Exposing indirect discrimination

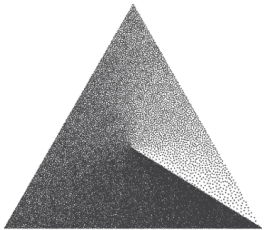
A scalable toolbox for fairness assessment of insurance rates

Presented by

Olivier Côté

Joint work with

Prof. Marie-Pier Côté (U. Laval) **and**
Prof. Arthur Charpentier (UQÀM)



Séminaire étudiant UQAM

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UNIVERSITÉ LAVAL

Fairness and equity

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2021 Report by the Secretary General of the Council of Europe entitled “State of democracy, human rights and the rule of law : A democratic renewal for Europe”

Fairness and equity : no consensus

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The public release of these [Federal Equity Action] plans demonstrated immense public waste and **shameful discrimination**. That ends today. Americans deserve a government committed to **serving every person with equal dignity and respect** [...]

Executive order of The White House issued on January 20, 2025 entitled “Ending Radical And Wasteful Government DEI Programs And Preferencing”

Differentiation at the core of insurance pricing

Insurance pricing relies on grouping policyholders by risk to set adequate premiums.

Modern predictive models excel at detecting statistical associations to differentiate between risks, but they can learn spurious correlations.

This raises concerns when sensitive variables may (intentionally or inadvertently) affect the **fairness of insurance pricing**.

Notation

Age	Vehicle	Occupation	Gender	Religion	Credit	Claim
					800	
					700	
					650	
					435	
			Europe	California	Ontario	

Allowed variables
X

Prohibited variables
D
(Collected)

Response
Y

Some fair premiums

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These different premiums all aim to be *fair*. Again, no consensus.

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- Frees and Huang (2023) argue that **using variables related to** D constitutes indirect discrimination.
- Lindholm et al. (2024) equate indirect and **proxy discrimination**, where formulas implictly infer D.

Unclear fairness terms impede progress.

Goals

1. Understand the behaviour of fair pricing methodologies.
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This joint work with Marie-Pier Côté and Arthur Charpentier is supported by a Canadian insurance company.

Exploiting causal graphs for fairness

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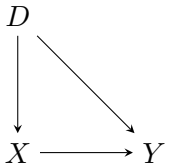
Both are **supported by causal graphs** (DAG).



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  - Indirect discrimination lacks a consensual definition.
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- Many fairness methodologies exist and do not match. The *Pre-In-Post* categorization **does not clarify the expected fairness properties**.

Dependence implications of a causal graph

		Causal type of C		
		Confounder	Mediator	Collider
Status of C	Unconditioned	$A \leftarrow C \rightarrow B$		
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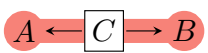
Conditioned			

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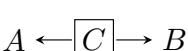
Conditioned			

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Causal relationships have **dependence implications**.

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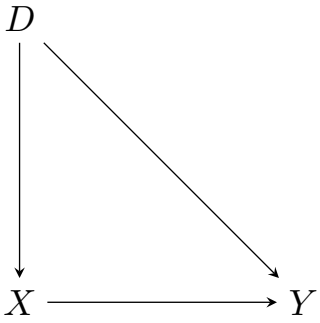

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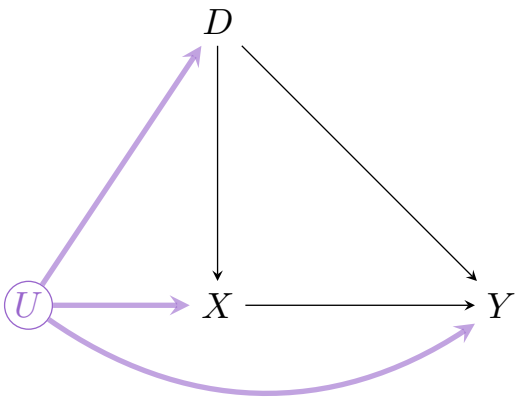

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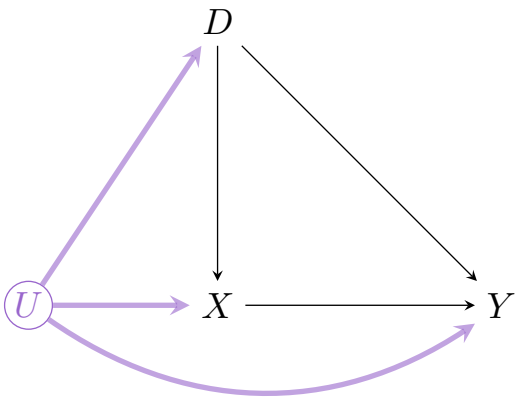

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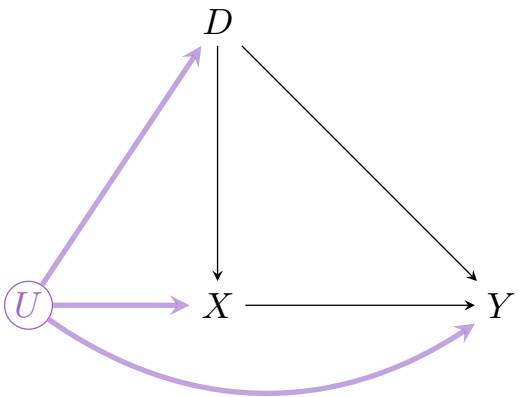
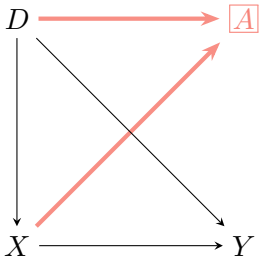


- **Omitted variable bias** arises because $D \leftarrow U \rightarrow X$ is indistinguishable from $D \rightarrow X$.
- Detecting unobserved confounders relies on expert judgment, making these confounders **unverifiable**.

Portfolio selection bias



Selection bias in insurance : why portfolio-specific fairness fails to extend market-wide, *available on SSRN*

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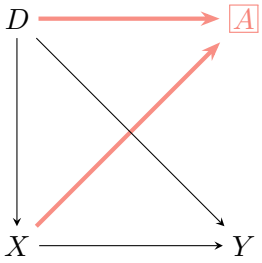

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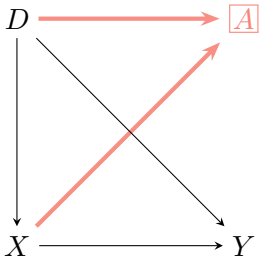

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- Should insurers focus on **portfolio or market-wide** fairness ?

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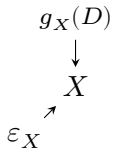

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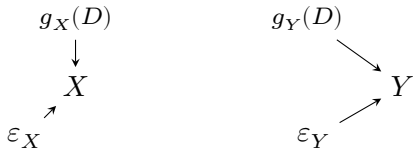

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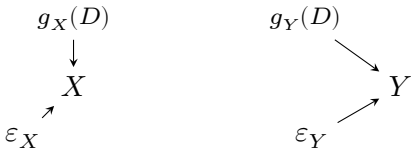

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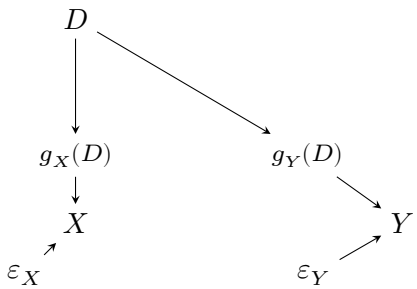

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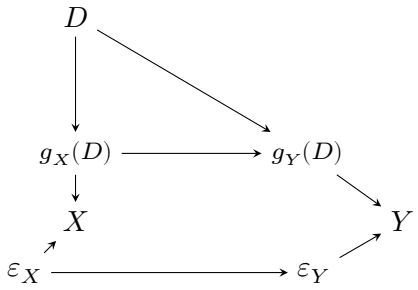

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(a) Causal relationship **(b)** **Sufficient** premium $\mu(A)$

Indirect discrimination from the legal perspective

"A situation in which an **apparently neutral provision**, criterion or practice would put persons of a racial or ethnic origin at a **particular disadvantage compared with other persons**, unless that provision, criterion or practice is **objectively justified** by a legitimate aim and the means of achieving that aim are appropriate and necessary."

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We formalize for elements 1 and 2.

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- A **disparate impact** implies a decision $\mu(X, D)$ affecting protected groups D.
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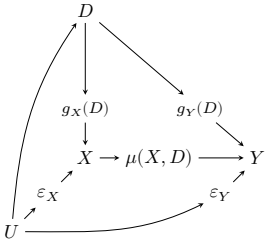
- We assume there is no direct discrimination.

Sources of disparate impact



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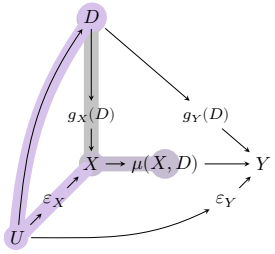
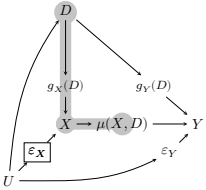
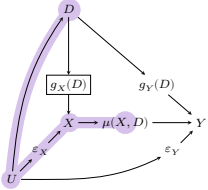


Disp. Impact through X

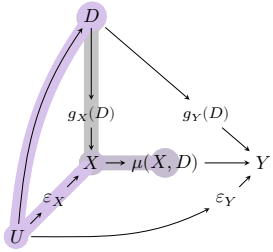
Sources of disparate impact



Purely through X



Through an conf. of $D \to X$



Disp. Impact through X

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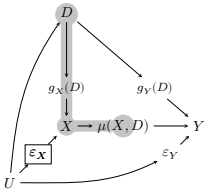
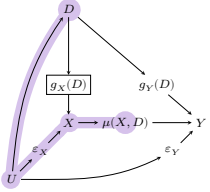
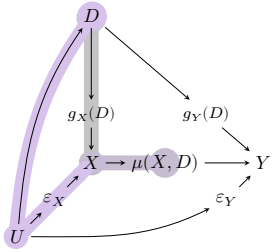


