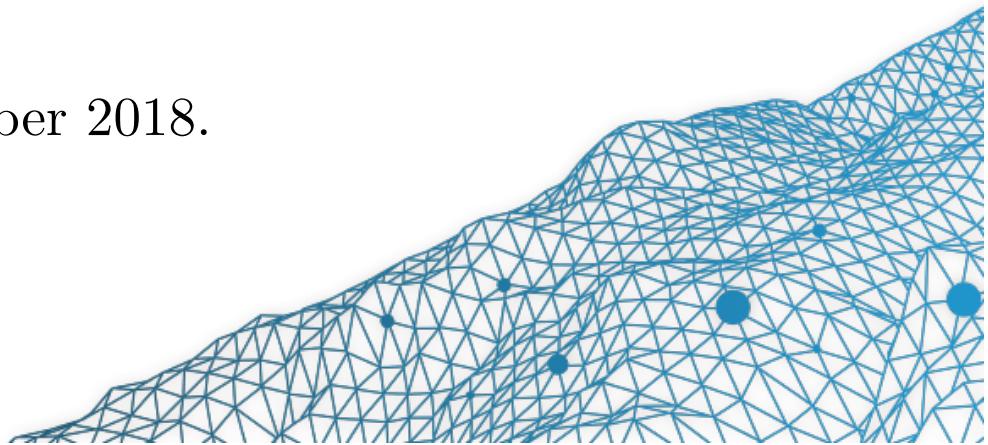


# Segmentation et mutualisation, les deux faces d'une même pièce ?

A. Charpentier (Université du Québec à Montréal)

Rencontres Mutualistes, Beaune, November 2018.



## A. Charpentier (Université du Québec à Montréal)

Professor Mathematics Department, Université du Québec à Montréal

previously Econ. Dept, Université de Rennes & ENSAE Paristech

actuary in Hong Kong, IT & Stats FFA

director Data Science for Actuaries Program, Institute of Actuaries

PhD in Statistics (KU Leuven), Fellow of the Institute of Actuaries

MSc in Financial Mathematics (Paris Dauphine) & ENSAE

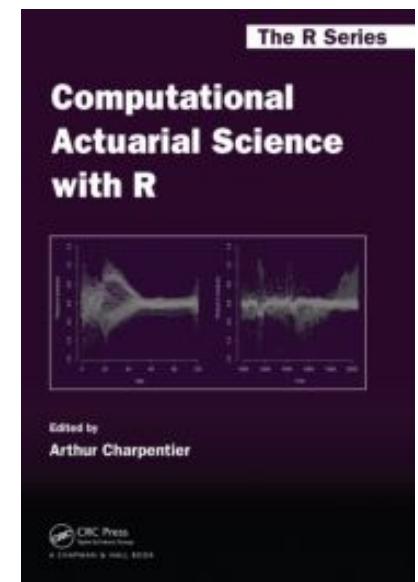
Research Chair :

ACTINFO ([valorisation et nouveaux usages actuariels de l'information](#))

Editor of the [freakonometrics.hypotheses.org](#)'s blog

Editor of Computational Actuarial Science, CRC

Author of [Mathématiques de l'Assurance Non-Vie](#) (2 vol.), Economica



# Insurance, “segmentation” & “mutualisation”

## SEGMENTATION ET MUTUALISATION LES DEUX FACES D'UNE MÊME PIÈCE ?

Insurance is the contribution of the many  
to the misfortune of the few

- what is actuarial pricing ?
- why a “spirale de la segmentation” ?
- how to compare actuarial models ?
- field experiment : pricing games

Arthur Charpentier  
Professeur à l'Université du Québec, Montréal

Michel Denuit  
Professeur à l'Université catholique de Louvain

Romuald Elie  
Professeur à l'Université de Marne-la-Vallée

L'assurance repose fondamentalement sur l'idée que la mutualisation des risques entre des assurés est possible. Cette mutualisation, qui peut être vue comme une relecture actuarielle de la loi des grands nombres, n'a de sens qu'au sein d'une population de risques « homogènes » [Charpentier, 2011]. Cette condition (actuarielle) impose aux assureurs de segmenter, ce que confirment plusieurs travaux économiques (1). Avec l'explosion du nombre de données, et donc de variables tarifaires possibles, certains assureurs évoquent l'idée d'un tarif individuel, semblant remettre en cause l'idée même de mutualisation des risques. Entre cette force qui pousse à segmenter et la force de rappel qui tend (pour des raisons sociales mais aussi actuarielles, ou au moins de robustesse statistique (2)) à imposer une solidarité minimale entre les assurés, quel équilibre va en résulter dans un contexte de forte concurrence entre les sociétés d'assurance ?

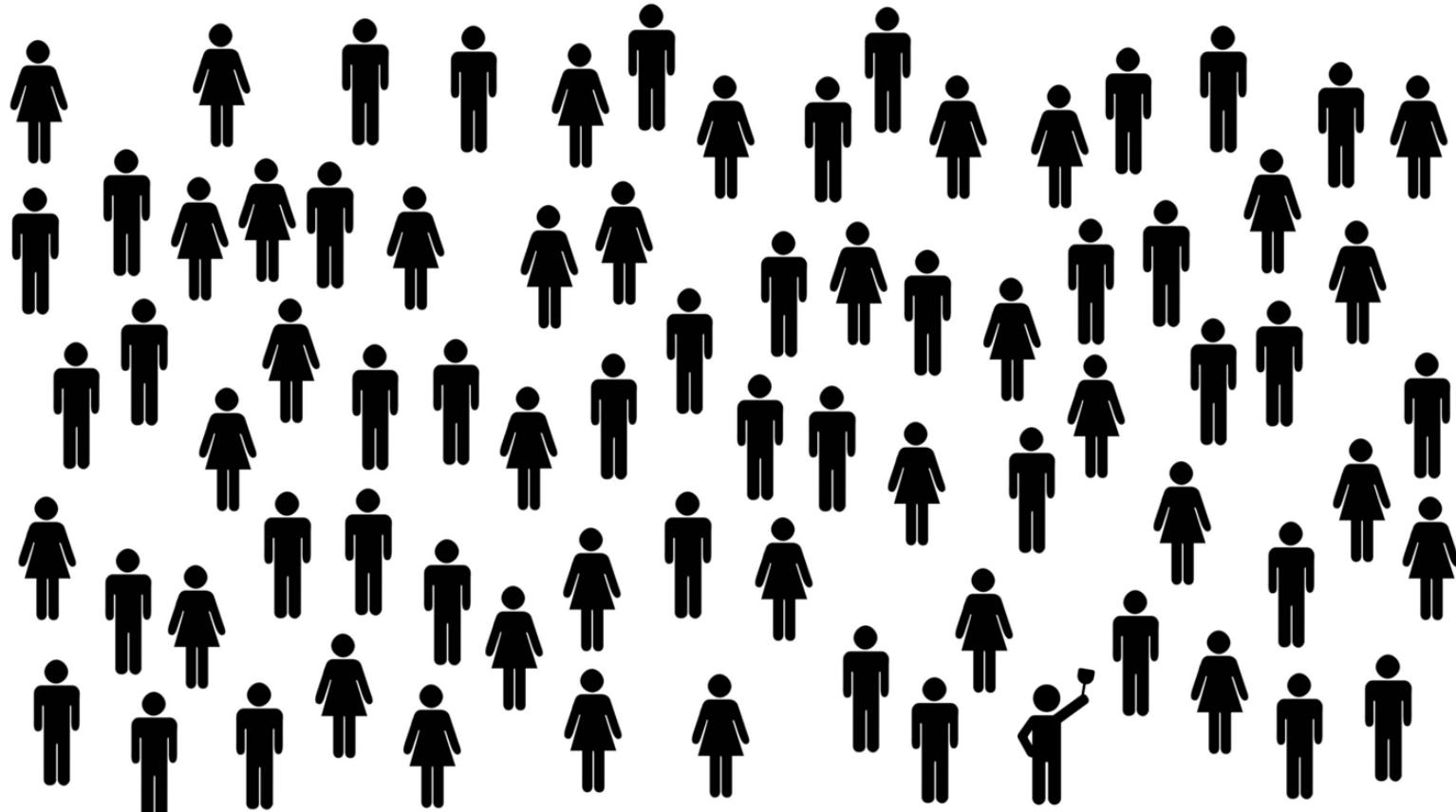
### Tarification sans segmentation

l'année. Afin d'illustrer les différents aspects de la construction du tarif et ses conséquences, on va utiliser les données présentées dans le tableau 1 (voir p. xx), qui indique la fréquence annuelle de sinistres.

**S**ans segmentation, le « prix juste » d'un risque est l'espérance mathématique de la charge annuelle. C'est l'idée du théorème fondamental de la valorisation actuarielle : en moyenne, la somme des primes doit permettre d'indemniser l'intégralité des sinistres survenus dans

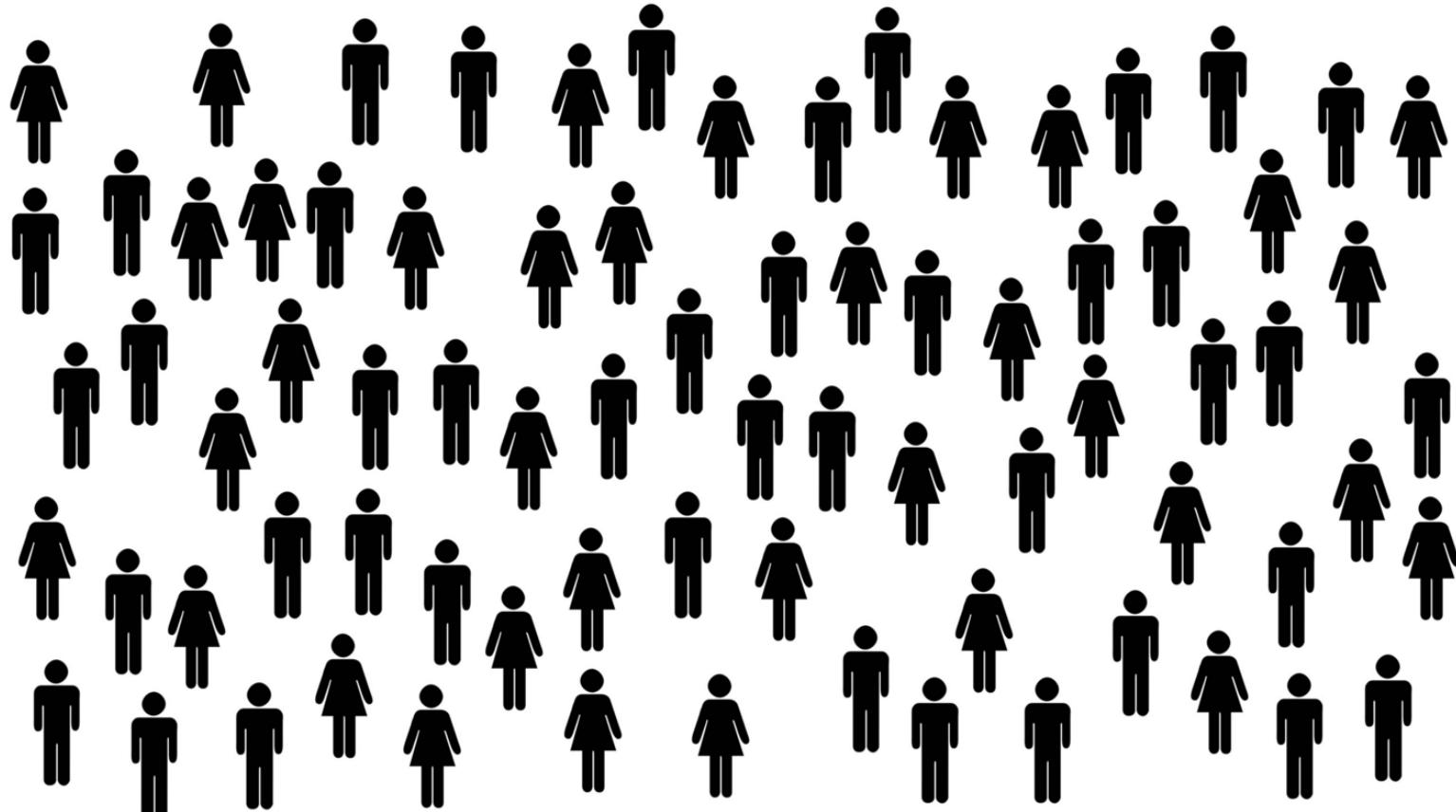
Les facteurs de risque sont ici le lieu d'habitation et l'âge de l'assuré, et on observe la fréquence de sinistre par classe. Le coût unitaire, supposé fixe, équivaut à 1 000 euros. La prime pure est alors  $E[S] = 1 000 \times E[N]$ . Dans cet exemple, la prime pure sans segmentation sera de 82,30 euros.

## Actuarial Pricing in a Nutshell



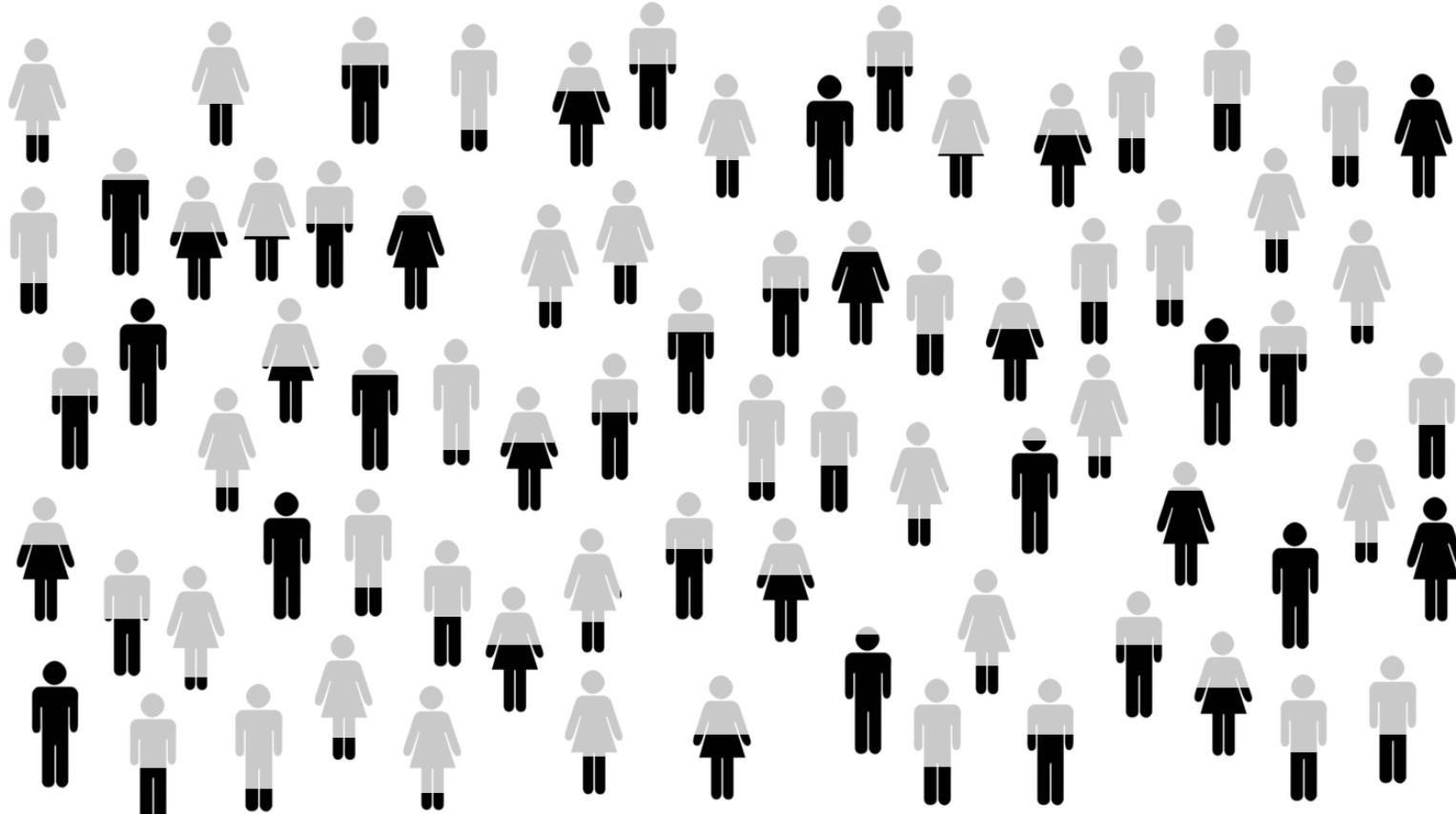
Consider some portfolio with  $n$  insured

