **specific deterrence**:

- Backward-looking agents who "*are responsive to the actual experience of punishment*" (Chalfin & McCrary 2017)
- Update priors about parameters of enforcement process and respond accordingly

Competing model:

- *Bounded rational* agents w/ limited attention/cognition
  - Ticket pushes 'info' on top-of-mind (increased salience)
  - Scope for 'recency' → effect should fade over time

Regression Discontinuity

RD Design

Exploit local quasi-experiment, comparing cars with speed marginally below/above two different cutoffs:

1. Basic enforcement cutoff
    - Extensive margin variation in punishment
    - 14km/h above speed limit
2. Cutoff for low/high fine
    - Intensive margin variation in punishment
    - 23km/h above speed limit

Non-trivial transformation of repeated within-car observations into cross-sectional structure of RDD

Data Structure for RDD: illustration

- **Assignment period**: for each car, we compute the max speed $\mathbf{S_i}$ observed during a months after 1st ride
  - $a = \{3, 4, 5, 6\}$ months
- **Outcome period**: f subsequent months, starting with the date when $\mathbf{S_i}$ is recorded (+ accounting for delay in sending tickets)
  - $f = \{3, 4, 5, 6\}$ months
- Below: $a = f = 4$ (baseline specifications)
  - Results hardly sensitive to parameters

Analysis presented below:

- Purely cross-sectional, i.e., **one obs per car**
  - ‘Unweighted’, independent from number of rides
    ⇒ Effects on average car

Complementary estimates:

- Each single ride per car (‘weighted’ effects)
  ⇒ Effects on average ride

‘Fuzzy’ RDD: not every ride (car) will be ‘treated’

- Exceptions (police, foreign cars, etc.)
- Time gap: some cars get ticket earlier/later

RD Estimates

Treatment discontinuity (ticket or high-fine ticket, resp.):

$$T_i^k = \delta^k D_i^k + g^k(S_i) + u_i^k$$

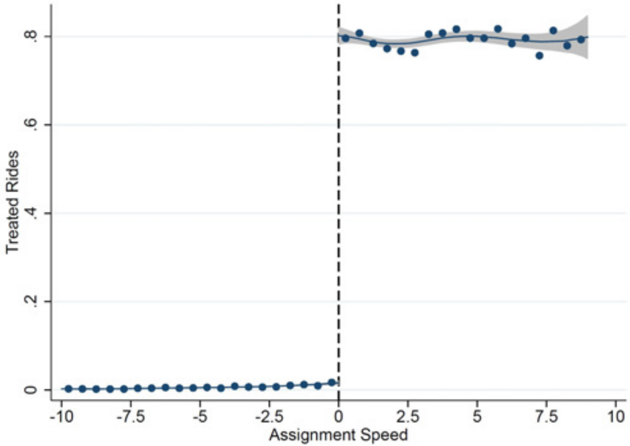
Reduced form effect on outcome Y:

$$Y_i = \tau^k D_i^k + h^k(S_i) + v_i^k$$

Wald estimate: $\beta^k = \tau^k / \delta^k$ for cutoff $k = \{1, 2\}$ with

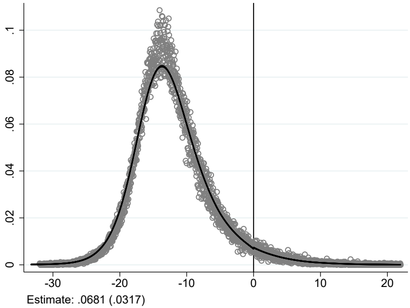
$$D_i^{k=1} = \begin{cases} 0 & \text{if } S_i < 14\text{km/h} \\ 1 & \text{if } S_i \geqslant 14\text{km/h} \end{cases} \quad \text{and} \quad D_i^{k=2} = \begin{cases} 0 & \text{if } S_i < 23\text{km/h} \\ 1 & \text{if } S_i \geqslant 23\text{km/h} \end{cases}$$

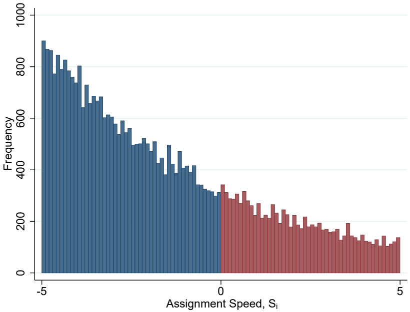
Treatment rates (1st cutoff)



≈ 80pp increase in share of treated rides

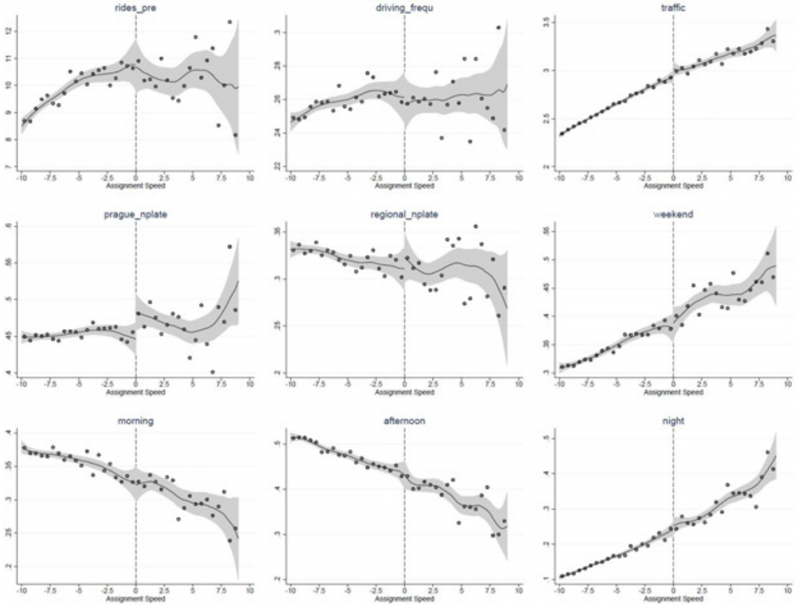
Bunching (sorting)? No!





- No emergence of bunching over time heaping (cut1)
- Same (null-)results for 2nd cutoff

Balance? Yes!


rides_pre
driving_frequ
traffic
prague_nplate
regional_nplate
weekend
morning
afternoon
night
-10 -7.5 -5 -2.5 0 2.5 5 7.5 10
Assignment Speed

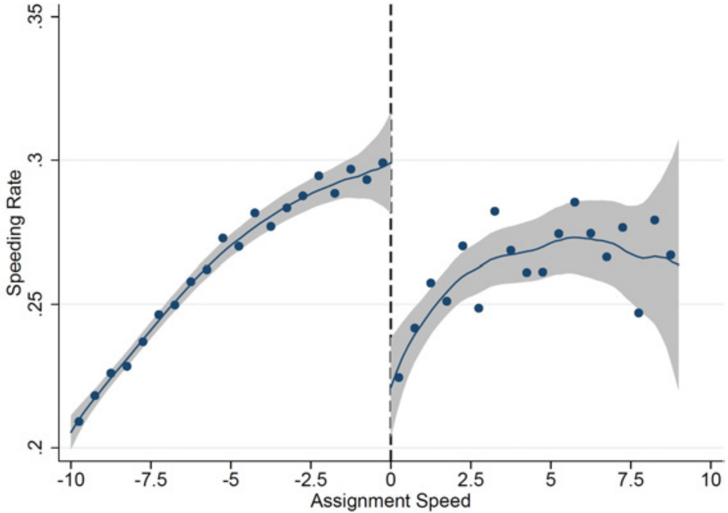
Responses in Driving Frequency?

