Dynamically updating motor insurance prices with telematics collected driving behavior data

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Paper will appear in Insurance: Mathematics and Economics.

Recent work on insurance pricing analytics

[Henckaerts et al., 2018] — A data driven binning strategy for the construction of insurance tariff classes — SAJ

[Henckaerts et al., 2021] — Boosting Insights in Insurance Tariff Plans with Tree-Based Machine Learning Methods — NAAJ

[Henckaerts et al., 2022] — When stakes are high: balancing accuracy and transparency with Model-Agnostic Interpretable Data-driven suRRogates — Expert Syst. Appl.

[Henckaerts & Antonio, 2022] — The added value of dynamically updating motor insurance prices with telematics collected driving behavior data — IME

distRforest

github/henckr/distRforest

maidrr

github/henckr/maidrr

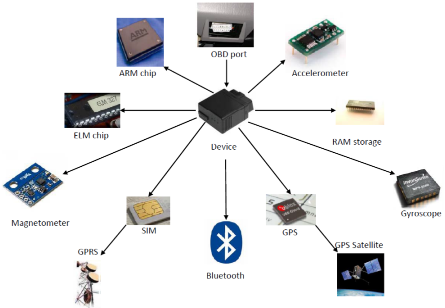
- Denote for policyholder i in a given policy period:
  - e_i: exposure-to-risk
  - N_i: number of claims filed during the exposure period
  - L_i: total loss amount reported during the exposure period.
- The pure premium π_i:

$$\pi_i = \mathbb{E}\left[\frac{L_i}{e_i}\right] \overset{indep.}{=} \mathbb{E}\left[\frac{N_i}{e_i}\right] \times \mathbb{E}\left[\frac{L_i}{N_i} \mid N_i > 0\right] = \underbrace{Freq_i}_{\textbf{frequency}} \times \underbrace{\mathrm{Sev}_i}_{\textbf{severity}}$$

- Build f(risk factors) to predict frequency and severity, respectively.

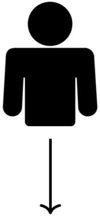
Telematics insurance

Products: usage-based insurance (UBI)
pay-as-you-drive (PAYD)
pay-how-you-drive (PHYD)



- **Telematics** is the integrated use of **tele**communications and infor**matics**.
- Black-box device is installed in the vehicle.
- **Real driving behavior** is monitored.
- Very often targets **young drivers**.