## Actuarial Pricing in a Nutshell



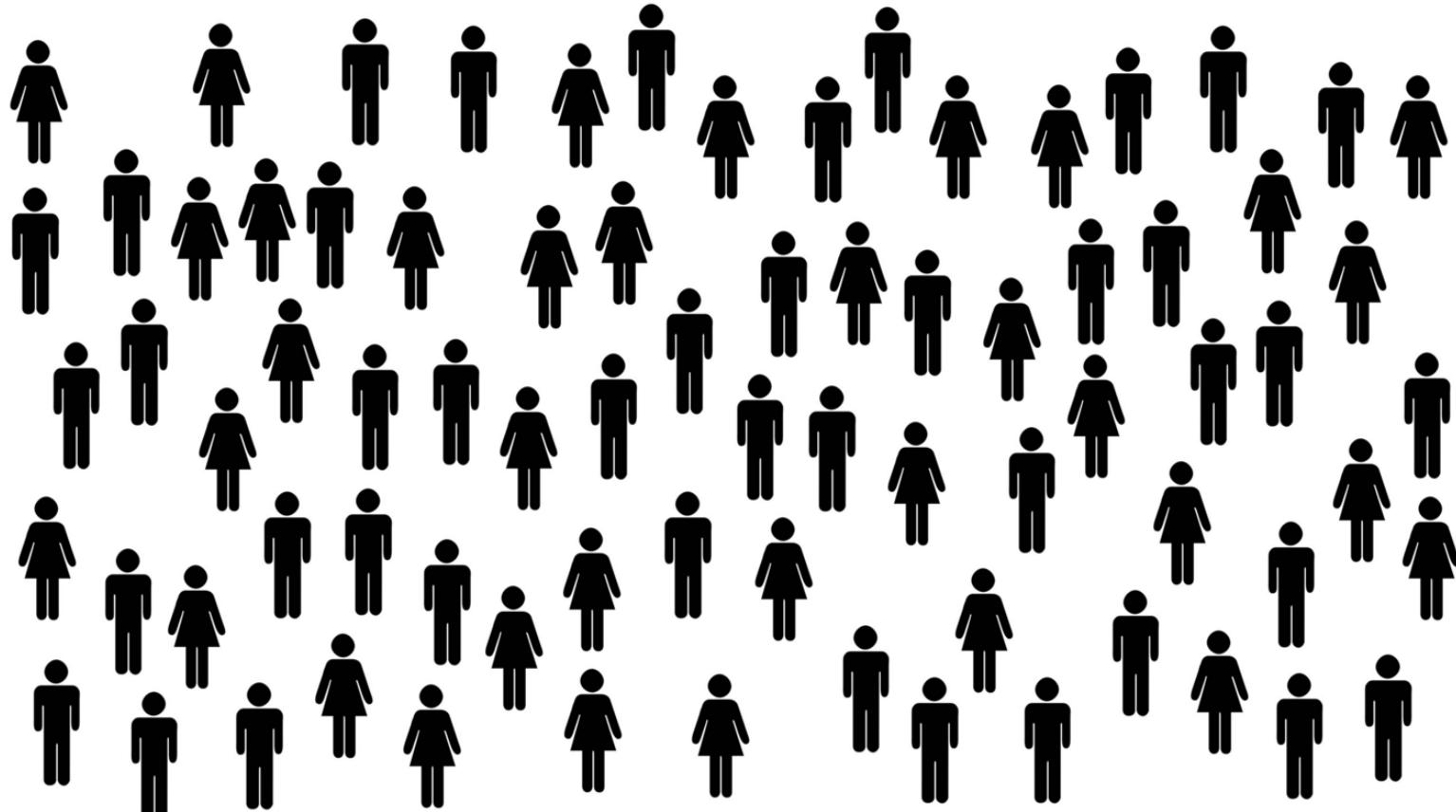
Consider some portfolio with  $n$  insured

## Actuarial Pricing in a Nutshell



The  $n$  insured have heterogeneous **unobservable** risk factors  $\omega_1, \dots, \omega_n$

## Actuarial Pricing in a Nutshell



Nevertheless, they have characteristics  $x_1, \dots, x_n$  (that can approximate  $\omega_i$ 's)

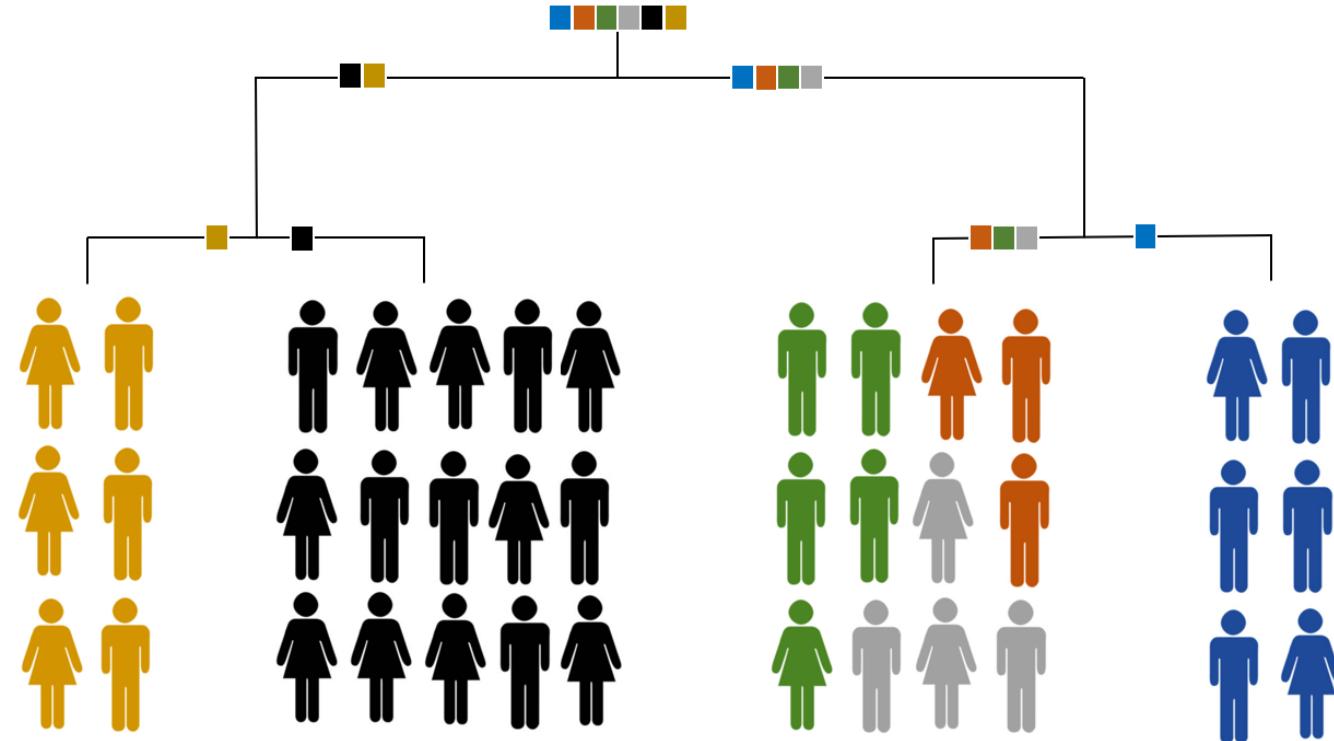
## Actuarial Pricing in a Nutshell



e.g.  $x_1$  can be the color of the car,  $x_2$  can be the gender, etc.

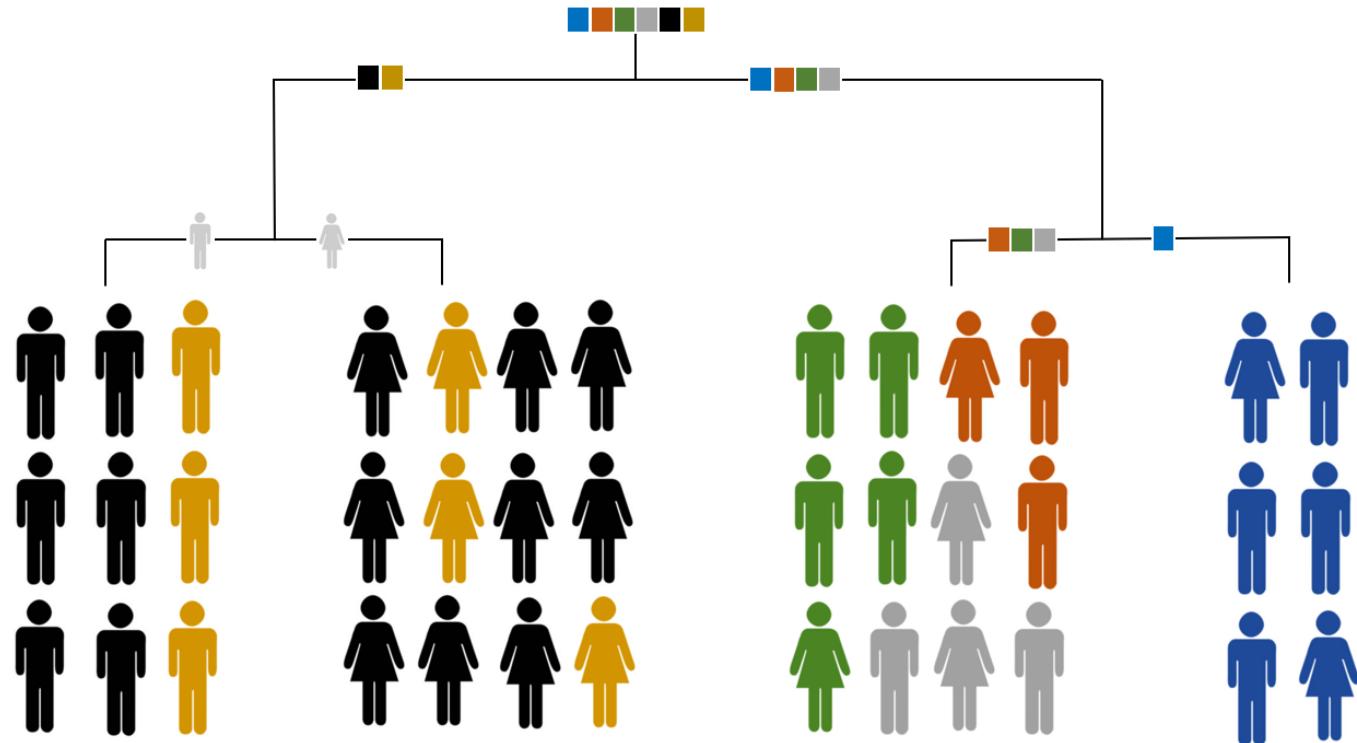
Those characteristics are **observable**, a priori.

## Actuarial Pricing in a Nutshell



Actuaries can use a regression tree to create homogeneous rate classes (or GLMs)  
Here classes are based on  $x_1$  (only)

## Actuarial Pricing in a Nutshell



Actuaries can use a regression tree to create homogeneous rate classes (or GLMs)

But classes can be based on  $x_1$  and  $x_2$  – see **Bailey (1963)**

## Risk Transfert without Segmentation

	Insured	Insurer
Loss	$\mathbb{E}[S]$	$S - \mathbb{E}[S]$
Average Loss	$\mathbb{E}[S]$	0
Variance	0	$\text{Var}[S]$

All the risk -  $\text{Var}[S]$  - is kept by the insurance company.

**Remark:** all those interpretation are discussed in [Denuit & Charpentier \(2004\)](#).

## Risk Transfert with Segmentation and Perfect Information

Assume that information  $\Omega$  is observable,

	Insured	Insurer
Loss	$\mathbb{E}[S \Omega]$	$S - \mathbb{E}[S \Omega]$
Average Loss	$\mathbb{E}[S]$	0
Variance	$\text{Var}[\mathbb{E}[S \Omega]]$	$\text{Var}[S - \mathbb{E}[S \Omega]]$

Observe that  $\text{Var}[S - \mathbb{E}[S|\Omega]] = \mathbb{E}[\text{Var}[S|\Omega]]$ , so that

$$\text{Var}[S] = \underbrace{\mathbb{E}[\text{Var}[S|\Omega]]}_{\rightarrow \text{insurer}} + \underbrace{\text{Var}[\mathbb{E}[S|\Omega]]}_{\rightarrow \text{insured}}.$$