	(1) Rides (count)	(2) Ever-return (binary)	(3) Rides (count)	(4) Ever-return (binary)
	1st cutoff		*2nd cutoff*	
Estimate	0.8812	0.0389**	–0.2831	0.0022
(τ)	[0.6501]	[0.0173]	[1.6193]	[0.0382]
Y(left)	7.263	0.509	7.420	0.557
Bandwidth	2.710	2.293	2.589	2.661
Obs. (Cars)	465,518	465,518	27,774	27,774

Reduced form results for the enforcement cutoff (col. 1–2) and the high-fine cutoff (col. 3–4). Dependent variables: number of rides during outcome period (col. 1 and 3); dummy indicating at least one observation during outcome period (col. 2 and 4). Bias-corrected RD estimates with MSE-optimal bandwidth and robust standard errors in brackets (Calonico et al., 2014, 2017). Y($left$) indicates the mean outcome in the 0.5km/h bin below the cutoff.

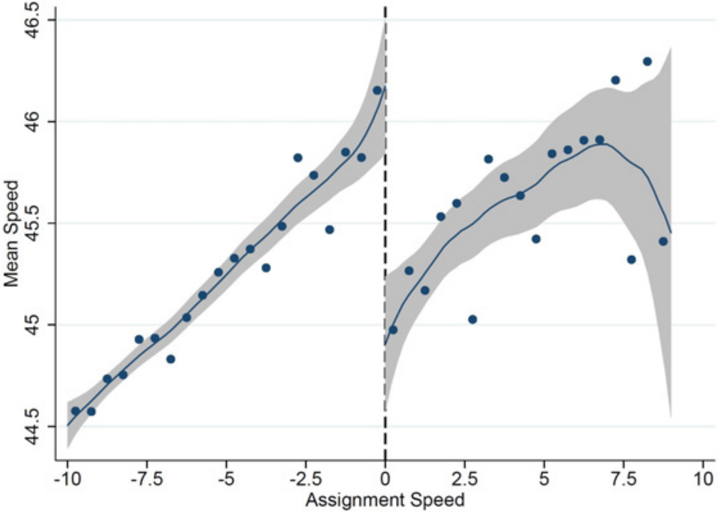
RD Results

Reduced Form: Speeding Rate (1st cutoff)



≈ 8pp drop in speeding rate

Reduced Form: Speed (1st cutoff)



$\approx$ 1.3km/h drop in mean speed

Wald Estimates (1st cutoff)

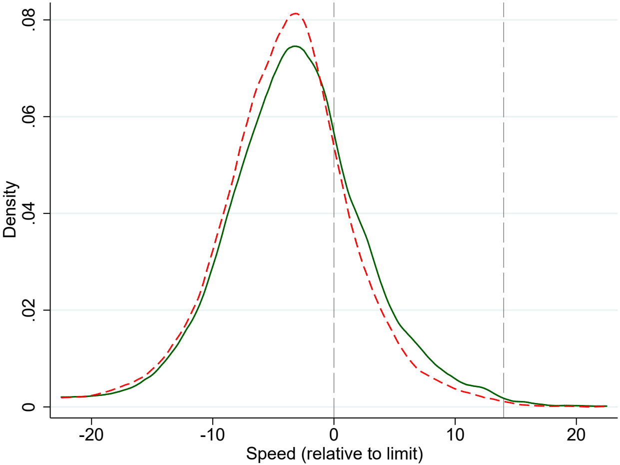
reduced form

	(1) Speeding	(2) (Re)Offending	(3) Speed	(4) Speed^{p50}	(5) Speed^{p75}	(6) Speed^{p90}
Estimate	–0.0951***	–0.0051***	–1.4602***	–1.3097***	–1.4972***	–1.7723***
($\beta^{k=1}$)	[0.0136]	[0.0019]	[0.2774]	[0.2794]	[0.2663]	[0.3032]
Y(left)	0.299	0.007	46.153	46.608	49.678	51.703
Relative effect	–31.80%	–70.31%	–3.16%	–2.81%	–3.01%	–3.43%
Bandwidth	4.483	5.776	4.199	3.871	4.583	4.542

Bias-corrected Wald estimates with a MSE-optimal bandwidth and robust standard errors in brackets. Effect size relative to mean outcome in the 0.5km/h bin below the cutoff, Y(left). Number of observations: 224,816 cars.

- 9.5pp drop in speeding rate
  $\Leftrightarrow$ **32% reduction** in speeding
- 70% drop in (re)offending
- 1.5km/h drop in mean speed (–3%)
- Stronger effects at top of speed distribution

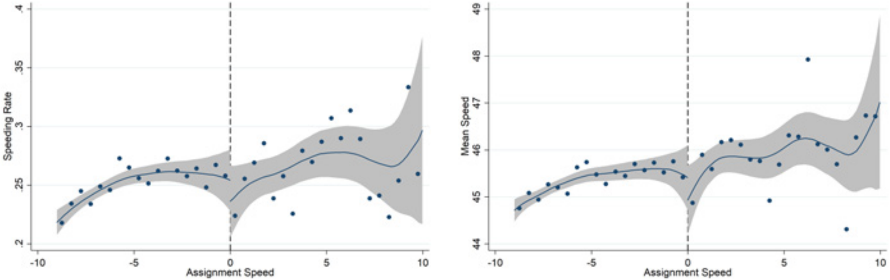
Effect on Speed Distribution (1st cutoff)



Distribution of speed during outcome period for cars with assignment speed S_i within a 0.5km/h-range below (green) and above (dashed-red) the enforcement cutoff.

relative change

Reduced Form: 2nd cutoff (lower/higher fine)



- Imprecisely estimated **additional** effects from higher fines
  - Relatively large but statistically insignificant ▸ estimates
- Additional evidence:
  - Expanding sample period (larger *N*) yields higher precision: higher fines amplify drop in speed
  - Consistently with coarse updating: stronger differential effect under favourable driving conditions (→ next slide)

Wald Estimates at 2nd cutoff: high- (vs. low-)fine tickets

	(1) Speeding (binary)	(2) Speed (mean)	(3) Speed^{p90}	(4) Speeding (binary)	(5) Speed (mean)	(6) Speed^{p90}
	Good Conditions			*Bad Conditions*		
Estimate	–0.0808*	–1.4711*	–2.0812**	–0.0075	–0.0809	–0.5930
($\beta^{k=2}$)	[0.0471]	[0.8681]	[1.0525]	[0.0330]	[0.7750]	[0.8070]
Y(left)	0.381	47.665	53.142	0.176	43.997	48.086
Relative effect	–21.18%	–3.09%	–3.92%	–4.28%	–0.18%	–1.23%
Bandwidth	2.628	2.865	2.409	3.124	2.952	3.273
Obs.	13,446	13,446	13,446	13,639	13,639	13,639

Notes: Effect of high-fine tickets on speeding rate, mean speed and the p90-speed for riders under good (Columns 1 – 3) and bad driving conditions (Columns 4 – 6). 'Good conditions' are defined by a ride with at least 5.84 seconds gap to the next car ahead. Bias-corrected Wald estimates with a MSE-optimal bandwidth and robust standard errors in brackets. Effect size relative to mean outcome in the 0.5km/h bin below the cutoff, Y(left).

