Telematics Data in U.S. Auto Insurance

Evidence from Telematics Contracts and an Accident Prevention Program

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IVASS
Dec 2022

Experience Rating

Old idea and new challenges.

Caricature on Bismarck's social insurance program. The True Jacob, No. 1, Stuttgart, January 1884.

- One of the first use cases is Bismarck's social insurance system in Germany in 1880s.
  - The industrial accident insurance featured coarse experience rating for member firms primarily as a "means to reduce accidents." (Guinnane and Streb, 2015)

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  - The industrial accident insurance featured coarse experience rating for member firms primarily as a "means to reduce accidents." (Guinnane and Streb, 2015)
- Modern experience-rating regimes are adopted widely across private insurance industries
  - Effective at claim mitigation (ex-post moral hazard); mixed evidence on accident prevention (ex-ante moral hazard).
  - Finer ratings often lead to higher penalties and reclassification risk, effectively reducing risk-sharing.
  - Accidents are useful to reveal risky drivers, but are too sparse to differentiate among safer ones.

Two Studies on the Use of Telematics Data in Auto Insurance

- 3 main differences between the economics of traditional (claim, age,...) data vs. telematics
  1. mandatory vs. **voluntary disclosure**
  2. data sharing (across insurers) vs. **proprietary ownership**
  3. outcome-based vs. **behavioral pricing**

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Jin and Vasserman (2019)

- telematics contracts by a large private passenger auto insurer
- **voluntary disclosure**: identify selection and moral hazard effects.
- **proprietary data**: understand pricing dynamics and potential impact of data-sharing regulation.

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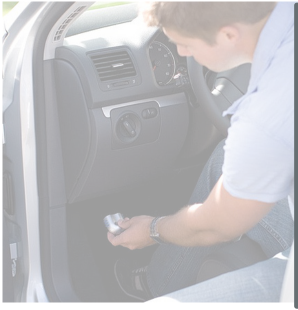
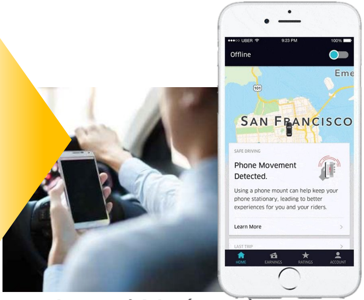


Jin and Vasserman (2019)

- self-insured ride-sharing firm
- experimental evidence on behavioral modification: moral hazard vs. inattention
- **contracting on driving behavior**: pricing on *handheld phone use* to prevent accidents



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  1. we use economic theory to model how consumers and firm *behaviors* respond to *incentives*.
  2. we use (quasi-)*experimental* evidence to identify these behavioral responses, facilitating the simulation of "counterfactual" worlds with different regulations and contract structures.
     * consumers select into contracts, have moral hazard, inertia, and inattention problems; firms optimize pricing and screening strategies to maximize profits facing oligopolistic competition.

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? what if regulators mandate that firms must share **proprietary** data with competitors?

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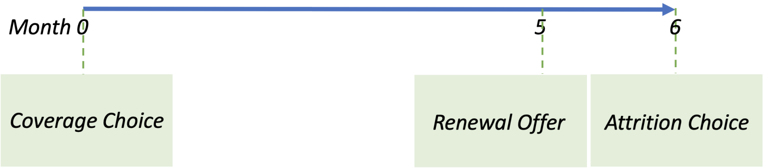
Private Passenger Auto



