Re-examining Moral Hazard in Risky Driving

New Evidence from Behavioral Data in Auto Insurance

(in four graphs)

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University of Toronto



Moral hazard in risky driving: unresolved in the literature

- **Unresolved in the literature**
  - **Empirics are mixed:** some programs cut claims (Weisburd 2015; Jeziorski et al. 2017; Jin and Vasserman 2026), fatality studies find no effect (Cohen and Einav 2003; Cohen and Dehejia 2004), and none observe driving behavior (Chiappori and Salanié 2000; Einav and Finkelstein 2018)
  - **Theoretically ambiguous:** small tail risks overweighted in static choices (Sydnor 2010; Barseghyan et al. 2013) vs. neglected amid overconfidence in daily driving (Kunreuther and Pauly 2004; Gennaioli and Shleifer 2010)

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- **This paper in four graphs: observing risky driving directly**
  1. **Riskiness:** handheld phone use (HPU) nearly doubles crash risk on the road
  2. **Weather:** granular, sudden precipitation barely reduces HPU (-0.189%)
  3. **Insurance:** an unanticipated \$1,000 $\rightarrow$ \$2,500 deductible hike does not reduce HPU
  4. **Platform RCT:** a one-time text reminder of suspension risk cuts HPU by 19.1%

Setting: smartphone sensor data turned into risky driving via ML

Handheld Phone Use





- **Insurer's high-frequency smartphone sensor data**
  - Rideshare app records continuous gyroscope, accelerometer & GPS streams across active drivers (no opt-in selection)
  - One national insurer underwrites both platforms we study from ride acceptance to drop-off

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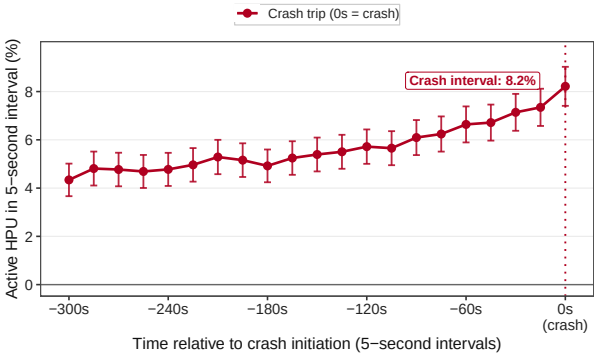
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  - One national insurer underwrites both platforms we study from ride acceptance to drop-off
- **Turned into risky driving (HPU) via an in-house ML algorithm**
  - Isolates handheld phone use (HPU)—texting, handheld calls, or handheld navigation while moving—excluding a cradle or pocket
  - Why focus on HPU: largely unaffected by environmental factors and very precise ($> 99.9\%$ per-second precision on video ground truth)

Graph 1: Handheld phone use nearly doubles crash risk

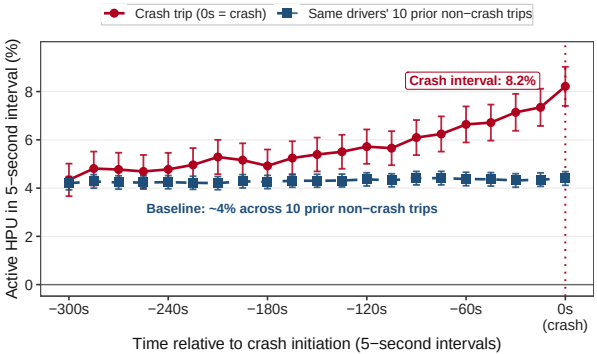


Dataset 1 (4,430 crash drivers): 5-second intervals over a 5-minute window, 95% CIs.

- **Crash trips (red)**
  - Dataset 1: 4,430 crashes tracked in 5-second bins up to crash ($t = 0$)
  - Active HPU climbs to 8.2% right before impact

B1: trip details | B1b: controls & FEs | B5: spec ladder | B5a: hazard table | B5b: IPSW

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  - Active HPU climbs to 8.2% right before impact
- **Same-driver control trips (blue)**
  - 10 randomly sampled prior non-crash trips per driver sit flat at ∼4%
  - Hazard model: HPU nearly doubles crash odds (rain raises marginal risk further)

B1: trip details | B1b: controls & FEs | B5: spec ladder | B5a: hazard table | B5b: IPSW

Do drivers respond to incentives? Three settings

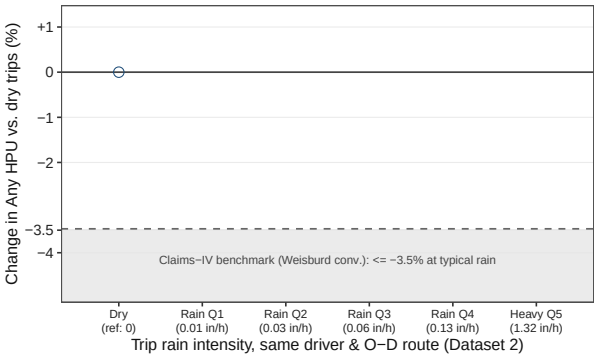
1. **Weather (Graph 2):** granular, sudden precipitation
   Dataset 2 — stratified trip panel on the first platform

2. **Insurance (Graph 3):** one-time, unanticipated \$1,000 → \$2,500 deductible hike
   Dataset 3 — driver-day panel on the second platform

3. **Platform (Graph 4):** text-message reminder of suspension risk
   Dataset 2 — randomized experiment on the first platform

B1: trip details | B1a: sum stats | B1b: 15 controls & FEs | B8: calibrated elasticities

Graph 2: Sudden precipitation barely reduces phone use

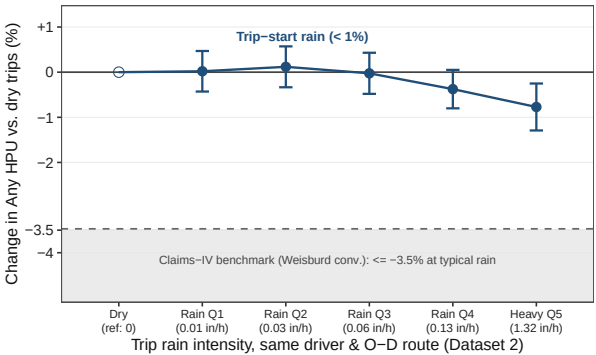


Within-driver %ΔAny HPU across active rain quintiles vs. dry trips, 95% CIs (Dataset 2: 1,821,908 trips).

- **Dataset 2 & within-driver design**
  - 1,821,908 trips (15,251 drivers) matched to minute-by-minute radar rain
  - Same driver, route, date & hour + 15 controls

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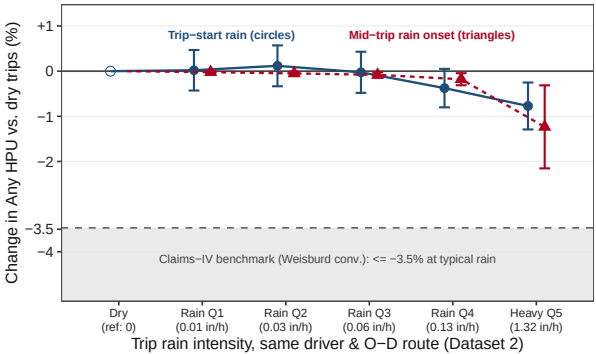


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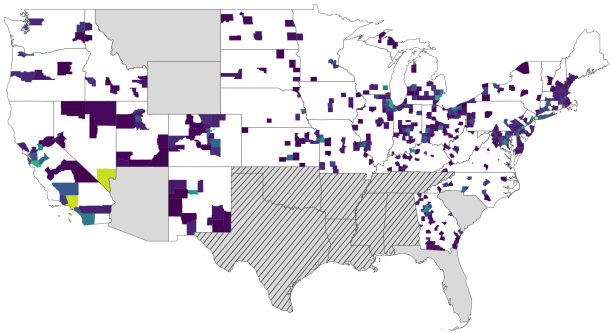


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  - Holds for both trip-start rain and mid-trip rain onset

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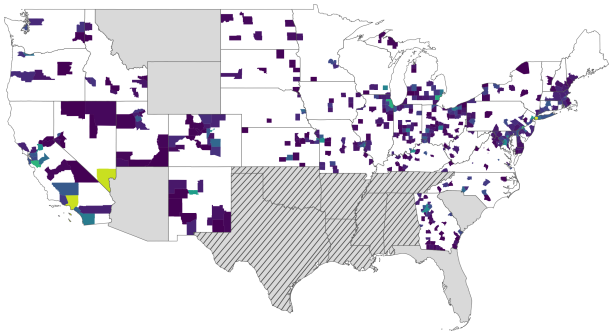
Insurance setting: unanticipated $1,000 to $2,500 deductible hike



- **Dataset 3 & the March 1, 2021 hike**
  - Mandatory commercial policy (no driver coverage choice)
  - Deductible raised $1,000 → $2,500 (143,116 driver-days, 12,881 drivers)

B2: coverage periods B7b: state exclusions

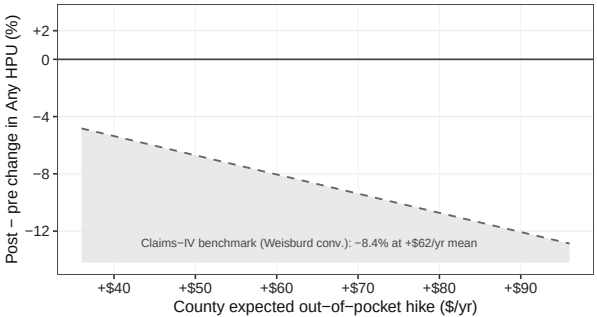
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- **County dose & excluded states**
  - County $\Delta EOOP_c$ backed out from insurer collision pricing
  - Grey states excluded: 7 hatched (Winter Storm Uri) & 5 solid (COVID policy shifts)