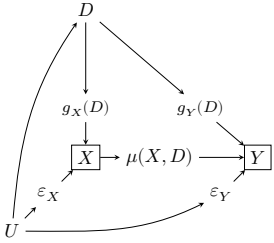
Purely through X



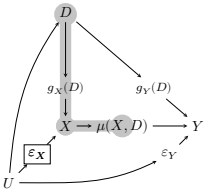
Through an conf. of $D \to X$



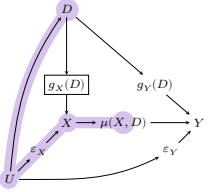
Disp. Impact through X



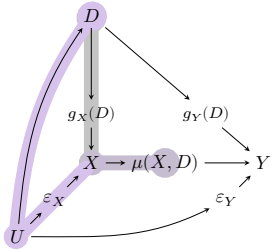
Sources of disparate impact



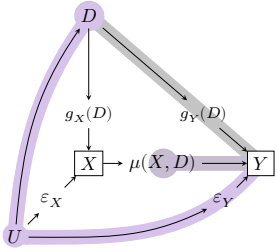
Purely through X



Through an conf. of $D \to X$

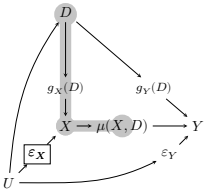


Disp. Impact through X

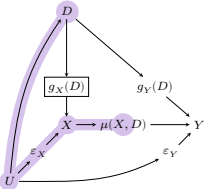


Disp. Impact through $\boxed{Y}$

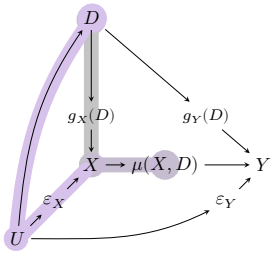
Sources of disparate impact



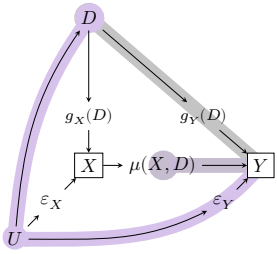
Purely through X



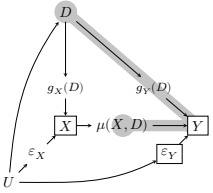
Through an conf. of $D \to X$



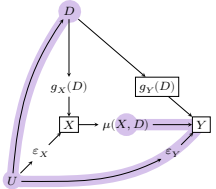
Disp. Impact through X



Disp. Impact through $\boxed{Y}$

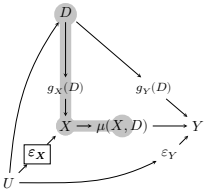


Purely through $\boxed{Y}$

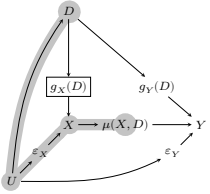


Through a conf. of $D \to Y$

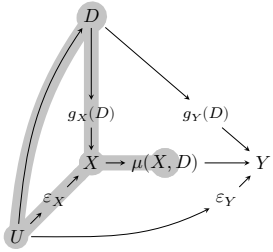
Sources of disparate impact



Purely through X



Through an conf. of $D \to X$

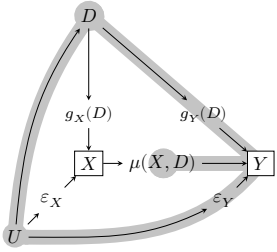


Disp. Impact through X

Mitigation leads to

Solidarity

(Levelled premiums)

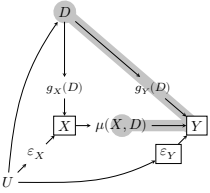


Disp. Impact through $\boxed{Y}$

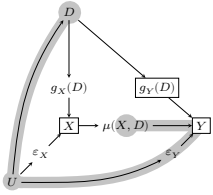
Mitigation leads to

Actuarial Fairness

(Levelled profits)



Purely through $\boxed{Y}$



Through a conf. of $D \to Y$

Discrimination is inevitable

Proposition. Unless $D \perp\!\!\!\perp Y$ and $D \perp\!\!\!\perp Y|X$, all premiums disparately impact D.

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Corollary.

Unless $D \perp\!\!\!\perp Y$ and $D \perp\!\!\!\perp Y|X$, all premiums **must discriminate** either directly or indirectly on D.

Discrimination is inevitable

Proposition. Unless $D \perp\!\!\!\perp Y$ and $D \perp\!\!\!\perp Y|X$, all premiums disparately impact D.

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Unless $D \perp\!\!\!\perp Y$ and $D \perp\!\!\!\perp Y|X$, all premiums **must discriminate** either directly or indirectly on D.

The **impossibility** theorem by Kleinberg et al. (2016) **extends to discrimination**.

Examples from the literature

Premium of Lindholm et al. (2022)

Premium of Frees and Huang (2023)

Examples from the literature

Premium of Lindholm et al. (2022)

The premium is

$$\pi^L(X) = \mathrm{E}_D\{\mathrm{E}(Y|X,D)\}$$

Premium of Frees and Huang (2023)

For $X^* = (\mathbf{I} - H_D)X$, the premium is

$$\pi^F(X,D) = X^\top(\mathbf{I} - H_D)(X^{*\top}X^*)^{-1}X^{*\top}Y.$$

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X^* is an **estimator of** ε_X.

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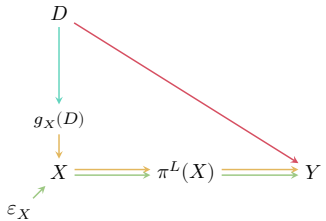

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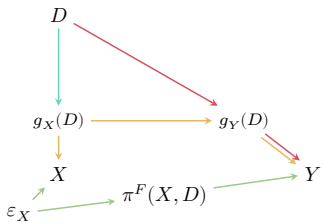
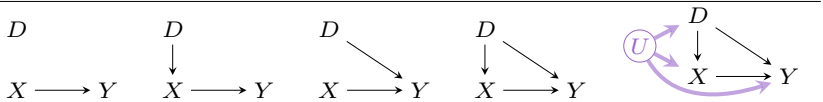


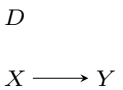
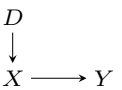
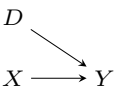
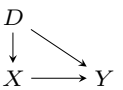
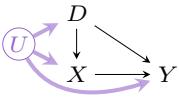
Discrimination for the premium $\pi^L(X)$

Data generating mechanism

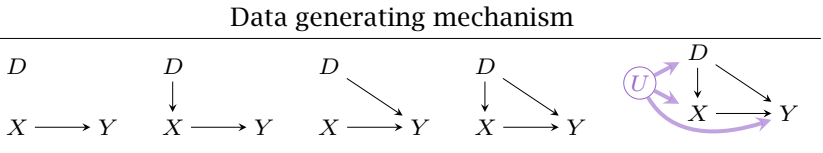


Discr.						
	Direct	○	○	○	○	○
	Indirect	○	●	●	●	●

Discrimination for the premium $\pi^L(X)$

			Data generating mechanism				
							
Discr.		Direct	○	○	○	○	○
		Indirect	○	●	●	●	●
Disp. Impact	X	Purely	○	●	○	●	●
		Conf.	○	○	○	○	●
	$\boxed{Y}$	Purely	○	○	●	●	●
		Conf.	○	○	○	○	●

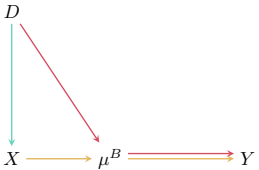
Discrimination for the premium $\pi^F(X, D)$



Discr.		Direct	○	●	○	●	●
		Indirect	○	○	●	○	○
Disp. Impact	X	Purely	○	○	○	○	○
		Conf.	○	○	○	○	●
	$\boxed{Y}$	Purely	○	●	●	●	●
		Conf.	○	○	○	○	●

Best-estimate premiums

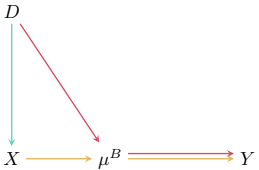
The **best-estimate** premium $(X, D) \mapsto \mu^B(X, D)$ uses (X, D) to predict Y.



$$\mu^B(x, d) = E(Y|X = x, D = d)$$

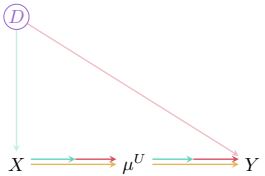
Best-estimate, unaware premiums

The **best-estimate** premium $(X, D) \mapsto \mu^B(X, D)$ uses (X, D) to predict Y.



$$\mu^B(x, d) = E(Y|X = x, D = d)$$

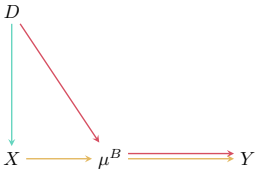
The **unaware** premium $X \mapsto \mu^I(X)$ uses X, ignoring D, to predict Y.



$$\mu^U(x) = E(Y|X = x)$$

Best-estimate, unaware, and aware premiums

The **best-estimate** premium $(X, D) \mapsto \mu^B(X, D)$ uses (X, D) to predict Y.



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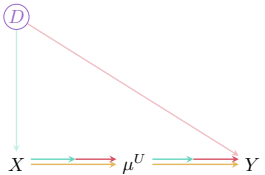
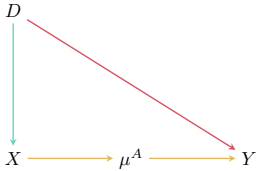
The **unaware** premium $X \mapsto \mu^I(X)$ uses X, ignoring D, to predict Y.



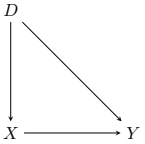
$$\mu^U(x) = E(Y|X = x)$$

The **aware** premium $X \mapsto \mu^A(X)$ uses X to predict Y while controling for D.

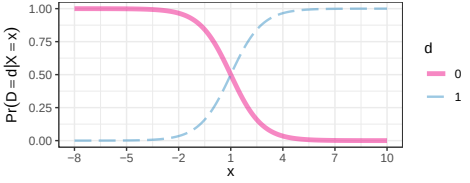


$$\mu^A(x) = E_D\{E(Y|X = x, D)\}$$

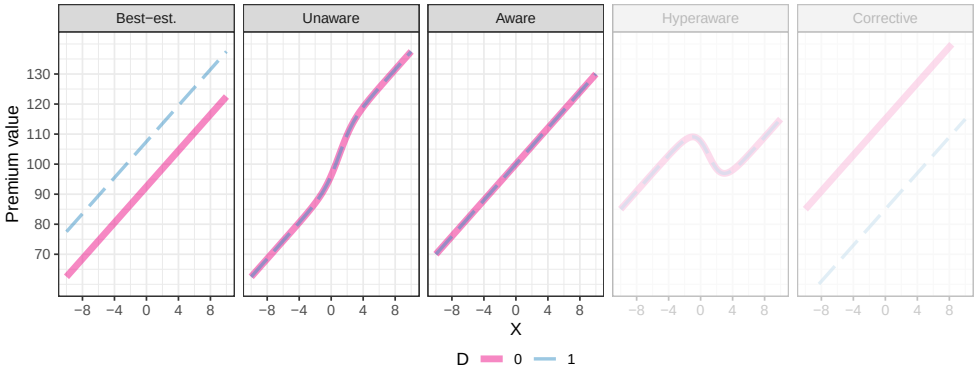
Configuration of the example



- Let $D \in \{0, 1\}$ be Bernoulli with $\Pr(D = 1) = 0.5$.
- The variables X and Y are Gaussian and the DAG is satisfied.

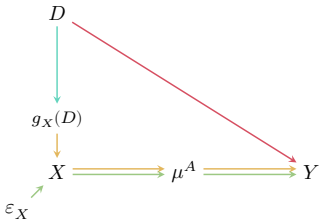


Premiums in terms of x and d



Hyperaware and corrective premiums

The **aware** premium $X \mapsto \mu^A(X)$ uses all of X to predict Y while correcting for the omitted variable bias associated with D.



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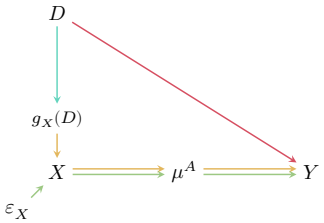
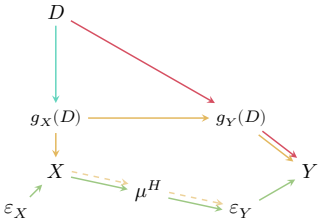


A **hyperaware** premium $X \mapsto \mu^H(X)$ use all of X to predict ε_Y.



