Measuring per-mile risk for pay-as-you-drive automobile insurance

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CAS Ratemaking & Product Management Seminar

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IBI GROUP

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"Measuring per-mile risk for pay-as-you-drive automobile insurance"

Full text of CLF report: goo.gl/exuSp or Google "CLF PAYD"

SURDNA FOUNDATION clf MIT Transportation Alliance EIA

Presentation Outline

- Background
- Datasets
- Per-mile risk modeling
- Equity and environmental impacts
- Conclusions

Background

What is pay-as-you-drive insurance?

- Cents-per-mile rate
- Customers billed for actual miles driven

- Potential benefits
  - Improved actuarial accuracy
  - Opportunity for consumers to save money
  - Reduced negative externalities (congestion, accidents, pollution)

Status of pay-as-you-drive insurance in U.S.

- MileMeter offers true cents-per-mile coverage in Texas
- Verified low-mileage or black box discount programs available from a variety of providers in many states

Status of pay-as-you-drive insurance in U.S.

- 50 state regulators
- 16 prohibit PAYD
  - Including Massachusetts
- Many regulatory barriers to introduction and adoption of PAYD

Our contribution

- Assess risk-mileage relationship with largest disaggregate dataset to date
- Classifies drivers by class and territory
- Characterize rate levels and relativities
- Model economic and environmental impacts

Dataset

Data sources

Data released by Massachusetts Executive Office of Energy and Environmental Affairs (EOEEA)

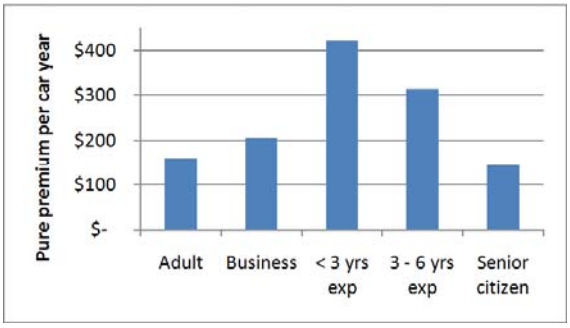
- Odometer readings from mandated annual safety checks (Mass RMV)
- Insurance policy and claims data from Mass "statistical plan" reporting (Commonwealth Automobile Reinsurers)

- Original dataset: goo.gl/la5fJ
- Analytic dataset: goo.gl/GiVxW

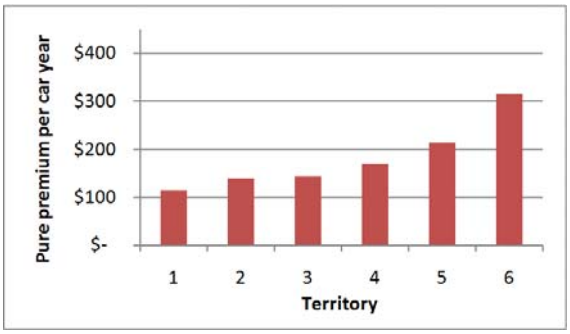
Data processing

- Estimate mileage from odometer readings
- Estimate pure premiums from losses plus outstanding reserves
- Join on VIN
- Consider only compulsory coverage categories and levels
- Divide drivers into coarse rate groups (five classes, six territories)
- Parse VINs to obtain fuel economy estimates

Five classes



Six territories



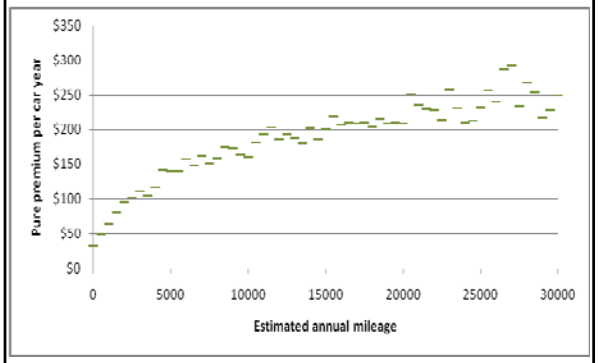
Sample size

Policy year 2006:

- 3M car-years of earned exposure
  - 71% of private, insured autos in Massachusetts
- $502M in claims
- 34B miles

Per-mile risk modeling

Pure premium vs. ann. mileage (all drivers)