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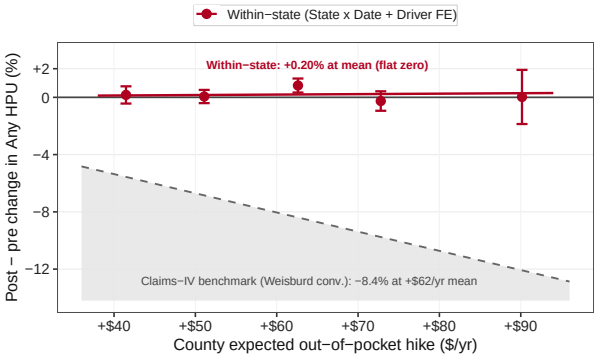
Graph 3: The deductible hike does not reduce phone use



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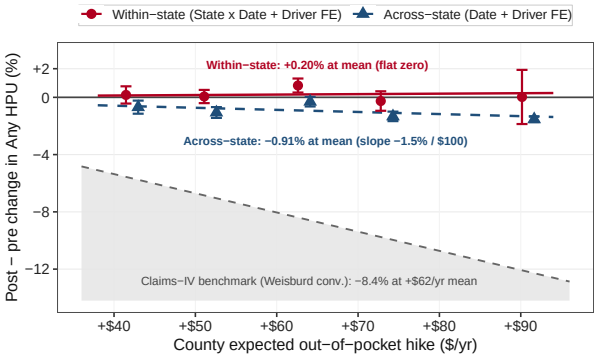


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  - Absorbing driver and state×date FEs, all five dose quintiles sit flat along zero

B1b: controls & FEs | B7: spec ladder | B7a: ded. table | B7b: robustness | B8: calibrated elasticities

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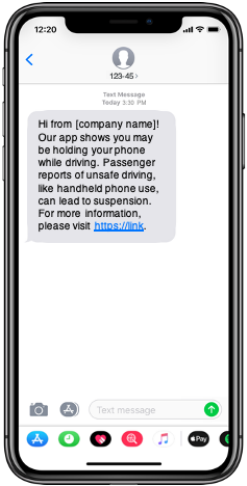


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  - Absorbing driver and state×date FEs, all five dose quintiles sit flat along zero
- **Across-state (blue: same day nationwide)**
  - Using between-state dose variation, estimates remain near zero for both HPU incidence and intensity

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Platform setting: text-message reminder of suspension risk

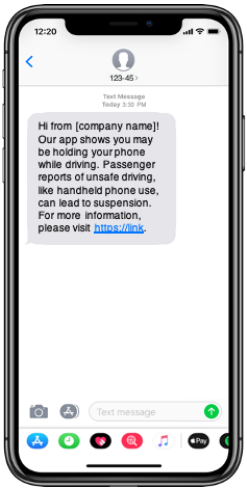


- **One-time text message** (actual prices & platform rules unchanged):

  "Our app shows you may be holding your phone while driving. Passenger reports of unsafe driving, like handheld phone use, can lead to suspension."

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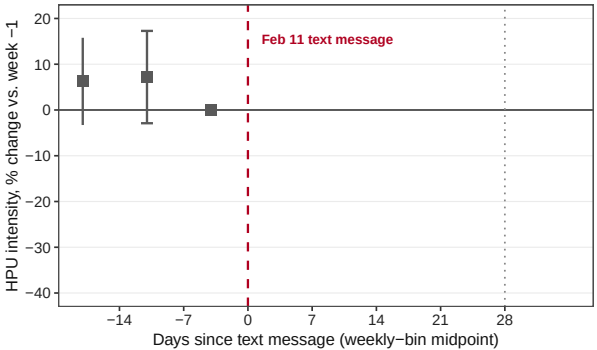
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- **Randomized design on Dataset 2** (Feb 11, 2020)
  - Target pool: 2,503 active top-quintile HPU drivers (20+ hrs/wk)
  - 5:00–5:30 pm EST shift starters randomized 50/50 (343 treated vs. untreated targeted drivers across 464,045 trips)

B1: trip details | B9: strict RCT

Graph 4: One text message cuts phone use sharply and persistently

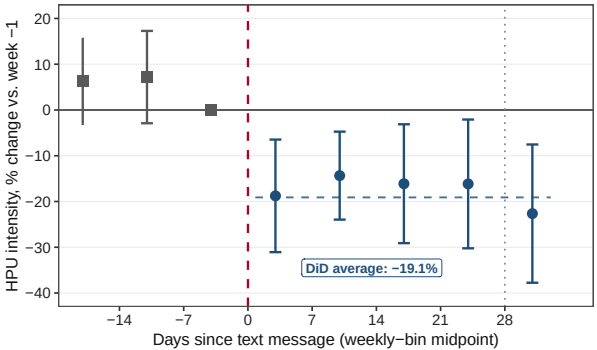


Weekly Poisson event-study on HPU intensity, 95% CIs (Dataset 2 RCT: 464,045 trips, to Mar 16, 2020).

- **Dataset 2 RCT & pre-trends**
  - Treated vs. untreated targeted drivers with driver, date & hour FEs + 15 trip controls
  - Flat pre-trends prior to the Feb 11 text message

B1b: controls & FEs | B11: RCT table | B11a: daily ES

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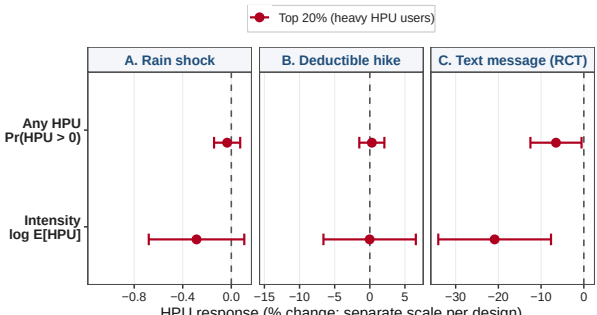


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- **Dataset 2 RCT & pre-trends**
  - Treated vs. untreated targeted drivers with driver, date & hour FEs + 15 trip controls
  - Flat pre-trends prior to the Feb 11 text message
- **Sharp, persistent drop across 5 weeks**
  - HPU plunges immediately and stays down over all 5 post-treatment weeks (hours & trips unchanged)
  - Falls even on pickup segments with no passenger aboard

B1b: controls & FEs | B11: RCT table | B11a: daily ES

Everyday incentives move only safer drivers; the text reminder moves both



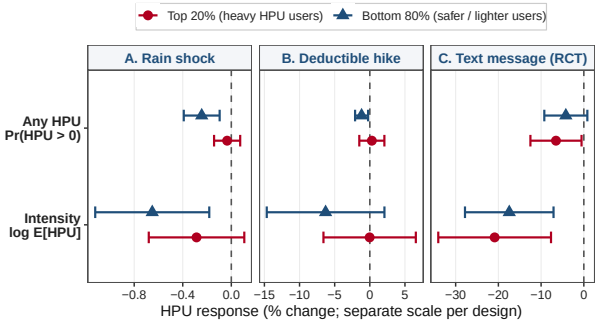
80th-pctl. pre-period HPU split, 95% CIs; experiment splits the targeted top-quintile pool.

Overall paper takeaway

1. **Safer drivers self-regulate:** respond to everyday incentives while heavy users do not—and account for too little HPU to move the aggregate

B11b: table | B11c: subgroup ES

Everyday incentives move only safer drivers; the text reminder moves both



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Overall paper takeaway

1. **Safer drivers self-regulate:** respond to everyday incentives while heavy users do not—and account for too little HPU to move the aggregate
2. **Salience moves both groups:** one text reminder cuts HPU sharply across both safer and heavy users

B11b: table B11c: subgroup ES

Conclusion: HPU responds to the price of risk drivers perceive

- **Muted moral hazard under passive incentives**
  - Implied elasticity $|\hat{\beta}| \leq 0.032$ from sudden rain and the \$1,000 $\rightarrow$ \$2,500 deductible hike—well below claims-based benchmarks (0.1–0.4 (Weisburd 2015)) and zero in the heavy tail
  - Consistent with neglect of rare, multifactorial crash risks in daily driving ($\hat{\beta} = \beta\phi$ with $\phi \ll 1$), not inelastic preferences

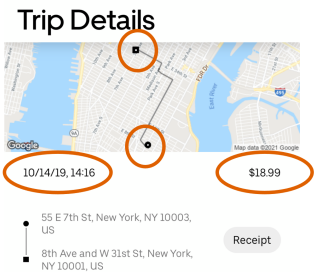
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  - Consistent with neglect of rare, multifactorial crash risks in daily driving ($\hat{\beta} = \beta\phi$ with $\phi \ll 1$), not inelastic preferences
- **Salience vs. higher deductibles in contract design**
  - A one-time text reminder of suspension risk cuts HPU by 19.1% over five weeks and moves heavy users (-20.9% in the top quintile)
  - High deductibles shift uninsured financial risk onto drivers without deterring distracted driving; targeted, salient feedback and telematics monitoring (Jin and Vasserman 2026) directly reduce road risk

B8: elasticity $\hat{\beta}$ | B10: 2023 model | B13: 2023 ctf.

Appendix B1: trip details, controls, and app telemetry

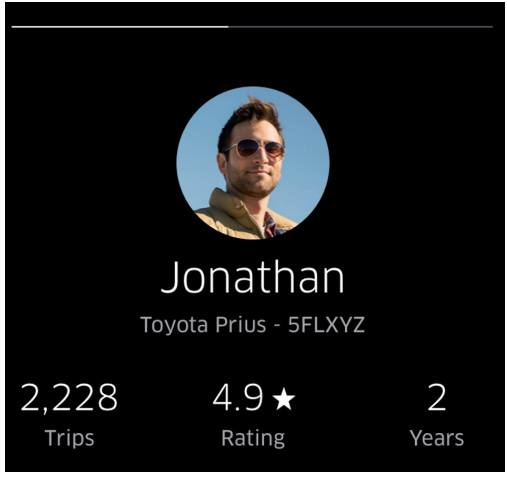


Trip-level telemetry and controls.