## Risk Transfert with Segmentation and Imperfect Information

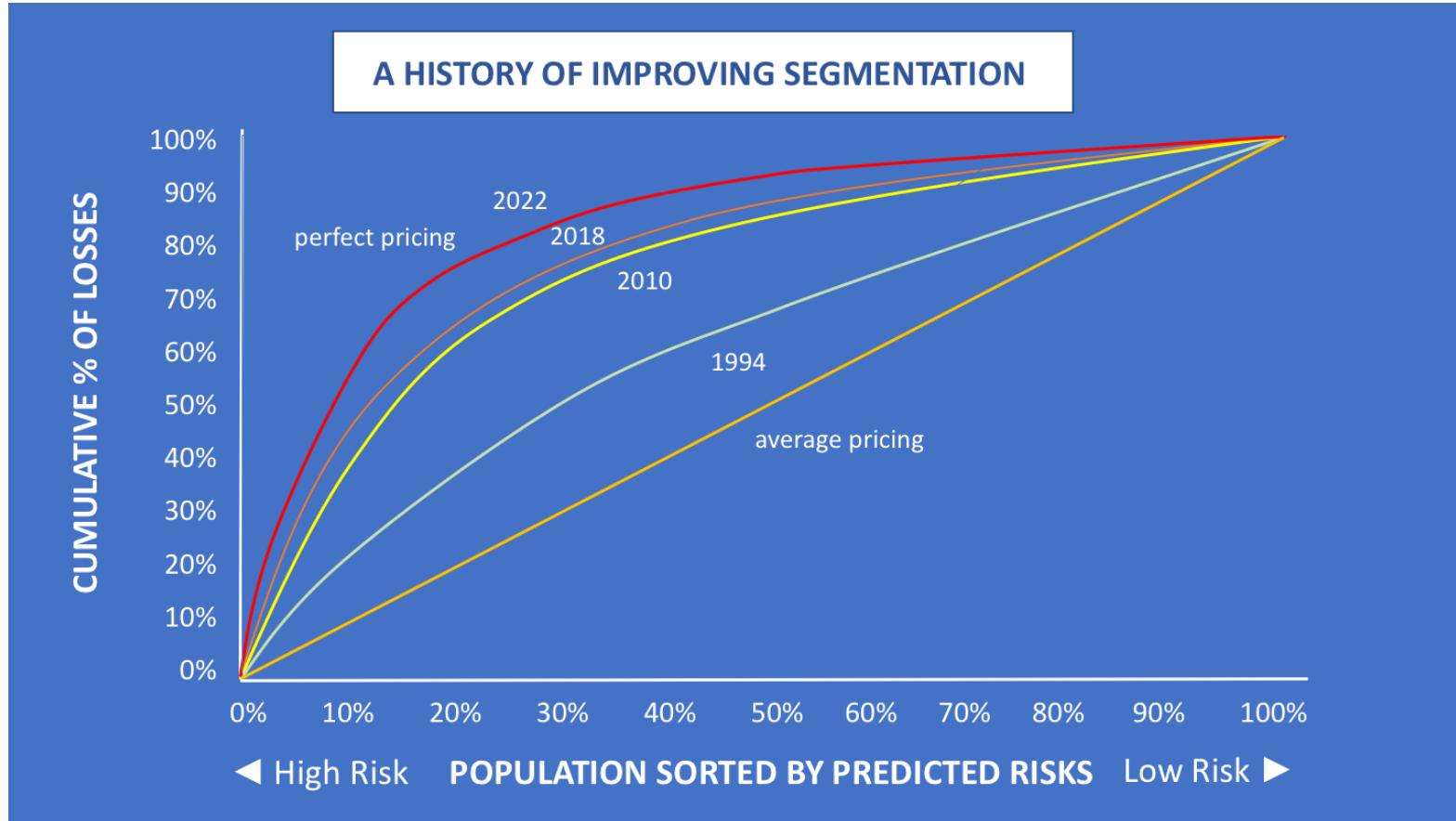
Assume that  $\mathbf{X} \subset \Omega$  is observable

	Insured	Insurer
Loss	$\mathbb{E}[S \mathbf{X}]$	$S - \mathbb{E}[S \mathbf{X}]$
Average Loss	$\mathbb{E}[S]$	0
Variance	$\text{Var}[\mathbb{E}[S \mathbf{X}]]$	$\mathbb{E}[\text{Var}[S \mathbf{X}]]$

Now

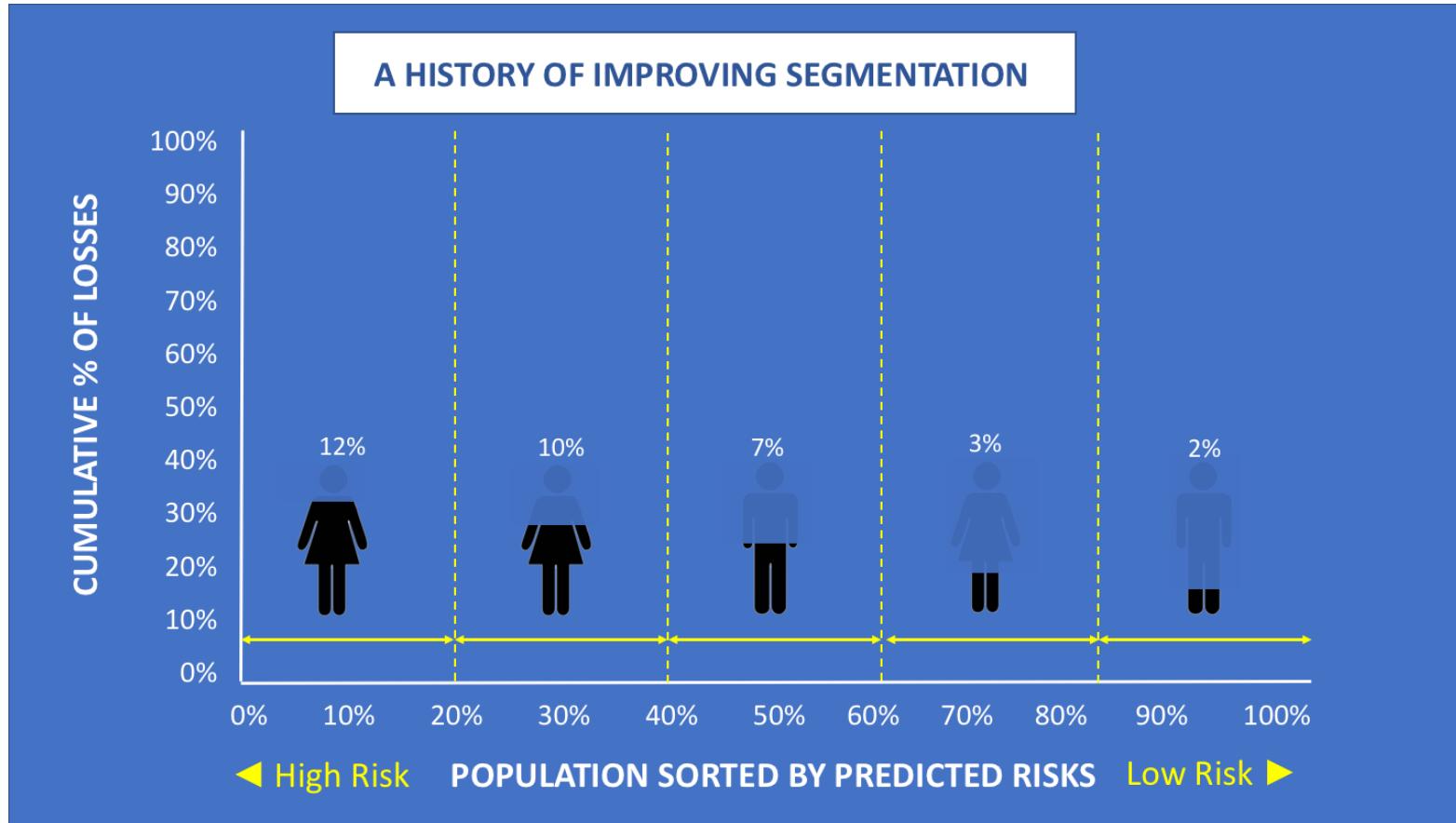
$$\begin{aligned}\mathbb{E}[\text{Var}[S|\mathbf{X}]] &= \mathbb{E}[\mathbb{E}[\text{Var}[S|\Omega]|\mathbf{X}]] + \mathbb{E}[\text{Var}[\mathbb{E}[S|\Omega]|\mathbf{X}]] \\ &= \underbrace{\mathbb{E}[\text{Var}[S|\Omega]]}_{\text{perfect pricing}} + \underbrace{\mathbb{E}\{\text{Var}[\mathbb{E}[S|\Omega]|\mathbf{X}]\}}_{\text{misfit}}.\end{aligned}$$

## How can we visualize the goodness of a model ?



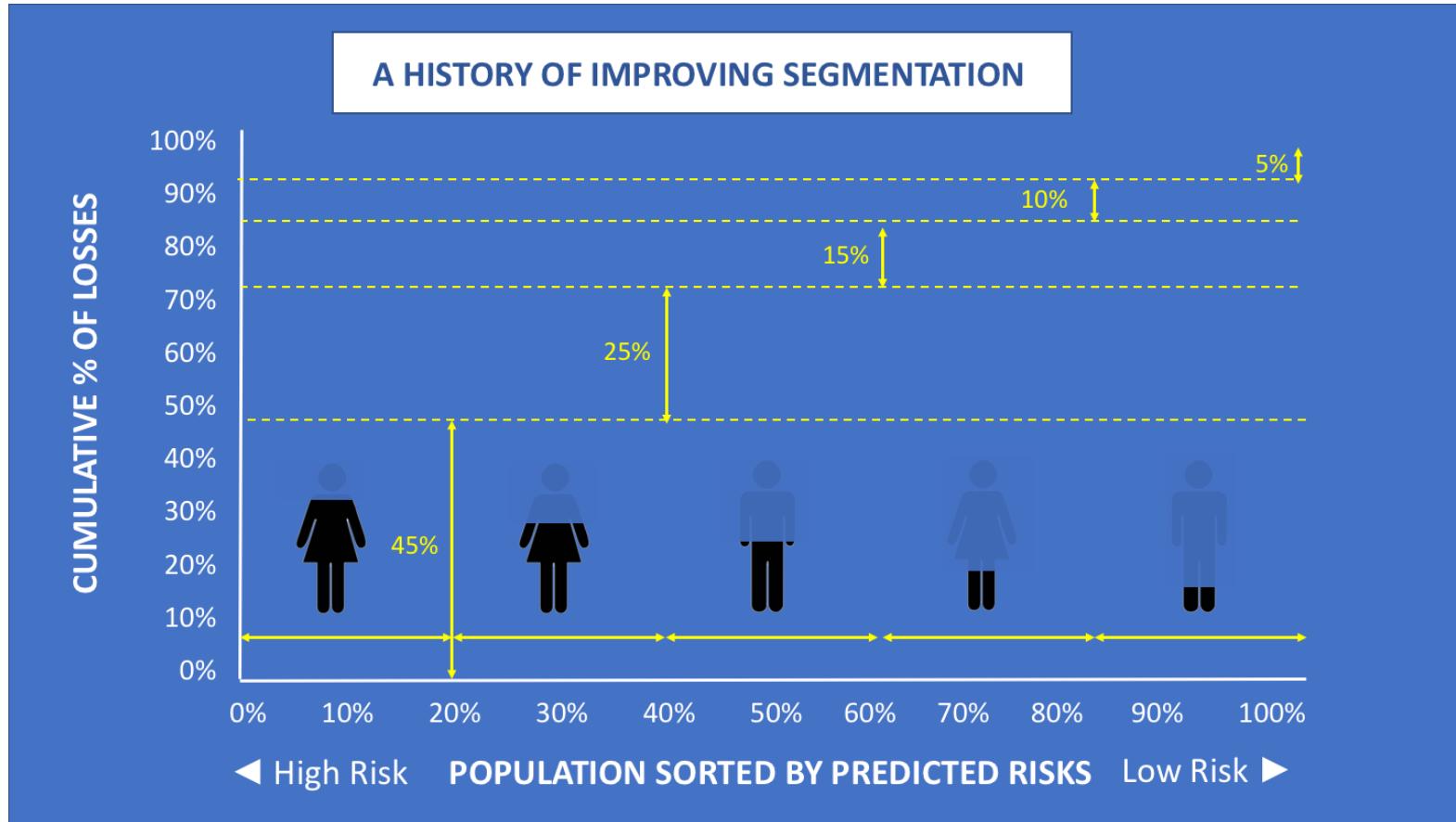
Source : <https://www.progressive.com/jobs/analyst-program/>

## Constructing the (*pseudo*)-Lorenz curve



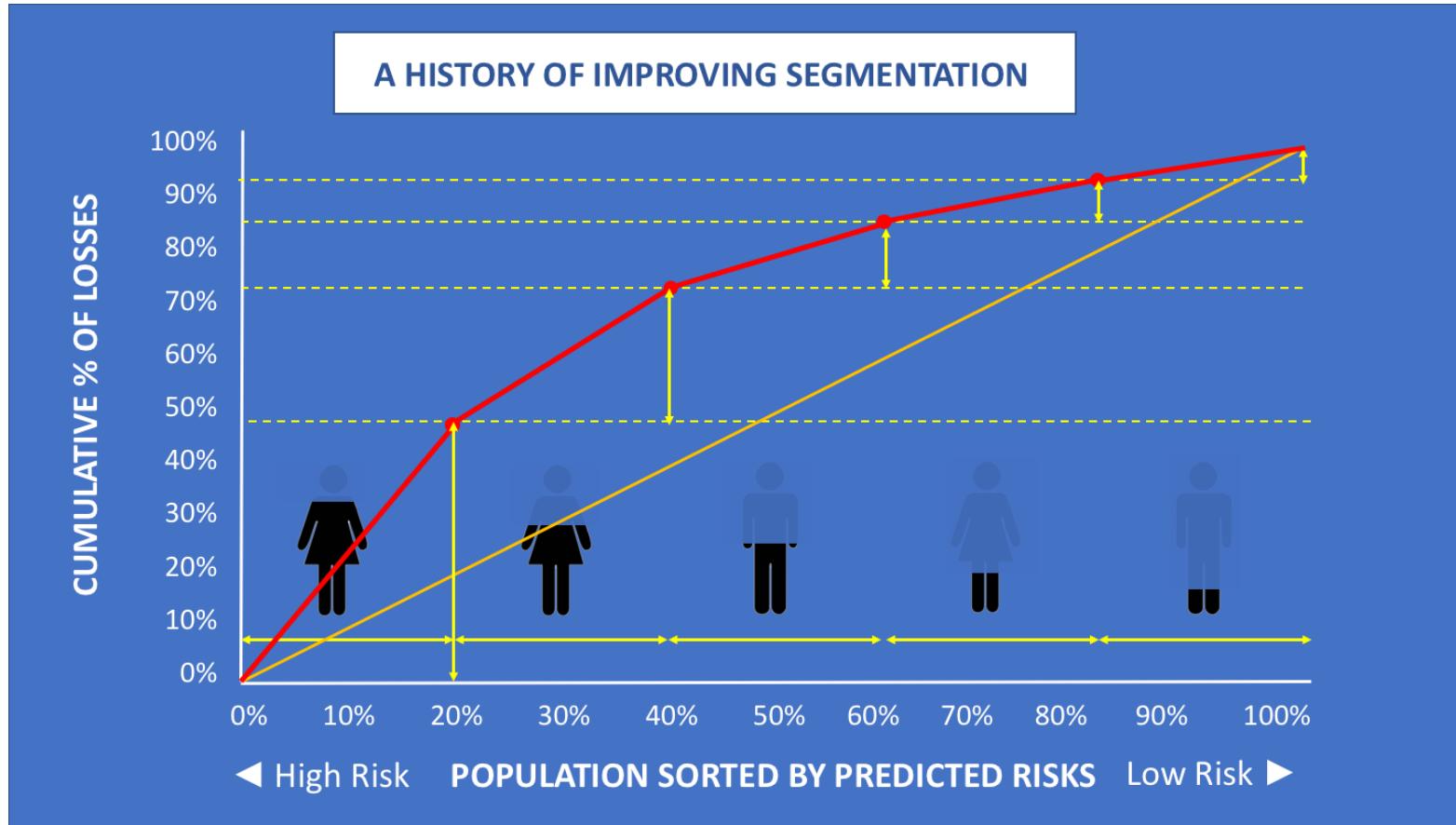
Sort the  $n$  risks according to the model  $m(\mathbf{x}_1) \geq m(\mathbf{x}_2) \geq \cdots m(\mathbf{x}_n)$