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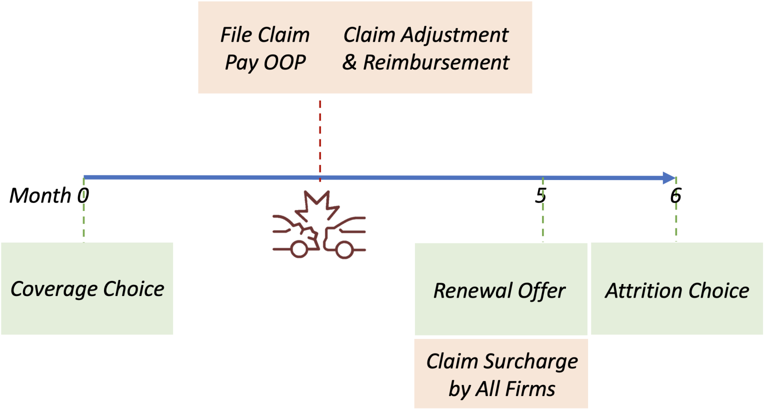
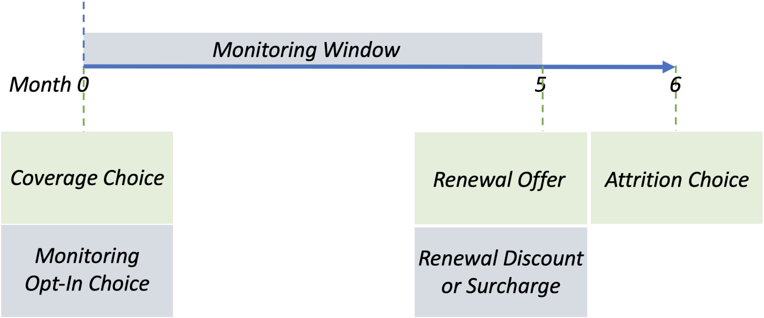


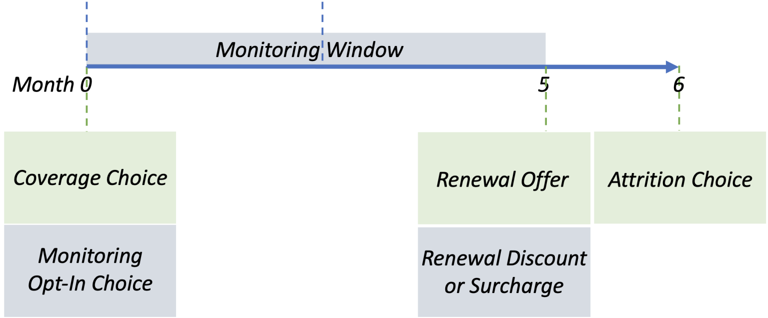
Monitoring in Telematics Contract

- ***Monitored behavior***: mileage, hard brakes, speed, late night driving
- ***Duration***: First period only (before renewal offer)
- ***Opt-in discount***: First period only
- ***Renewal discount range***: Lasts forever after first period



Monitoring in Telematics Contract

- *Monitored behavior*
- *Duration*
- *Opt-in discount*
- *Renewal discount range*
- ***Real-time feedback***



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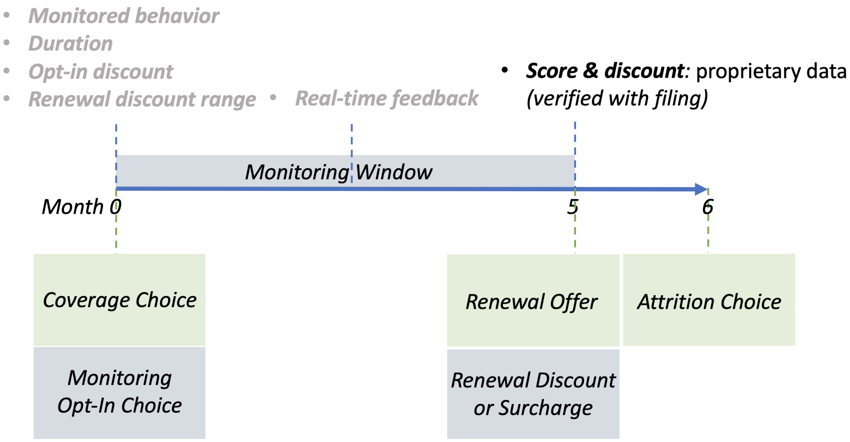
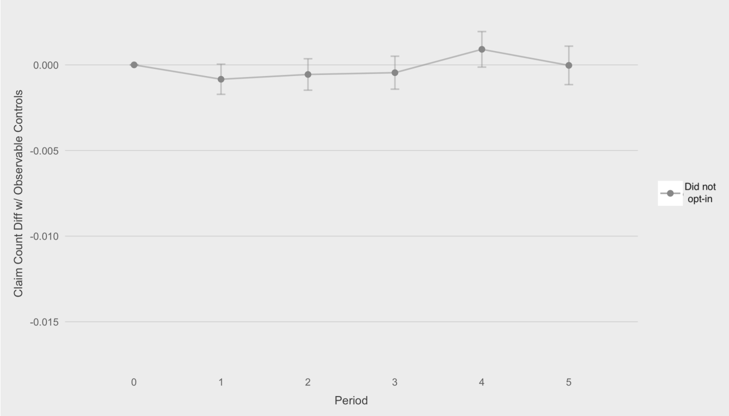


Monitoring is "Useful" in Two Ways...



controlling for all pricing observables and state-calendar-year fixed effects.