Robustness & Extensions (I):

- Car- (‘unweighted’) vs ride-level (‘weighted’) estimates ▸ est
  - Slightly smaller estimates ⇔ infrequent drivers more responsive
- Bandwidth choice ▸ sensitivity checks I
- Length of assignment/outcome period ▸ sensitivity checks II
- Heterogeneity analysis ▸ heterogeneity
- Permutation exercise: null effects at placebo cutoffs ▸ CDFs

Extension (II): ‘Narrow’ vs ‘broad’ learning?

1. Do ticketed cars slow down at *other camera zones*, too?
   - Yes! Effect is smaller in absolute, more similar in relative terms
     ▸ RDD ▸ Event
   - Supplementary data further indicate drop in speed at speed cameras outside Ricany
2. Do ticketed cars slow down *outside camera zones*, too?
   - Or are there ‘catch-up’ effects (*more* speeding)?
   - Data include time of exit from one and entry into other zone
     $\Rightarrow$ Average speed on un-monitored road in between
   - Estimates indicate null/weakly negative effects, rejecting catch-up

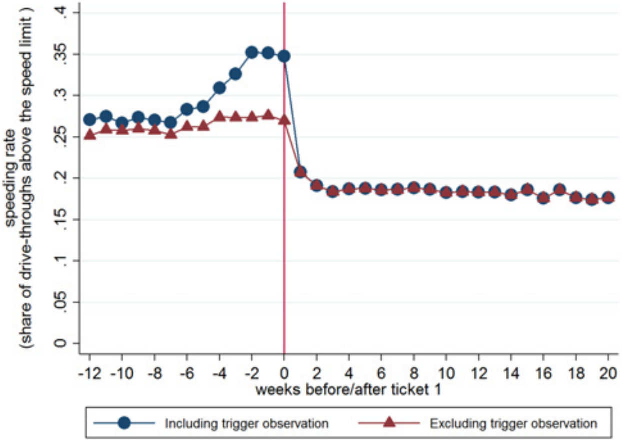
Event Study

How quickly do drivers respond? Persistence of responses?

Event: receiving the 1st ticket

- Identify day when the ticket was delivered
- Observe driving behavior before/after this day
- Implementation:
  - Time window: 12 weeks before, 20 weeks after ticket
  - At least one ride after ticket was delivered and at least one ride (other than trigger) before
- Note
  - Only ticketed cars (ATE, ToT)
  - Restrict sample to low-fine tickets: estimates directly comparable to LATE from RDD at 1st cutoff

Weekly Speeding Rates (raw)



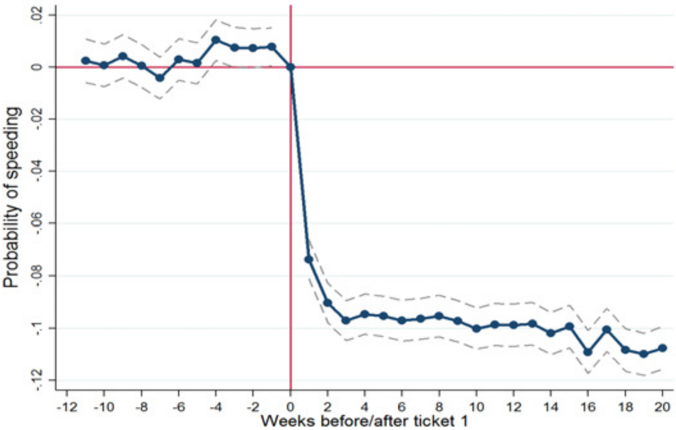
Mean reversion issue! We drop trigger observation in regressions

Estimation Strategy:

$$y_{irt} = \sum_{w=-12}^{20} \beta_w D_{wit} + \gamma_r X_{irt} + \lambda_i + \lambda_r + \lambda_{mr} + \lambda_{dr} + \lambda_{hr} + \varepsilon_{irt}$$

- Unit of obs: every drive-through during the time window
- y_{it} speeding measure, car i at time t
- D_{wit} dummies indicating weeks before/after the ticket
- X_{irt} measures of traffic density
- λ_i car fixed effects
- $\lambda_{r.}$ zone fixed effects + zone $\times$ month of year, day of week, hour of the day, etc.
- 2-way clustered SEs: by car & camera zone-day-hour

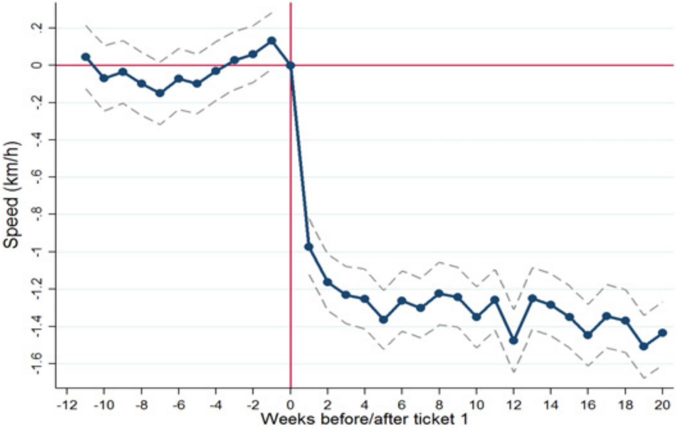
Estimated Speeding Rate (pre/post 1st ticket)



pre-ticket mean: 0.270 cars: 16,407 obs: 626,430

$\approx$ **37 % reduction in speeding rate**

Estimated Speed (pre/post 1st ticket)



pre-ticket mean: 44.858 km/h cars: 16,407 obs: 626,430

$\approx$ **3 % reduction in speed**

Further results:

- Long outcome window (24 months)
  - **No 'backsliding'** over 2+ years ▸ long-run
- Analysis by the number of rides (rather than weeks) ▸ rides
  - Clear, positive pre-ticket trend
- **Re-offenders**: small(er) response to 1st ticket ▸ reoffenders
  - But: respond to **2nd ticket** ▸ 2nd-ticket
- Heterogeneity analyses:
  - Smaller & slower responses of corporate cars ▸ private/corp
  - Slightly larger responses by infrequent cars ▸ frequency
  - Ticket paid? ▸ paid/unpaid
    - Drivers who do not pay slow down nevertheless
    - But: much smaller responses