- **Three datasets across two U.S. platforms**
  - **Dataset 1 (first platform):** 4,430 crash drivers, crash + 10 prior trips (12,965,344 5-s intervals)
  - **Dataset 2 (first platform):** 1,821,908 trips, 15,251 drivers (31% rainy; rain & SMS RCT)
  - **Dataset 3 (second platform):** 143,116 driver-days, 12,881 drivers (deductible hike)
- **High-dimensional fixed effects & 15 trip controls**
  - **FEs:** driver i, origin–destination geohash-5 location pair, calendar date, hour of day
  - **15 controls:** earnings/mi, pickup share, geohash-6 origin demand, rider calls/texts, platform pushes, reroutes, cancellations, pickups/drop-offs

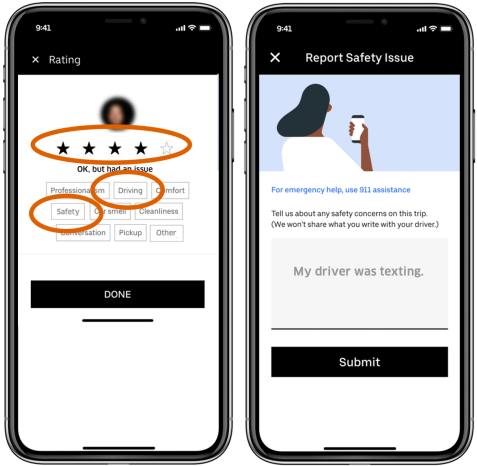
B1a: sum stats | B1b: control coefs | ⟷ Setting | ⟷ Weather

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Driver detail.

Appendix B1: trip details, controls, and app telemetry



Event classification.

Appendix B1a: summary statistics by dataset

Variable	Mean	Std. Dev.	Pctl(10)	Median	Pctl(90)
Panel A: Accident-Driver Panel (Dataset 1) — N = 12,965,344 five-second intervals, 4,430 accident drivers					
HPU (= 1 if active)	0.039	0.194	0.000	0.000	0.000
Speed (mph)	27.5	29.4	0.8	17.0	75.4
Has precip. (= 1)	0.336	0.472	0.000	0.000	1.000
Precip. (in/hr | precip.)	0.186	0.281	0.010	0.060	0.511
Trip-mean precip. (in/hr | precip.)	0.186	0.074	0.104	0.178	0.274
Is night (= 1)	0.394	0.489	0.000	0.000	1.000
Accident (= 1)	0.00034	0.01848	0.00000	0.00000	0.00000
Panel B: Trip-level Panel (Dataset 2) — Jan–Mar 2020, N = 1,821,908 trips, 15,251 drivers					
Age (years)	37.7	11.5	24.8	35.0	55.0
Is female	0.21	0.41	0.00	0.00	1.00
Tenure (years)	1.5	1.2	0.2	1.3	3.2
Past rides completed	213.2	287.0	0.0	111.0	564.0
Distance (miles)	8.5	8.3	2.0	6.1	17.8
Duration (minutes)	21.6	12.9	9.7	18.6	36.8
Pct. drive-time with passenger	0.71	0.16	0.48	0.74	0.90
Speed (mph)	21.2	10.0	9.8	19.4	35.3
Is weekend	0.26	0.44	0.00	0.00	1.00
Is night	0.27	0.45	0.00	0.00	1.00
Has precip.	0.31	0.46	0.00	0.00	1.00
Precip. intensity (in/hr | precip.)	0.309	0.898	0.016	0.055	0.736
HPU (m/km)	66.5	130.1	0.0	9.0	207.2
Harsh acceleration per 1k miles	26.97	96.42	0.00	0.00	79.54
Harsh braking per 1k miles	53.85	126.27	0.00	0.00	172.99
Harsh cornering per 1k miles	6.96	34.36	0.00	0.00	0.00
Panel C: Driver-Day Policy Panel (Dataset 3) — Feb–Mar 2021, N = 143,116 driver-days, 12,881 drivers					
Age (years)	46.6	12.1	31.0	46.1	63.1
Is female	0.17	0.37	0.00	0.00	1.00
Tenure (years)	2.0	1.5	0.1	1.9	3.9
HPU (m/km)	70.0	136.9	0.0	9.5	218.0
Pct. drive-time with passenger	0.63	0.12	0.50	0.65	0.77
Driving hours per day	3.61	2.56	0.74	3.10	7.25
Driving miles per day	90.6	67.3	16.6	76.6	183.8
Expected OOP increase, $1,000→$2,500 ($/yr)	62.1	15.5	42.3	61.3	91.3

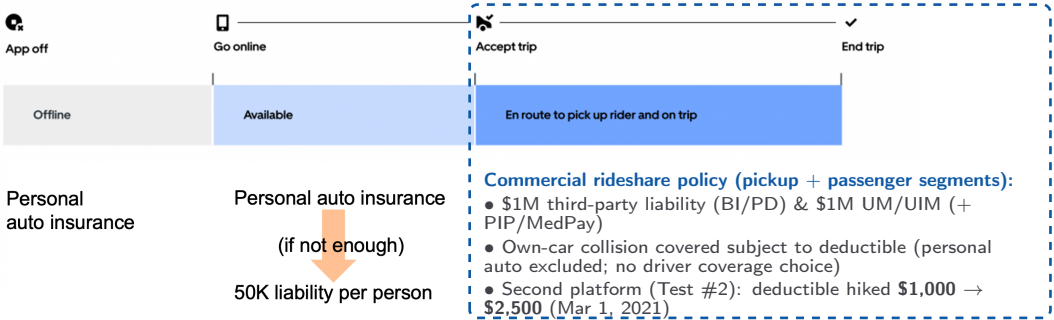
↩ Settings ↩ Weather

Appendix B1b: trip-level control estimates

	(1) Precipitation T.B6 col. 4 LPM $\Pr(\text{HPU} > 0)$	(2) Precipitation T.B6 col. 8 Poisson log $E[\text{HPU}]$	(3) Experiment T.B11 col. 3 Poisson log $E[\text{HPU}]$
Harmonized trip-level controls (trip economics, origin demand, in-app interactions)			
Driver earnings ($/mi)	0.0034^{***}	0.0026^{**}	-0.0632^{***}
	(1.97×10^{-4})	(0.0012)	(0.0032)
Pickup-phase (P2) duration share	0.1347^{***}	1.1345^{***}	—
	(0.0036)	(0.0218)	
Origin population density (per sq. mi)	$1.55 \times 10^{-7*}$	$-7.81 \times 10^{-7**}$	$-3.78 \times 10^{-6***}$
	(8.01×10^{-8})	(3.68×10^{-7})	(6.61×10^{-7})
Origin ride requests (per hour)	$-9.23 \times 10^{-5***}$	$-5.84 \times 10^{-4***}$	-0.0019^{***}
	(1.68×10^{-5})	(7.66×10^{-5})	(2.27×10^{-4})
Rides added (per mi)	-0.0625^{***}	0.1952^{***}	0.5628^{***}
	(0.0023)	(0.0144)	(0.0340)
Rides canceled (per mi)	0.0698^{***}	-0.1501^{***}	abs.
	(0.0055)	(0.0269)	
Rider cancellations (per mi)	4.02×10^{-4}	0.0269^{*}	-0.0360
	(0.0034)	(0.0148)	(0.0578)
Pickups (per mi)	-3.10×10^{-4}	-0.0797^{***}	0.1414^{***}
	(0.0024)	(0.0104)	(0.0163)
Dropoffs (per mi)	-1.66×10^{-4}	0.1414^{***}	-0.0716^{*}
	(0.0049)	(0.0225)	(0.0385)
Reroutes (per mi)	4.49×10^{-4}	3.95×10^{-4}	0.0233^{***}
	(3.99×10^{-4})	(0.0016)	(0.0085)
Calls from rider (per mi)	0.0461^{***}	0.0847^{***}	0.2065^{***}
	(0.0017)	(0.0079)	(0.0132)
Texts from rider (per mi)	0.0304^{***}	0.0567^{***}	0.2543^{***}
	(0.0024)	(0.0104)	(0.0323)
Platform pushes (per mi)	0.0055^{***}	0.0098^{***}	0.1400^{***}
	(7.03×10^{-4})	(0.0025)	(0.0422)
Texts from platform (per mi)	0.0443^{***}	0.0959^{***}	0.3378^{***}
	(0.0039)	(0.0156)	(0.0528)
App crashes (per mi)	0.0248	-0.2206	-2.49×10^{3}
	(0.0316)	(0.1550)	(2.08×10^{3})
Exposure offset	—	log(miles)	log(miles)
Location-pair FE	Yes	Yes	—
Date FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Driver FE	Yes	Yes	Yes
SE cluster	Driver × date	Driver × date	Driver
Observations	1,687,611	1,675,350	463,872

↩ Weather ↩ Deductible ↩ Experiment

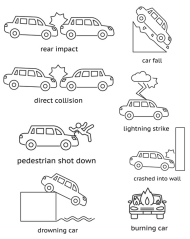
Appendix B2: rideshare insurance coverage periods



Rideshare insurance across app states; our data and all three empirical designs study active trips from request acceptance to drop-off.