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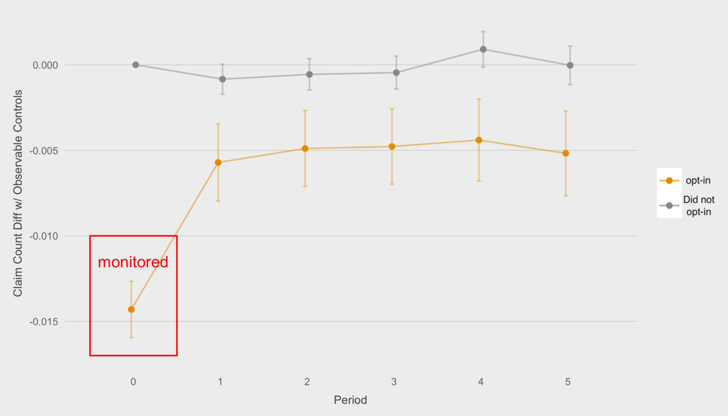

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Result #1 Monitoring changes consumer behavior - drivers become 30% safer when they are monitored

Incentive Effect: drivers can exert effort to send a better signal of their type (Fama 1980, Holmstrom 1999).

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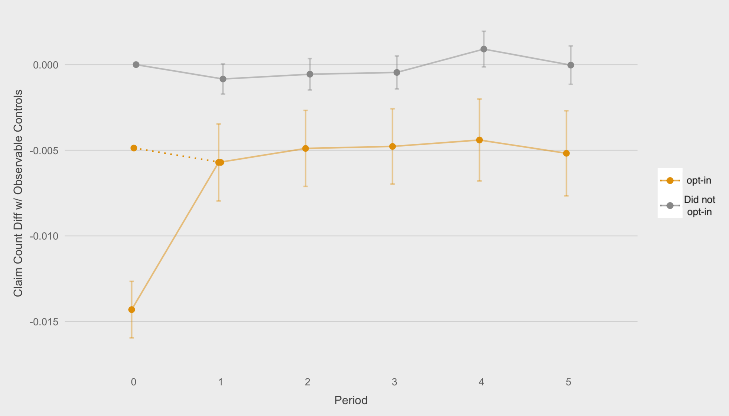

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Result #2 Telematics data still signals unobserved risk differences across drivers post-monitoring → safer drivers are more likely to opt in.

Selection Effect: better risk-rating can mitigate adverse selection and improve risk-sharing (Akerlof 1970, Einav *et al.* 2010).

...But Adoption is Limited by Large Demand Frictions

Result #3 Most drivers who can financially benefit from monitoring do not opt in.

- Friction against telematics opt-in is $93 on average
  - privacy or hassle costs, etc.
  - more severe in higher risk classes due to more potential savings.
  - more severe for privately riskier drivers → exacerbates advantageous selection

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  - more severe in higher risk classes due to more potential savings.
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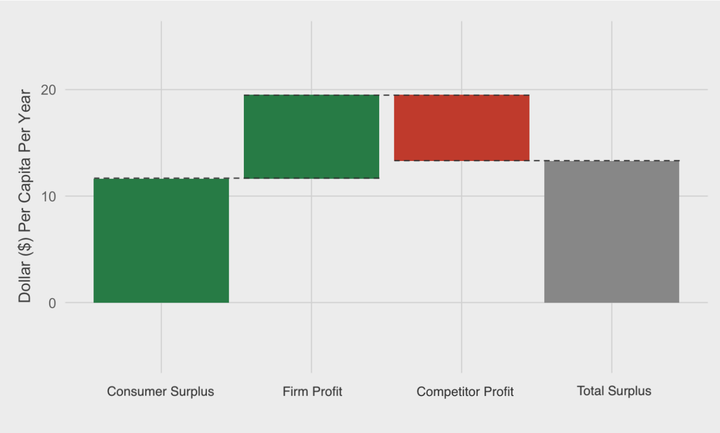
- Friction against firm-switching costs the average consumer $284 per year.
  - privately safer drivers at other firms are unlikely to switch firms due to telematics
  - most important source of market power in the absence of proprietary data
  - caveat: without market-level claims/choice data (track customers before they come to the firm and after they leave), a "symmetric-firm" assumption is needed.