Conclusions

Key findings:

- Strong effects of receiving a speeding ticket
  - $\approx$ 70% drop in offenses, $\approx$ 33% drop in speeding rate; $\approx$ 3% drop in *average* speed
  - ATE (event) $\simeq$ LATE (RDD)
  - Responses occur immediately and are persistent over time
- Higher fines tend to amplify effects
  - But less precisely estimated
- Evidence consistently supports 'coarse' learning...
  - rejects 'fine-grained' mode of updating
- Evidence on 'broad' learning
  - Speed adjustments also at other speed camera locations

Implications:

- Information transmission $\Rightarrow$ (specific) deterrence
    - Optimize which information is (not) conveyed in which way
    - With coarse learning, partial ambiguity might be preferable
- Trade-off: probability vs. severity of punishment
    - Learning effects seem to be primarily driven by extensive rather than the intensive margin variation in punishment
    - Novel argument in favor of probability over severity (for a given general deterrence level)

Related work (in progress):

- Swiftness/velocity of punishment
  (Dušek & Traxler 2021)
  - ‘Quickly’ vs ‘slowly’ delivered tickets
  - Natural variation and RCT

- Enforcement of speeding tickets (payments)
  (Dušek, Pardo, Traxler 2020 (web))
  - RCT testing behavioral interventions
  - RDD: variation in fees

Thanks for your interest!

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Model

Reduced form model of **rational speeding choice**

$$\max_{s_t} \; v(s_t, c_t) - q^t(s_t)$$

- Net utility from speed s_t, $v(s_t, c_t)$, given driving condition c_t
- Concave in s_t and $\frac{\partial^2 v(s_t, c_t)}{\partial s \partial c} > 0 \, \forall s, c$
- Belief (and updating) of *expected* costs, $q^t(s) = p^t(s) \times \phi^t(s)$
- $q^t(.)$ smooth, twice diff'tl, weakly convex in s

Model

Optimal speeding choice: $MB = MC$

$$\frac{\partial v(s_t^*, c_t)}{\partial s_t} = \frac{\partial q^t(s_t^*)}{\partial s_t}.$$

How does the optimal speeding choice in s_t^* compare with s_{t-1}, given that a ticket from ride in $t-1$ arrived in t?

Depends on specific form of updating

Model

Updating of expectations conditional on past experience:

$$q^t(s) = P\left(\{s_{t-1}, D^t(s_{t-1})\}, \{s_{t-2}, D^t(s_{t-2})\}, \ldots\ q^{t-1}(s)\right),$$

$D^t(s_\tau)$ indicates if ticket from ride in period τ arrived in t

Iterating the mapping $P(.)$ yields

$$q^t(s) = \Pi_t\left(\left(\{s_\tau, \vec{D}(t, s_\tau)\}\right)_{\tau=0,\ldots,t-1},\ q^0(s)\right),$$

where $\vec{D}(t, s_\tau) = (D^t(s_\tau), D^{t-1}(s_\tau), \ldots, D^{\tau+1}(s_\tau))$

back

Basic Summary Statistics:

back

	'Not-ticketed' cars	'Ticketed' cars	Total (all cars)
Car characteristics			
Observations (rides)	22,049,809	4,084,958	26,134,767
Number of cars	1,304,791	48,422	1,353,213
Number of tickets	0	56,056	56,056
Observations per car	16.90	84.36	19.31
	(74.84)	(192.02)	(82.93)
Driving frequency	2.33	3.06	2.45
	(2.76)	(2.87)	(2.79)
Number plate: Local region	0.453	0.455	0.453
	(0.498)	(0.498)	(0.498)
Number plate: Prague	0.393	0.439	0.400
	(0.488)	(0.496)	(0.490)
Ride characteristics			
Speed	–6.00	–5.17	–5.87
	(7.73)	(8.60)	(7.88)
Speeding	0.125	0.189	0.135
	(0.331)	(0.391)	(0.342)
Offending	0.000	0.015	0.003
	–	(0.120)	(0.051)
Ticket characteristics			
Fine amount (CZK)		1,039	
		(377)	
Probability of paying the fine		0.933	
		(0.250)	

Wald Estimates at 2nd cutoff:

	(1) Speeding	(2) (Re)Offending	(3) Speed	(4) Speed^{p50}	(5) Speed^{p75}	(6) Speed^{p90}
Estimate	–0.0243	–0.0058	–0.7225	–0.6508	–0.8824	–0.6883
($\beta^{k=2}$)	[0.0288]	[0.0104]	[0.7913]	[0.7782]	[0.7895]	[0.7819]
Y(left)	0.258	0.015	45.416	45.789	48.706	50.746
Relative effect	–9.42%	–39.43%	–1.59%	–1.42%	–1.81%	–1.36%
Bandwidth	3.784	2.794	2.793	2.825	3.041	4.013

Bias-corrected Wald estimates with a MSE-optimal bandwidth and robust standard errors in brackets. Effect size relative to mean outcome in the 0.5km/h bin below the cutoff, Y(left). Number of observations: 16,148 cars.

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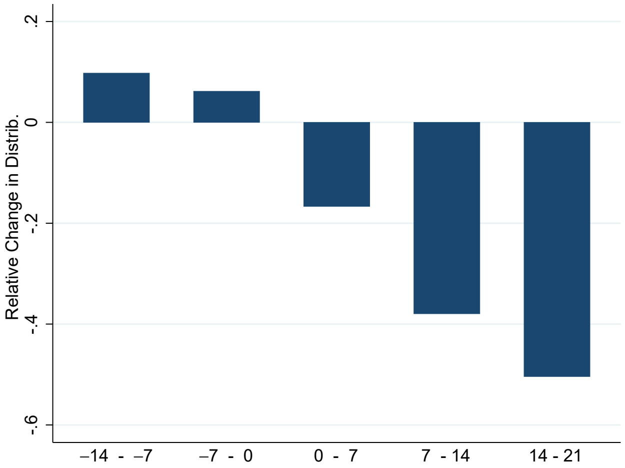
Reduced Form Estimates at 1st cutoff:

	(1) Ticketed	(2) Speeding	(3) (Re)Offending	(4) Speed	(5) Speed^{p90}
Estimate	0.7866***	–0.0812***	–0.0044**	–1.3512***	–1.4023***
(δ, τ)	[0.0127]	[0.0146]	[0.0019]	[0.2814]	[0.2711]
Y(left)	0.017	0.299	0.007	46.153	51.703
Bandwidth	2.428	2.228	2.619	2.270	3.353

Bias-corrected RD estimates with MSE-optimal bandwidth and robust standard errors in brackets (Calonico et al., 2014, 2017). Number of observations: 224,816 cars.

back

Relative Change in Speed Distribution

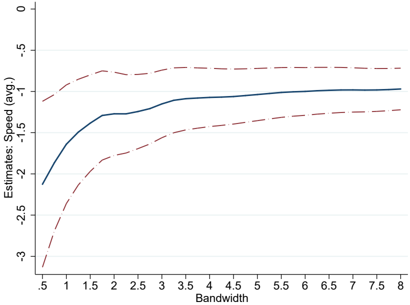


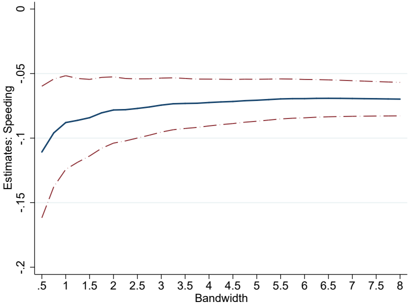
Percentage difference in the speed distribution among cars with assignment speed S_i within a 0.5km/h-range below and above the enforcement cutoff.

back

Sensitivity check: different bandwidth

Reduced-form estimates for speeding & mean speed (1st cutoff):





Figures plot RD-estimates (w/ 95%-CI) for a bandwidth ranging from 0.5 to 8.0.