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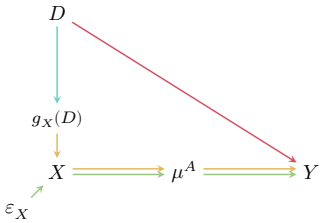

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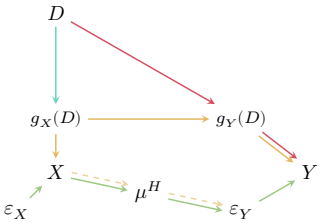
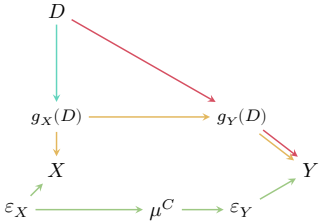
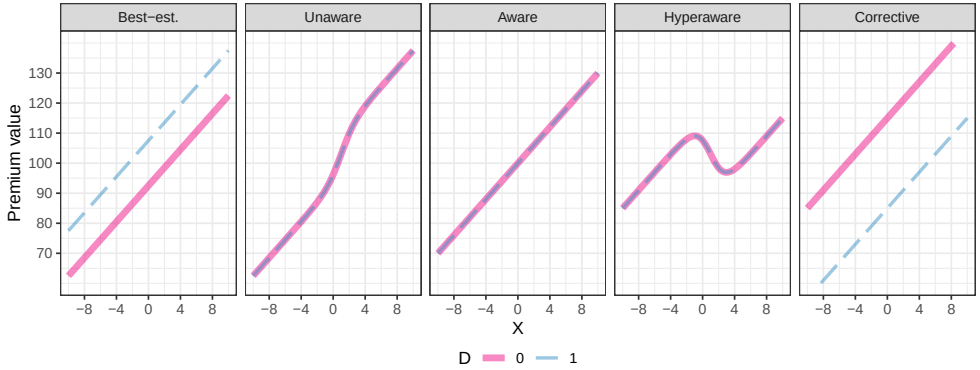


The **corrective** premium $\varepsilon_X \mapsto \mu^C(\varepsilon_X)$ models the residual information independent from D.



Premiums in terms of x and d



Our classification : a few examples

Expected premium	Type of intervention: *Pre-processing*	*In-processing*	*Post-processing*
Aware	Plečko et al. (2021) Charpentier et al. (2023a)	Lindholm et al. (2024) Gabric et al. (2024)	Pope and Sydnor (2011) Aseervatham et al. (2016) **Lindholm et al. (2022)**
Hyperaware	Zemel et al. (2013)	Grari et al. (2022)	
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Expected premium (*what*)	Type of intervention (*when*)		
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How does this framework make a difference **in practice**?

A scalable toolbox for exposing indirect discrimination

1 Exploiting causal graphs for fairness

2 A scalable toolbox for exposing indirect discrimination
- What does it mean to be fair ?
- Can one benchmark for fairness ?
- Is unfairness truly material ?
- Where indirect discrimination concentrates ?

Context around this project

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Figure 2 – Journée de collaboration au local **Desjardins** du MILA, 20 février 2025, Montréal

Context around this project

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Outlook

Congratulations on Achieving Your ACAS! CRM:0100683

De CAS Portal - NO REPLY <cobaltams@casact.org>
Date Ven 2025-06-06 12:26
À Olivier Côté <olivierc_actuariat@outlook.com>

Olivier Côté, ACAS
870 av Marguerite-Bourgeoys
Lévis QC G1S3X2
Canada

Expertise. Insight. Solutions.®

Dear Olivier,

On behalf of the Casualty Actuarial Society, it is our pleasure to notify you that you are now an Associate of the CAS. You may begin using the designation "Associate, Casualty Actuarial Society" or "ACAS" immediately. CAS credentials are unmatched for their rigor, integrity, and relevance, making it the gold standard among property & casualty actuarial credentials. Congratulations on attaining this milestone in your actuarial career!

Sincerely,

David Cummings, FCAS
President

Victor Carter-Bey, DM
Chief Executive Officer

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  - E.g. Financial Services Regulatory Authority of Ontario (2024)

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  - Their units are abstract.
- Fairness is debated in theory, but **unfairness unfolds in practice**.
  - Few Canadian insurance case studies exist.

Vulnerability to proxies in Québec auto insurance

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Data : $\approx$ 768,000 insured vehicles in Quebec, from 2016–2017. Data obtained via insurer partnership.

Note : Personal data anonymized ; strict confidentiality measures applied.

Data overview

Notation	Concept	Domain	Notes
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$\mathbf{X}$	Policyholder info	Dim. 16	E.g., gender, driving experience, mileage, education, occupation
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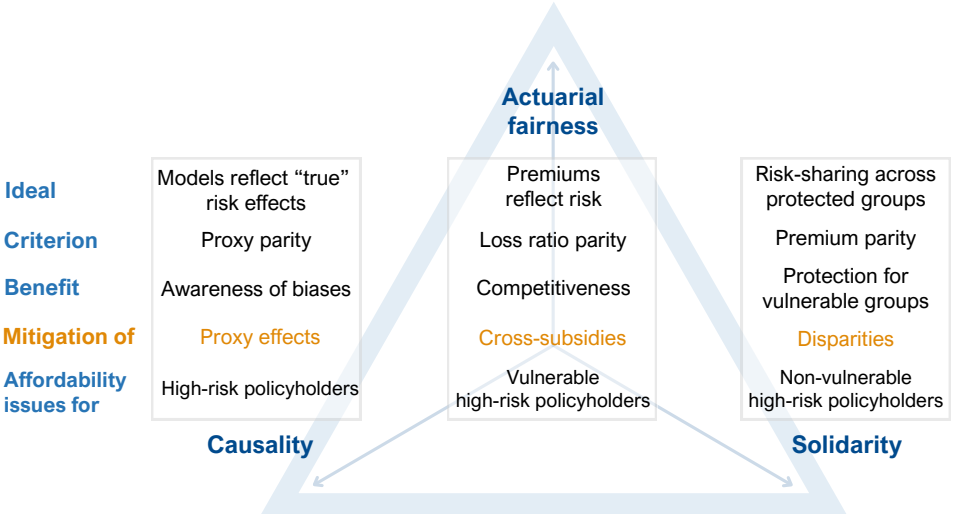
The **non-equivalence of the pseudoprice to the actual pricing function** precludes any conclusion regarding the fairness of the partner insurer's pricing.

The dimensions of fairness



Actuarial Fairness

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- Avoids **non-risk-based adjustments.**

Solidarity

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In the presence of admissible variables $\mathbf{X}$ and sensitive ones D,

- we can leverage the effect of $\mathbf{X}$ on the response variable Y
- while aiming for solidarity on D : equal premiums (in expectation or distribution) across all protected groups.

This is referred to as **demographic parity of premiums**.

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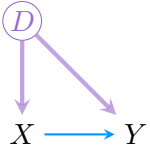
In fairness analysis with respect to D, causality seeks to identify the **effect of X on Y** without **proxy effects from D**.



Five fair benchmarks

Premium	Best-estimate	Unaware	Aware	Hyperaware	Corrective
Notation	$\mu^B(\mathbf{x}, d)$	$\mu^U(\mathbf{x})$	$\mu^A(\mathbf{x})$	$\mu^H(\mathbf{x})$	$\mu^C(\mathbf{x}, d)$
Formula	$\mathbb{E}(Y\|\mathbf{X}=\mathbf{x}, D=d)$	$\mathbb{E}(Y\|\mathbf{X}=\mathbf{x})$	$\mathbb{E}_D\{\mu^B(\mathbf{x}, D)\}$	$\mathbb{E}\{\mu^C(\mathbf{x}, D)\|\mathbf{X}=\mathbf{x}\}$	$\mathcal{T}^{d\to\star}\{\mu^B(\mathbf{x}, d)\}$
Direct discrimination	✔	✘	✘	✘	✔
Proxy discrimination	–	✔	✘	✔	–
Demographic disparities	✔	✔	✔	✘	✘
Pillar	**AF**	**AF**	**C**	**S**	**S**

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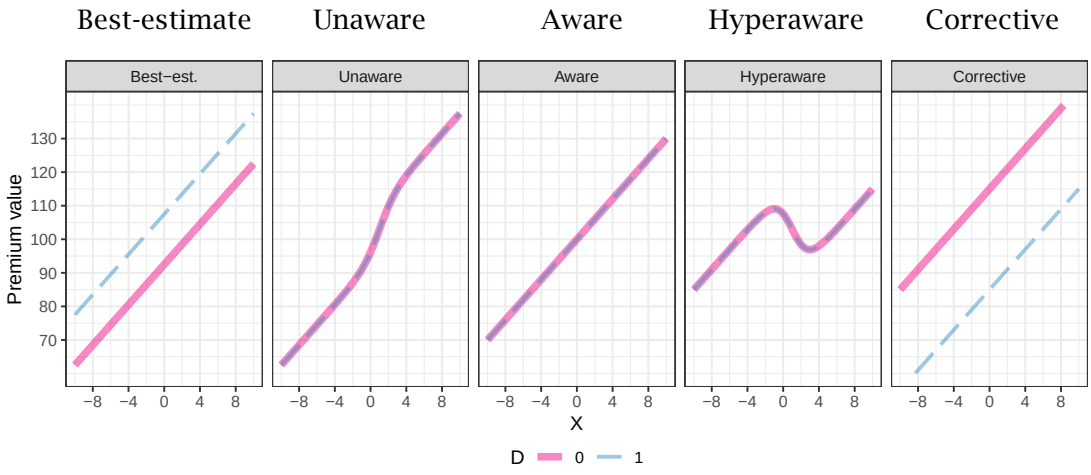
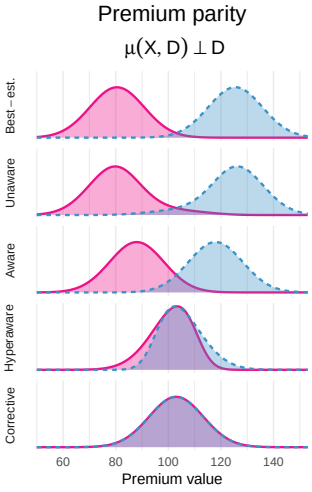
Pillar	**AF**	**AF**	**C**	**S**	**S**

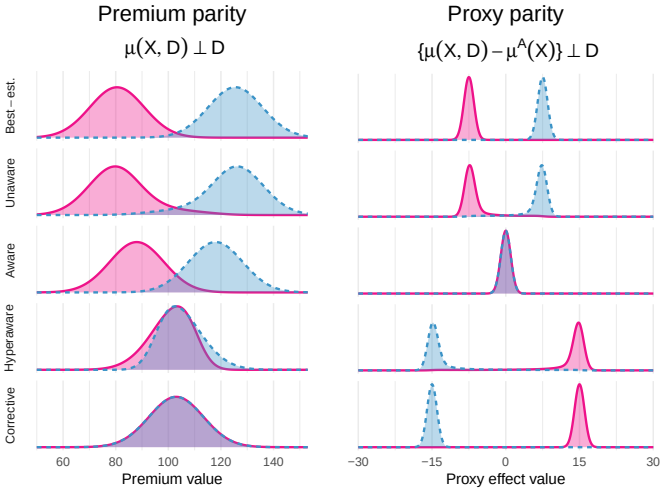
We estimate the premium spectrum using :

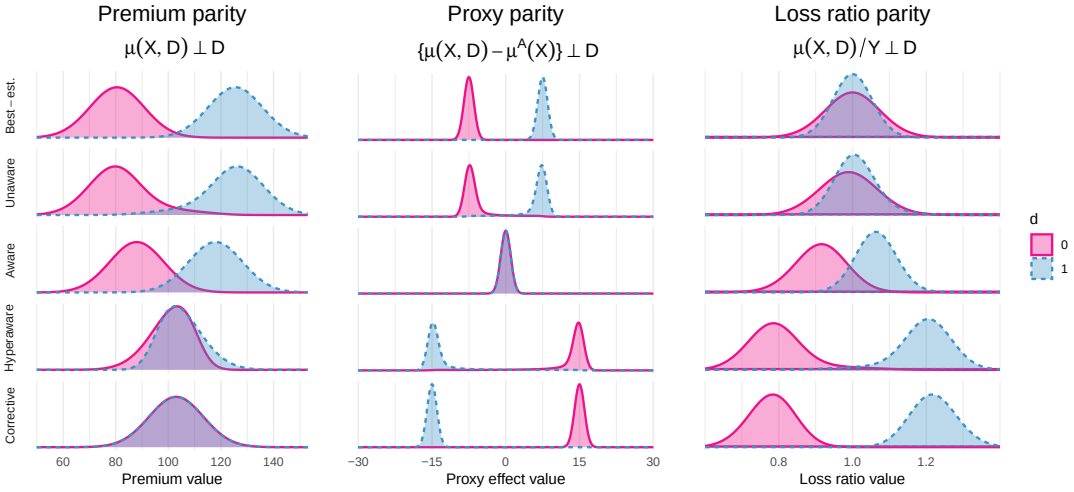
- `lightGBM` (Ke et al., 2017) to learn conditional expectations,
- empirical marginals of D for population-level integration, and
- optimal transport mappings via `Equipy` (Fernandes Machado et al., 2025).