Welfare Calculation: Current World - No Telematics World

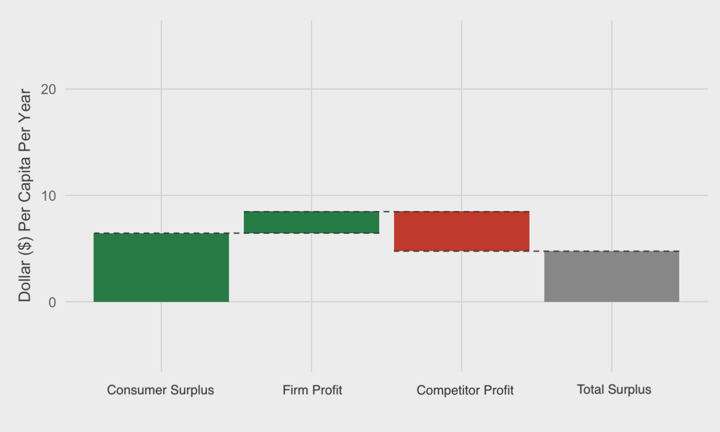
Introducing monitoring increases firm profit, consumer welfare, and total surplus.



- firm did not change baseline (opt-out pool) prices
- set resource cost of monitoring is $35 per capita

Welfare Decomposition: Allocative vs. Incentive Effect

assume away incentive effect: drivers are no safer when monitored.



- ∼64% of the surplus gain comes from risk reduction (incentive effect)
- competitive cream-skimming with better risk information (vs. Rothschild and Stiglitz 1976): overall profit ↓ and quantity ↑

Firm's Pricing and Screening Strategies

- Firm's profit motives: 2 considerations
  - "invest-and-harvest" pricing dynamic
  - opt-in pool cream-skims the opt-out pool

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- Firm's profit motives: 2 considerations
  - "invest-and-harvest" pricing dynamic
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- Firm actions: 3 types of price adjustments for telematics

$$t = 0, \text{telematics} = 0 : \kappa_0 \text{ surcharge opt-out pool}$$
$$t = 0, \text{telematics} = 1 : \kappa_1 \text{ discount opt-in pool}$$
$$t = 1, \text{telematics} = 1 : \kappa_s \text{ degree of rent-sharing with opt-in drivers}$$

Optimal Pricing

Result #4: Product market competition → firm can't coerce drivers into monitoring.

	Current Regime	Optimal Pricing
Surplus & division (/capita/year)		
Firm Profit		+14.7
Competitor Profit		−11.0
Consumer Welfare (in CE)		+4.7
Total Surplus		+8.4
Telematics Market Share (%)	3.0%	4.4% ↑
Pricing: First Period (%)		
Opt-out surcharge κ_0	0.0%	2.7% ↑
Opt-in discount κ_1	4.6%	22.1% ↑↑
Pricing: Second Period		
Rent-sharing κ_s	1x	0.80x ↓
Competitor rent-sharing $\kappa_{s,-f^\star}$	-	-

Optimal Pricing

Result #4: Firm can raise profit by raising upfront discount expecting ex-post rent.

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Counterfactual Equilibrium: Information Sharing

Result #5: Data sharing undermines firm incentives to "buy" consumer data.

	Optimal Pricing	Proprietary Data Ban
Surplus & division (/capita/year)		
Firm Profit		-11.9
Competitor Profit		$+8.9$
Consumer Welfare (in CE)		-2.5
Total Surplus		-5.5
Telematics Market Share (%)	4.4%	3.4% ↓
Pricing: First Period (%)		
Opt-out surcharge κ_0	2.7%	1.6% ↓
Opt-in discount κ_1	22.1%	8.3% ↓
Pricing: Second Period		
Rent-sharing κ_s	0.80x	1.14x ↑
Competitor rent-sharing $\kappa_{s,-f^\star}$	-	1.81x

Jin and Yu (2020): Smartphone Telematics in Ride-Sharing Insurance

An ML algorithm that identifies risky driving behaviors from smartphone sensor data with 99%+ precision and 70% recall.