↩ Setting ↩ Deductible

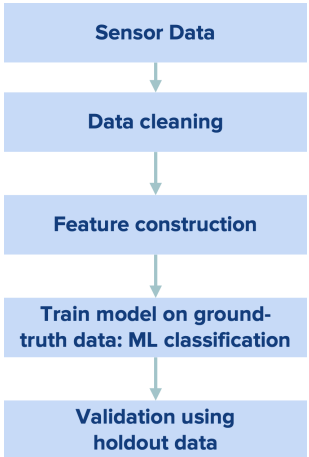
Appendix B3: phone movements that are not HPU

Handheld Phone Use	Mounted Phone Use	Misc. Phone Move	Accidents/Brakes	Bumps/Swerving
				
				

↩ Back

Appendix B4: ML algorithm development steps

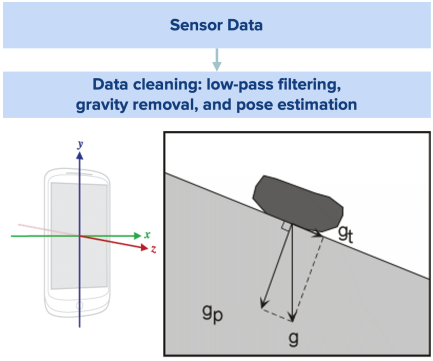
- smartphone sensor data → handheld phone use ("HPU") events

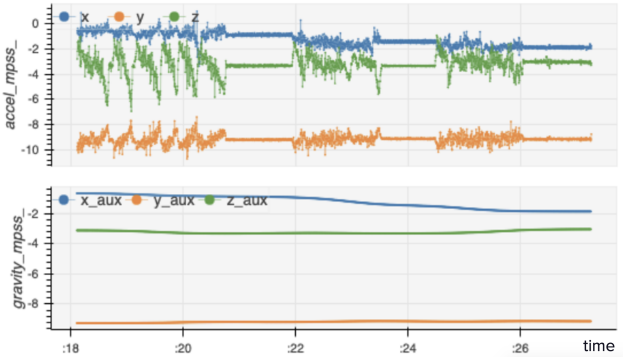


↩ Back

Appendix B4: ML algorithm development steps

- smartphone sensor data → handheld phone use ("HPU") events

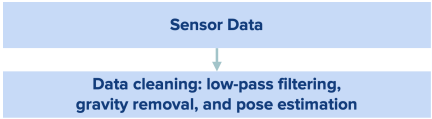


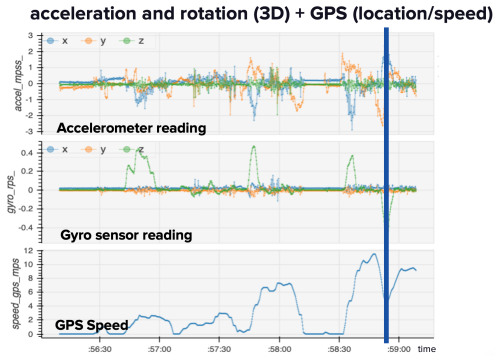


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Appendix B4: ML algorithm development steps

- smartphone sensor data → handheld phone use ("HPU") events

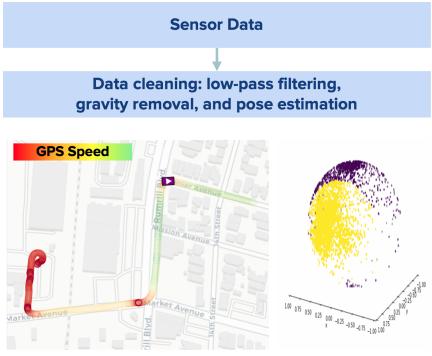


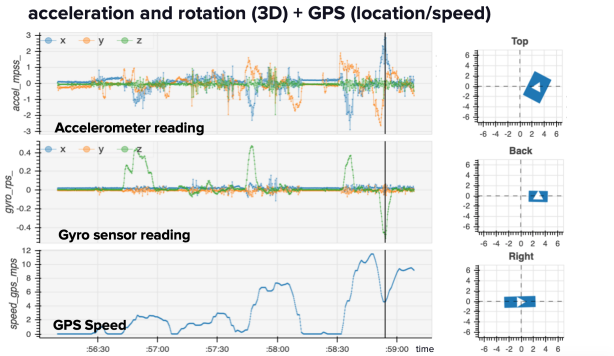


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Appendix B4: ML algorithm development steps

- smartphone sensor data → handheld phone use ("HPU") events





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Appendix B4: ML algorithm development steps

- smartphone sensor data → handheld phone use ("HPU") events

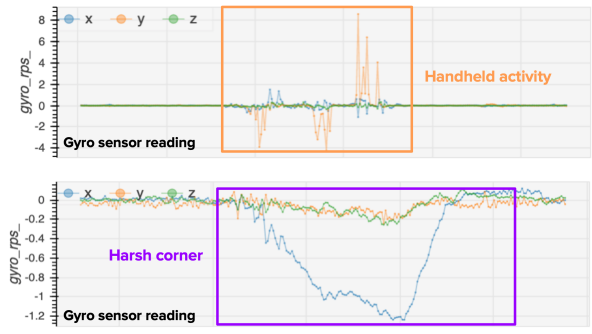
Sensor Data

↓

Data cleaning: low-pass filtering, gravity removal, and pose estimation

↓

Feature construction: abnormal sensor movement based on moment thresholds on all three sensors



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Appendix B4: ML algorithm development steps

- smartphone sensor data → handheld phone use ("HPU") events

Sensor Data

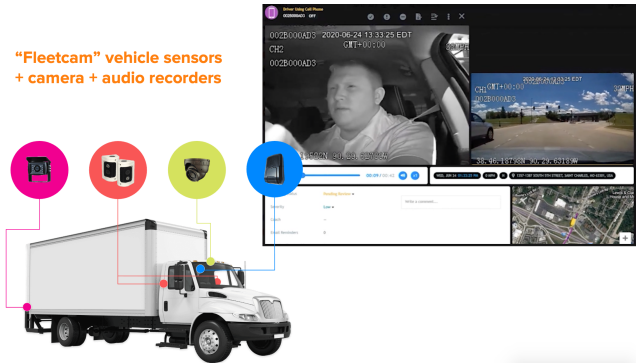
Data cleaning: low-pass filtering, gravity removal, and pose estimation

Feature construction: abnormal sensor movement based on moment thresholds on all three sensors

Train: ML classification problem based on ground-truth training data (kNN/GBDT)

Validation: model tuning based on ground-truth holdout data

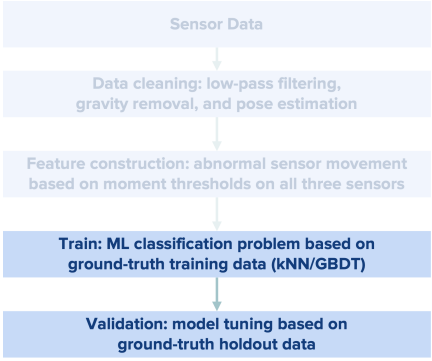
"Fleetcam" vehicle sensors + camera + audio recorders

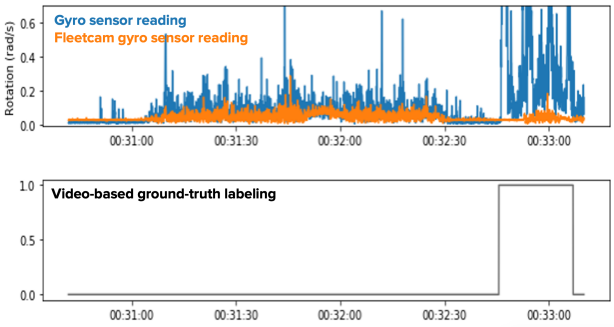


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Appendix B4: ML algorithm development steps

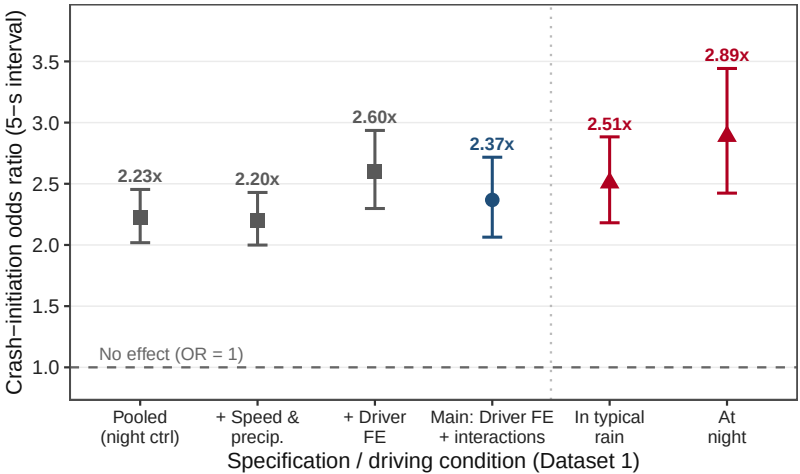
- smartphone sensor data → handheld phone use ("HPU") events





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Appendix B5: hazard specification ladder



5-s crash-initiation odds ratios across progressive fixed-effects saturations and driving conditions, 95% CIs (Dataset 1: 12,965,344 intervals, 4,430 drivers; main spec = Col. 7 driver FE + condition interactions).