Example : Premiums in terms of x and d




Premium parity
μ(X, D) ⊥ D
Best − est.
Unaware
Aware
Hyperaware
Corrective
60
80
100
120
140
Premium value
d
0
1


Premium parity
$\mu(X, D) \perp D$
Proxy parity
$\{\mu(X, D) - \mu^A(X)\} \perp D$
Best – est.
Unaware
Aware
Hyperaware
Corrective
60
80
100
120
140
Premium value
−30
−15
0
15
30
Proxy effect value
d
0
1


Premium parity
$\mu(X, D) \perp D$
Proxy parity
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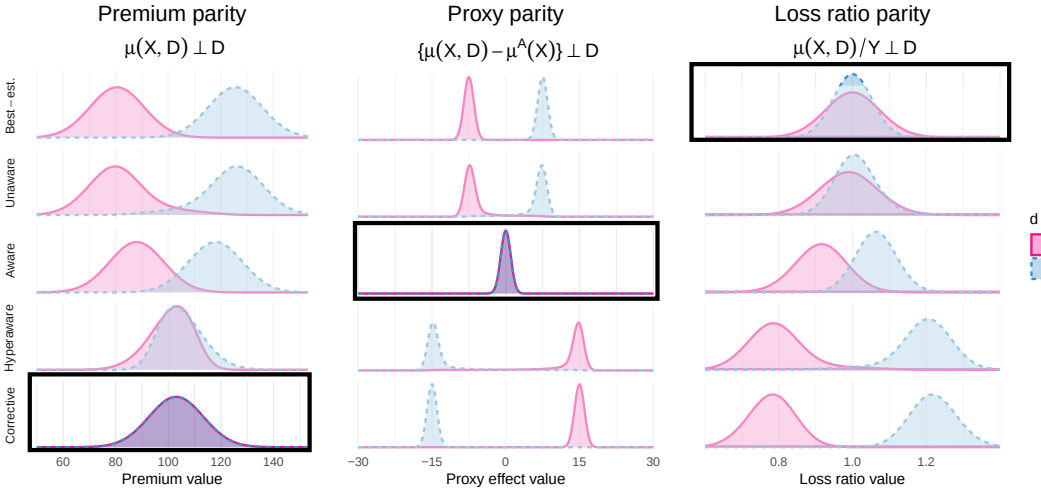
Loss ratio parity
$\mu(X, D)/Y \perp D$
Best – est.
Unaware
Aware
Hyperaware
Corrective
60
80
100
120
140
Premium value
−30
−15
0
15
30
Proxy effect value
0.8
1.0
1.2
Loss ratio value
d
0
1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Premium value
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0.8
1.0
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Loss ratio value
d
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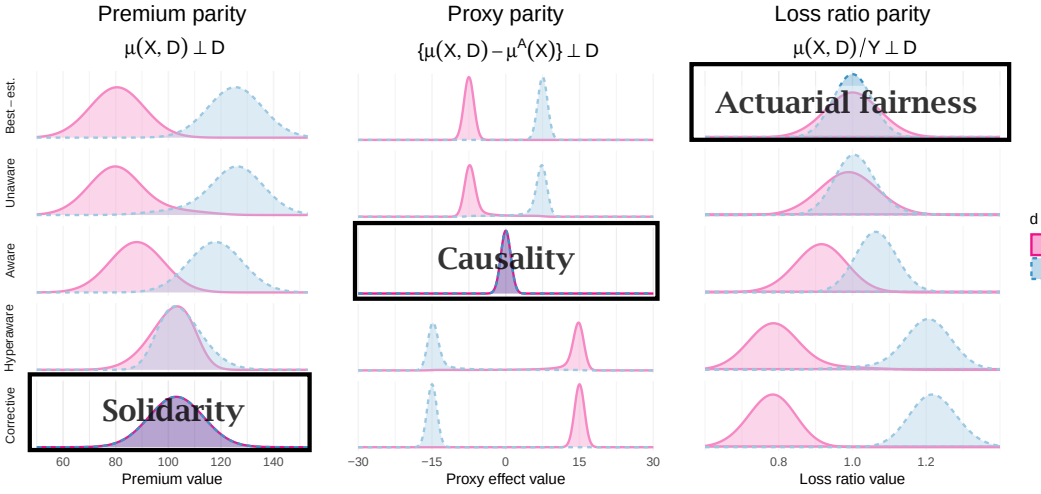
Premium parity
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Proxy parity
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Loss ratio parity
$\mu(X, D)/Y \perp D$
Actuarial fairness
Causality
Solidarity
Best – est.
Unaware
Aware
Hyperaware
Corrective
60
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15
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Proxy effect value
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Loss ratio value
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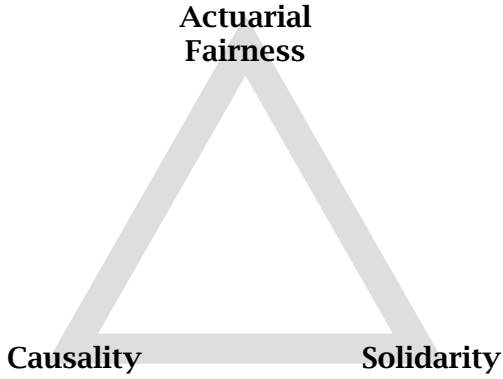
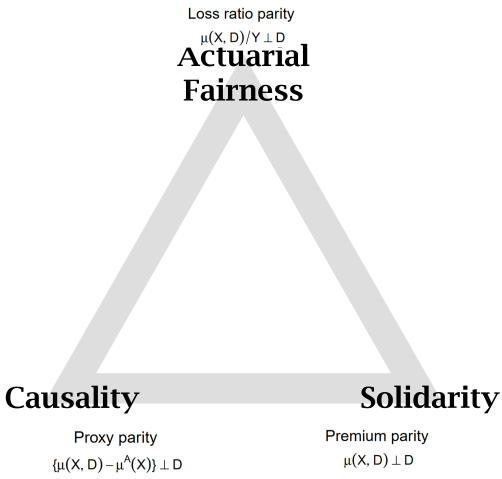
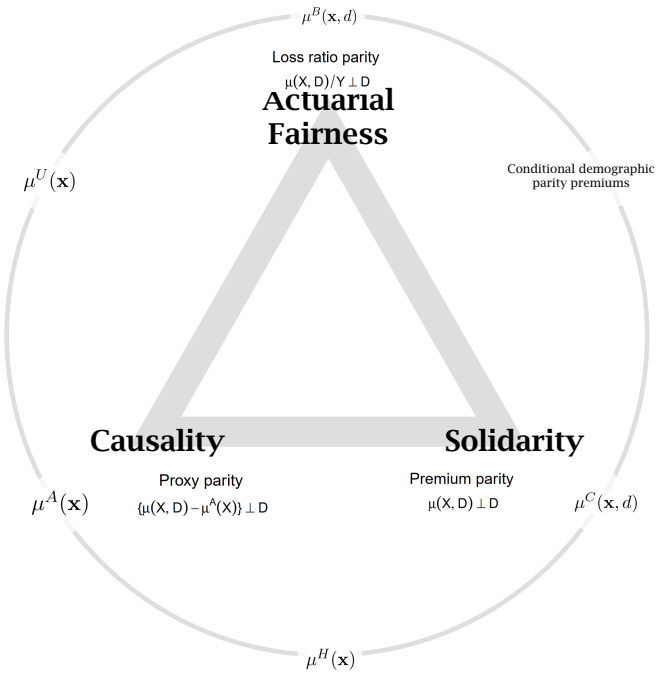
1


Actuarial
Fairness
Causality
Solidarity


Loss ratio parity
$\mu(X, D)/Y \perp D$
Actuarial Fairness
Causality
Solidarity
Proxy parity
$\{\mu(X, D) - \mu^{A}(X)\} \perp D$
Premium parity
$\mu(X, D) \perp D$


$\mu^B(\mathbf{x}, d)$
Loss ratio parity
$\mu(X, D)/Y \perp D$
Actuarial Fairness
$\mu^U(\mathbf{x})$
Conditional demographic parity premiums
Causality
Solidarity
Proxy parity
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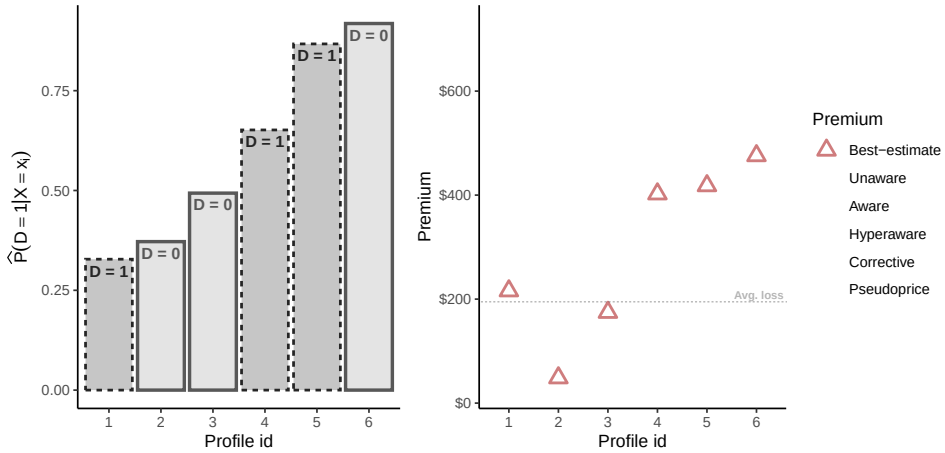
Premium parity
$\mu(X, D) \perp D$
$\mu^A(\mathbf{x})$
$\mu^C(\mathbf{x}, d)$
$\mu^H(\mathbf{x})$