## Constructing the (*pseudo*)-Lorenz curve



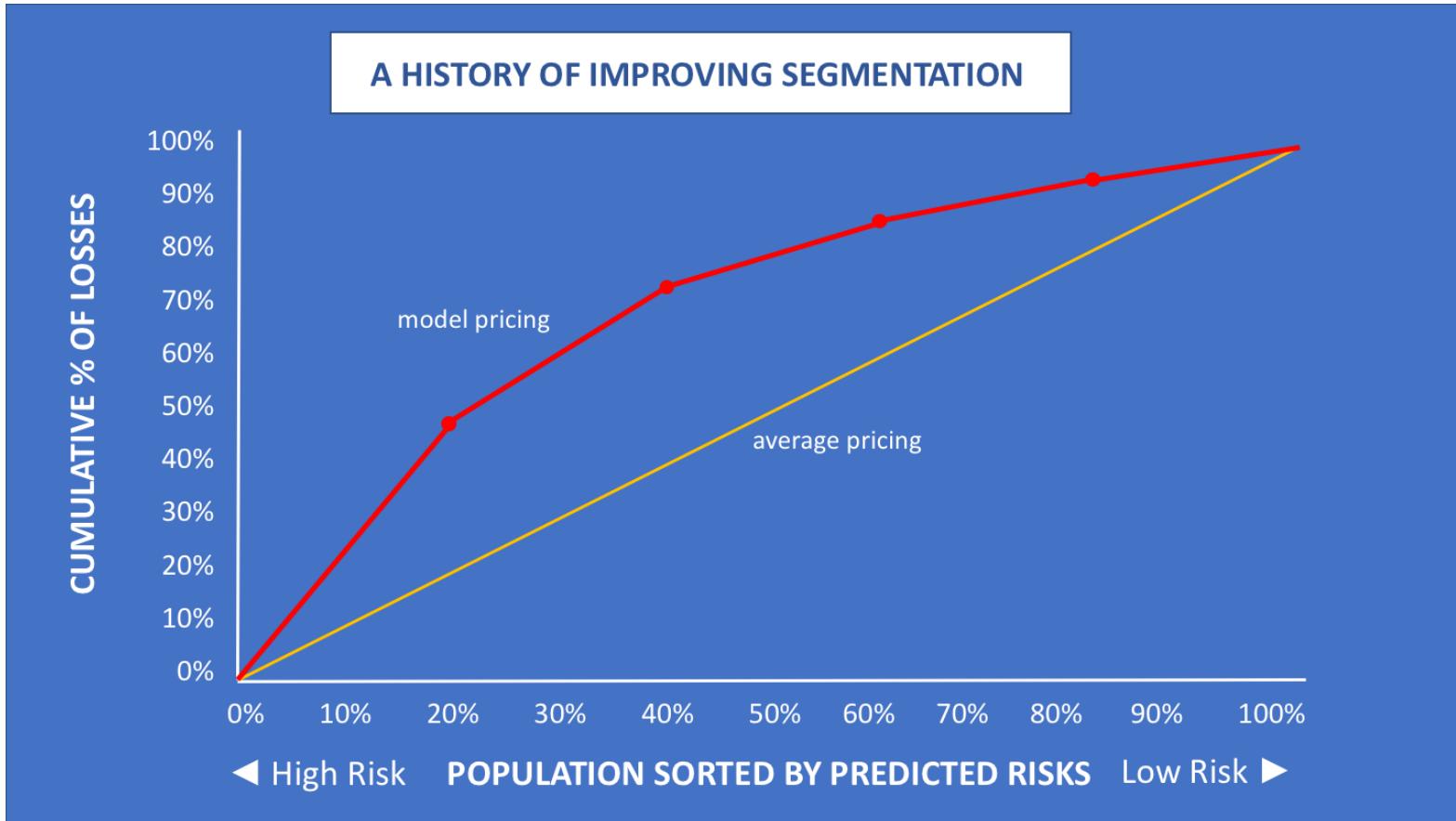
On the  $x$ -axis,  $x_i = i/n$ , on the  $y$ -axis,  $y_i = \sum_{j=1}^i y_j / \sum_{j=1}^n y_j$

## Constructing the (*pseudo*)-Lorenz curve



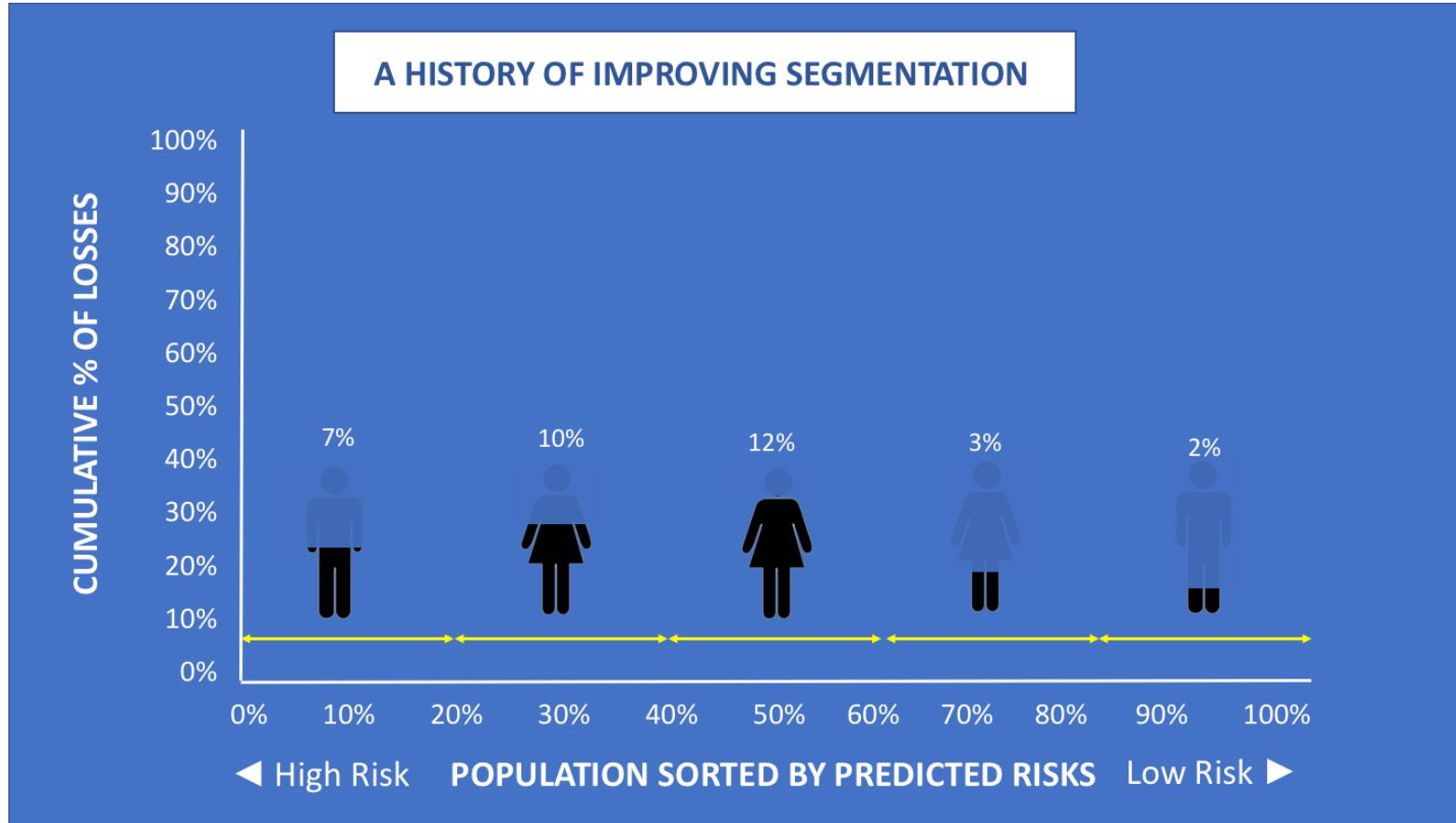
Connect points  $(x_i, y_i)$

## Constructing the (*pseudo*)-Lorenz curve



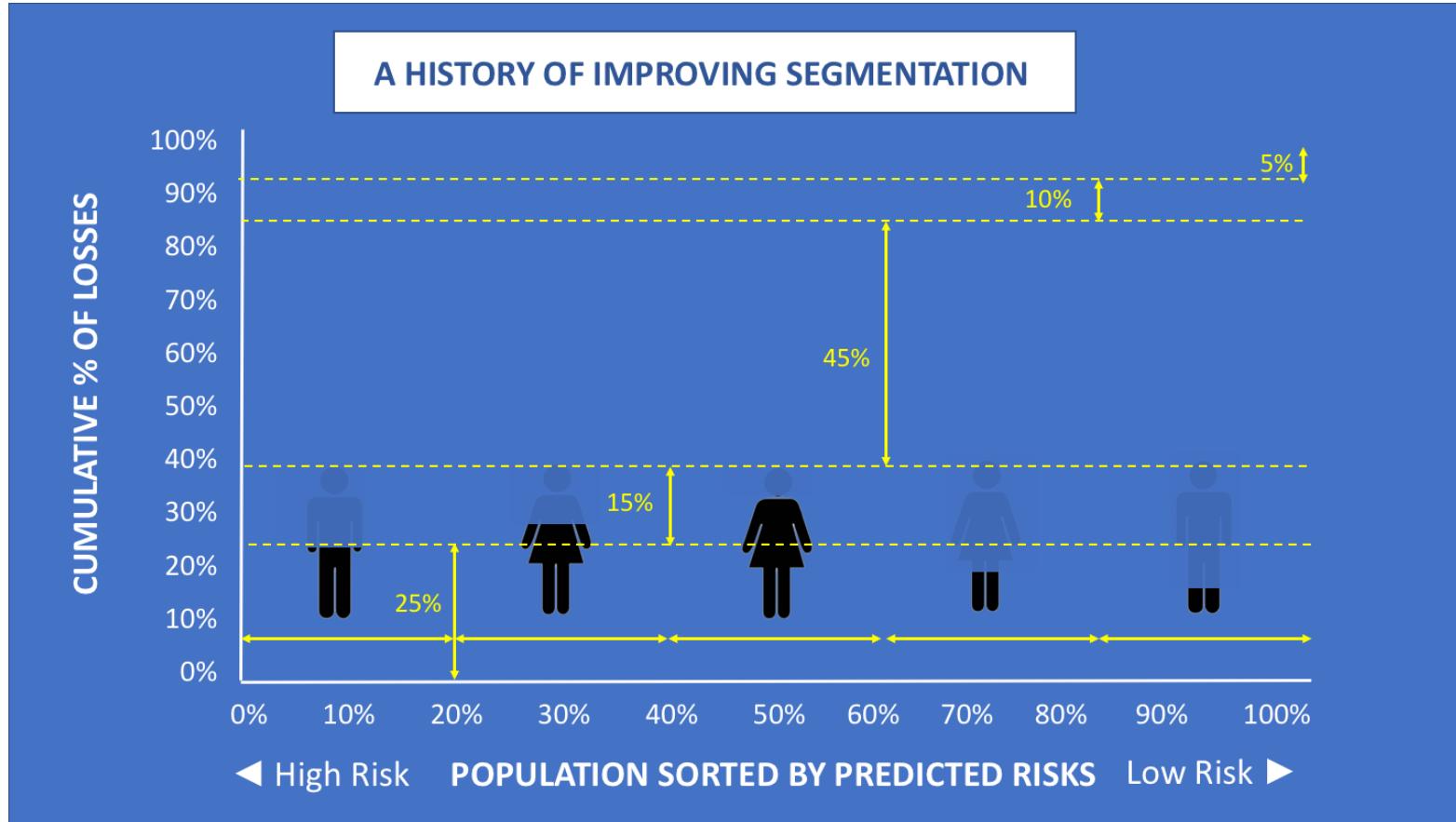
see Frees, Meyers & Cummins (2014).

## Practice of (*pseudo*)-Lorenz curves



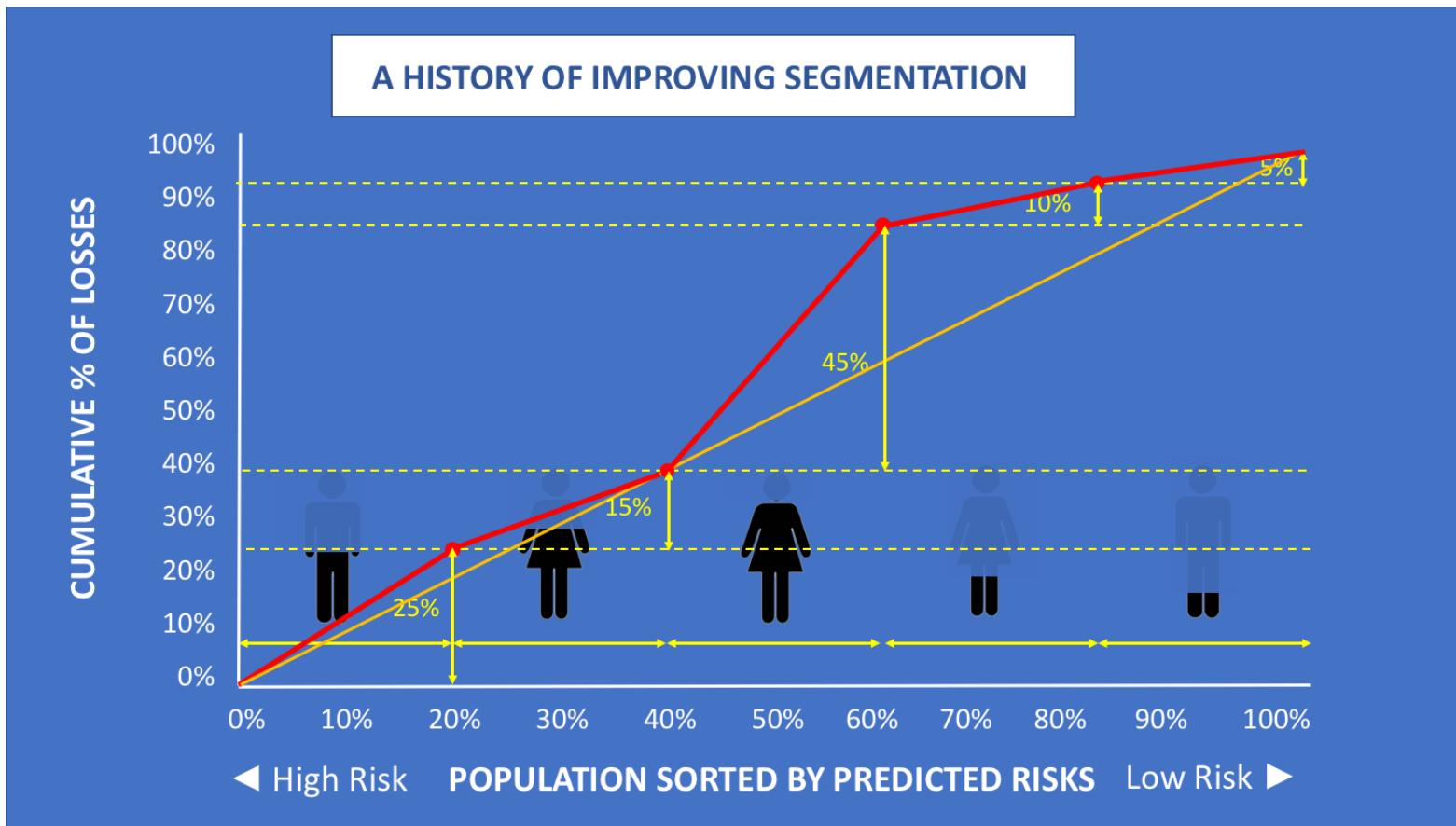
What if  $\hat{m}$  and  $m$  are not perfectly correctly correlated...?