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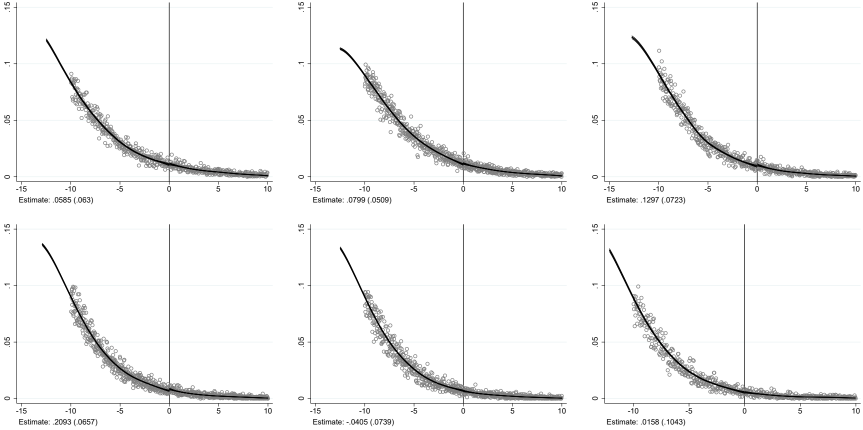
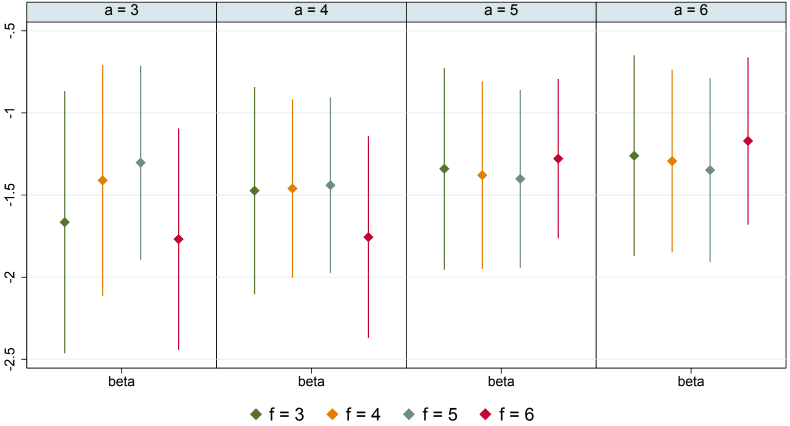
Learning to bunch?

Heaping tests by six-month intervals (1st cutoff)



back

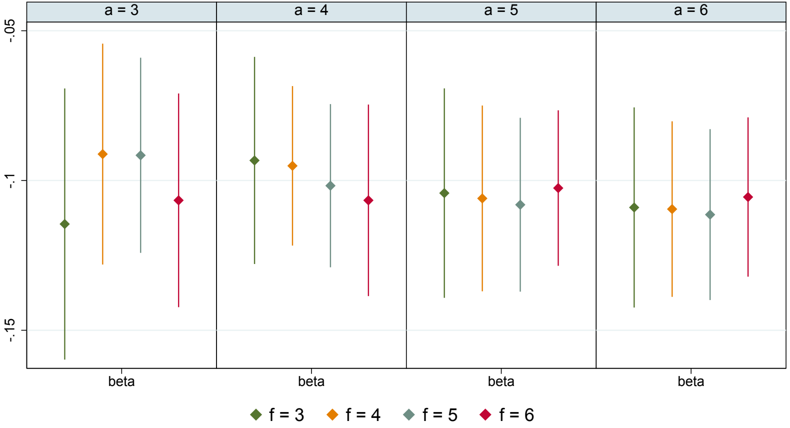
a-, *f*- Parameter Sensitivity: Speed



Notes: The figure depicts Wald estimates (at the car-level) with 95% CI for the enforcement cutoff (1st cutoff) for different assignment (*a*, in months) and follow-up periods (*f*). Outcome: Speed (in km/h).

back

a-, *f*- Parameter Sensitivity: Speeding



Notes: The figure depicts Wald estimates (at the car-level) with 95% CI for the enforcement cutoff (1st cutoff) for different assignment (*a*, in months) and follow-up periods (*f*). Outcome: Speeding (binary).

back

Further Results: 1st Cutoff

Further Results I: **Heterogeneity**

- Non-local (vs local) and infrequent (vs frequent) drivers respond *more strongly*

▸ heterogeneity I

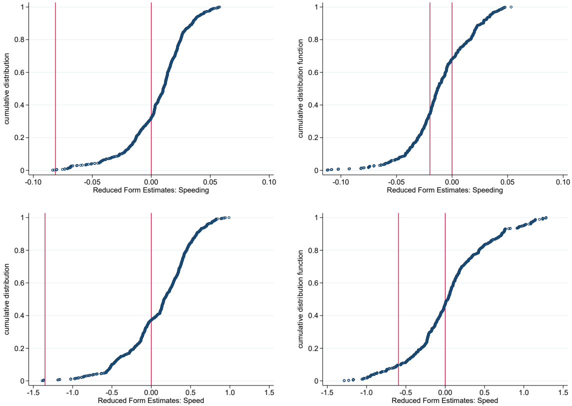
Further Results II: **2nd Ticket**

- Low chance of (strong-) speeding after 1st ticket
  → small sample
- No evidence on *recency effect*

▸ 2nd-ticket

◂ back

Placebo Estimates: enforcement (left) and high-fine cutoff (right panels)



Notes: We randomly shift the respective cutoff by $\pm$2km/h and then run reduced form estimates for our two main outcomes. We iterate this process 1,000 times and compile the resulting point estimates. The figures illustrate the cumulative distribution functions from these placebo estimates for speeding (top panels) and mean speed (bottom panels), with the results for the enforcement cutoff in the left and the high-fine cutoff in the right panels. The vertical red lines indicate null effects and the 'true' reduced form estimates, respectively.