Fairness range for six profiles



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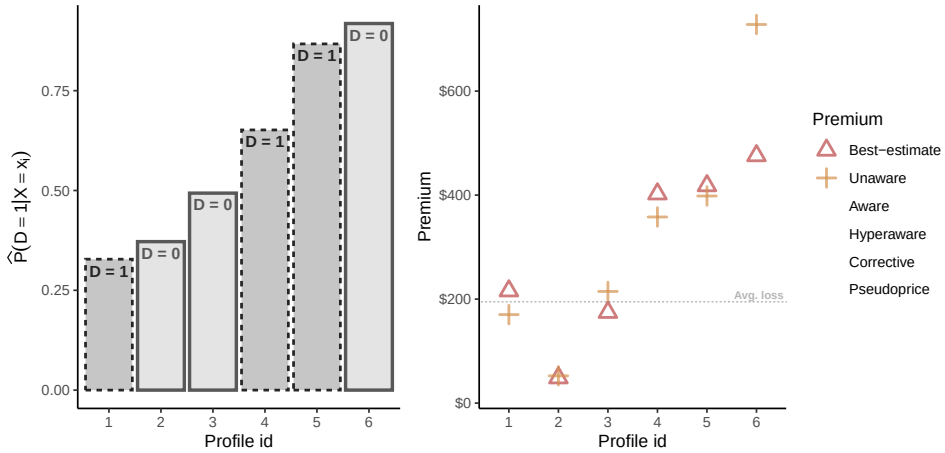

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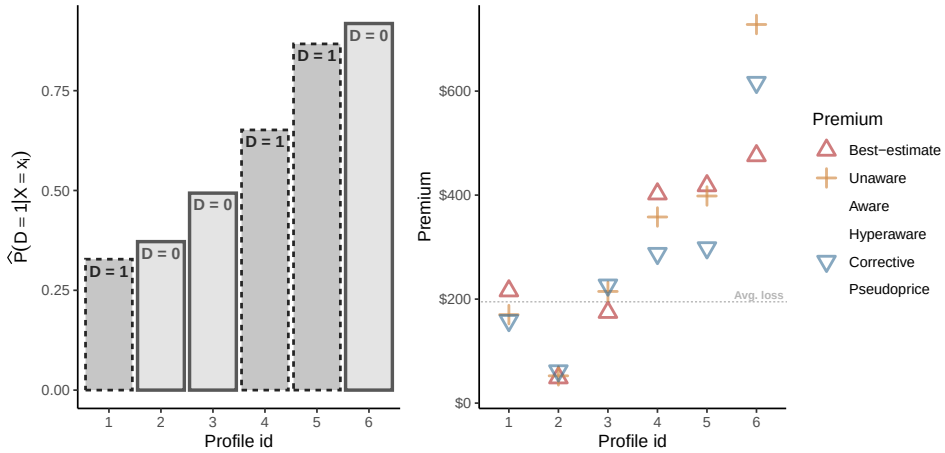

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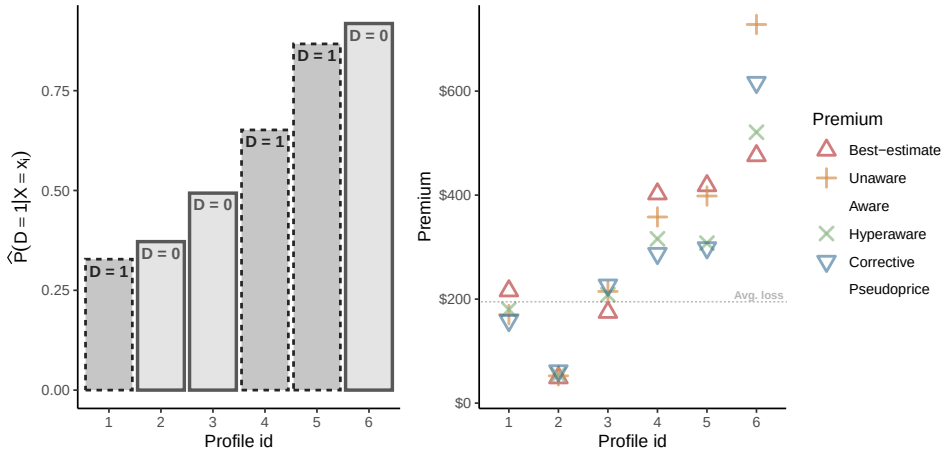
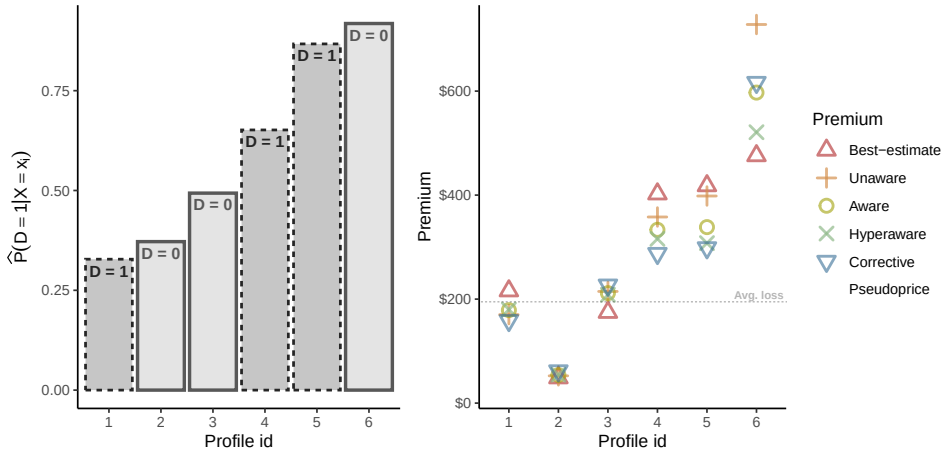
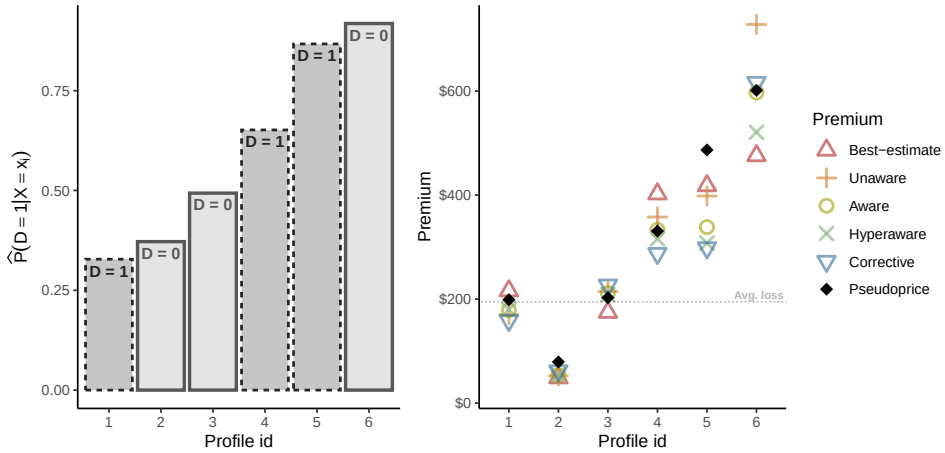


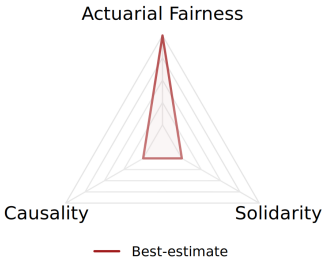
Fairness range for six profiles

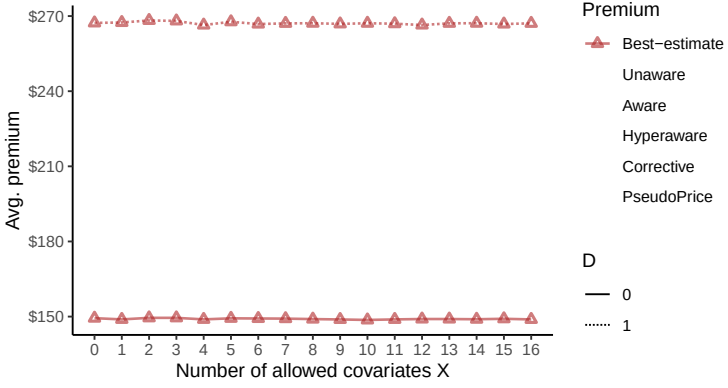


Fairness range for six profiles



Grasping behavior of families





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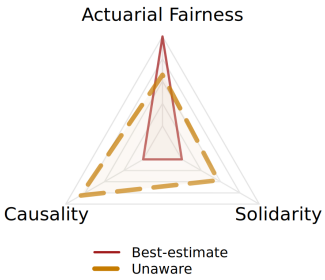

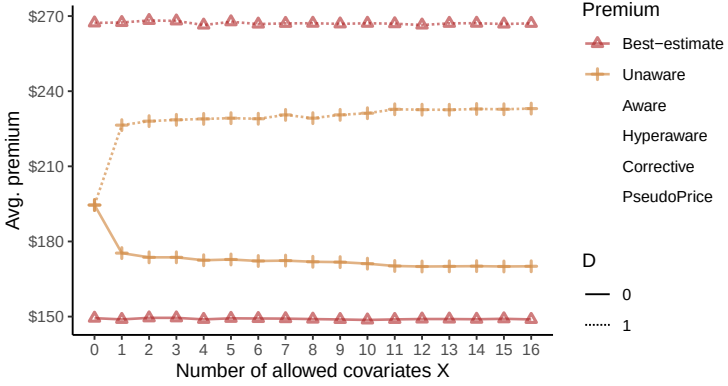

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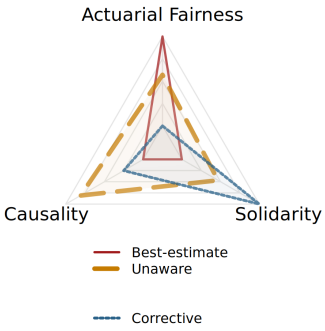

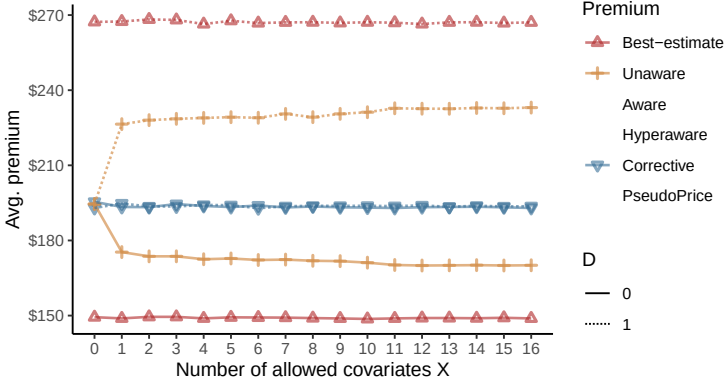

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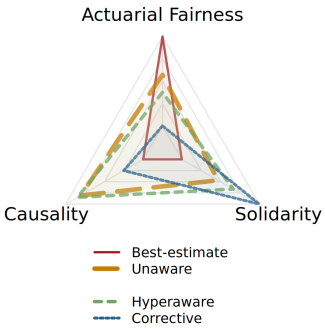