Risk factors for motor insurance pricing

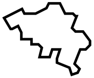


Static, demographic data

License age

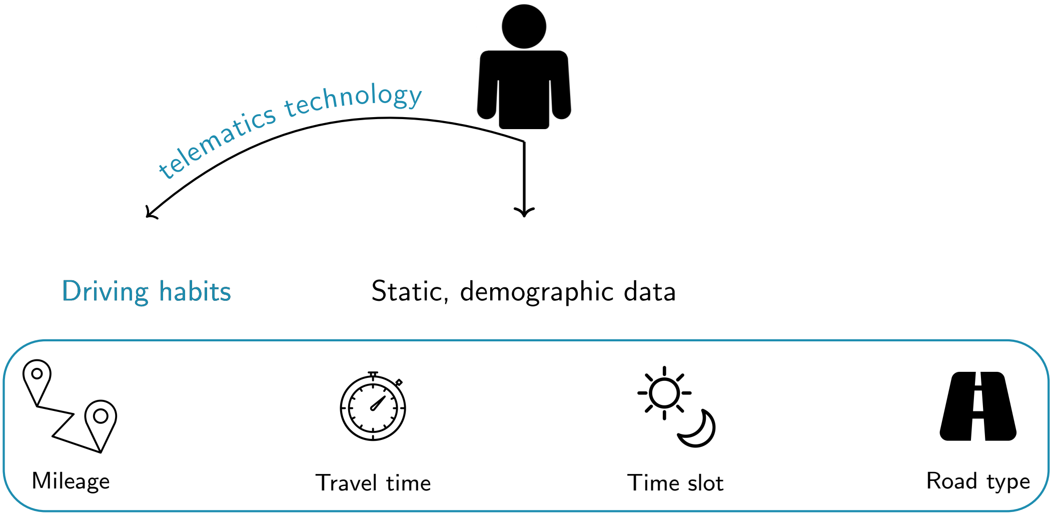
Car make/model

Type of fuel

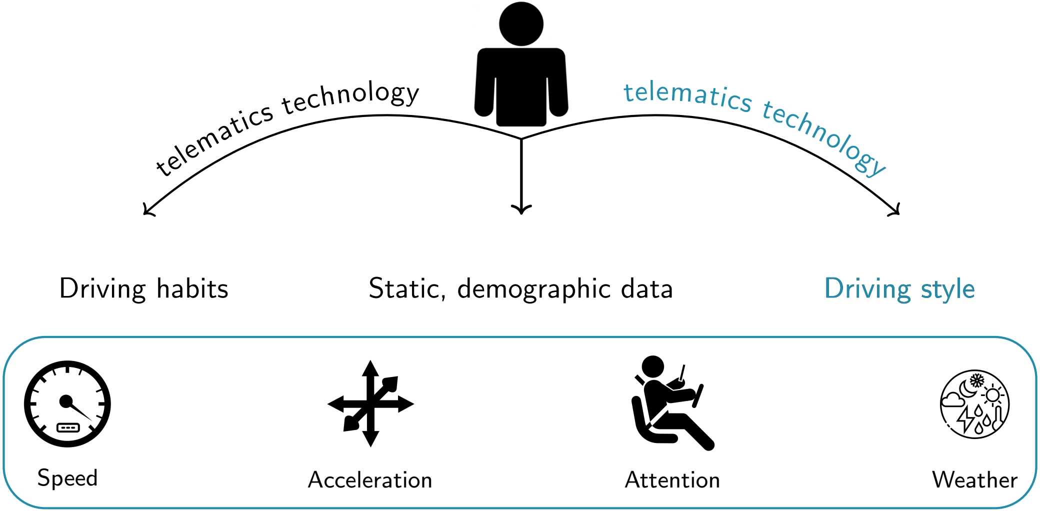


Postal code

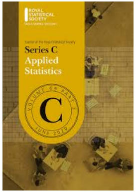
Risk factors for motor insurance pricing



Risk factors for motor insurance pricing



Insurance analytics literature on telematics



- Verbelen, Antonio & Claeskens (2018, JRSS C):
  - claim frequency models with classic, static features and driving habit information
  - compositional data and their use in GAMs.
- Wüthrich (2017, EAJ), Gao & Wüthrich (2018, EAJ), Gao et al. (2019, SAJ) and more papers:
  - the construction of $v - a$ **heatmaps from GPS signals**
  - feature-engineering on these heatmaps
  - use of these features in claim frequency models.

Insurance analytics literature on telematics

Open Access | Feature Paper | Article

Address Identification Using Telematics: An Algorithm to Identify Dwell Locations

by Christopher Grumiau [1], Mina Mostoufi [1,*], Solon Pavlioglou [1,*] and Tim Verdonck [2,3]

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(This article belongs to the Special Issue Data Mining in Actuarial Science: Theory and Applications)

- Denuit, Guillen & Trufin (2019, Annals of Actuarial Science) on **Multivariate credibility modelling for usage-based motor insurance pricing with behavioural data**.

- Grumiau, Mostoufi, Pavlioglou & Verdonck (2020, Risks) on **Address identification using telematics: an algorithm to identify dwell locations**.

- Banghee So, J.-P. Boucher & E. Valdez (2021, Risks) on **Synthetic dataset generation of driver telematics**.

Managerial insights, based on Carbone & Taub (2018) UBI insurance is not usage-based. Sorry, not sorry!

- In 2017, 14 million policies sent telematics data to insurers around the world.
- However, less than 9 percent of the global insurance telematics policies were characterized by **usage-based pricing**.
- **Use of driving data in pricing**:
  - use driving score at underwriting stage
  - propose tailored renewal price (with discounts, or discounts + surcharges)
  - usage-based, i.e. charge price for period of coverage based on how policyholder behaves during this period, and avoid **premium leakage**.