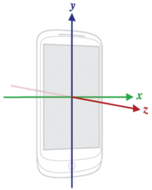
Smartphone Sensor Data

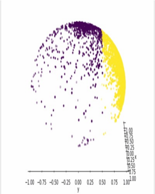
↓

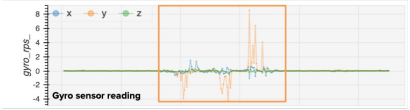
Data cleaning

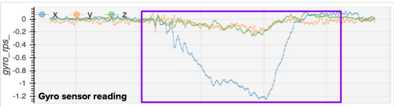
↓

Feature construction









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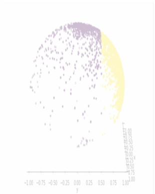
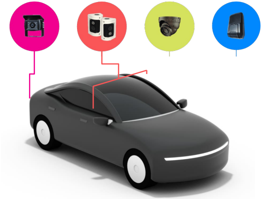
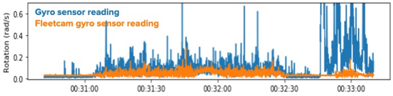
Train model on ground-truth data: ML classification

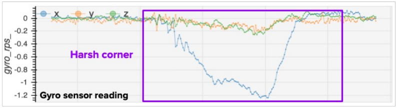
↓

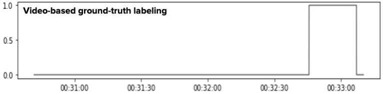
Validation using holdout data











Data & Reduced-Form Results: Is there Ex-Ante Moral Hazard?

HPU strongly increases accident risk, but drivers do not reduce HPU when they are exposed to higher risk.

Handheld phone use ("HPU") is risky

- Smartphone sensor data from self-insured ride-sharing firm
- HPU frequency jumps by 11X in the 30-second window before accidents
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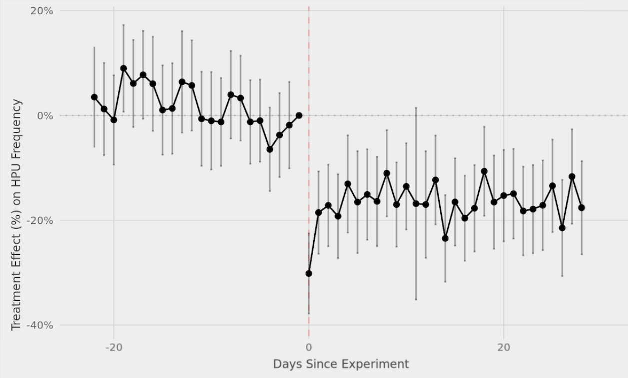
Little ex-ante moral hazard w.r.t. HPU

- HPU is 38% riskier in trips with rain, but only lower by 1%
- Insurance coverage (provided by the firm) dropped significantly in some states, but HPU did not change

$\rightarrow$ Less insurance / more experience rating might mitigate claims but can't prevent accidents!

Field Experiment: Why is HPU Insensitive to Risk Exposure Changes?

An experiment says the role of inattention ≫ preference.



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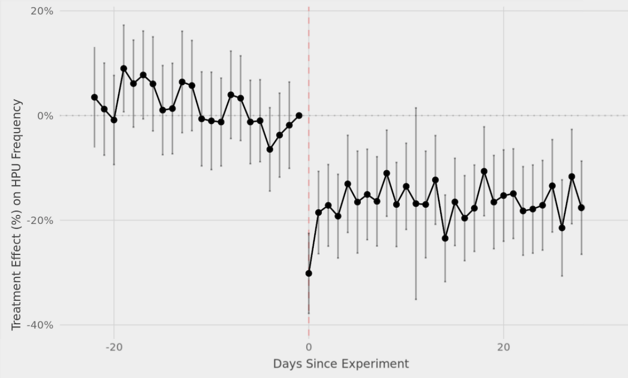