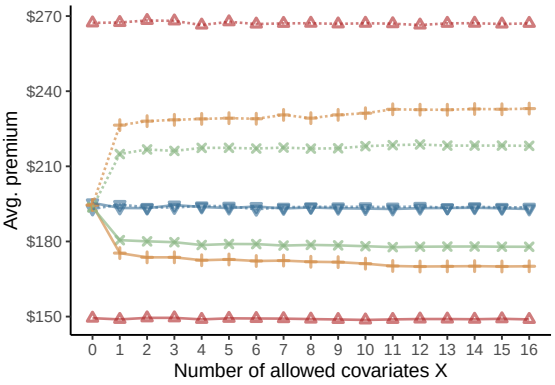

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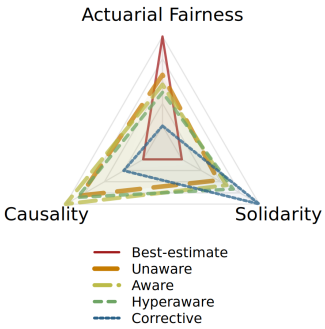

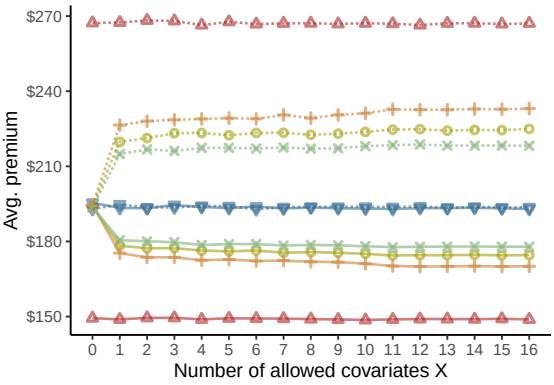

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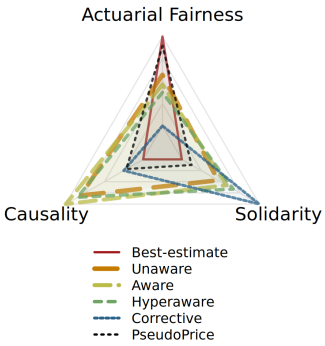
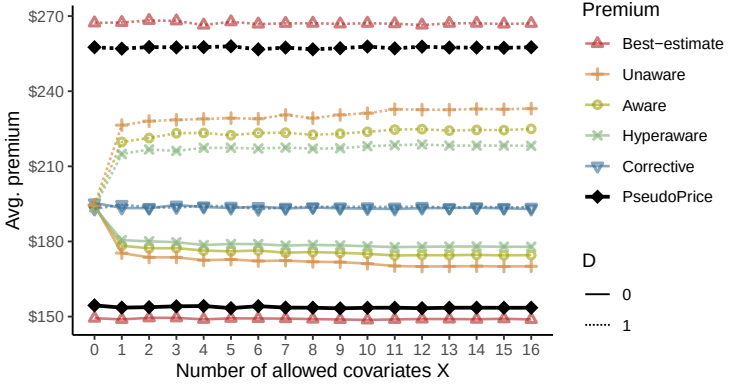
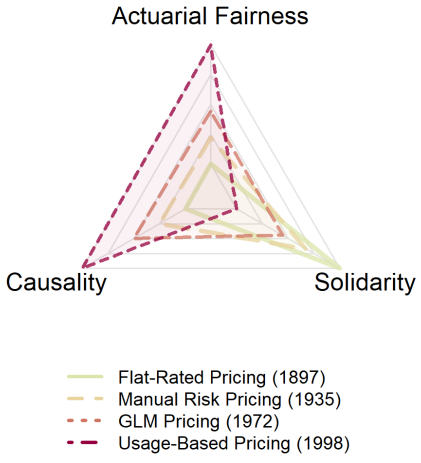


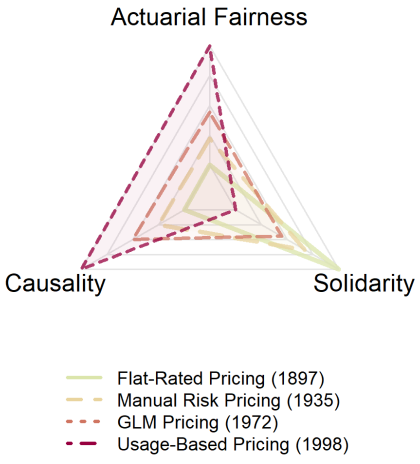


The history of risk classification revisited



The history of risk classification revisited

As data granularity increases, so does the potential for actuarial justification in perpetuating disparities.



Prior-pricing local fairness metrics

The potential for disparate treatment on D is the **risk spread** :

$$\Delta_{\text{risk}}(\mathbf{x}) = \sup_{d\in\mathcal{D}} \mu^B(\mathbf{x}, d) - \inf_{d\in\mathcal{D}} \mu^B(\mathbf{x}, d).$$

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The **parity cost** is the (monetary) cost of enforcing premium parity :

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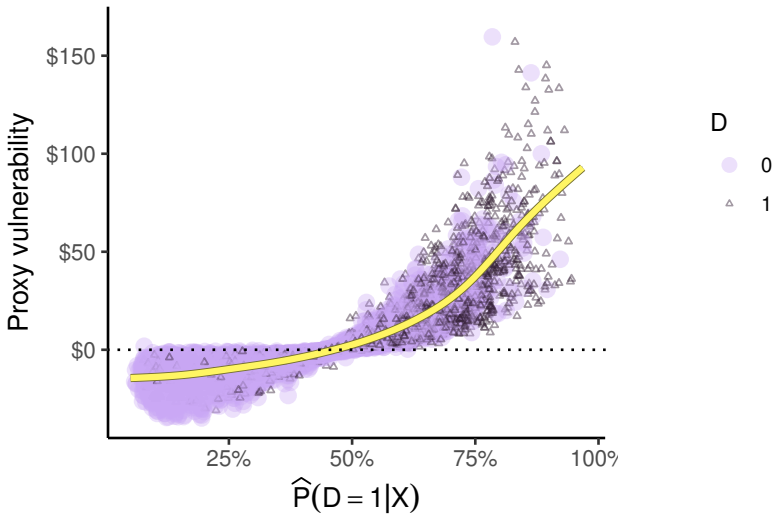
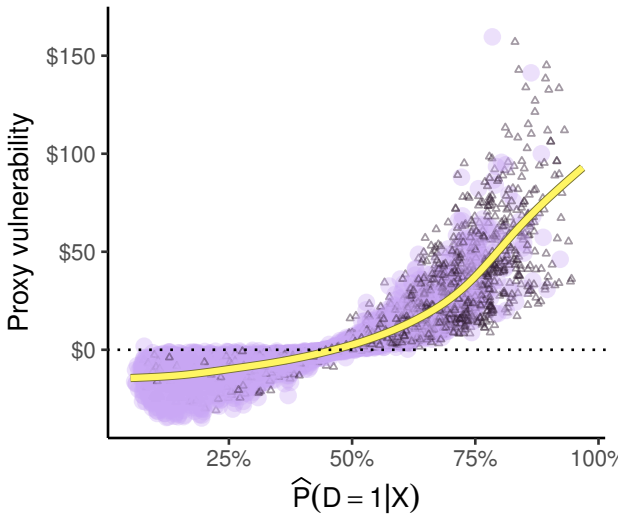
Visualizing the proxy vulnerability

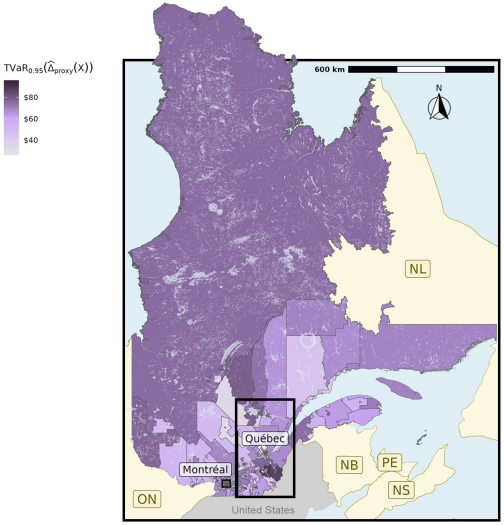


Visualizing the proxy vulnerability



Proxy vulnerability is both material and skewed

Geographic distribution of the 95% TVaR of proxy vulnerability



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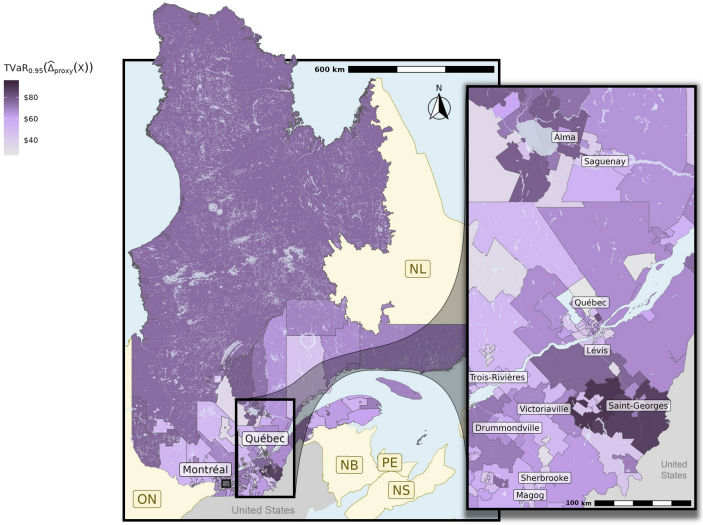

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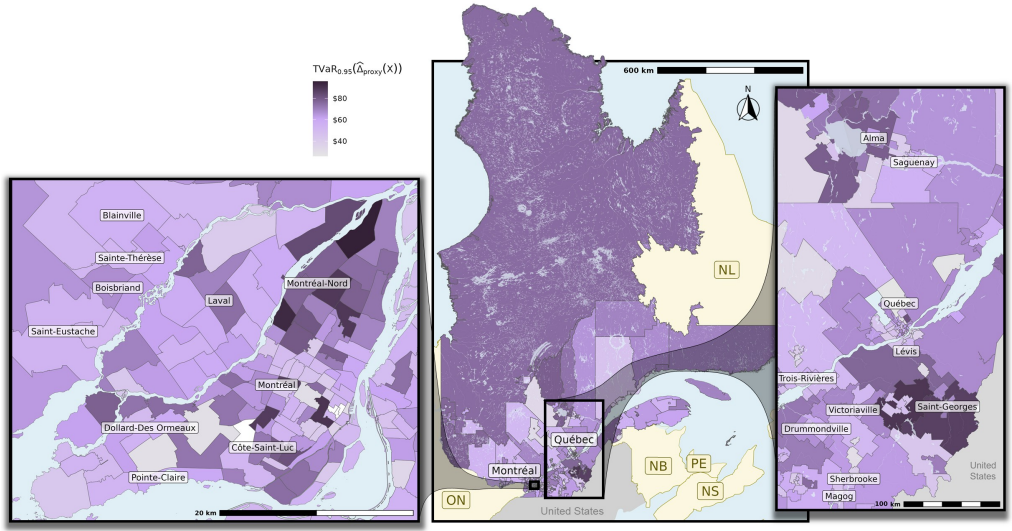
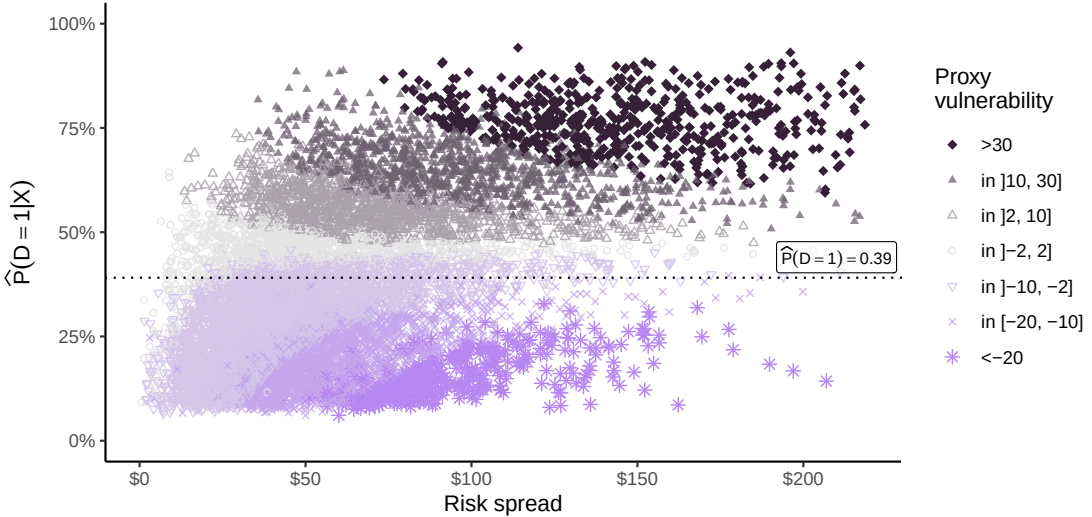