## Practice of (*pseudo*)-Lorenz curves



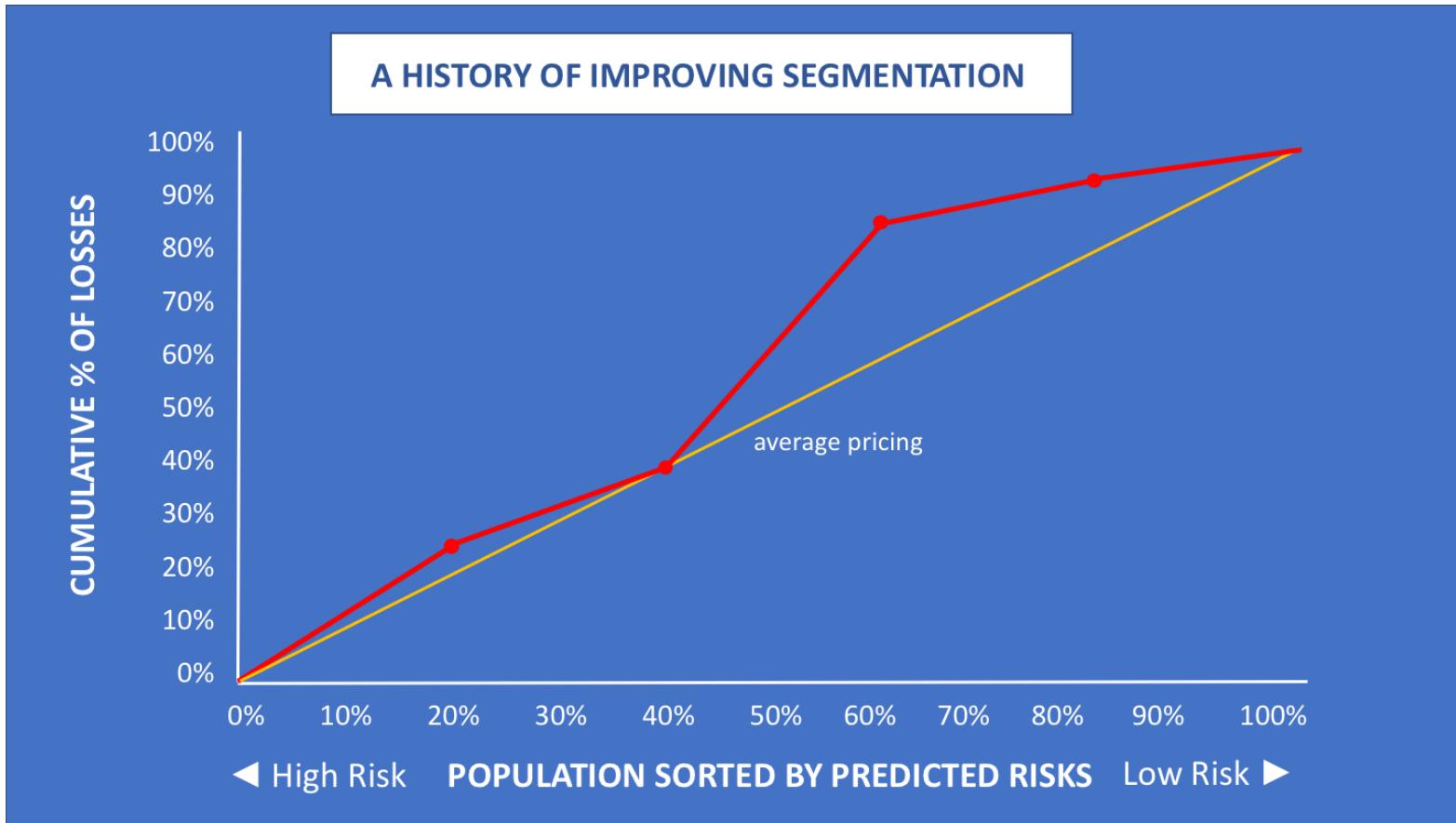
What if  $\hat{m}$  and  $m$  are not perfectly correctly correlated...?

## Practice of (*pseudo*)-Lorenz curves



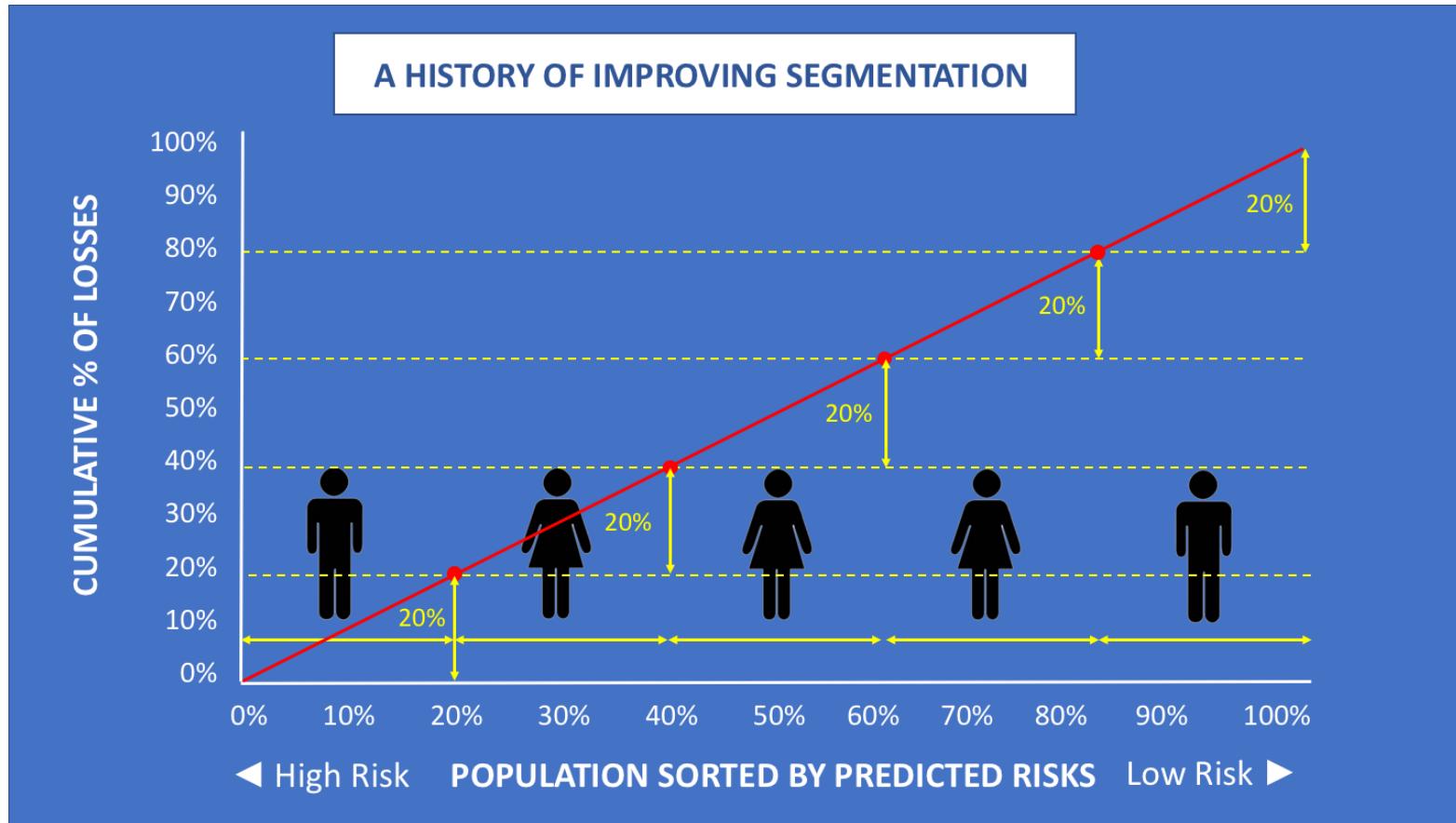
What if  $\hat{m}$  and  $m$  are not perfectly correctly correlated...?

## Practice of (*pseudo*)-Lorenz curves



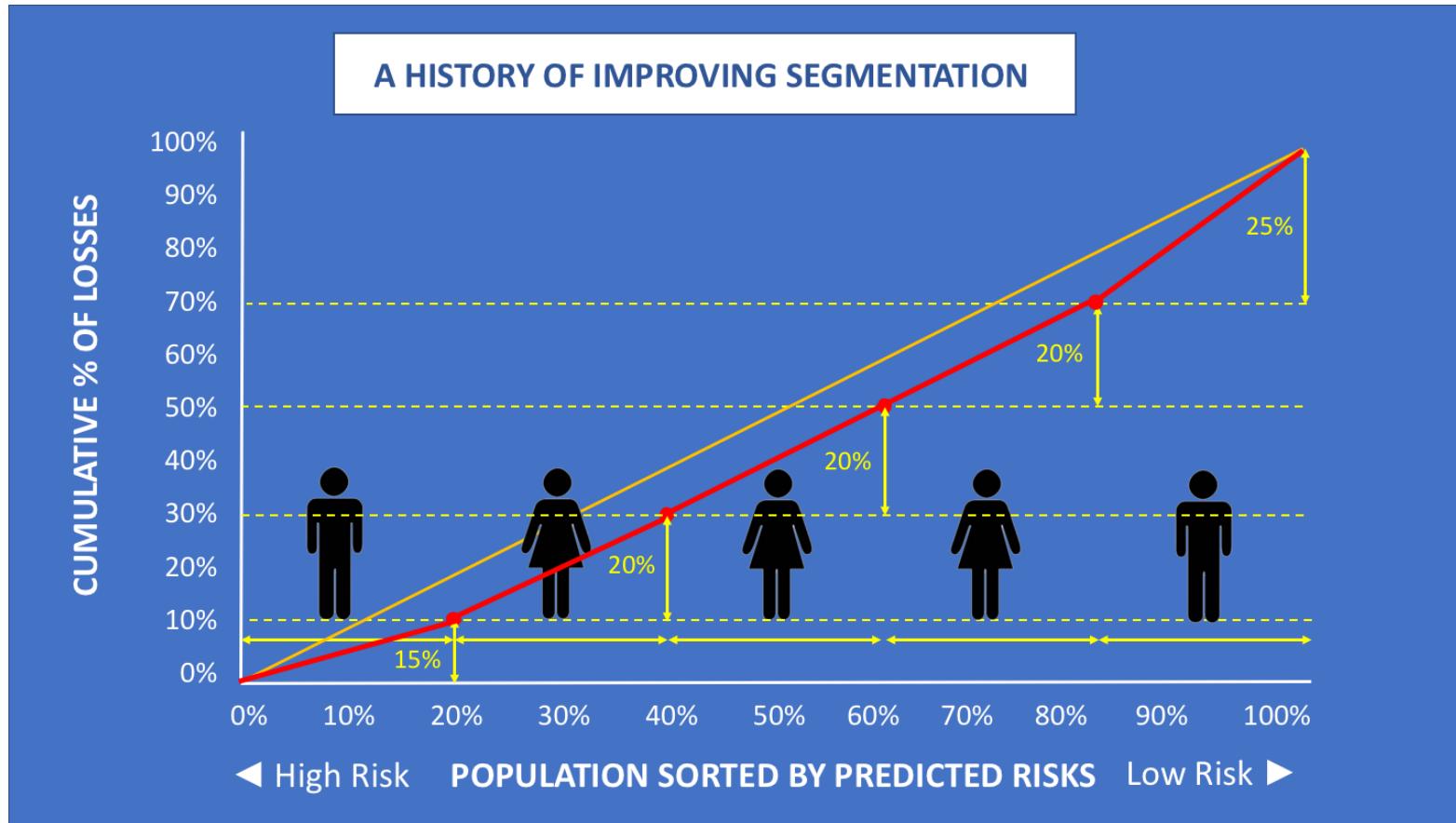
What if  $\hat{m}$  and  $m$  are not perfectly correctly correlated...?

## What is the “average” model ?



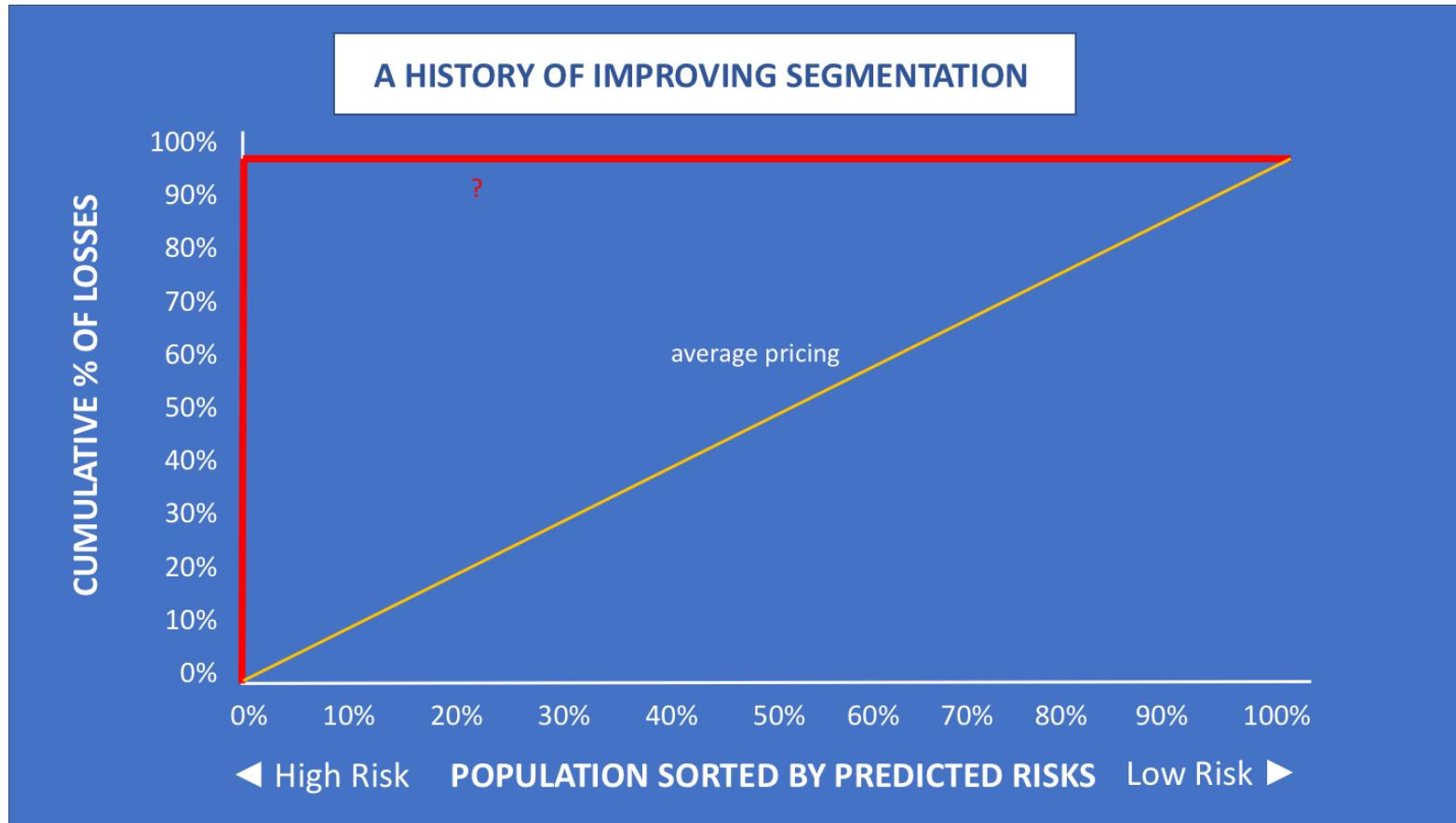
What is this “*average pricing*” ?