Our focus in this talk:

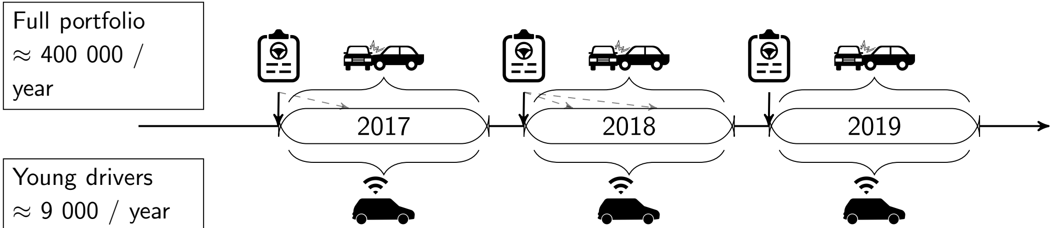
- How to use driving behavior (i.e. habits + style) to **update** a baseline **tariff** (with only self-reported characteristics)?
- What is the **added value** of telematics for pricing via risk classification?
- Managerial insights? Impact on retention rates, profit?

Focus on **frequency, severity and churn models** in the presence of static self-reported characteristics as well as telematics collected data.

Aim for an **explainable** updating mechanism.

Data and methodology

Motor third party liability (MTPL) portfolio

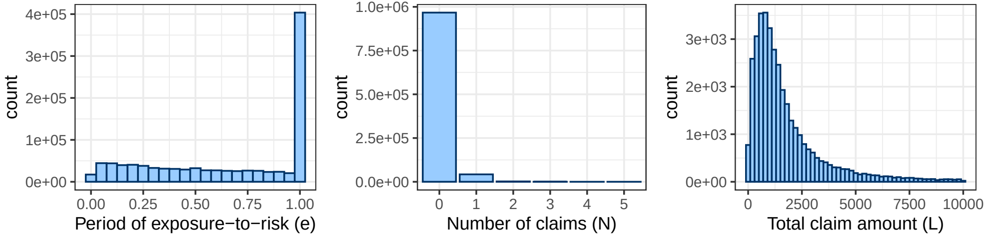


Policy information at the start of the policy period, subject to possible changes during the policy period (e.g., new vehicle).

Claims reported (68 196 in total).

Driving behavior (only for drivers $<$ 26 years at underwriting time, 308M kilometers driven in total).

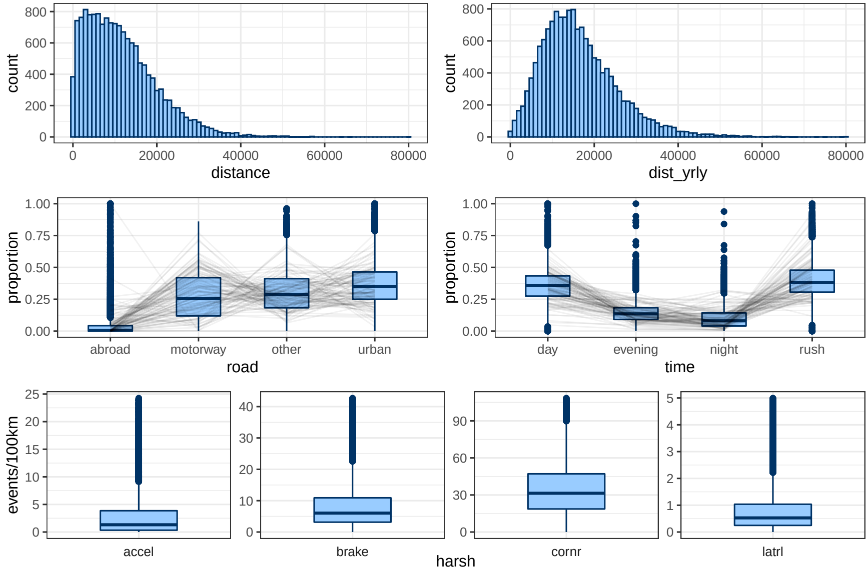
Claims and policy information for the complete portfolio



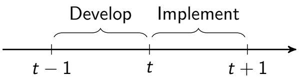
Policy information with **self-reported** risk characteristics:

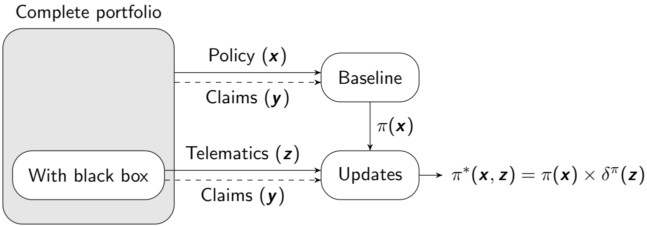
- **driver**: age, experience, additional young drivers, etc.
- **payments**: frequency and SEPA indicator
- **geographical**: postal code and mosaic segment
- **vehicle**: age, weight, value, power, fuel, make, etc.

Driving behavior information for young drivers



Updating methodology





The idea:

- charge baseline tariff $\pi(\boldsymbol{x})$ at t
- ex post, multiplicative update $\delta^\pi(\boldsymbol{z})$ at $t+1$, based on driving data in $[t, t+1]$.

Baseline pricing and churn models

Baseline model training

- Predictive models for the **complete portfolio** using traditional features $\boldsymbol{x}$
  - claim frequency *and* severity $\rightarrow$ **tariff**
  - customer churn prediction $\rightarrow$ client **retention** analysis.
- Stochastic gradient boosting (Friedman, 2002) with the following **assumptions**:

	Distribution	Prediction $f(\boldsymbol{x})$	Loss function $D(y, f(\boldsymbol{x}))$
Claim frequency	$N \sim$ Poisson	$\mathbb{E}(N \mid \boldsymbol{x}, e)$	$\frac{2}{n}\sum_{i=1}^{n}\left[y_i \ln\left\{\frac{y_i}{f_i}\right\} - \{y_i - f_i\}\right]$
Claim severity	$L/N \sim$ gamma	$\mathbb{E}(L/N \mid \boldsymbol{x})$	$\frac{2}{\sum_i N_i}\sum_{i=1}^{n} N_i\left[\frac{y_i - f_i}{f_i} - \ln\left\{\frac{y_i}{f_i}\right\}\right]$
Customer churn	$C \sim$ Bernoulli	$\mathbb{E}(C \mid \boldsymbol{x})$	$-\frac{1}{n}\sum_{i=1}^{n}\left[y_i \ln\{f_i\} + (1 - y_i)\ln\{f_i\}\right]$

Baseline model training

- Parameter **tuning**:

  H2O random grid search + 5-fold cross-validation (LeDell et al., 2020).

- Enforce the **balance property** by scaling predictions (for the young drivers):

  $\sum_{i=1}^{n} f_i = \sum_{i=1}^{n} y_i$

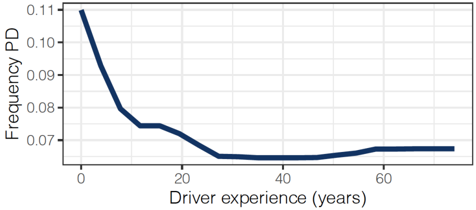
  automatically fulfilled for GLMs with canonical link

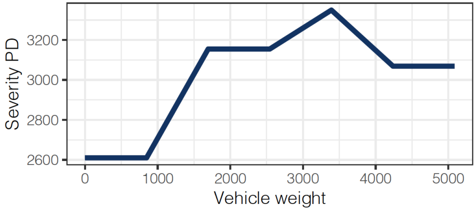
  see e.g. Wüthrich (2020).