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Estimates at level of rides

	(1) Speeding	(2) (Re)Offending	(3) Speed	(4) Speeding	(5) (Re)Offending	(6) Speed
		1st cutoff			*2nd cutoff*	
Estimate	–0.0707***	–0.0031***	–0.8804***	–0.0279	–0.0025	–0.8247
(β^k)	[0.0139]	[0.0009]	[0.3191]	[0.0271]	[0.0034]	[0.6856]
Y(left)	0.253	0.005	44.515	0.216	0.008	44.424
Relative effect	–27.96%	–60.99%	–1.98%	–12.89%	–29.98%	–1.86%
Bandwidth	3.368	3.633	3.718	3.346	2.086	2.844
Obs.	2,505,113	2,505,113	2,505,113	264,587	264,587	264,587

Bias-corrected RD estimates (reduced form and Wald) with MSE-optimal bandwidth (below/above cutoff) and cluster robust standard errors in brackets (235,335 clusters = cars). Number of observations is 3,219,358 rides.

back

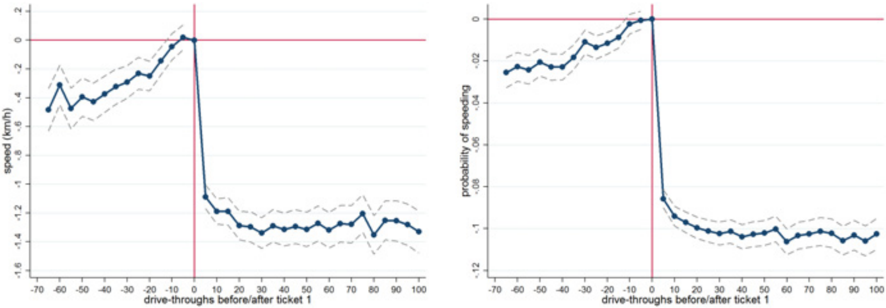
Heterogeneity

	(1) Infrequent	(2) Frequent	(3) Local Region	(4) Prague	(5) Other Regions
	Outcome: Speed (km/h)				
β	-1.6382***	-0.8958***	-0.8913**	-1.4664***	-1.4894**
	[0.3941]	[0.3029]	[0.3673]	[0.3689]	[0.6065]
Y(left)	47.043	45.472	45.719	46.625	46.339
Effect	-0.035	-0.020	-0.019	-0.031	-0.032
	Outcome: Speeding (dummy)				
β	-0.1133***	-0.0807***	-0.0970***	-0.0842***	-0.1099***
	[0.0193]	[0.0163]	[0.0195]	[0.0183]	[0.0308]
Y(left)	0.353	0.274	0.296	0.315	0.335
Effect	-0.321	-0.294	-0.328	-0.267	-0.328
N	125,376	119,959	80,929	110,461	53,945

Bias-corrected RD estimates – frequently vs infrequently (Col. 1–2) observed cars and number plates from Central Bohemia ('Region'), Prague and other areas (Col. 3–5) – with MSE-optimal bandwidth (below/above cutoff) and robust standard errors in brackets. Mean Y (L) indicates baseline within a 0.25km/h bin below cutoff.

back

Estimates by Number of Rides (1st ticket)



Positive pre-treatment trend: consistent with ‘experimentation’ *before* ticket

back

Same vs other camera zones

	(1) same	(2) other	(3) same	(4) other
	Outcome: Speed (km/h)			
β	-1.4297***	-0.9277***	-1.1459***	-1.0742***
	[0.3178]	[0.2671]	[0.3468]	[0.2980]
Y(left)	47.537	44.253	46.946	44.162
Effect	-0.030%	-0.021%	-0.024%	-0.024%
	Outcome: Speeding (dummy)			
β	-0.1236***	-0.0628***	-0.1102***	-0.0656***
	[0.0178]	[0.0137]	[0.0170]	[0.0145]
Y(left)	0.401	0.210	0.378	0.215
Effect	-0.308%	-0.299%	-0.291%	-0.305%
N	194,650	185,710	135,025	135,025

Bias-corrected RD Wald estimates – for the 'same' and 'other' camera zones – with MSE-optimal bandwidth (below/above cutoff) and robust standard errors in brackets. Mean Y (L) indicates baseline within a 0.25km/h bin below cutoff.

back

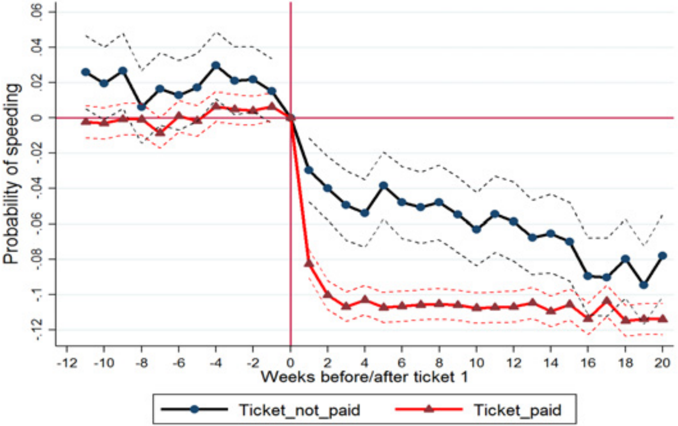
Wald Estimates for 2nd ticket

	(1)	(2)	(3)	(4)	(5)	(6)
	Speeding	Speed	Speeding		Speed	
			Recent	**Non-recent**	**Recent**	**Non-recent**
β	-0.0899***	-0.9432	-0.0737**	-0.1633***	-0.5724	-1.3595
	[0.0335]	[0.6476]	[0.0364]	[0.0607]	[0.9776]	[1.0544]
Y(left)	0.246	44.929	0.213	0.269	45.647	44.441
Effect	-0.365	-0.021	-0.346	-0.607	-0.013	-0.031
N	12,093	12,093	4,991	7,102	4,991	7,102

Bias-corrected RD Wald estimates with MSE-optimal bandwidth (below/above cutoff) and robust standard errors in brackets. Mean Y (L) indicates baseline within a 0.25km/h bin below cutoff. Sample: first, relevant assignment episode after 1st ticket.