## Can it be worst than the “average” model ?



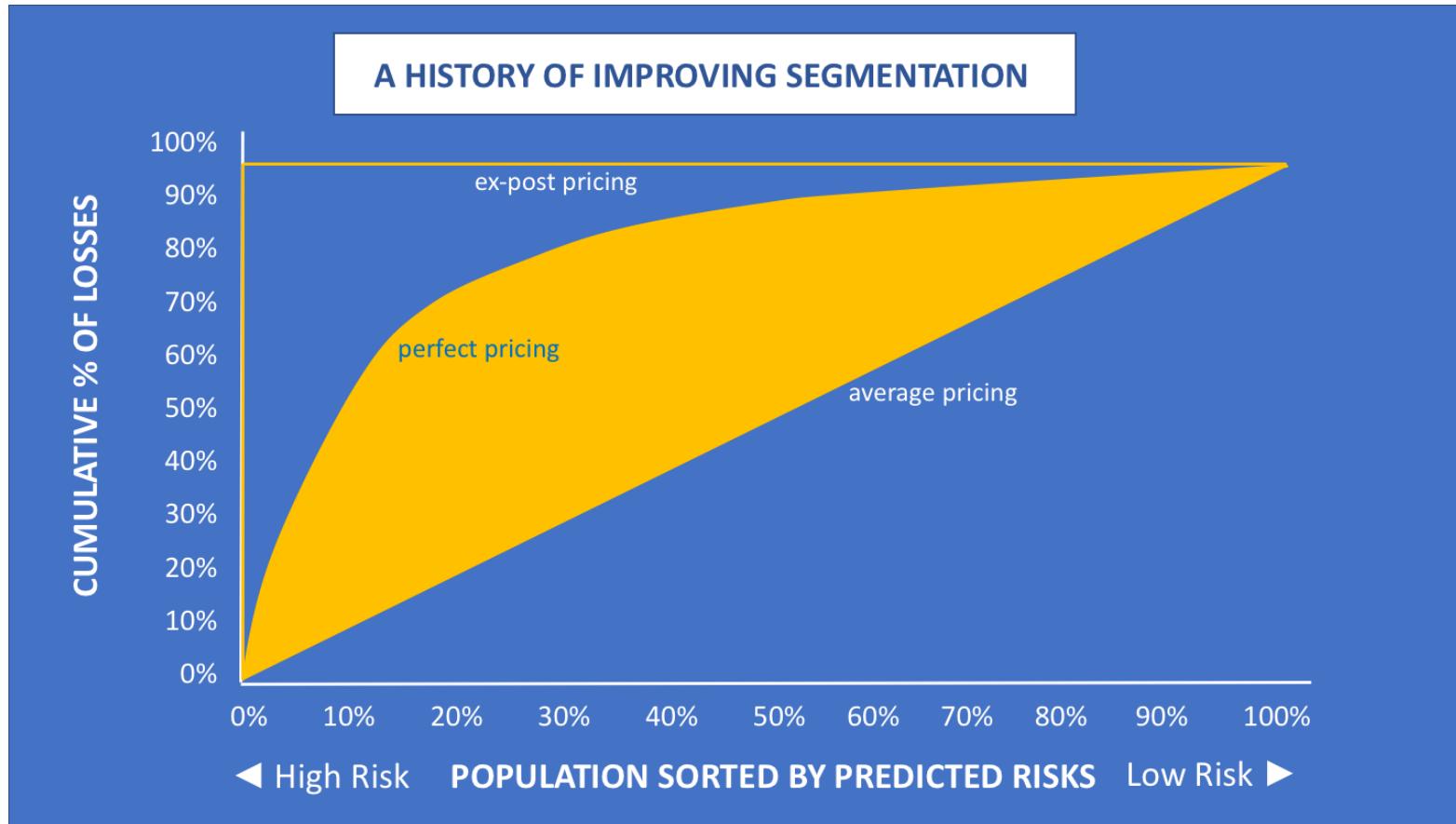
Is it a lower bound ? Is it possible to be below that curve ?

## What is in the upper corner ?



What is the upper bond ? Ex-post pricing...

## How to understand this (*pseudo*)-Lorenz curve ?

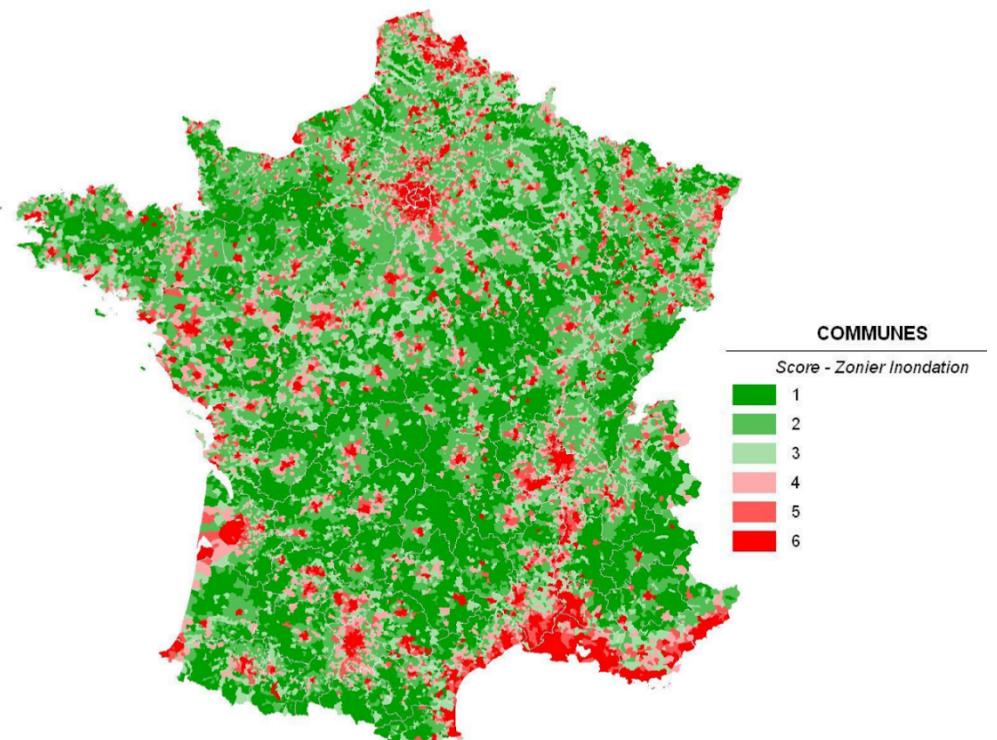
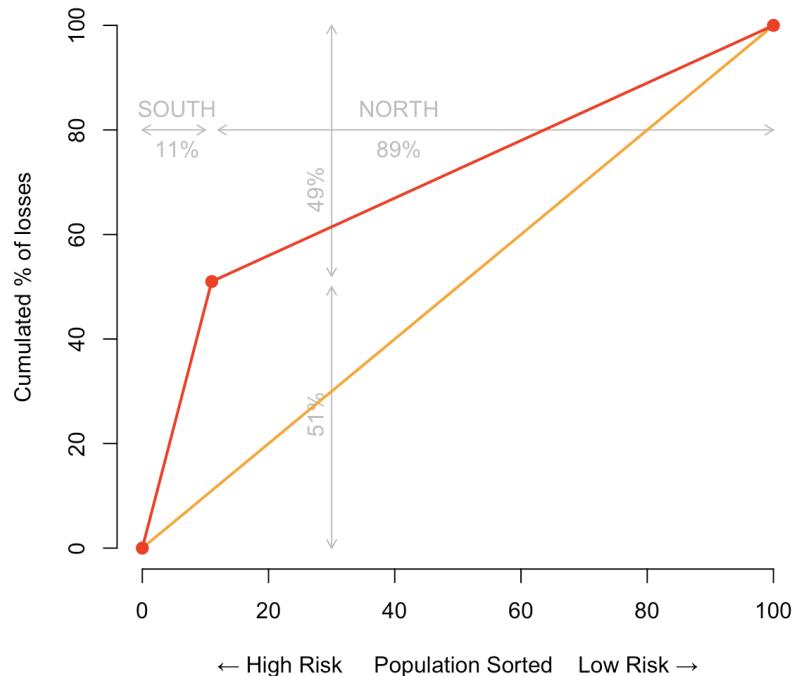


Is there a continuity between mutualization and hyper-segmentation ?

## Insurance, Risk Pooling and Solidarity

Consider flood risk

One can look at the “Lorenz curve”



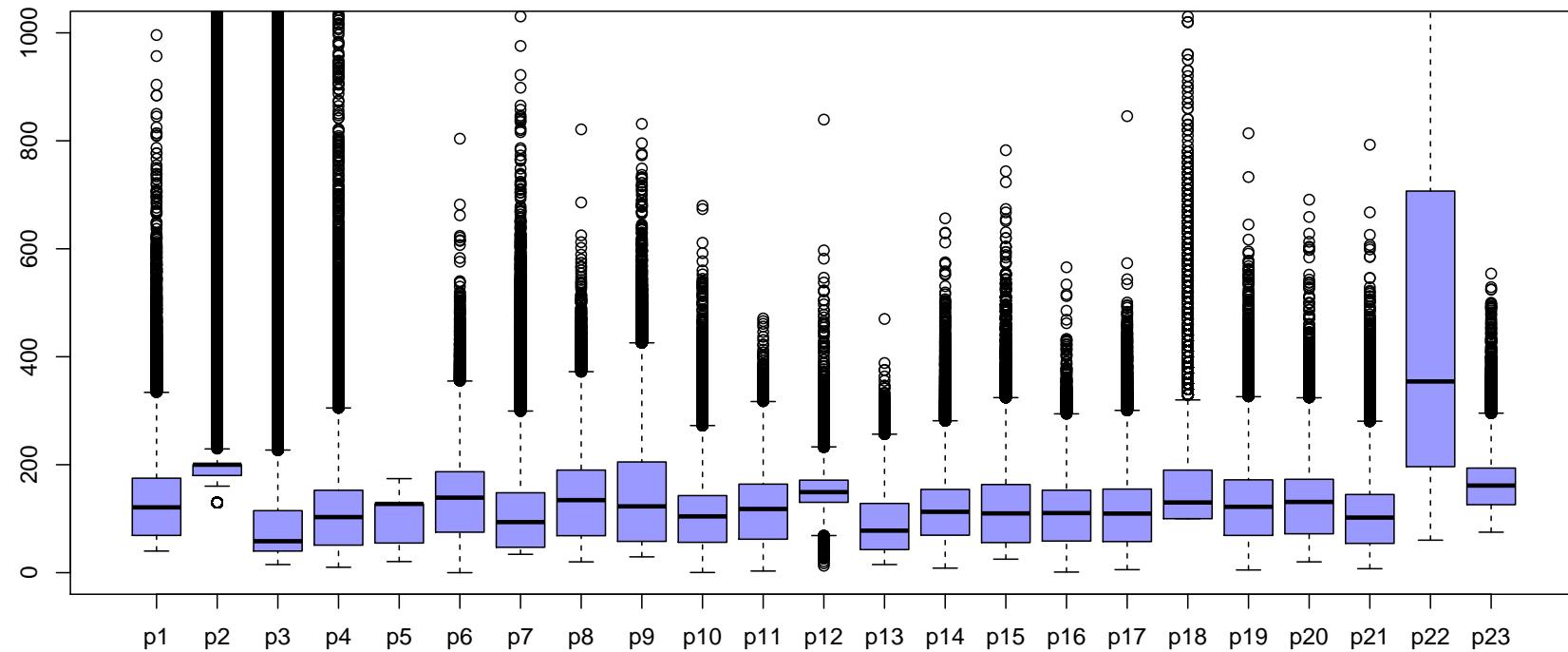
## Field experiment: the actuarial pricing games

Actuarial pricing is **data based**, and model based

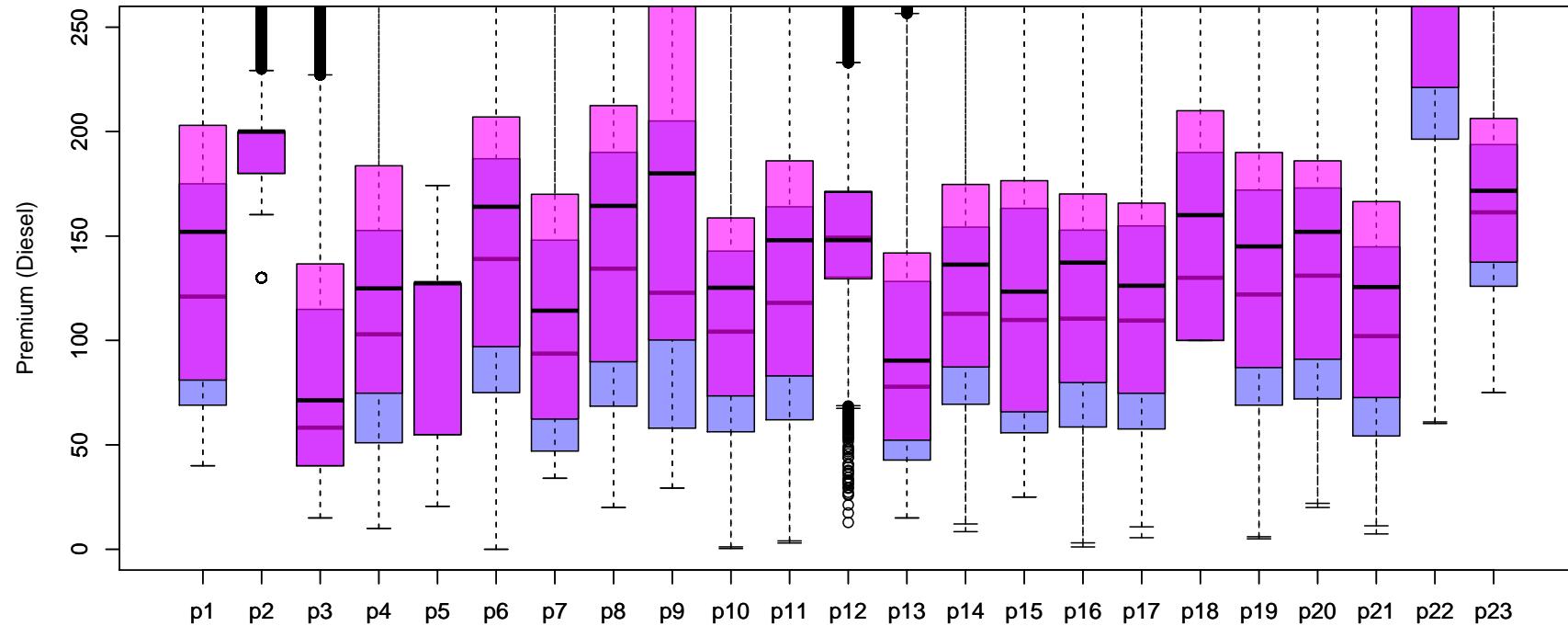
To understand how model influence pricing  
we ran some actuarial pricing games