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Appendix B5a: hazard model estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HPU	0.8000***	0.7922***	0.7901***	0.9545***	1.3270***	0.5637***	0.7075***	1.2829***
	(0.0498)	(0.0497)	(0.0497)	(0.0625)	(0.0937)	(0.0838)	(0.0949)	(0.0983)
Speed (mph)		0.0110***	0.0114***	0.0128***	0.0158***	0.0081***	0.0086***	0.0157***
		(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0008)	(0.0008)	(0.0009)
Precipitation			0.7281***	0.7528***	0.7356***	0.6754***	0.6923***	0.6833***
			(0.0552)	(0.0573)	(0.0818)	(0.0745)	(0.0770)	(0.0923)
Night	0.5236***	0.4055***	0.4225***	0.5234***		0.3466***	0.4333***	
	(0.0302)	(0.0303)	(0.0305)	(0.0354)		(0.0354)	(0.0398)	
HPU × Speed						0.0021	0.0027	0.0023
						(0.0017)	(0.0018)	(0.0024)
HPU × Precip						0.3751**	0.4068**	0.3406
						(0.1487)	(0.1669)	(0.2295)
Speed × Precip						0.0017	0.0021	−0.0018
						(0.0019)	(0.0021)	(0.0026)
HPU × Night						0.2996***	0.3278***	
						(0.1139)	(0.1210)	
Speed × Night						0.0050***	0.0068***	
						(0.0010)	(0.0011)	
Precip × Night						0.0084	0.0224	
						(0.1162)	(0.1228)	
Interactions	No	No	No	No	No	Yes	Yes	Yes
Driver FE	No	No	No	Yes	No	No	Yes	No
Trip FE	No	No	No	No	Yes	No	No	Yes
Observations (intervals)	12,965,344	12,965,344	12,965,344	12,965,344	840,152	12,965,344	12,965,344	840,152

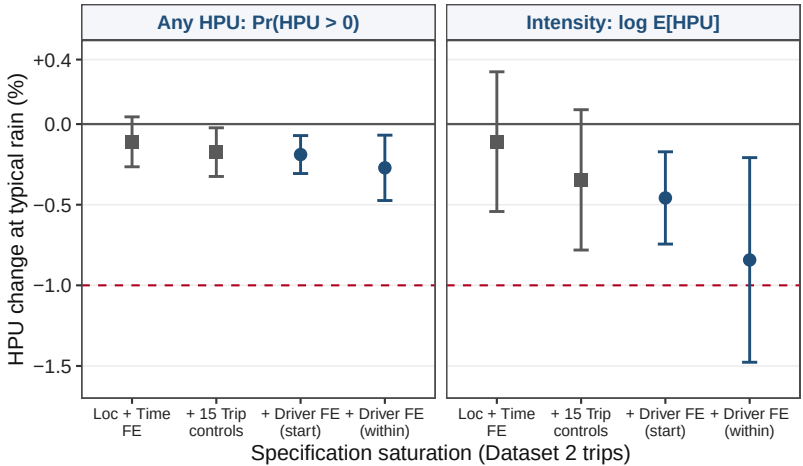
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Appendix B5b: hazard sampling and IPSW robustness

	(A) Main	(B) Accident trips only	(C) 2 earlier trips	(D) IPSW	(E) Crash interval vs. earlier trips	(F)
HPU	0.7075***	1.2626***	0.7637***	0.7042***	0.7060***	0.5643***
	(0.0949)	(0.1054)	(0.1071)	(0.0980)	(0.0977)	(0.0859)
Speed (mph)	0.0086***	0.0157***	0.0100***	0.0089***	0.0089***	0.0084***
	(0.0008)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0008)
Precipitation	0.6923***	0.6993***	0.6704***	0.7082***	0.7092***	0.6892***
	(0.0770)	(0.0890)	(0.0885)	(0.0785)	(0.0783)	(0.0753)
Night	0.4333***		0.6044***	0.4893***	0.4913***	0.3856***
	(0.0398)		(0.0583)	(0.0427)	(0.0428)	(0.0373)
HPU × Precip	0.4068**	0.3406	0.4952**	0.4624**	0.4495**	0.4092**
	(0.1669)	(0.2295)	(0.1953)	(0.1888)	(0.1819)	(0.1631)
HPU × Speed	0.0027	0.0023	0.0037*	0.0030	0.0031	0.0023
	(0.0018)	(0.0024)	(0.0021)	(0.0020)	(0.0020)	(0.0018)
Speed × Precip	0.0021	−0.0018	0.0005	0.0031	0.0030	0.0024
	(0.0021)	(0.0026)	(0.0023)	(0.0022)	(0.0022)	(0.0021)
HPU × Night	0.3278***		0.3020**	0.3604***	0.3610***	0.3167***
	(0.1210)		(0.1411)	(0.1258)	(0.1257)	(0.1176)
HPU odds ratio at mean conditions	2.37	3.61	2.49	2.40	2.40	2.04
	[2.06, 2.72]	[2.95, 4.42]	[2.14, 2.90]	[2.08, 2.76]	[2.09, 2.77]	[1.82, 2.30]
Driver FE	Yes	No	Yes	Yes	Yes	No
Trip FE	No	Yes	No	No	No	No
Sampling weights	No	No	No	Yes	No	No
Observations (intervals)	12,965,344	840,152	3,269,882	12,965,344	12,129,618	12,129,620
Trips	48,661	4,428	13,284	48,661	48,659	48,661
Crashes	4,430	4,428	4,430	4,430	4,428	4,430

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Appendix B6: precipitation specification ladder



%ΔHPU at mean rainy-trip intensity across progressive controls and driver fixed effects, 95% CIs (Dataset 2: 1,821,908 trips).

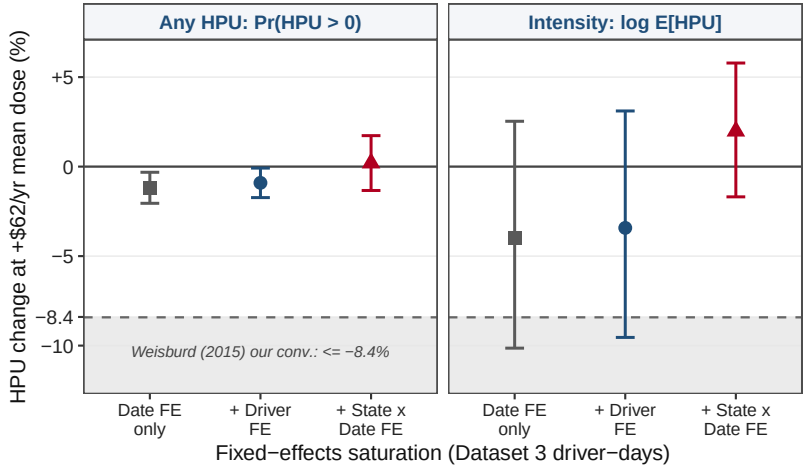
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Appendix B6a: precipitation and HPU

	Extensive: P(HPU > 0) (LPM)				QMLE: log $E[\mathrm{HPU}]$ (Poisson)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rain indicator	−0.0004	−0.0001	−0.0001	−0.0001	−0.0154**	−0.0135**	−0.0024	−0.0023
	(0.0015)	(0.0015)	(0.0011)	(0.0011)	(0.0064)	(0.0063)	(0.0037)	(0.0037)
Rain × start intensity	−0.0040	−0.0063**	−0.0068***		−0.0059	−0.0187	−0.0248***	
	(0.0028)	(0.0028)	(0.0021)		(0.0119)	(0.0120)	(0.0079)	
Rain × Δ intensity	−0.0100**	−0.0108**	−0.0098**		−0.0247	−0.0367	−0.0457***	
	(0.0045)	(0.0044)	(0.0037)		(0.0237)	(0.0229)	(0.0176)	
Rain × avg intensity				−0.0065***				−0.0237***
				(0.0021)				(0.0078)
%Δ HPU at mean rain	−0.110	−0.174**	−0.189***	−0.181***	−0.109	−0.346	−0.458***	−0.435***
	(0.079)	(0.077)	(0.060)	(0.059)	(0.221)	(0.222)	(0.146)	(0.143)
Location + Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trip-level controls (15)	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Driver FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1,689,022	1,689,022	1,687,611	1,687,611	1,677,339	1,677,339	1,675,350	1,675,350

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Appendix B7: deductible specification ladder



%ΔHPU at +$62/yr mean dose across progressive fixed-effects saturations, 95% CIs (Dataset 3, Feb 19–Mar 9, 2021).

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Appendix B7a: the deductible increase and HPU

	Extensive: Pr(HPU > 0) (LPM)			QMLE: log E[HPU] (Poisson)		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEOOP ($100/yr)	−0.01916	—	—	−0.01618	—	—
	(0.02385)			(0.27239)		
Post × ΔEOOP	−0.016794***	−0.012874**	+0.002818	−0.06598	−0.05611	+0.03159
	(0.006274)	(0.005971)	(0.011094)	(0.05421)	(0.05379)	(0.03012)
Semi-elasticity k (%ΔHPU per $100/yr)	−1.91***	−1.46**	+0.32	−6.38	−5.46	+3.21
	(0.71)	(0.68)	(1.26)	(5.08)	(5.09)	(3.11)
Driver-day controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	-	Yes	Yes	-
State × Date FE	No	No	Yes	No	No	Yes
Driver FE	No	Yes	Yes	No	Yes	Yes
Pre-trend F (p)	3.82 (0.00)	1.72 (0.08)	1.01 (0.43)	0.47 (0.90)	0.63 (0.77)	0.71 (0.70)
N (driver-day × phase obs.)	284,370 (N_{drv} = 12,881, N_{cty} = 466, N_{st} = 39)					

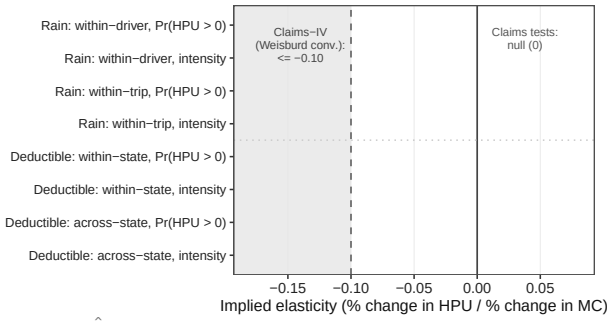
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Appendix B7b: deductible robustness