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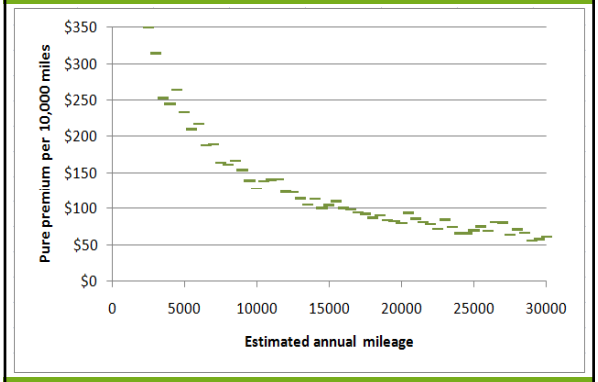
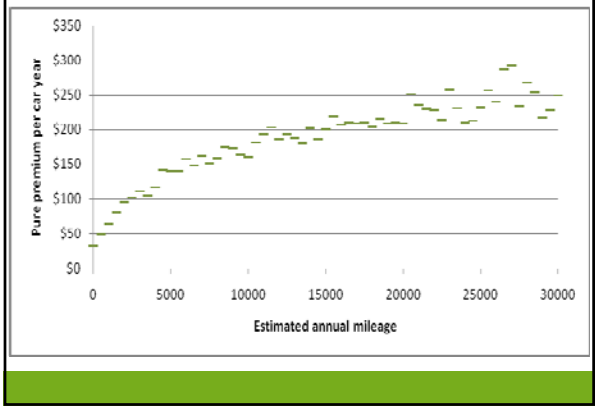


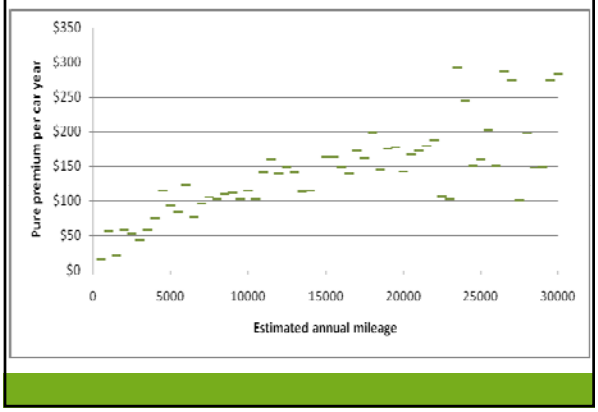
Reasons for non-proportionality

- All drivers are considered together
- Regression to the mean
- Experience and driving habits

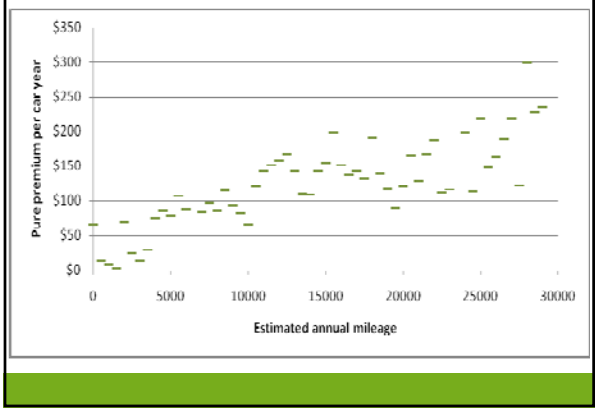
Pure premium vs. ann. mileage (all drivers)



Pure premium vs. ann mileage (T3 adults)



Pure premium vs. ann. mileage (T3 adults 90%+)



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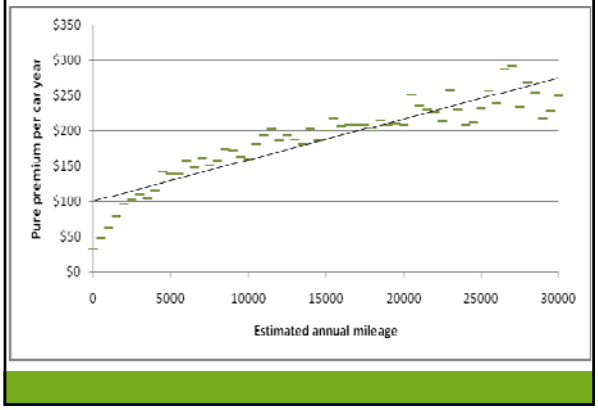

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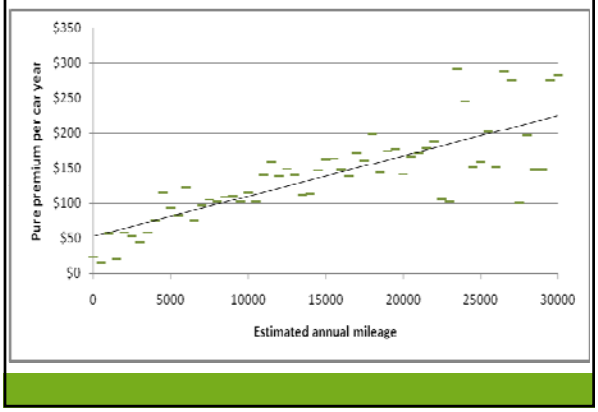