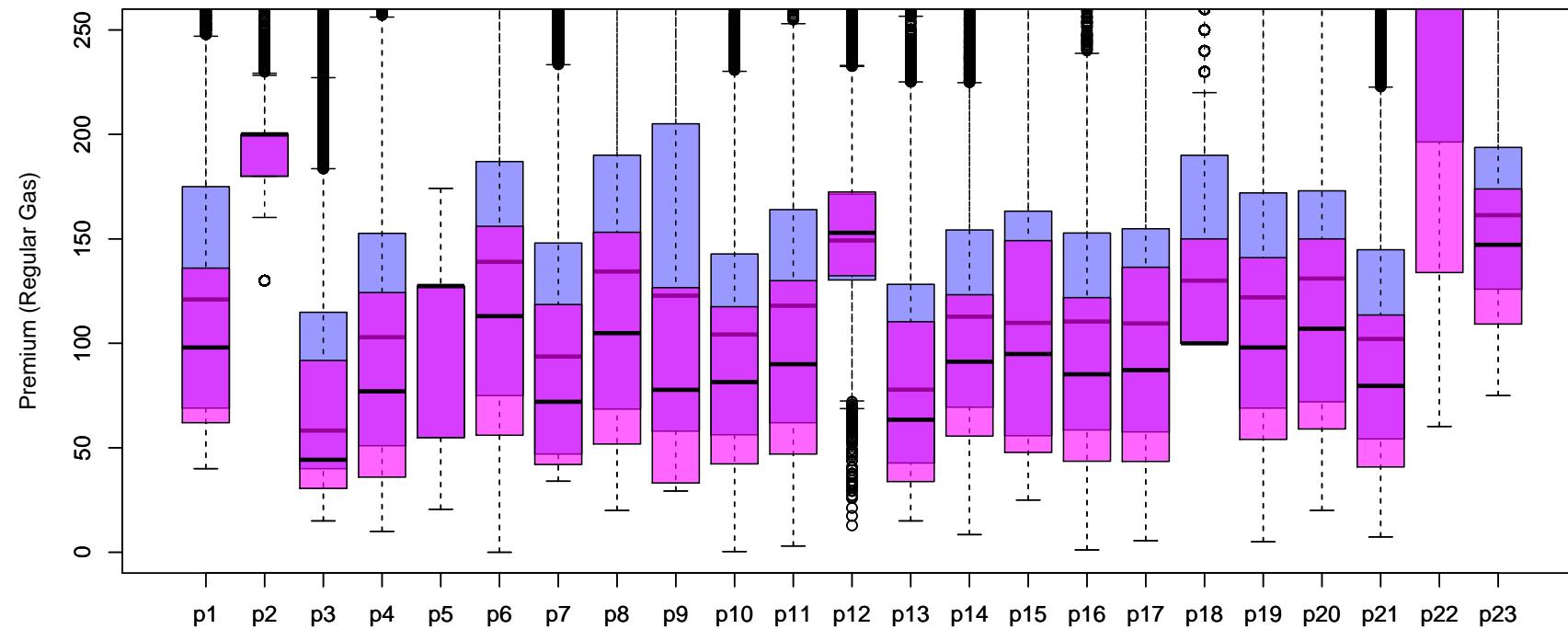
## Insurance Ratemaking Before Competition



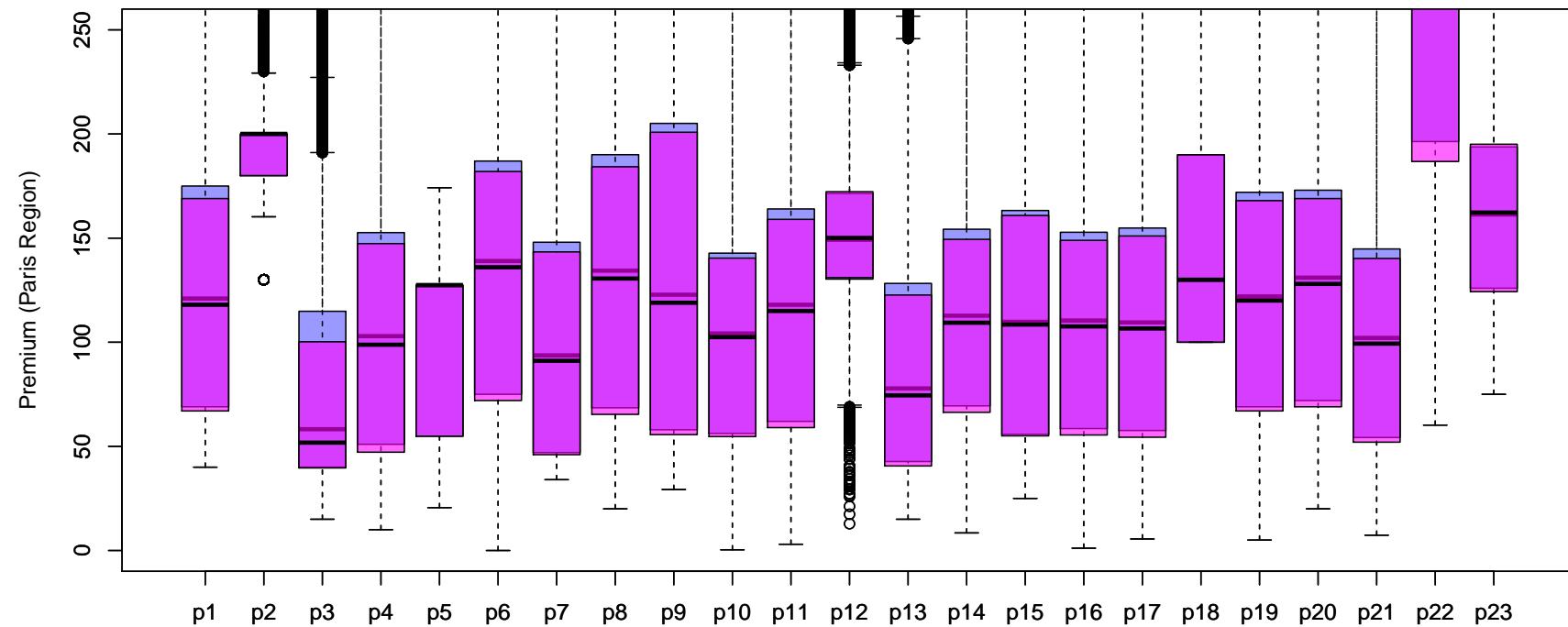
## Insurance Ratemaking Before Competition Gas Type Diesel



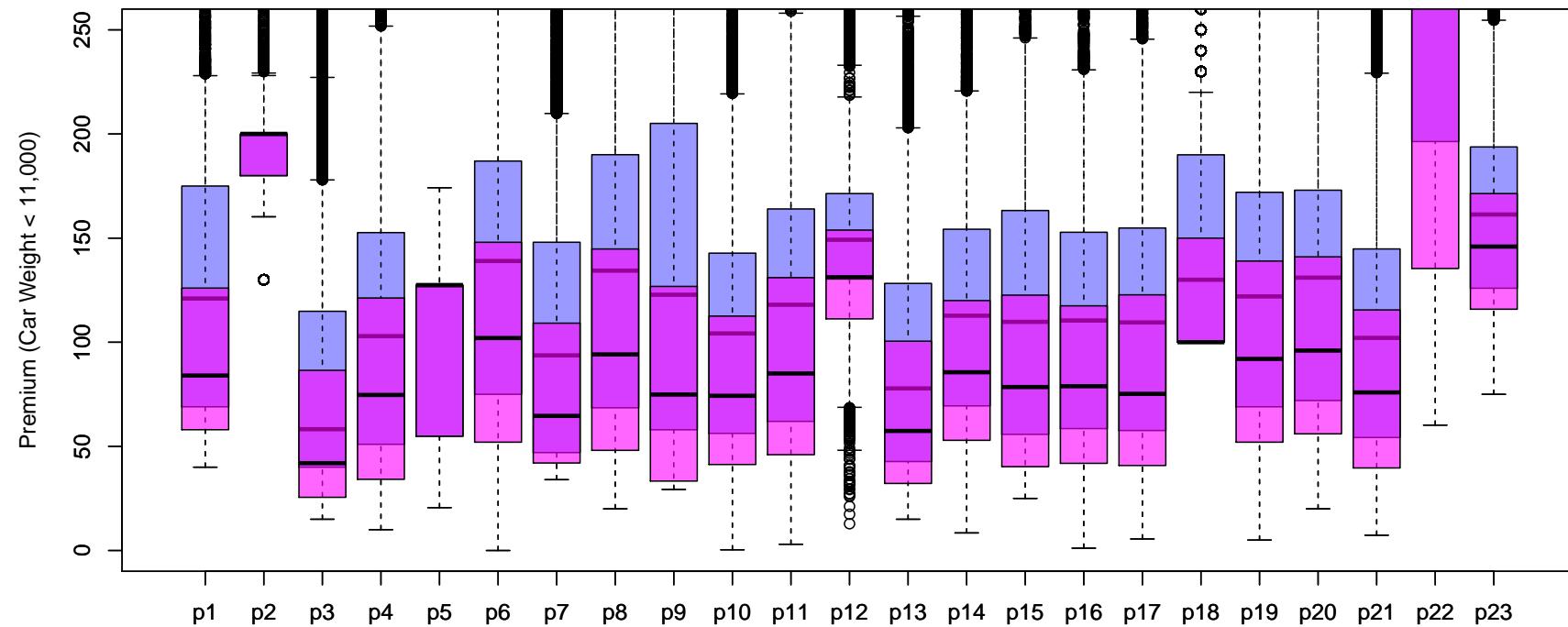
## Insurance Ratemaking Before Competition Gas Type Regular



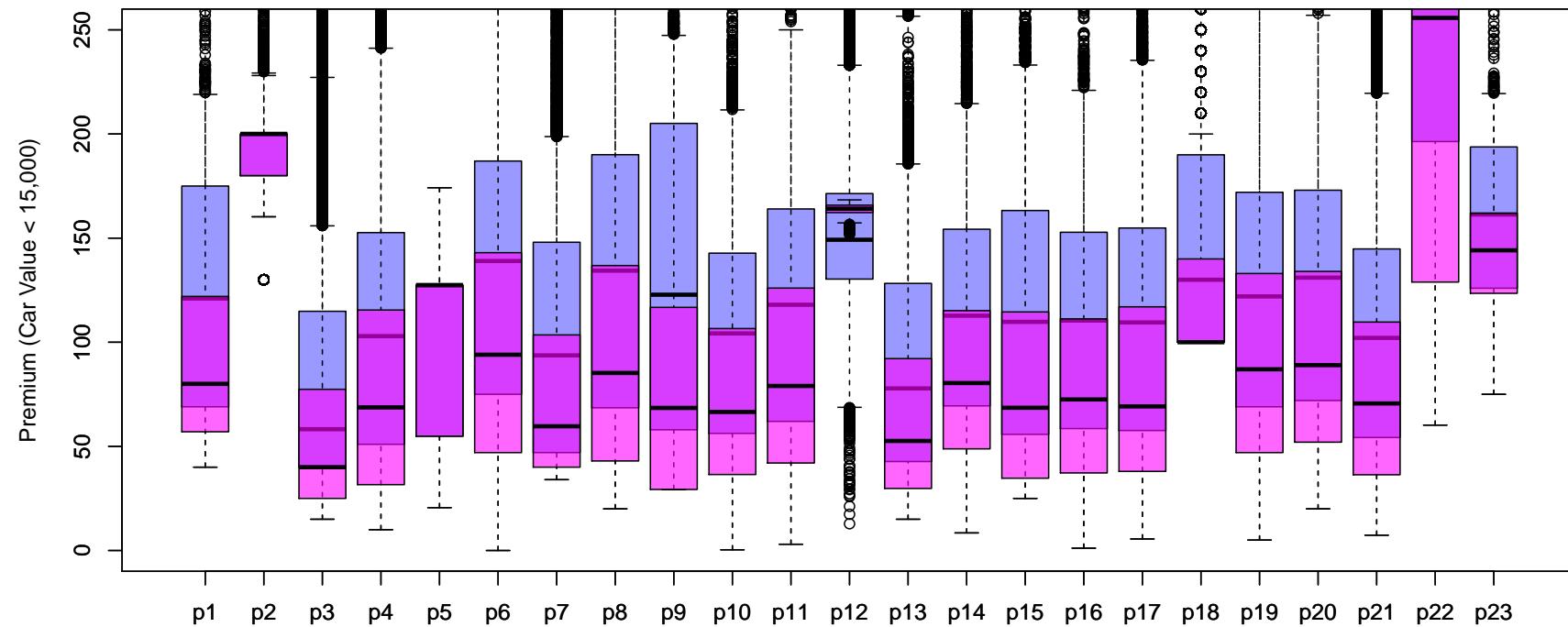
## Insurance Ratemaking Before Competition Paris Region