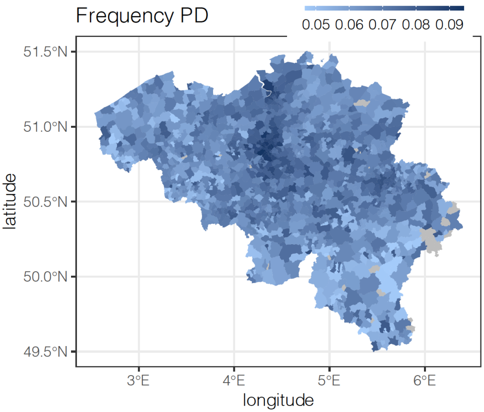
Insights in the optimal GBMs

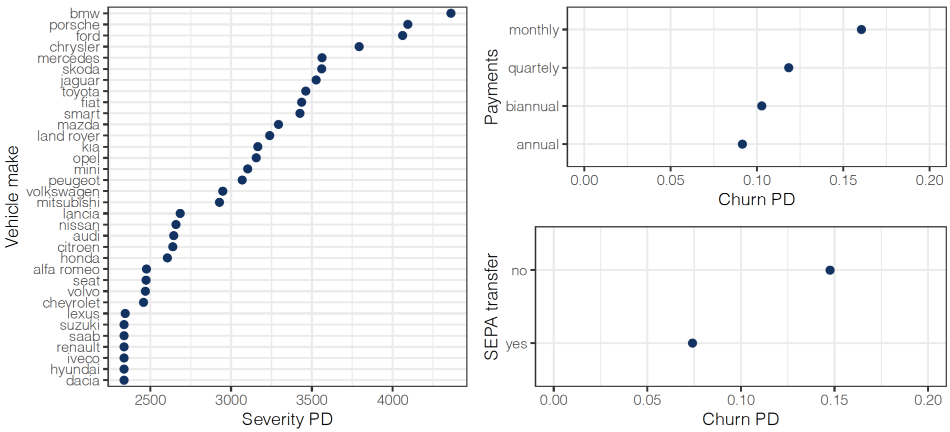
	Claim frequency		Claim severity		Customer churn	
Rank	Feature	%	Feature	%	Feature	%
1	geo_postcode	34.72	veh_weight	23.21	paym_split	43.48
2	driv_experience	14.08	veh_make	21.37	geo_postcode	11.67
3	driv_seniority	8.52	geo_postcode	10.54	veh_age	9.85
4	veh_make	6.25	veh_segment	10.48	paym_sepa	9.44
5	geo_mosaic	5.85	geo_mosaic	6.59	driv_seniority	6.90
6	veh_fuel	5.09	driv_seniority	5.83	veh_make	3.43
7	veh_segment	4.66	veh_value	3.50	driv_experience	2.85
8	paym_split	3.91	veh_age	3.44	geo_mosaic	2.45
9	driv_add_younger26	3.29	driv_experience	2.98	driv_age	2.43
10	driv_age	2.75	driv_add_younger26	2.91	veh_use	1.99
$\sum$		89.12		90.86		94.48

Insights in the optimal GBMs (cont.)









Vehicle make
bmw
porsche
ford
chrysler
mercedes
skoda
jaguar
toyota
fiat
smart
mazda
land rover
kia
opel
mini
peugeot
volkswagen
mitsubishi
lancia
nissan
audi
citroen
honda
alfa romeo
seat
volvo
chevrolet
lexus
suzuki
saab
renault
iveco
hyundai
dacia
2500
3000
3500
4000
Severity PD
Payments
monthly
quartely
biannual
annual
0.00
0.05
0.10
0.15
0.20
Churn PD
SEPA transfer
no
yes
0.00
0.05
0.10
0.15
0.20
Churn PD

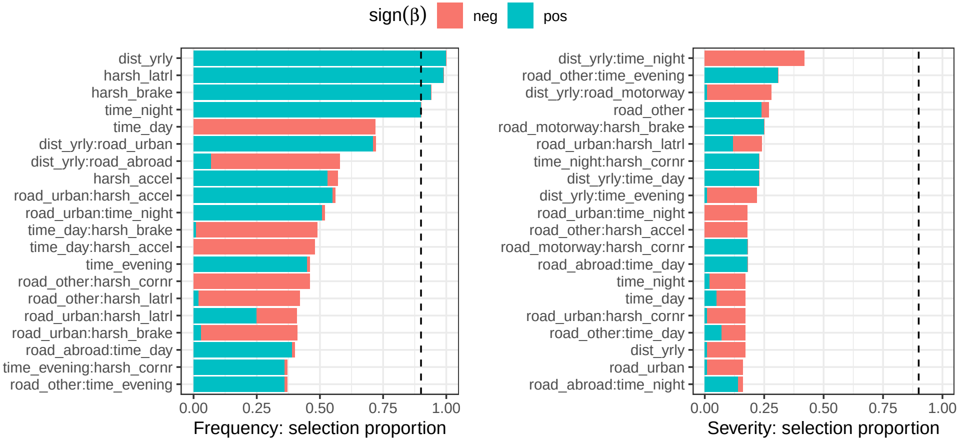
Updating pricing with driving behavior

- Aim is to update premiums for the drivers with telematics features $\boldsymbol{z}$.
- Log-link GLM with the baseline prediction $\ln[f(\boldsymbol{x})]$ as an offset:

$$\begin{aligned} \ln[\mathbb{E}(y \mid \boldsymbol{x}, \boldsymbol{z})] &= \ln[f(\boldsymbol{x})] + \beta_0 + \sum_{j=1}^{p} \beta_j z_j \\ \mathbb{E}(y \mid \boldsymbol{x}, \boldsymbol{z}) &= f(\boldsymbol{x}) \times \exp(\beta_0) \times \prod_{j=1}^{p} \exp(\beta_j z_j). \end{aligned}$$

- Updated prediction is then **multiplicative**:
  - baseline GBM prediction $f(\boldsymbol{x})$ for a policyholder with risk characteristics $\boldsymbol{x}$
  - overall update factor $\exp(\beta_0)$ via the intercept
  - update $\exp(\beta_j z_j)$ from each telematics feature z_j.

Telematics feature selection with LASSO



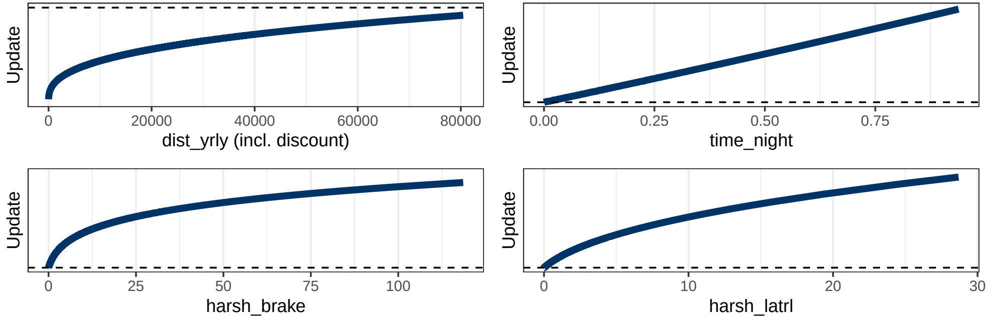
Update price via the claim frequency component

- Let $\boldsymbol{z}^* \in \mathbb{R}^4$ denote $\{$`dist_yrly`, `harsh_latrl`, `harsh_brake`, `time_night`$\}$.
- Log-link Poisson GLM with offset for **claim frequency**:

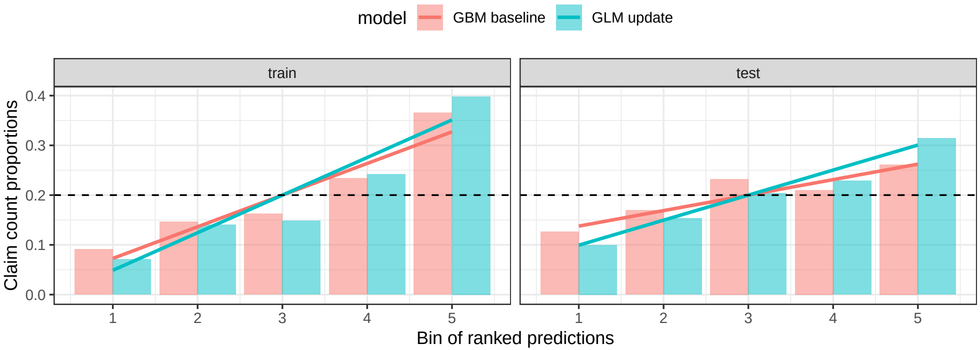
$$\ln[\mathbb{E}(N \mid \boldsymbol{x}, \boldsymbol{z}^*)] = \ln[\mathbb{E}(N \mid \boldsymbol{x}, e)] + \beta_0 + \sum_{j=1}^{4} \beta_j \log(z_j^* + 1)$$

$$\mathbb{E}(N \mid \boldsymbol{x}, \boldsymbol{z}^*) = \mathbb{E}(N \mid \boldsymbol{x}, e) \times \exp(\beta_0) \times \prod_{j=1}^{4} (z_j^* + 1)^{\beta_j}.$$

- Updated prediction is **multiplicative** in the following terms:
  - baseline GBM prediction $\mathbb{E}(N \mid \boldsymbol{x}, e)$ for a policyholder with risk characteristics $\boldsymbol{x}$
  - overall discount factor $\exp(\beta_0) \approx 2\%$
  - update $(z_j^* + 1)^{\beta_j}$ from each telematics feature z_j^*.