	Within-state (Driver + State×Date)			Across-state (Driver + Date)		
Variant	Ext. %Δ	Int. %Δ	PT	Ext. %Δ	Int. %Δ	PT
Baseline	+0.20 (0.78)	+1.98 (1.91)	✓✓	−0.91** (0.42)	−3.42 (3.23)	✓✓
Clustering						
driver-clustered SE	+0.20 (0.77)	+1.98 (1.92)	✓✓	−0.91* (0.47)	−3.42*** (1.07)	✓✓
state-clustered SE	+0.20 (0.61)	+1.98 (2.39)	××	−0.91** (0.43)	−3.42 (2.98)	✓✓
Sample						
+ storm states	−0.16 (0.39)	+1.47 (1.70)	✓×	−0.83*** (0.29)	−5.34*** (1.65)	××
±8-day window	+0.04 (0.82)	+1.90 (1.92)	✓✓	−0.79* (0.44)	−2.92 (2.72)	✓✓
Dose construction						
Pareto severity	+0.10 (0.67)	+1.49 (1.66)	✓✓	−0.77** (0.31)	−2.96 (2.72)	✓✓
2023 pricing	+0.19 (0.65)	+1.48 (1.56)	✓✓	−0.80** (0.36)	−2.37 (2.81)	✓✓
Labor supply						
Driving hours	−1.31 (1.64)	−0.04 (2.24)	××	−1.50 (1.16)	+2.01 (2.03)	××

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Appendix B8: calibrated elasticity summary across settings

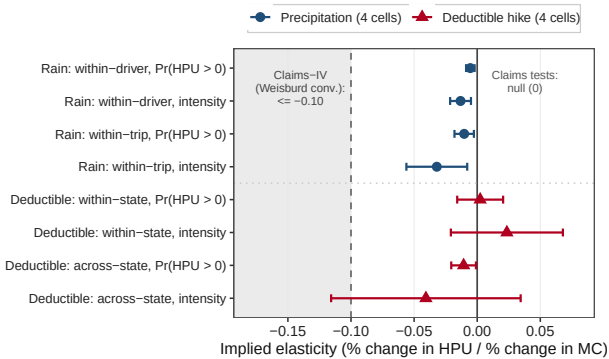


Calibrated $\hat{\beta} = \%\Delta\text{HPU}/\%\Delta\text{MC}$ across all 8 rows of Table 5, 95% CIs.

- **Unified $\hat{\beta}$ scale & claims benchmarks**
  - Divide %ΔHPU by %ΔMC across rain (4 cells) & deductible (4 cells)
  - Claims IV 0.1–0.4 (left grey (Weisburd 2015)) vs. claims-test nulls at 0 (Chiappori and Salanié 2000; Abbring et al. 2003)

B8a: table ⟷ Settings ⟷ Deductible

Appendix B8: calibrated elasticity summary across settings



Calibrated $\hat{\beta} = \%\Delta\text{HPU}/\%\Delta\text{MC}$ across all 8 rows of Table 5, 95% CIs.

- **Unified $\hat{\beta}$ scale & claims benchmarks**
  - Divide $\%\Delta$HPU by $\%\Delta$MC across rain (4 cells) & deductible (4 cells)
  - Claims IV 0.1–0.4 (left grey (Weisburd 2015)) vs. claims-test nulls at 0 (Chiappori and Salanié 2000; Abbring et al. 2003)
- **Behavioral estimates reconcile both**
  - Rain $|\hat{\beta}| \in [0.005, 0.032]$; deductible ≈ 0.011 across states, ≈ 0 within state
  - Claims IV bundles reporting & miles; $|\hat{\beta}| \leq 0.032$ looks like 0 in rare claims

B8a: table ⟷ Settings ⟷ Deductible

Appendix B8a: calibrated elasticity $\hat{\beta}$ table

Identification	% Δ HPU (SE)	% Δ MC	$\hat{\beta}$ (SE)
Panel A: Precipitation (weather-amplified marginal cost)			
Within-driver variation			
Extensive margin	-0.189^{***} (0.060)	$+34.71$	-0.005^{***} (0.002)
QMLE	-0.458^{***} (0.146)	$+34.71$	-0.013^{***} (0.004)
Within-trip variation			
Extensive margin	-0.271^{***} (0.103)	$+26.32$	-0.010^{***} (0.004)
QMLE	-0.842^{***} (0.324)	$+26.32$	-0.032^{***} (0.012)
Panel B: Collision deductible \$1,000→\$2,500 (out-of-pocket cost)			
Within-state variation			
Extensive margin	0.20 (0.78)	$+84.23$	0.002 (0.009)
QMLE	1.98 (1.91)	$+84.23$	0.024 (0.023)
Across-state variation			
Extensive margin	-0.91^{**} (0.42)	$+84.23$	-0.011^{**} (0.005)
QMLE	-3.42 (3.23)	$+84.23$	-0.041 (0.038)

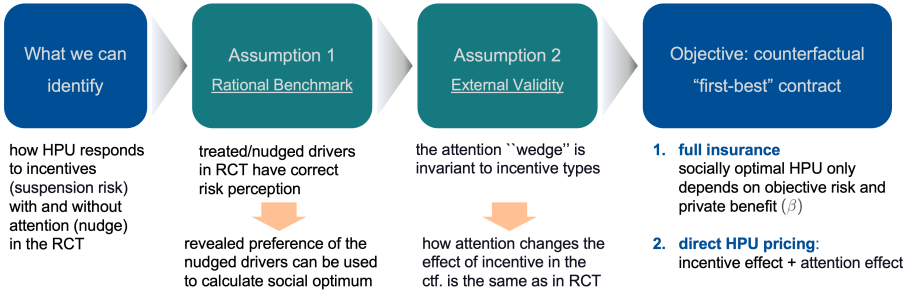
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Appendix B9: randomized controls only

- main difference-in-differences: 343 treated vs. all 2,160 untreated targeted drivers, with driver fixed effects
- strict experimental comparison: 343 treated vs. the 407 drivers who logged on in the same window and were randomized to control, used as a robustness check (Online Appendix)
- restricting the comparison to the randomized controls gives a similar estimate to the -19.1% main difference-in-differences (Online Appendix)
- balance against both control groups: age, gender, and the platform-recorded histories of accidents, unsafe rides, safety tickets, rides and earnings are balanced; treated drivers start with pre-period HPU roughly a fifth below either control mean and about 0.2 years less tenure, which driver fixed effects absorb

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Appendix B10: companion structural model (2023 draft)



A structural model with an attention wedge: "How to Prevent Traffic Accidents" (SSRN 4102446, 2023 draft); estimates are from that draft's sample. 2023 draft notation: α is a level wedge on the perceived price ($\alpha\,\xi$); the main slides use ϕ, the share of a price change that is perceived; ξ is the implicit price ($\lambda_b\, y$ here).

B10a: 2023 model | B12: 2023 est. | B13: 2023 ctf. | ↩ Back

Appendix B10a: model: baseline homogeneous case

$$b_{it} = \arg\max_{b} \{g(b;\beta) + CE(b, y_i;\gamma)\}$$

- for each trip t, driver i chooses HPU b by trading off its private benefit against the added risk exposure
- $g(\cdot)$: private benefit of b (cost of safe driving)
- $CE(\cdot)$: certainty equivalent of the risk exposure associated with b

Variables

- b_{it}: HPU frequency
- y_i: deductibles

Parameters

- β: HPU price elasticity
- γ: risk aversion

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Appendix B10a: model: baseline homogeneous case

$$b_{it} = \arg\max_{b} \{g(b;\beta) + CE(b, y_i;\gamma)\}$$

- for each trip t, driver i chooses HPU b by trading off its private benefit against the added risk exposure
- $g(\cdot)$: private benefit of b (cost of safe driving)
  - let $g(b;\beta) = b^{1+\frac{1}{\beta}}/(1+\frac{1}{\beta})$ (Nevo, Turner, and Williams 2016)
- $CE(\cdot)$: certainty equivalent of the risk exposure associated with b

$$\underset{\text{FOC}}{\Longrightarrow} \; b_{it}^* = \left[\underbrace{-\frac{\partial CE(b, y_i;\gamma)}{\partial b}}_{\text{implicit price of } b} \right]^{\beta}$$

Variables

- b_{it}: HPU frequency
- y_i: deductibles

Parameters

- β: HPU price elasticity
- γ: risk aversion

Appendix B10a: model: baseline homogeneous case

$$b_{it} = \arg\max_{b} \{g(b;\beta) + CE(b, y_i;\gamma)\}$$

- for each trip t, driver i chooses HPU b by trading off its private benefit against the added risk exposure
- $g(\cdot)$: private benefit of b (cost of safe driving)
  - let $g(b;\beta) = b^{1+\frac{1}{\beta}}/(1+\frac{1}{\beta})$ (Nevo, Turner, and Williams 2016)
- $CE(\cdot)$: certainty equivalent of the risk exposure associated with b
  - $\lambda(b)$: Poisson accident arrival rate
  - assume drivers expect to pay y_i in accident (Cohen and Einav 2007)
  - use Arrow-Pratt approximation to simplify CE

$$\underset{\text{FOC}}{\Longrightarrow} b_{it}^* = \left[\underbrace{-\frac{\partial CE(b, y_i;\gamma)}{\partial b}}_{\text{implicit price of } b}\right]^{\beta}$$

Variables

- b_{it}: HPU frequency
- y_i: deductibles

Parameters

- β: HPU price elasticity
- γ: risk aversion

Appendix B10a: model: baseline homogeneous case

$$b_{it} = \arg\max_b \{g(b;\beta) + CE(b, y_i; \gamma)\}$$

- for each trip t, driver i chooses HPU b by trading off its private benefit against the added risk exposure
- $g(\cdot)$: private benefit of b (cost of safe driving)
  - let $g(b;\beta) = b^{1+\frac{1}{\beta}}/(1+\frac{1}{\beta})$ (Nevo, Turner, and Williams 2016)
- $CE(\cdot)$: certainty equivalent of the risk exposure associated with b
  - $\lambda(b)$: Poisson accident arrival rate
  - assume drivers expect to pay y_i in accident (Cohen and Einav 2007)
  - use Arrow-Pratt approximation to simplify CE

$$\log b_{it}^* = \underbrace{\beta}_{\text{HPU elasticity}} \cdot \left[\underbrace{\log \lambda_b(b)}_{\substack{\text{HPU's effect on} \\ \textbf{accident rate}}} + \underbrace{\log(y_i)}_{\text{deductibles}} + \underbrace{\log(1+\frac{\gamma}{2}y_i)}_{\text{risk aversion}} \right]$$