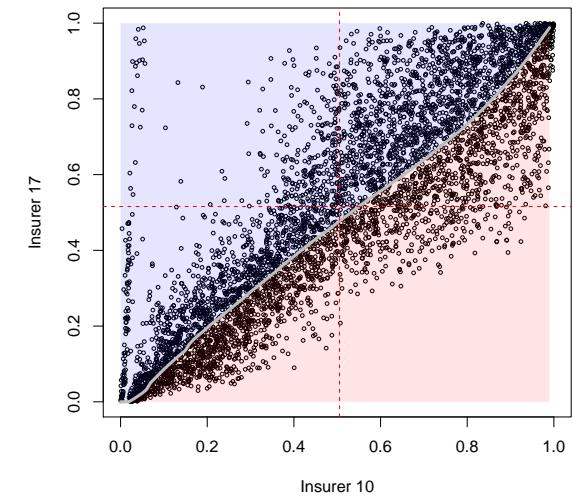
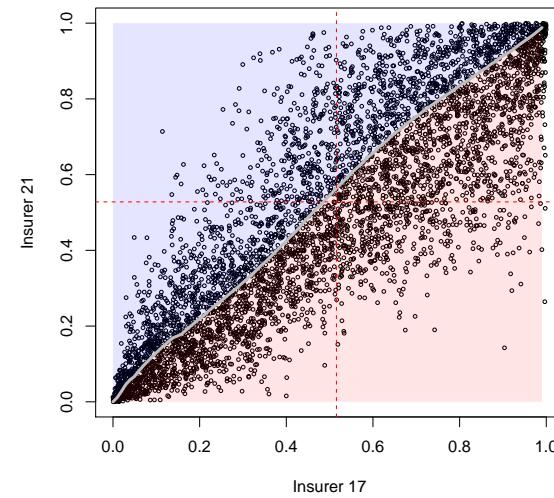
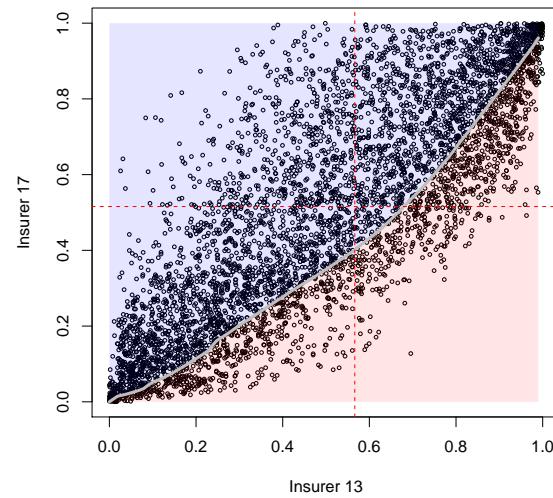
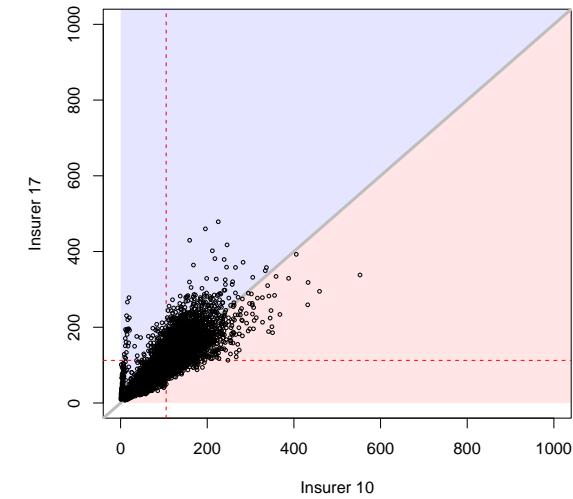
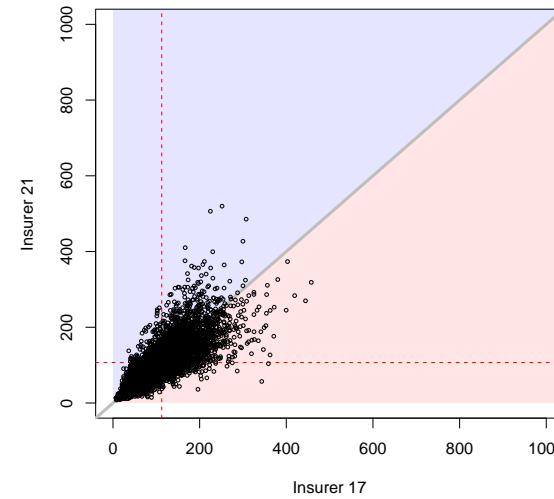
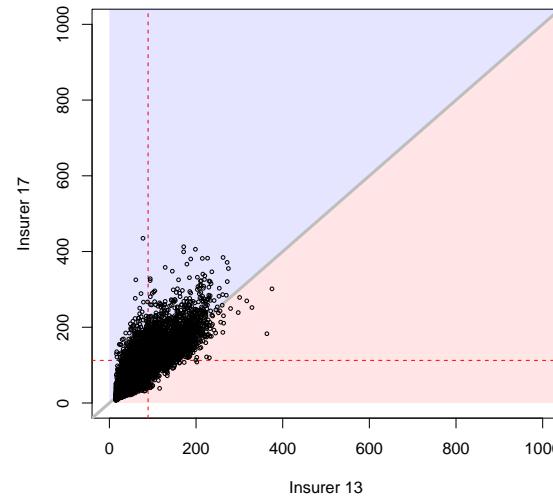
## Insurance Ratemaking Before Competition Car Weight



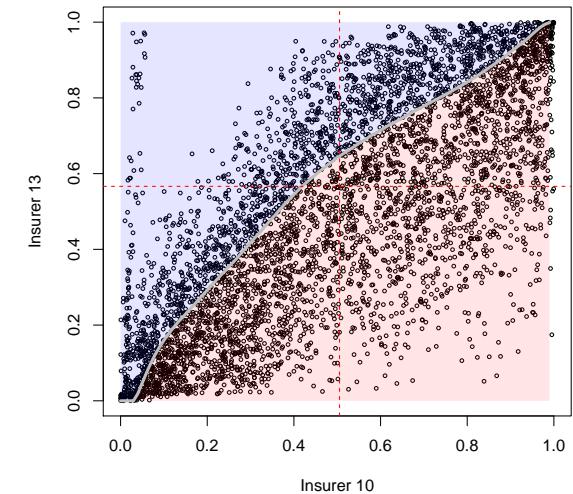
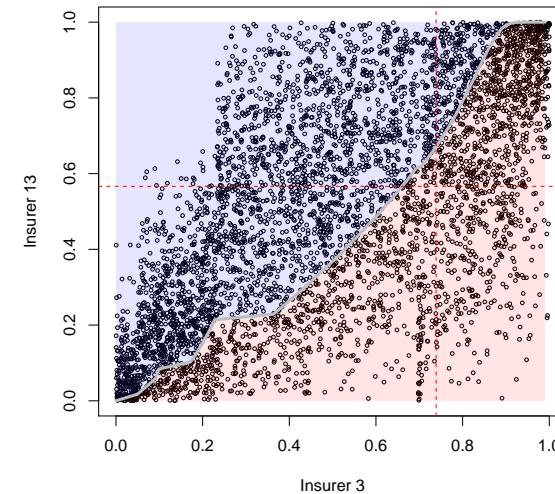
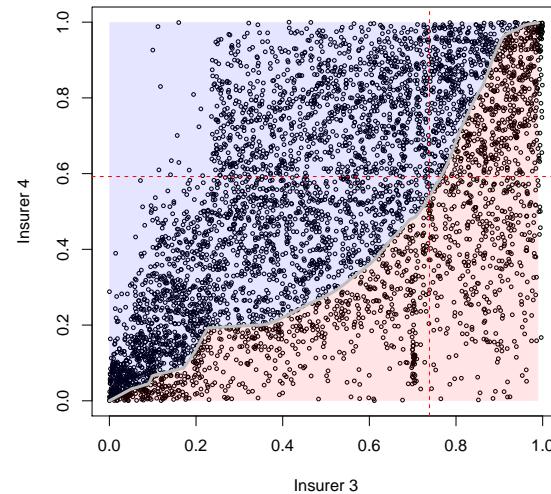
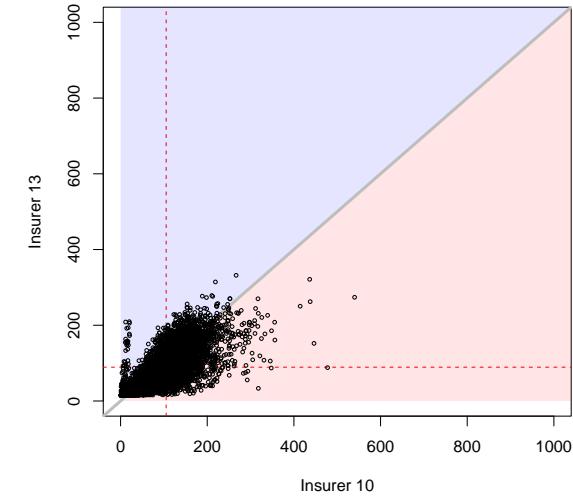
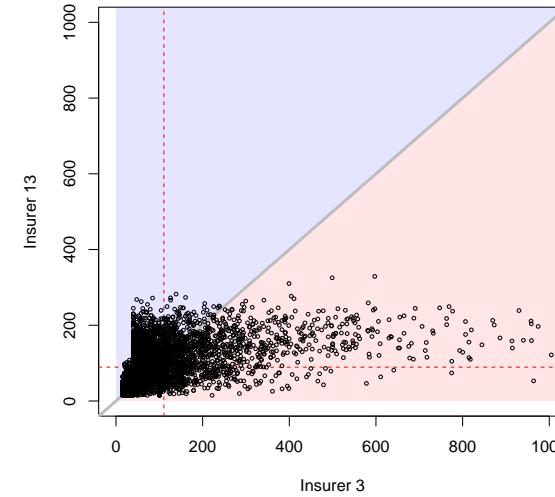
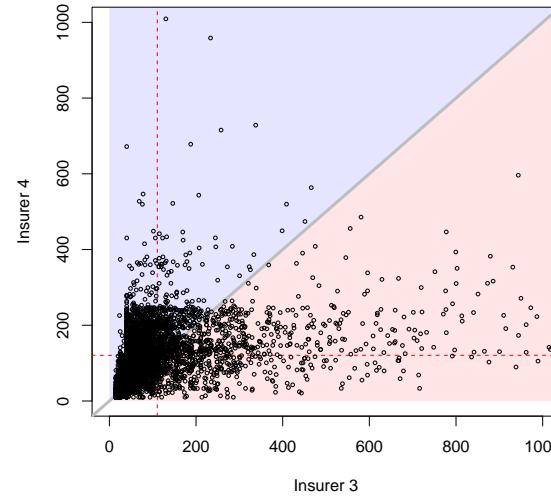
## Insurance Ratemaking Before Competition Car Value



# Insurance Ratemaking Competition : High Correlation ?



# Insurance Ratemaking Competition : High Correlation ?



## Insurance Ratemaking Competition

We need a **Decision Rule** to select premium chosen by insured  $i$

	Ins1	Ins2	Ins3	Ins4	Ins5	Ins6
	787.93	706.97	1032.62	907.64	822.58	603.83
	170.04	197.81	285.99	212.71	177.87	265.13
	473.15	447.58	343.64	410.76	414.23	425.23
	337.98	336.20	468.45	339.33	383.55	672.91

## Insurance Ratemaking Competition

Basic ‘**rational rule**’  $\pi_i = \min\{\hat{\pi}_1(\mathbf{x}_i), \dots, \hat{\pi}_d(\mathbf{x}_i)\} = \hat{\pi}_{1:d}(\mathbf{x}_i)$

	Ins1	Ins2	Ins3	Ins4	Ins5	Ins6
	787.93	706.97	1032.62	907.64	822.58	603.83
	170.04	197.81	285.99	212.71	177.87	265.13
	473.15	447.58	343.64	410.76	414.23	425.23
	337.98	336.20	468.45	339.33	383.55	672.91

## Insurance Ratemaking Competition

A more **realistic rule**  $\pi_i \in \{\widehat{\pi}_{1:d}(\boldsymbol{x}_i), \widehat{\pi}_{2:d}(\boldsymbol{x}_i), \widehat{\pi}_{3:d}(\boldsymbol{x}_i)\}$

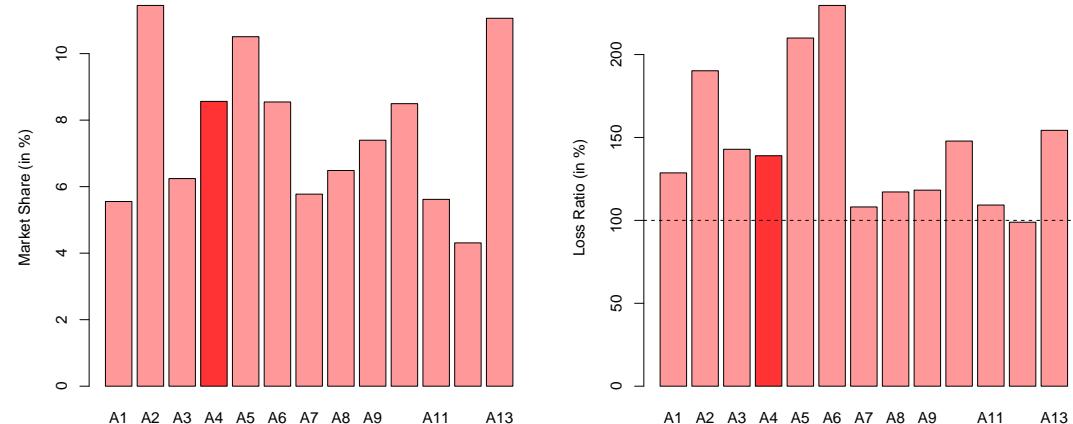
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	473.15	447.58	343.64	410.76	414.23	425.23
	337.98	336.20	468.45	339.33	383.55	672.91

## Pricing Game in 2015

### Insurer 4

GLM for frequency and standard cost (large claims were removed, above 15k), Interaction Age and Gender

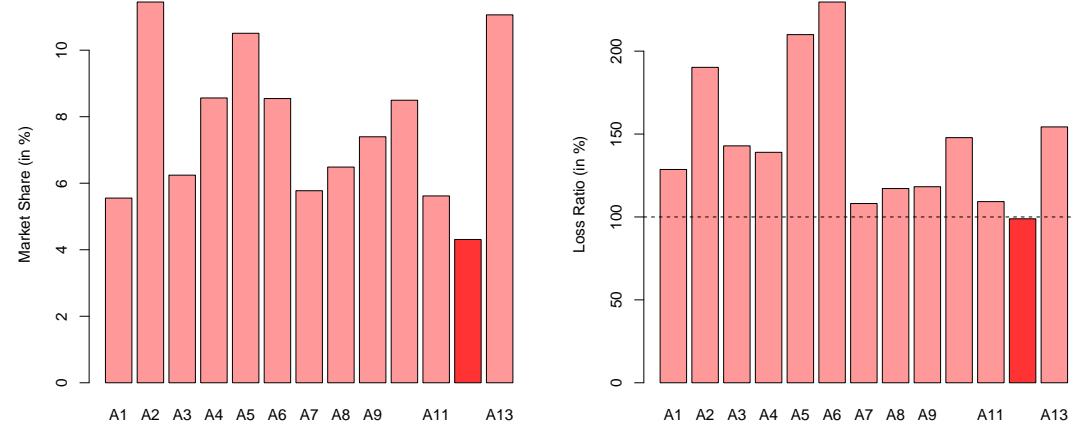
Actuary working for a *mutuelle* company



### Insurer 11

Use of two XGBoost models (bodily injury and material), with correction for negative premiums

Actuary working for a private insurance company



## Additional References (to go further)

- L'intelligence artificielle dilue-t-elle la responsabilité (2018)
- Les modèles prédictifs peuvent-ils être loyaux et justes (2017)
- L'éthique de la modélisation dans un monde où la normalité n'existe plus (2017)
- Les dérives du principe de précaution (2016)
- Segmentation et mutualisation, les deux faces d'une même pièce (2015)
- La tarification par genre en assurance, corrélation ou causalité ? (2016)
- Big data : passer d'une analyse de corrélation à une interprétation causale (2015)

and much more soon on  [freakonometrics.hypotheses.org](https://freakonometrics.hypotheses.org)