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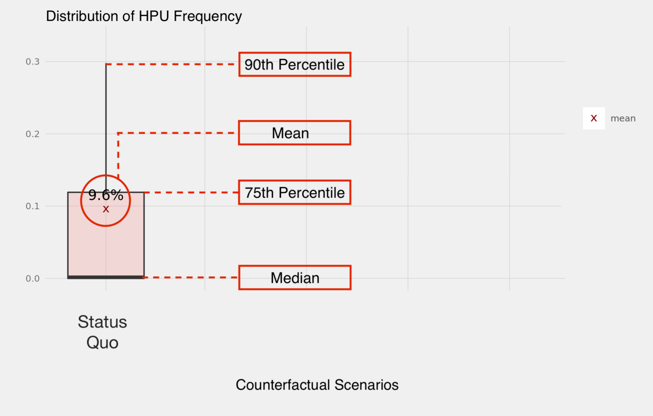
- no detectable change in driving hours or other unsafe driving behavior
- "near-misses"/harsh braking: -8% (2%)

Estimation & Counterfactual "First-Best" Contract



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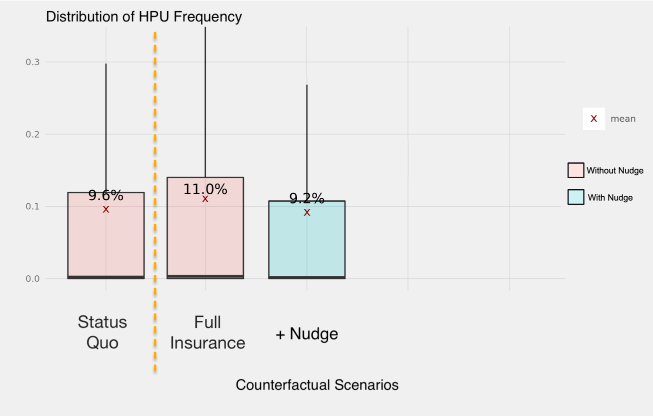

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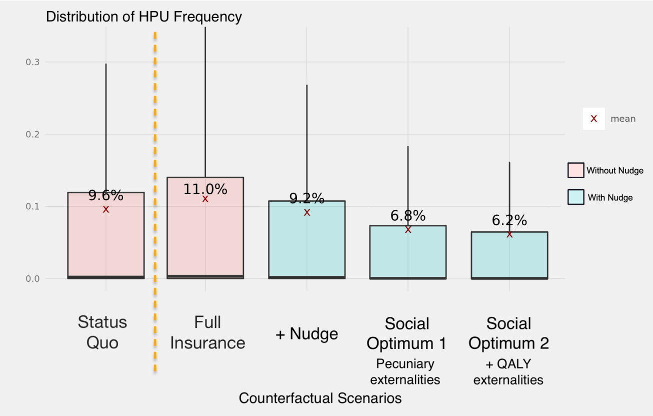

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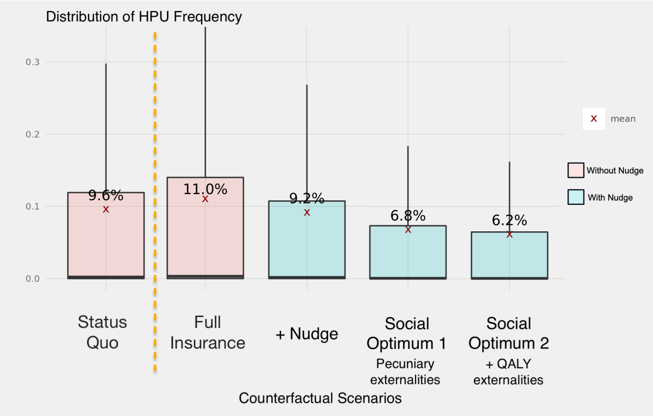

In the socially-optimal equilibrium, the average driver is fully insured, pays \$3.8 HPU charge per 100 miles driven. The HPU reduction alone leads to 2% fewer accidents.

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as well as to understand the interaction with insurance equilibrium and regulations.

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? What if regulators mandate that firms must share **proprietary** data with competitors?

  ▷ large demand frictions hinder adoption while raising the "cost" of data collection → protecting firms' data property right and incentivizing collection can outweigh ex-post markup concerns.

  → large potential for government intervention: centralized data collection avoids duplicate efforts; coordination can lead to better disclosure equilibrium