Variables

- b_{it}: HPU frequency
- y_i: deductibles

Parameters

- β: HPU price elasticity
- γ: risk aversion

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$$b_{it} = \arg\max_{b} \{g(b;\beta) + CE(b, y_i;\gamma)\}$$

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- $CE(\cdot)$: certainty equivalent of the risk exposure associated with b
  - $\lambda(b)$: Poisson accident arrival rate
  - assume drivers expect to pay y_i in accident (Cohen and Einav 2007)
  - use Arrow-Pratt approximation to simplify CE
- attention α scales the implicit price: drivers act on the **perceived** price $\alpha \cdot \xi$

$$\log b_{it} = \beta \cdot [\log \alpha_{it} + \log \xi_{it}]$$

Variables

- b_{it}: HPU frequency
- y_i: deductibles

Parameters

- β: HPU price elasticity
- γ: risk aversion
- α: attention

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Appendix B10b: modeling risk exposure

Modeling certainty equivalent

$$CE(b, y_i; \gamma) = \mathbb{E}\left[e(\tilde{\ell}, y_i)|b\right] - \frac{\gamma}{2}\mathbb{V}\left[e(\tilde{\ell}, y_i)|b\right]$$

- Arrow-Pratt approximation for small risk exposure

Risk exposure from accident losses

- Poisson arrival rate $p^a(b, x_{it})$
- risk exposure: $e(\tilde{\ell}, y_i) = \underline{C}_{it} + y_i^{\text{ded}}$
  - $\underline{C}_{it}$: average accident QALY cost (DOT) scaled by passengers aboard

Risk exposure from suspension (in passenger trips)

- rating-based: $p^r(b, r_{it}) = \Pr(r' \leq \underline{R}|b, r_{it})$
- treatment: $p^D(b, r_{it}) = \Pr(\text{safety complaints } \& \ r' > \underline{R}|b, r_{it})$
- risk exposure is loss of average weekly earning: w_i (wage - gas spending)

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Appendix B10c: heterogeneity in attention and elasticity

$$\beta_{it} = x_{it}'\theta_\beta$$

$$\log \alpha_{it} = -(1 - D_{it}) \cdot \left[\underbrace{x_{it}'\theta_\alpha + \varepsilon_i}_{\substack{\text{attention} \\ \textbf{nudge effect}}} \right] + D_{it} \cdot \left[\underbrace{\frac{\alpha_H^0(x_{it})}{(1 + \alpha_H^1 \cdot t)}}_{\text{Hawthorne}} \right]$$

$$\varepsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_\alpha)$$

- identification (2023 specification): the cue's effect on no-passenger trips identifies attention; precipitation and treatment intensity identify β

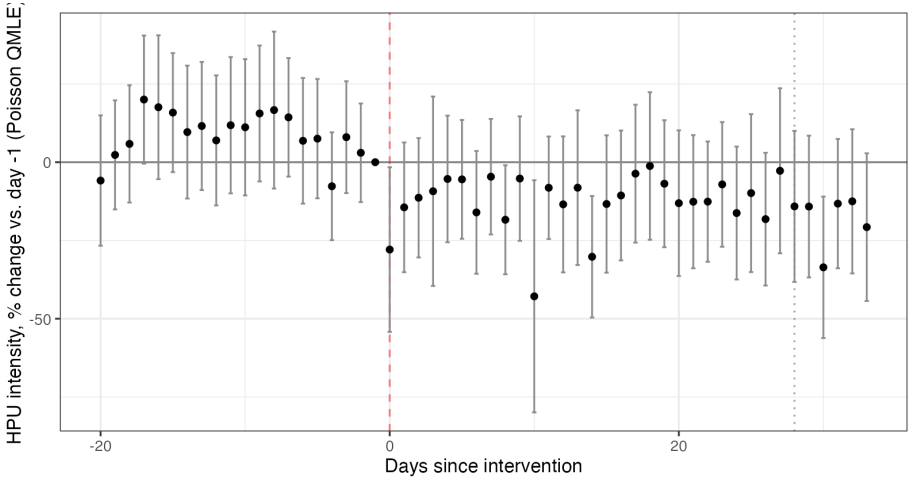
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Appendix B11: experiment: average effect and passenger targeting

	Average effect (trip)				Passenger targeting (trip segment)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × Treated	−0.2098**	−0.2095**	−0.2114***	−0.1956***	−0.1252*	−0.1242*	−0.1328***	−0.1224**
	(0.0967)	(0.0960)	(0.0542)	(0.0525)	(0.0697)	(0.0697)	(0.0471)	(0.0547)
× Passenger					−0.2000**	−0.1994**	−0.1865*	−0.1982*
					(0.0913)	(0.0911)	(0.0978)	(0.1044)
Trip-segment controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Driver + Date + Hour FE	No	No	Yes	Yes	No	No	Yes	Yes
Location-pair FE	No	No	No	Yes	No	No	No	Yes
Pre-trend F (p)	1.46 (0.09)	1.46 (0.09)	1.06 (0.39)	1.06 (0.39)	1.11 (0.33)	1.14 (0.31)	1.17 (0.27)	1.17 (0.27)
Observations	464,045 trips				849,488 segments			

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Appendix B11a: daily experimental event study



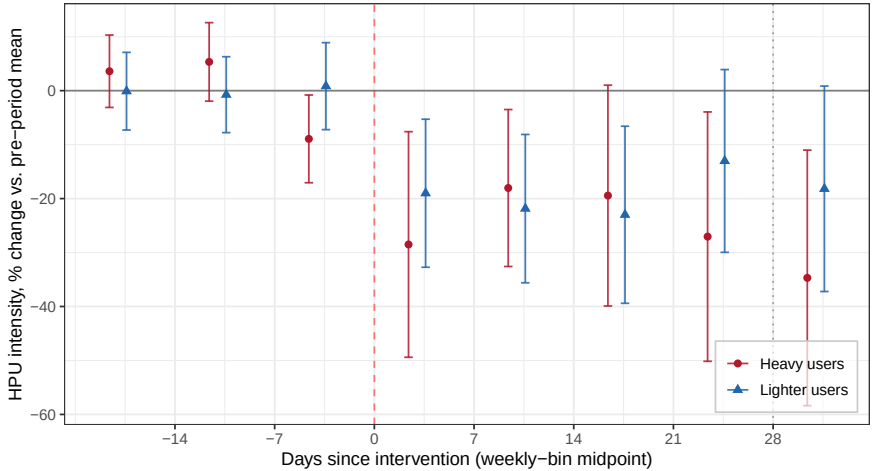
Daily Poisson event-study coefficients on HPU intensity vs. day −1, 95% CIs; red dashed = text message, grey dotted = day 28.

Appendix B11b: who responds across specifications

	Precipitation		Deductible		Experiment	
	$\Pr(\text{HPU} > 0)$	$\log E[\text{HPU}]$	$\Pr(\text{HPU} > 0)$	$\log E[\text{HPU}]$	$\Pr(\text{HPU} > 0)$	$\log E[\text{HPU}]$
Lighter users						
HPU $\leq$100 m/km	-0.23^{***}	-0.66^{***}	-1.29^{***}	-6.28	-4.6^{*}	-17.8^{***}
	(0.07)	(0.23)	(0.47)	(4.39)	(2.5)	(5.2)
Bottom 80%	-0.24^{***}	-0.65^{***}	-1.17^{**}	-6.29	-4.2	-17.5^{***}
	(0.08)	(0.24)	(0.47)	(4.27)	(2.6)	(5.3)
Heavier users						
HPU >100 m/km	-0.03	-0.23	0.68	-0.67	-5.5^{*}	-20.6^{***}
	(0.06)	(0.22)	(0.81)	(3.24)	(3.1)	(6.9)
Top 20%	-0.03	-0.29	0.29	-0.02	-6.5^{**}	-20.9^{***}
	(0.05)	(0.20)	(0.91)	(3.35)	(3.1)	(6.7)

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Appendix B11c: heavy- vs. lighter-user weekly event study



Weekly Poisson event study by 80th-percentile pre-period HPU split (within targeted top-quintile pool), 95% CIs.

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Appendix B12: estimation results (2023 draft)

	Price elasticity β_{it}	Log Inattention $\log \alpha_{D,it}$	First Stage w	Private Optima τ_p	Social Optima τ_s
Mean [sd]	-0.73 [0.11]	-0.70 [0.52]	808.3 [591.1]	40 [43]	62 [66]
Converted Mean [sd]		0.44 [0.27]			
– intercept	-0.58*** (0.25)	-1.34*** (0.45)	569.7 [14.9]	0.69	0.71
driver characteristics					
– age	-0.02 (0.05)	0.13 (0.49)	1.6 (1.2)	-0.02	-0.02
– male	-0.04 (0.04)	-0.20 (0.71)	1.3* (0.7)	-0.66	-0.92
– tenure	-0.03 (0.03)	0.12 (0.07)	2.6*** (1.1)	-0.01	-0.02
– lux	-0.03* (0.01)	-0.03** (0.00)	0.03** (0.00)	0.09	0.14
– referral lead	0.24* (0.13)	1.52*** (0.62)	-0.0 (0.0)	-0.51	-1.24
– organic lead	0.04 (0.03)	-0.01 (0.30)	-0.0 (0.0)	-0.05	-0.67
– paid lead	0.07*** (0.02)	0.74 (0.68)	-1.0 (0.8)	-0.49	-0.71
driver experience					
– past trip	0.14** (0.07)	1.06** (0.53)	10.7 (8.0)	0.35	0.47
– past accident	0.03*** (0.01)	0.48** (0.23)	2.7 (2.0)	0.00	0.01
– past complaint	0.03* (0.02)	-0.24 (0.17)	5.0 (3.7)	0.02	0.04
trip characteristics					
– distance	-0.10** (0.03)	-0.74 (0.66)		-0.79	-1.08
– weekday	0.02*** (0.01)	0.09 (0.20)		-0.64	-0.84
– weekday commute	-0.02 (0.03)	0.25*** (0.13)		-0.62	-0.67
– wknd day	0.02 (0.01)	0.16 (0.13)		-0.80	-0.99
– wknd night	0.02 (0.02)	0.21 (0.32)		-0.77	-1.00
– pop dens	-0.00 (0.01)	0.07 (0.20)		0.05	0.08
– req dens	-0.01** (0.01)	0.17 (0.74)		-0.34	-0.47
– passenger ind	0.00 (0.00)	0.14 (0.65)		-10.56	-15.98
– comms	0.00 (0.00)	-0.06 (0.28)		0.02	0.03
– precipitation	0.01** (0.02)	-0.17 (0.26)		36.06	66.47
other					
– ψ control function		0.0 (0.00)			
– $\sigma_{\alpha,z}$ random coef.		-0.11*** (0.02)			
– z trailing gas price shock		0.26* (0.16)	175.0*** (1.4)		
– σ_w			364.5*** (0.4)		