◂ back

Heterogeneity: ticket paid (in 90 days), speeding

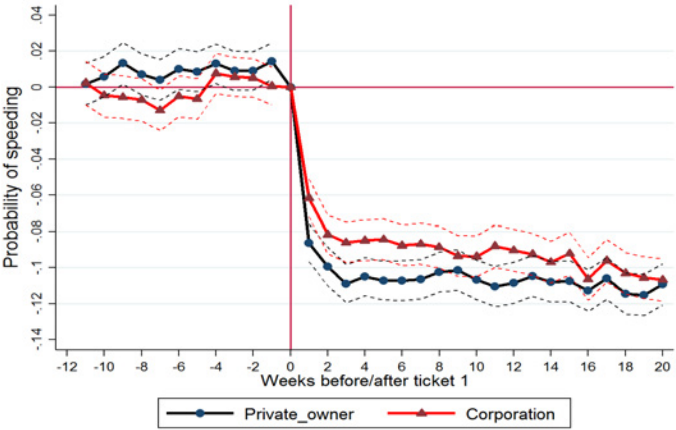


paid:	pre-ticket mean: 0.269	cars: 13,933	obs: 526,066
not paid:	pre-ticket mean: 0.274	cars: 2,474	obs: 100,364

Drivers who do not pay slow down nevertheless

back speed

Heterogeneity: by private/corporation, speeding



private: pre-ticket mean: 0.262 cars: 8,393 obs: 312,885

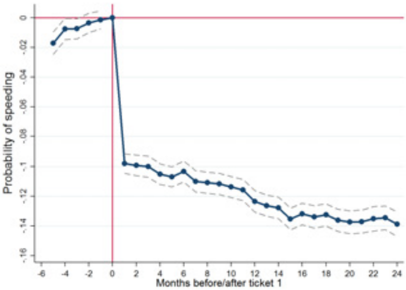
corporation: pre-ticket mean: 0.278 cars: 8,104 obs: 313,545

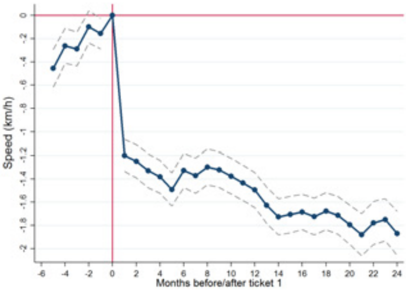
Slightly smaller and slower response by corporate cars

back

speed

Responses to 1st ticket: **24-month period**

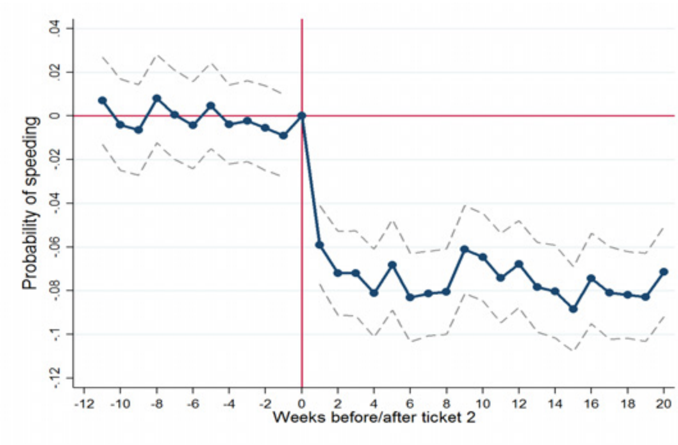




Cars: 4,291. Obs.: 991,333

back

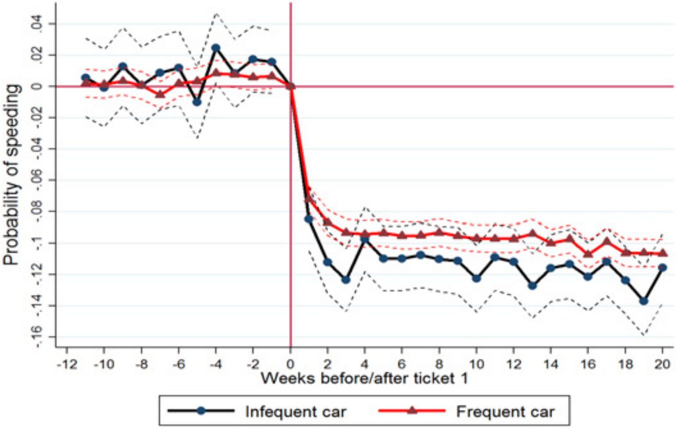
Event study estimates: responses to **2nd Ticket**