Decomposing proxy vulnerability



Local metrics between commercial premium and fair benchmarks

The **commercial loading** relative to the reference premium μ^A is :

$$\Delta_{\text{load}}(\mathbf{x}, d; \pi) = \pi(\mathbf{x}, d) - \mu^A(\mathbf{x}),$$

The **implied propensity** is the implicit* weight of $D = 1$ in $\pi(\mathbf{x})$:

$$\tilde{P}_D(\mathbf{x}; \pi) = \frac{\pi(\mathbf{x}) - \mu^B(\mathbf{x}, 0)}{\mu^B(\mathbf{x}, 1) - \mu^B(\mathbf{x}, 0)}.$$

The **excess lift** measures excessive price differentiation on D :

$$\Delta_{\text{excess}}(\mathbf{x}; \pi) = \left\{ \sup_d \pi(\mathbf{x}, d) - \inf_d \pi(\mathbf{x}, d) \right\} - \Delta_{\text{risk}}(\mathbf{x}).$$

Revealing disparities via partitioning

Problem : Fairness metrics over large groups can hide disparities within vulnerable subgroups.

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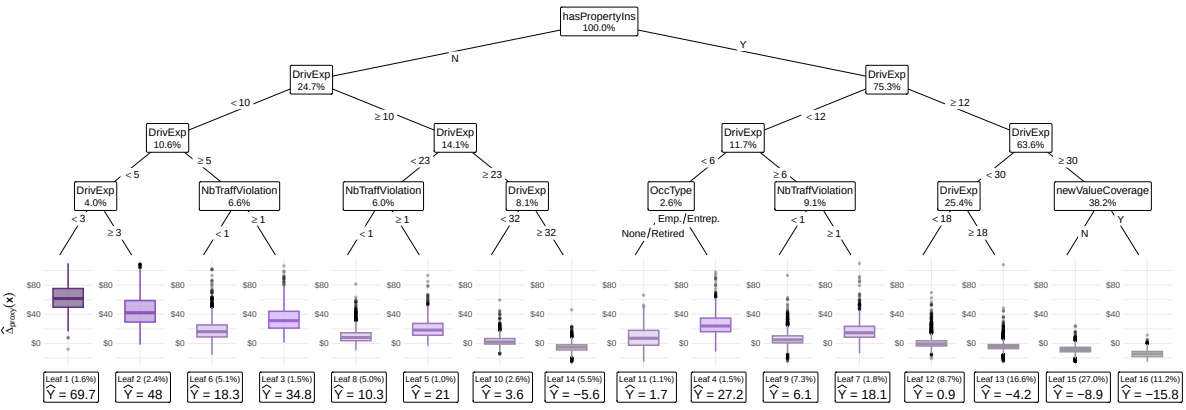
Goal : Identify groups that are systematically **vulnerable** and **overloaded**.

Partitioning policyholders following proxy vulnerability



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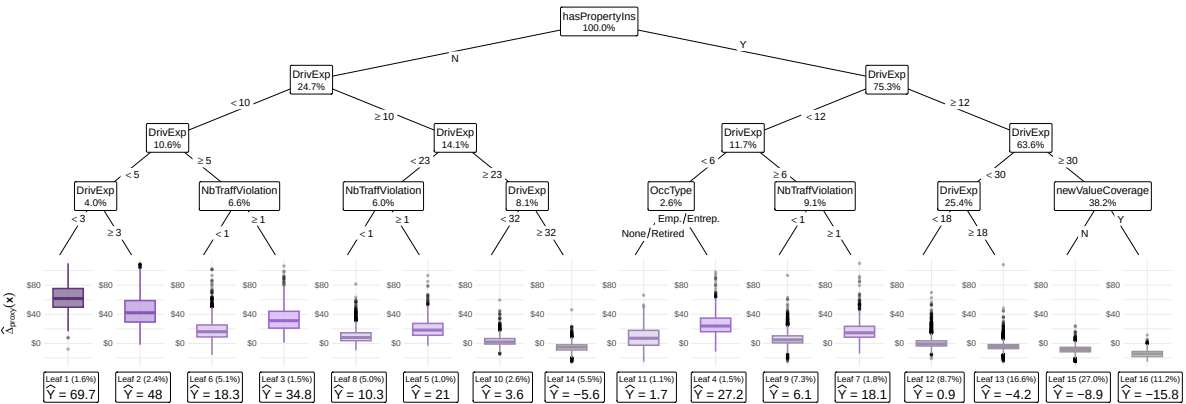
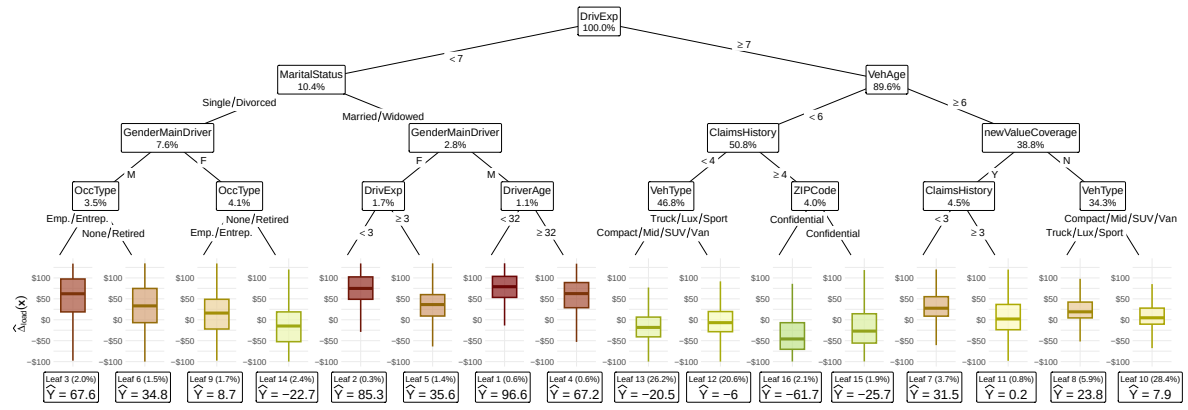
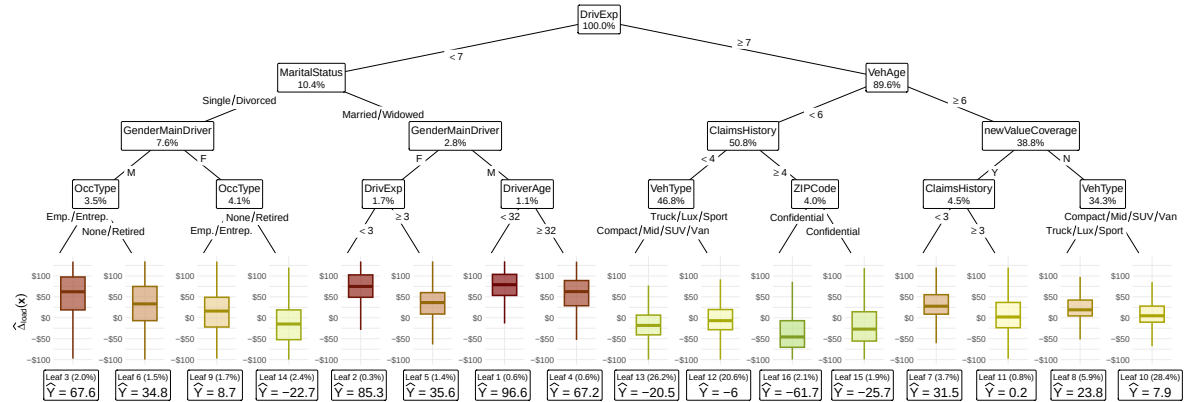


Leaves with high predictions signal **segments where proxy effects are most likely** to be exploited by a model.

Partitioning policyholders following commercial loading



Partitioning policyholders following commercial loading



Monitoring commercial loadings means **monitoring the cumulative impact of pricing decisions** – likely beyond the insurer's intent or awareness.

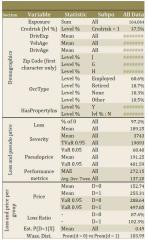
An integrated fairness assessment framework

Is the pseudo-price fair ?

Section	Variable	Statistic	Subpo	All Data
Demographics	Exposure	Sum	All	164.064
	Credrisk (lvl %)	Level %	Credrisk = 1	37.5%
	DrivExp	Mean	All	#######
	VehAge	Mean	All	#######
	DrivAge	Mean	All	#######
	Zip Code (first character only)	Level %	J	#######
		Level %	G	#######
		Level %	H	#######
	OccType	Level %	Employed	60.6%
		Level %	Retired	18.7%
		Level %	None	10.3%
		Level %	Other	10.5%
	HasPropertyIns	Level %	Y	#######
		Level %	lvl % : N	#######
Loss and pseudo price	Loss	% of 0	All	97.2%
		Mean	All	189.25
	Severity	Mean	All	3743
		TVaR 0.95	All	19093
	Pseudoprice	VaR 0.05	All	68.40
		Mean	All	191.25
		VaR 0.95	All	401.59
	Performance metrics	MAE	All	272.15
		Avg. Dev. Twee.	All	137.20
Loss and price per group	Price	Mean	D=0	152.74
		Mean	D=1	255.31
		VaR 0.95	D=0	288.64
		VaR 0.95	D=1	497.85
	Loss Ratio	-	D=0	87.4%
		-	D=1	102.3%
	Est. P(D=1|X)	Mean	All	0.49
	Wass. Dist.	Prem(d = 0) vs Prem(d = 1)		103.99

An integrated fairness assessment framework

Is the pseudo-price fair ?