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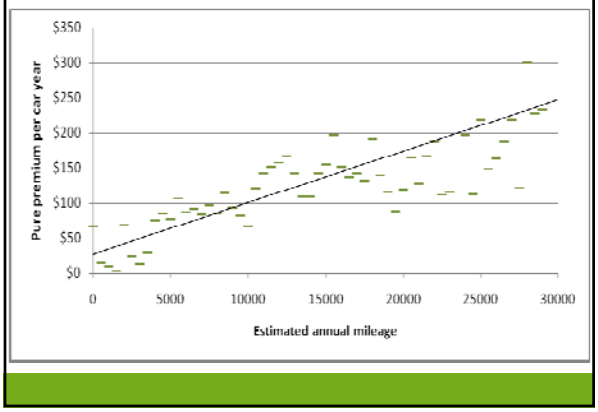
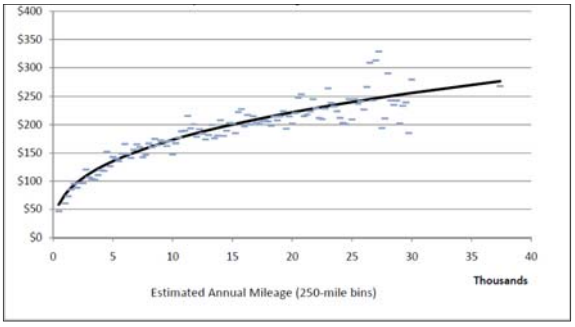


Regression analysis

- Poisson regression
  - Respects “rare event” nature of accidents
  - Allows true disaggregate analysis
  - Results in an exponential model of the risk-mileage relationship

Poisson regression #1

Pure premium = \$6.53 * (ann_miles$^{0.36}$)



Poisson regression #2

- Pure premium = \$2.35 * (ann_miles$^{0.40}$) * (class relativity) * (terr relativity)
- Limitation: relativities only affect magnitude of curve, not its shape.

Poisson regression #3

- T3 adults only
- Pure premium=$1.70×ann_miles$^{0.46}$
- Exponent is higher for any *one* class-territory group than for all class-territory groups together
- Limitation: regression to the mean is still present

Poisson regression #4

- T3 adults only
- 90% or greater overlap between mileage and policy periods–reliable mileage estimates
- Pure premium= $0.74×ann_miles$^{0.54}$

Poisson regression conclusions

- Mileage-risk relationship may be even stronger than we observe here as industry would use:
  - Finer rate groups
  - More rating factors
  - Better mileage estimates

Poisson regression conclusions

- Mileage and risk are strongly correlated
- Relationship becomes stronger and more nearly proportional when controlling for class, territory and RTM.

Regression analysis

- Linear regression
  - Shows how much of variation is explained by different factors
  - Results in a flat rate plus cents-per-mile model, a more realistic model of how PAYD might be priced

Linear regression

- Vehicles aggregated into “bins” by class, territory and 500-mile annual mileage range; weighted by number of vehicles

Factors	Adjusted R^2
Mileage	.09
Class and territory	.57
Mileage, class and territory	.72

Linear regression conclusions

- The whole is better than the sum of the parts
  - .72 > .09 + .57
  - Mileage is a better predictor of risk when paired with some control (class and territory) on where and how miles are being driven

Per-mile risk assessment conclusions

- Mileage is correlated with risk
- Correlation is stronger with class-territory control
- PAYD could be priced with individual per mile rates based on class and territory

Equity and environmental impacts

VMT reduction model

- Model consumer response to increase in *marginal* cost of driving a mile due to PAYD
- Modeled for each individual vehicle based on its annual mileage, fuel economy and insurance rate group
- Constant elasticity of -0.15 assumed

VMT reduction model

- Results–if all MA drivers adopted PAYD:
  - 9.5% aggregate VMT reduction if pricing is strictly per mile,
  - 5.0% if a flat fee covers first 2000 miles, with a lower per mile fee thereafter

Fairness and equity impacts

Assumption: PAYD would be offered as a consumer option

Key findings:

- No geographic impacts
- Cross-subsidy alleviated
- Congestion and safety benefits
- Controllable individual factors improve fairness

Conclusions

Summary of key findings

- PAYD is actuarially justified
- PAYD is equitable and fair
- Statewide adoption would result in VMT reductions of 5 – 9.5%

Policy implications

- Regulators should support PAYD
- Consumer protections needed for:
  - Consumer awareness
  - Uninsured driving
  - 'Tracking data'

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Special thanks to:

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