Cars: 1,694. Obs.: 101,530

back

Heterogeneity: by driving frequency, speeding

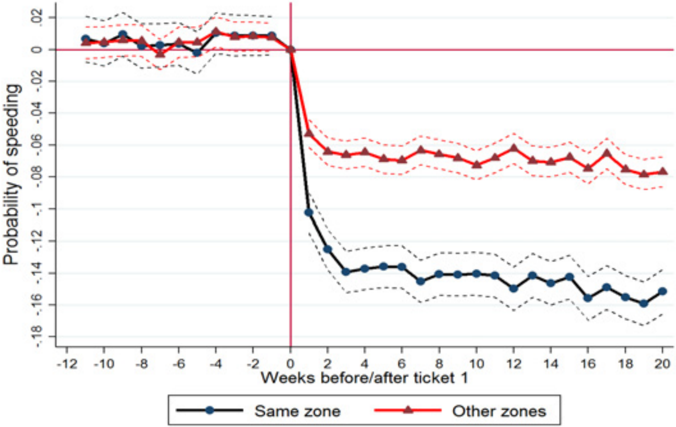


infrequent: pre-ticket mean: 0.321 cars: 8,148 obs: 88,557

frequent: pre-ticket mean: 0.261 cars: 8,259 obs: 537,873

speed back

Heterogeneity: same vs other camera zones, speeding

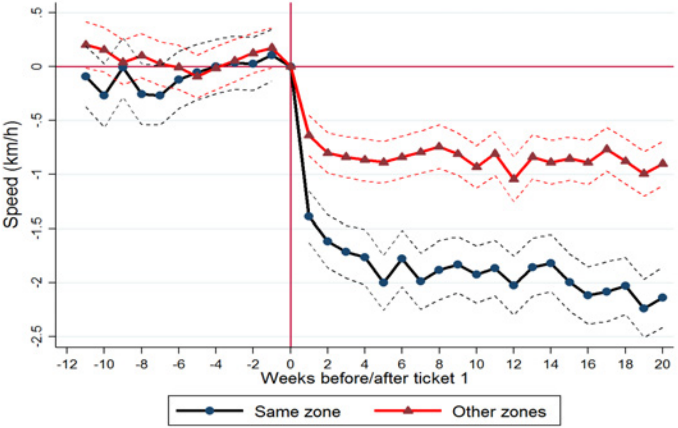


same zone: pre-ticket mean: 0.362 cars: 13,769 obs: 262,282

other zones: pre-ticket mean: 0.199 cars: 14,104 obs: 361,352

speed back

Heterogeneity: same vs other camera zones, speed

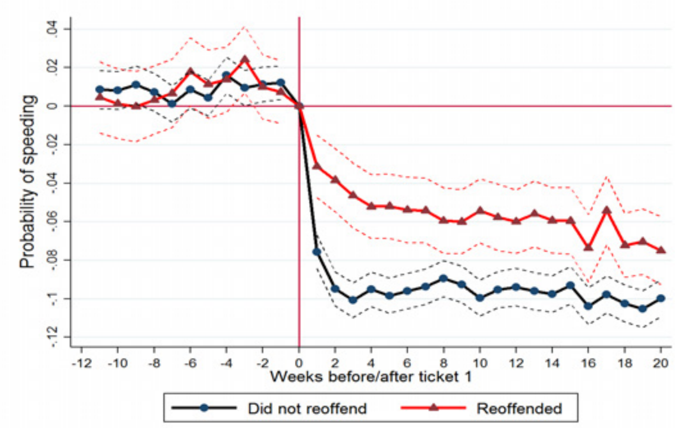


same zone: pre-ticket mean: 46.951 cars: 13,769 obs: 262,282

other zones: pre-ticket mean: 43.244 cars: 14,104 obs: 361,352

speeding back

Response to 1st ticket by reoffence pattern, speeding

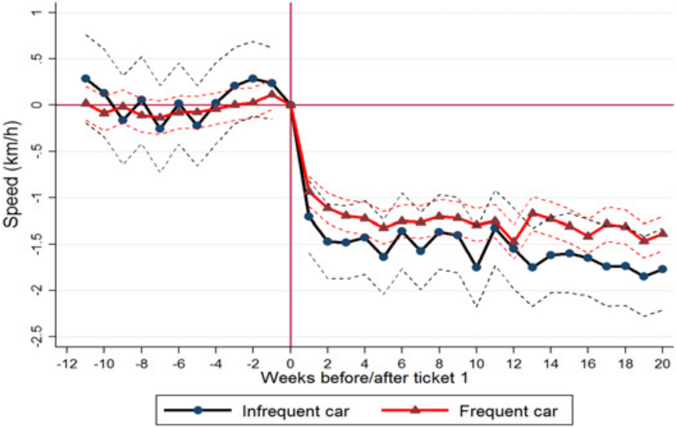


Non-reoffenders, pre-ticket mean: 0.245 cars: 12,802 obs: 417,829

Reoffenders, pre-ticket mean: 0.283 cars: 2,551 obs: 143,292

back

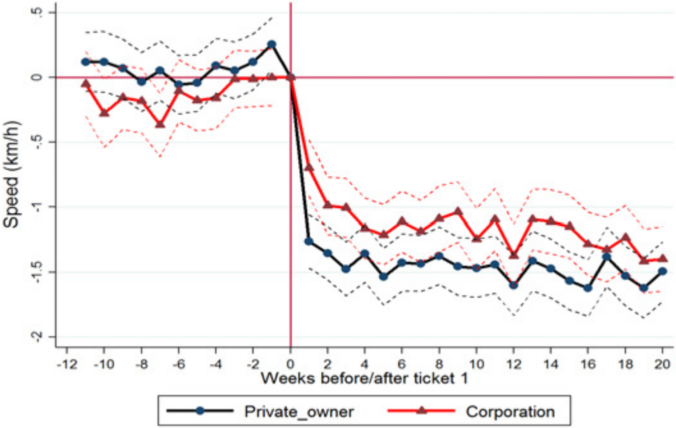
Heterogeneity: by driving frequency, speed



infrequent cars: pre-ticket mean: 46.48 cars: 8,148 obs: 88,557
frequent cars: pre-ticket mean: 44.57 cars: 8,259 obs: 537,873

speed back

Heterogeneity: by private/corporation, speed



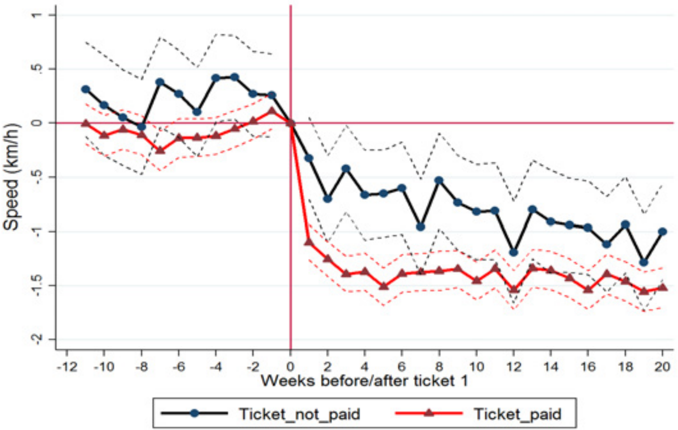
private: pre-ticket mean: 44.74 cars: 8,393 obs: 312,885

corporation: pre-ticket mean: 44.97 cars: 8,104 obs: 313,545

Slightly smaller and slower response by corporate cars back

speeding

Heterogeneity: ticket paid (in 90 days), speed

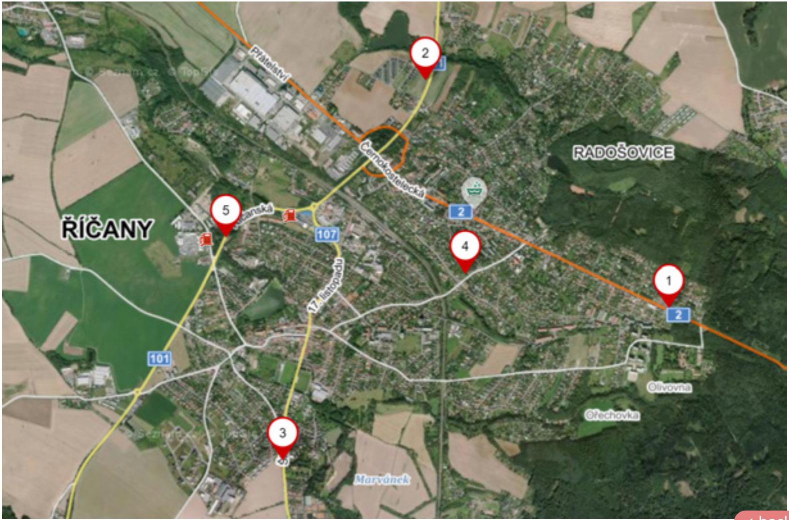


paid: pre-ticket mean: 44.809 cars: 13,933 obs: 526,066

not paid: pre-ticket mean: 45.099 cars: 2,474 obs: 100,364

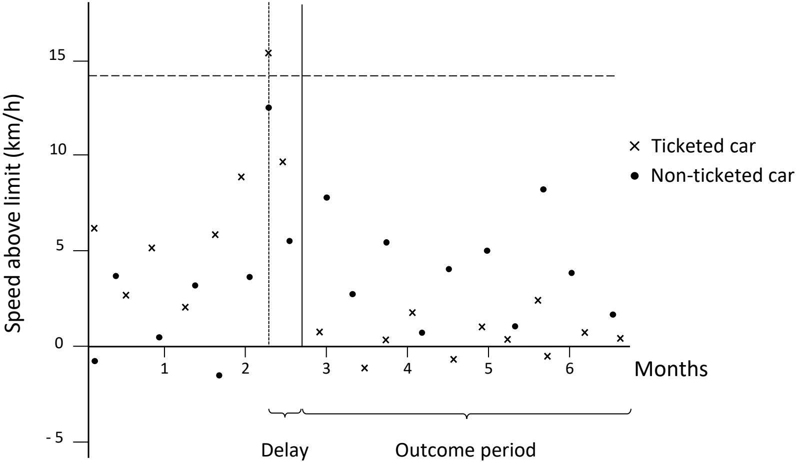
Drivers who do not pay slow down nevertheless. speeding back

Speed camera zones



back

Assignment and outcome windows: illustration



back