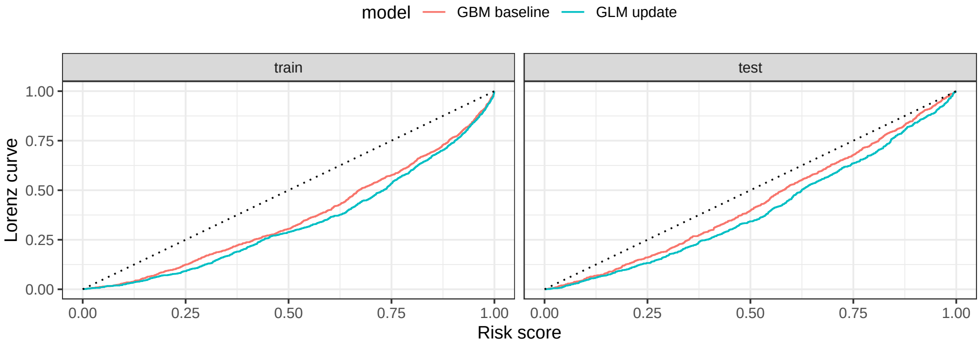
- Mileage + discount remains < 1.
- Penalty once night driving, harsh braking or lateral events are registered.
- Safe driving is the key to earn discounts!



Here we consider:

- $r_i^m = F_n\left(f^m(\boldsymbol{x}_i, \boldsymbol{z}_i^*)\right)$ with $F_n(.)$ the ecdf
- $PC^m(s) = \frac{\sum_{i=1}^n N_i \, \mathbb{1}\{\frac{s-1}{5} < r_i^m \leq \frac{s}{5}\}}{\sum_{i=1}^n N_i}$ for $s \in \{1, \ldots, 5\}$.

Telematics improving risk classification



Here we consider:

- $LC^m(s) = \frac{\sum_{i=1}^{n} N_i \, \mathbb{1}\{r_i^m \leq s\}}{\sum_{i=1}^{n} N_i}$ for $s \in [0, 1]$.

Managerial insights

For the discussion of managerial insights, I refer to our paper:

- **adjust baseline churn** $\rho(\boldsymbol{x})$ to $\rho^*(\boldsymbol{x}, \delta^\pi) = \rho(\boldsymbol{x}) + \epsilon_p \cdot (\delta^\pi - 1) = \rho(\boldsymbol{x}) + \delta^\rho$, with ϵ_p the price elasticity

- study expected **profit and retention rate**

$$P = \frac{1}{n}\sum_{i=1}^{n}(1 - (\rho_i + \delta_i^\rho)) \cdot (\delta_i^\pi \pi_i - L_i) \qquad R = \frac{1}{n}\sum_{i=1}^{n} 1 - (\rho_i + \delta_i^\rho)$$

- restrict penalties/discounts + redistribute $\Rightarrow$ **fairness, solidarity, commercially appealing**

$$\begin{aligned} \delta_{lo}^\pi &\leq \delta^\pi \leq \delta_{hi}^\pi \\ \sum_{i=1}^{n}(1-\rho_i) \cdot \pi_i &= \sum_{i=1}^{n}(1-\rho_i) \cdot \alpha \cdot \delta_i^\pi \cdot \pi_i \end{aligned}$$

Our paper puts focus on:

- a baseline pricing model with self-reported characteristics
- an explainable updating mechanism to incorporate driving behavioral information.

Added value of telematics for insurance pricing is studied from both a statistical and managerial perspective.