Section	Variable	Statistic	Subpa	All Data
Demographics	Exposure	Sum	All	664,644
	CrossVeh (M %)	Level %	CrossVeh = 1	37.5%
	DrivExp	Mean	All	########
	VehAge	Mean	All	########
	DrivAge	Mean	All	########
	Zip Code (first character only)	Level %	J	########
		Level %	G	########
		Level %	H	########
	OccType	Level %	Employed	68.6%
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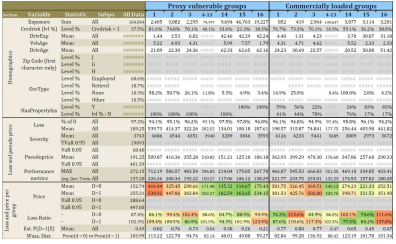
		Level %	None	18.3%
		Level %	Other	10.5%
	HasProperty(m	Level %	Y	########
		Level %	Int % > N	########
Loss and pseudo_price	Loss	% of O	All	97.2%
	Severity	Mean	All	189.25
		Mean	All	3763
		TVaR 0.95	All	19093
		VaR 0.95	All	60.44
	Pseudoprice	Mean	All	191.25
		VaR 0.95	All	461.56
	Performance metrics	MAE	All	272.15
		Avg. Dev. Tweed	All	137.18
Loss and price per group	Price	Mean	D=0	152.74
		Mean	D=1	253.31
		VaR 0.95	D=0	289.64
		VaR 0.95	D=1	497.68
	Loss Ratio	-	D=0	97.4%
		-	D=1	102.9%
	Est. P(D=1|X)	Mean	All	0.49
	Wass. Dist.	Price(X = 0) vs Price(X = 1)		183.99

An integrated fairness assessment framework

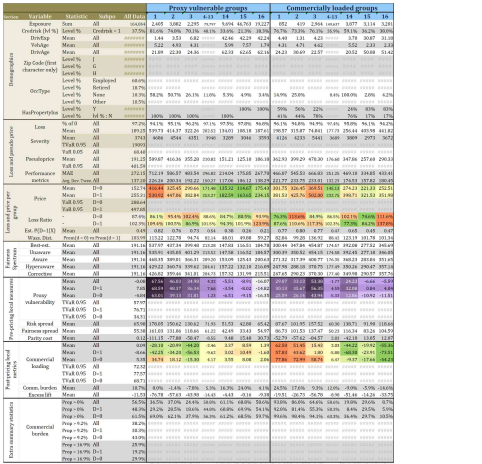


					Proxy vulnerable groups						Commercially loaded groups					
Version	Variable	Statistic	Subpop	All Data	1	2	3	4-13	14	15	16	1	2	3	4-13	14	15	16
Demographics	Exposure	Sum	All	164,644	3,605	3,082	2,295	########	9,094	44,763	19,227	852	419	2,944	########	3,077	53,114	5,281
	Credtrisk (M-%)	Level %	Credtrisk = 1	37.5%	81.6%	74.0%	70.1%	48.1%	33.0%	21.3%	18.3%	76.7%	73.3%	70.1%	35.9%	53.1%	26.2%	30.0%
	DrivExp	Mean	All	########	1.44	3.53	6.82	########	42.66	42.29	42.24	4.40	1.31	4.21	########	3.79	30.87	31.18
	VehAge	Mean	All	########	5.22	4.93	4.21	########	5.98	7.57	1.79	4.31	4.71	4.62	########	5.52	2.33	2.33
	DrivAge	Mean	All	########	21.89	22.20	24.56	########	62.59	62.65	62.16	24.23	30.49	22.57	########	20.52	50.88	51.42
	Zip Code (first character only)	Level %	J	########	########	########	########	########	########	########	########	########	########	########	########	########	########	########
		Level %	G	########	########	########	########	########	########	########	########	########	########	########	########	########	########	########
		Level %	H	########	########	########	########	########	########	########	########	########	########	########	########	########	########	########
	OccType	Level %	Employed	68.6%	########	########	########	########	########	########	########	########	########	########	########	########	########	########
		Level %	Retired	18.7%	########	########	########	########	########	########	########	########	########	########	########	########	########	########
		Level %	None	10.3%	58.2%	53.7%	20.1%	11.0%	5.3%	4.9%	3.4%	18.9%	25.6%	########	########	8.4%	108.0%	2.0%	4.2%
		Level %	Other	10.5%	########	########	########	########	########	########	########	########	########	########	########	########	########	########
	HasProperty(ies)	Level %	Y	########	########	########	########	########	########	100%	100%	75%	56%	22%	########	24%	83%	83%
		Level %	Int % / N	########	100%	100%	100%	########	100%	########	########	41%	44%	78%	########	76%	17%	17%
Loss and pseudo-price	Loss	% of	All		97.2%	94.1%	95.1%	94.2%	93.1%	97.9%	97.0%	94.0%	94.1%	94.8%	94.9%	97.6%	95.0%	94.1%	94.2%
		Mean	All		189.25	339.73	414.37	322.26	283.52	134.03	180.18	187.61	190.87	315.87	74.81	177.73	256.44	485.98	441.82
	Severity	Mean	All		375.1	606.1	654.4	619.1	574.0	320.9	329.9	304.4	359.9	612.6	323.3	544.1	369.9	509.9	497.1	367.2
		TVaR 0.95	All		1909.9	########	########	########	########	########	########	########	########	########	########	########	########	########	########
		TVaR 0.05	All		60.44	########	########	########	########	########	########	########	########	########	########	########	########	########	########
	Pseudoprice	Mean	All		191.25	599.87	616.36	355.20	210.81	151.21	125.18	186.18	162.93	399.29	478.30	176.68	347.86	257.68	290.33
		TVaR 0.95	All		481.56	########	########	########	########	########	########	########	########	########	########	########	########	########	########
	Performance metrics	MAE	All		272.15	712.19	586.57	460.54	296.81	214.04	175.65	247.70	466.87	585.53	664.83	351.29	469.18	334.85	410.41
		Avg. Sev/Tree	All		137.28	226.16	200.34	192.22	150.57	117.06	146.12	150.29	121.27	210.75	219.81	137.31	179.58	157.82	180.45
Loss and price per group	Price	Mean	D=0		152.74	516.48	525.45	290.66	171.49	125.12	114.67	175.44	201.75	326.45	366.51	146.11	274.23	221.33	252.51
		Mean	D=1		253.13	810.92	847.86	502.84	353.27	182.59	161.64	236.15	161.33	625.76	702.80	235.75	390.71	321.53	351.94
		VaR 0.95	D=0		288.64	########	########	########	########	########	########	########	########	########	########	########	########	########	########
		VaR 0.95	D=1		497.69	########	########	########	########	########	########	########	########	########	########	########	########	########	########
	Loss Ratio	-	D=0		97.6%	86.1%	95.6%	102.4%	98.6%	84.7%	88.9%	93.9%	76.3%	115.6%	88.9%	86.5%	102.1%	74.6%	111.4%
		-	D=1		102.9%	109.8%	110.5%	86.9%	101.5%	94.3%	101.9%	123.9%	87.6%	110.6%	117.3%	102.9%	77.7%	84.2%	117.8%
	Est. P(D=1|S)	Mean	All		0.69	0.82	0.76	0.75	0.64	0.38	0.26	0.21	0.57	0.80	0.77	0.41	0.65	0.45	0.47
	Wass. Dist.	Prem(d = 0) vs Prem(d = 1)			103.99	113.22	122.78	94.74	82.14	48.01	49.88	59.23	82.84	99.20	136.92	86.61	125.19	101.78	101.34

Is the pseudo-price fair ?

- Partitions define relevant subgroups (columns).

An integrated fairness assessment framework



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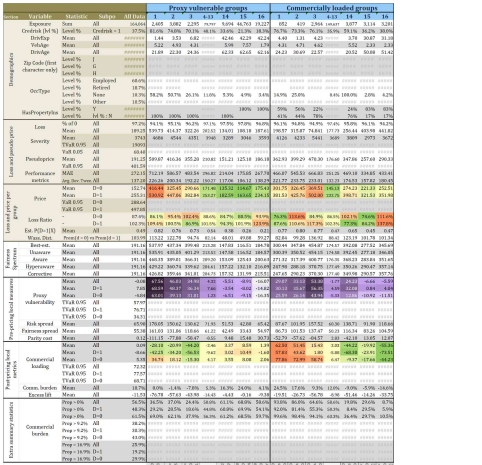

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The toolbox guide **fairness assessment**.

Question

Is the given pricing function $\pi(\mathbf{x}, d)$ fair?

Inputs

A pricing function: $\pi(\mathbf{x}, d)$

Data: $\{\mathbf{X}_i, D_i, Y_i\}_{i=1}^n$

Question

Is the given pricing function $\pi(\mathbf{x}, d)$ fair?

Inputs

A pricing function: $\pi(\mathbf{x}, d)$

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→ What does it mean for pricing to be fair?

→ Can one benchmark fairness?

→ Is unfairness truly material?

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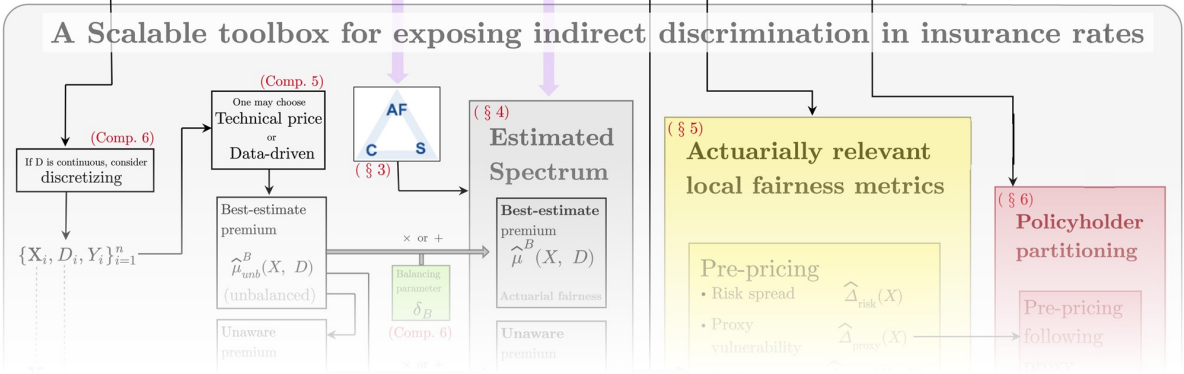

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What does it mean for pricing to be fair?

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Is unfairness truly material?

Where does unfairness concentrate?

The toolbox guides assessment.

(Fig. 14)

A Scalable toolbox for exposing indirect discrimination in insurance rates

(Comp. 6)

If D is continuous, consider discretizing

$\{\mathbf{X}_i, D_i, Y_i\}_{i=1}^n$

(Comp. 5)

One may choose Technical price or Data-driven

Best-estimate premium

$\widehat{\mu}^B_{unb}(X, D)$

(unbalanced)

Unaware premium

AF

C S

(§ 3)

× or +

Balancing parameter δ_B

(Comp. 6)

(§ 4)

Estimated Spectrum

Best-estimate premium

$\widehat{\mu}^B(X, D)$

Actuarial fairness

Unaware premium

(§ 5)

Actuarially relevant local fairness metrics

Pre-pricing

- Risk spread $\widehat{\Delta}_{\text{risk}}(X)$
- Proxy vulnerability $\widehat{\Delta}_{\text{proxy}}(X)$

(§ 6)

Policyholder partitioning

Pre-pricing following

Moving forward

This study had a specific scope. Advancing fairness requires expanding it :

1. Fairness often assumes **access to protected attributes**, which may unavailable.

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3. Fairness is typically studied as a one-year objective, but its **long-term welfare** effects remain unclear (Shimao et al., 2022).
4. Portfolio fairness may conflict with market fairness (Côté et al., 2024).

Thank you


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