Incentives: other		Attention other		Implicit Prices		Link Function	
Risk Aversion γ	1.16e-4*** (1.22e-7)	Hawthrone Halflife $1/\alpha_H^1$	0.68*** (0.01)	ζ_{accident} [sd]	3.00 [2.26]	δ_0	0.00*** (0.00)
Altruistic Motive κ	2.99*** (0.29)	– Log Magnitude α_H^0	0.06*** (0.00)	ζ_{rating} [sd]	0.08 [15.53]	δ_1	2.36*** (0.48)
				ζ_{treat} [sd]	0.05 [0.07]	σ	2.78*** (0.03)

- price elasticity of HPU (β) is -0.73
- drivers under-perceive (α) implicit price of HPU by 44% (compared to after the nudge)
- drivers are risk averse (γ) 1.16e-4

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driver characteristics					
– age	-0.02 (0.05)	0.13 (0.49)	1.6 (1.2)	-0.02	-0.02
– male	-0.04 (0.04)	-0.20 (0.71)	1.3* (0.7)	-0.66	-0.92
– tenure	-0.03 (0.03)	0.12 (0.07)	2.6*** (1.1)	-0.01	-0.02
– lux	-0.03* (0.01)	-0.03** (0.00)	0.03** (0.00)	0.09	0.14
– referral lead	0.24* (0.13)	1.52*** (0.62)	-0.0 (0.0)	-0.51	-1.24
– organic lead	0.04 (0.03)	-0.01 (0.30)	-0.0 (0.0)	-0.05	-0.67
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– past complaint	0.03* (0.02)	-0.24 (0.17)	5.0 (3.7)	0.02	0.04
trip characteristics					
– distance	-0.10** (0.03)	-0.74 (0.66)		-0.79	-1.08
– weekday	0.02*** (0.01)	0.09 (0.20)		-0.64	-0.84
– weekday commute	-0.02 (0.03)	0.25*** (0.13)		-0.62	-0.67
– wknd day	0.02 (0.01)	0.16 (0.13)		-0.80	-0.99
– wknd night	0.02 (0.02)	0.21 (0.32)		-0.77	-1.00
– pop dens	-0.00 (0.01)	0.07 (0.20)		0.05	0.08
– req dens	-0.01** (0.01)	0.17 (0.74)		-0.34	-0.47
– passenger ind	0.00 (0.00)	0.14 (0.65)		-10.56	-15.98
– comms	0.00 (0.00)	-0.06 (0.28)		0.02	0.03
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– lux	-0.03* (0.01)	-0.03** (0.00)	0.03** (0.00)	0.09	0.14
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– weekday commute	-0.02 (0.03)	0.25*** (0.13)		-0.62	-0.67
– wknd day	0.02 (0.01)	0.16 (0.13)		-0.80	-0.99
– wknd night	0.02 (0.02)	0.21 (0.32)		-0.77	-1.00
– pop dens	-0.00 (0.01)	0.07 (0.20)		0.05	0.08
– req dens	-0.01** (0.01)	0.17 (0.74)		-0.34	-0.47
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Appendix B13: counterfactuals (2023 draft)

Counterfactual: the "first-best" contract

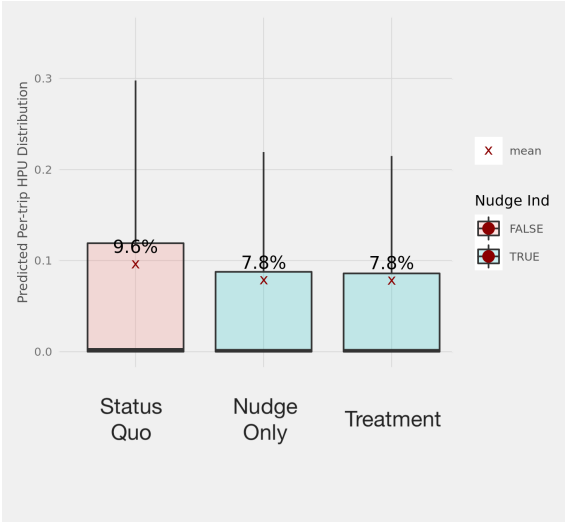
1. Full-insurance + attention to HPU $\rightarrow$ efficient risk-sharing but trigger moral hazard
2. Determine optimal amount of HPU for each trip: $\arg\max_b [g(b, x) - \text{cost}_b]$
   - private optimum: $\text{cost}_b = \underline{C} + e(y)$
   - social optimum 1: $\text{cost}_b +=$ average claim amount
   - social optimum 2: $\text{cost}_b +=$ other congestion/QALY costs
3. Starting from the HPU level in step 1, search for the direct HPU price(s) that helps achieve the optimal HPU in step 2

Caveats

1. the goal is understand optimal HPU pricing: assume no "ex-post" moral hazard and the only margin of adjustment is HPU $\rightarrow$ risk
2. Assume charging direct prices on HPU will have similar attention effect as the experimental nudge
3. Counterfactuals are computed for all drivers; the figure shows the experimental sample

B14: ctf. results ⟷ Back

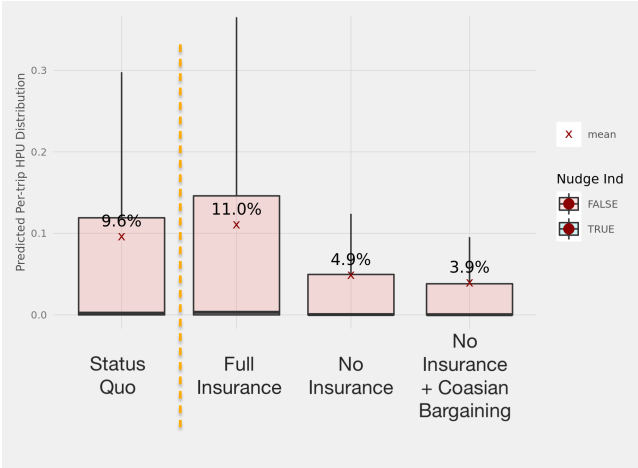
Appendix B14: counterfactual contracts (2023 draft)



- almost all HPU impact of our text-message reminder comes from the nudge

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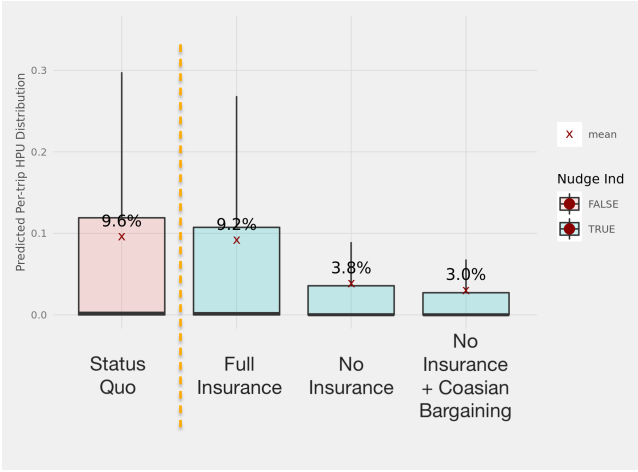
Appendix B14: counterfactual contracts (2023 draft)



- significant expansion of insurance will increase HPU
- but adding an HPU nudge will improve HPU compared to the Status Quo

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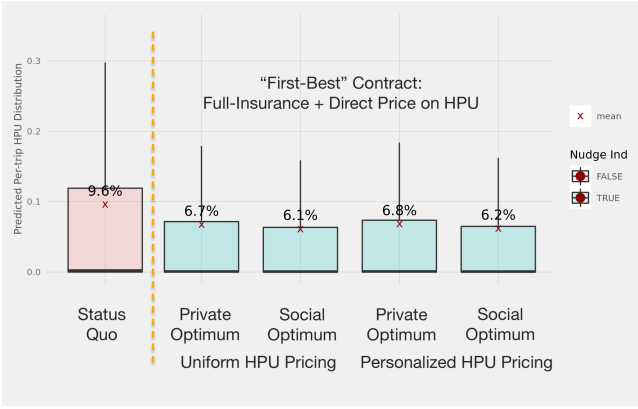
Appendix B14: counterfactual contracts (2023 draft)



- significant expansion of insurance will increase HPU
- but adding an HPU nudge will improve HPU compared to the Status Quo

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Appendix B14: counterfactual contracts (2023 draft)



- optimal HPU is not zero
- "personalizing" HPU prices reduces overall HPU charges by targeting trips and drivers where the implicit price of HPU is highest
- average charge per mile of HPU:

	uniform	personalized
social 1	\$0.77	\$0.40
social 2	\$1.20	\$0.62

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