More information

For more information, please visit:

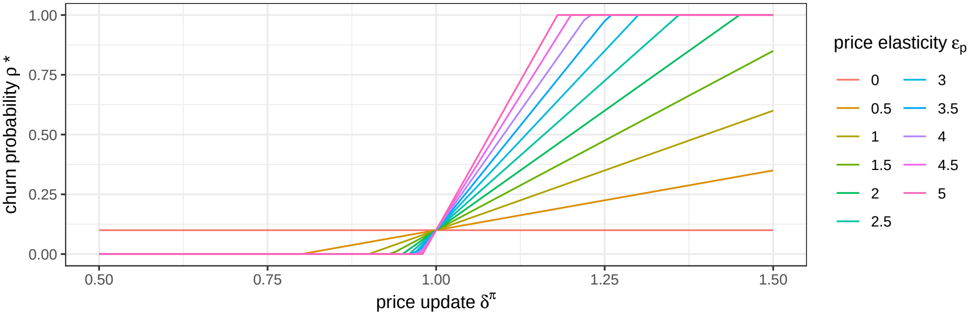
- draft of the paper, including complete set of references
- LRisk website, www.lrisk.be
- my homepage https://katrienantonio.github.io.

Special thanks to

- the organizers
- the companies and funding agencies supporting/having supported my research lab: Ageas, Argenta, Atlas Copco, CNP Assurances, FWO, KU Leuven internal funds.

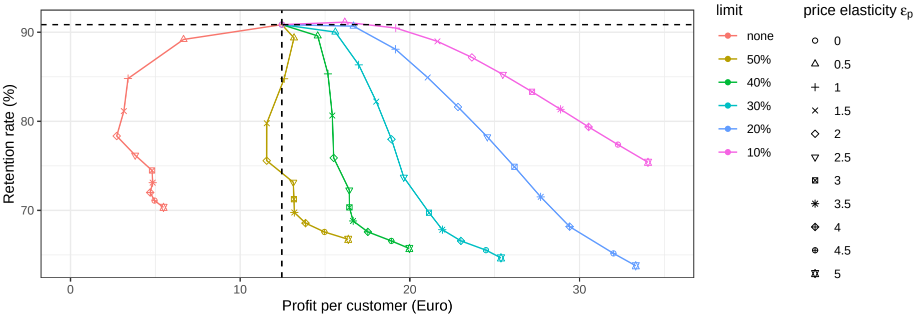
Extra sheets

- Adjust baseline churn via price **update** δ^{π} and **elasticity** of demand ϵ_p.
- $\rho^*(\boldsymbol{x}, \delta^{\pi}) = \rho(\boldsymbol{x}) + \epsilon_p \cdot (\delta^{\pi} - 1)$ for $\rho(\boldsymbol{x}) = 0.1$ and $\epsilon_p \in [0, 5]$:



- $\rho^* = \rho$ when $\delta^{\pi} = \pi^*/\pi = 1$ (no price change).
- Linear increases/decreases ($\delta^{\pi} > 1$ / $\delta^{\pi} < 1$) with slope ϵ_p.

- Expected profits and retention rates under different scenarios:



- Stricter limits result in higher profits
- Profits increase with ϵ_p at the cost of lower retention
- No limit results in lower profits than baseline (driven by low premiums on average)

- Maximize expected profit P while retaining a minimum proportion of the portfolio R^*:

$$\begin{aligned} \max_{\alpha} P(\alpha) =& \frac{1}{n}\sum_{i=1}^{n}(1-(\rho_i+\delta_i^{\rho}))\cdot(\alpha\delta_i^{\pi}\pi_i - L_i) \\ \text{subject to } R(\alpha) =& \frac{1}{n}\sum_{i=1}^{n} 1-(\rho_i+\delta_i^{\rho}) \geq R^* \\ & \delta_{lo}^{\pi} \leq \delta^{\pi} \leq \delta_{hi}^{\pi}. \end{aligned}$$

- Implicit dependence of R on α as $\delta^{\rho} = \epsilon_p \cdot (\alpha\delta^{\pi} - 1)$.
- Efficient frontier by varying R^* over a range of values and maximizing $P(R^*)$ via α.

Efficient frontiers for $R^* \in [0.75, 0.9]$ under different scenarios