FAIRNESS IN INSURANCE PRICING

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Direct discrimination

- when ***D*** is used as a rating factor

Indirect discrimination

- ***X*** variables are correlated with ***D***
- or pricing has a ***disparate impact*** on

If *D* and *Y* are correlated, why not discriminate**?**

1. *D* is not the real issue
   - e.g. race & immigrant mortality
2. Social solidarity
   - e.g. EU gender neutral pricing laws
3. Mitigate systemic inequality
   - e.g. anti-redlining initiatives
4. Differential inaccuracy
   - e.g. lack of credible data

What is fair?

T and J have identical careers – employers, salaries etc

T and J both retire at 65 with a DC pension fund of $1 million.

T and J both use the fund to purchase a pension

- Tom gets 6,500 per month for life
- Jane gets 5,000 per month for life

Is that fair?

Fair Premium Criteria

(Xin & Huang, 2023)

Fairness through unawareness

Counterfactual fairness

The premium would be the same if *D* were different

Discrimination-free premium (Lindholm et al, 2022)

$$P(\boldsymbol{X}) = \sum_{d \in D} E\left[Y \mid \boldsymbol{X}, d\right] \Pr^*[d]$$

Fair Premium Criteria

Demographic Parity

$$F_P\left(Y \middle| D = a\right) = F_P\left(Y \middle| D = b\right)$$

Conditional Demographic Parity

$$F_P\left(Y \middle| X_a, D = a\right) = F_P\left(Y \middle| X_a, D = b\right)$$

where X_a Ì $\boldsymbol{X}$ are designated allowable covariates

Weak Demographic Parity

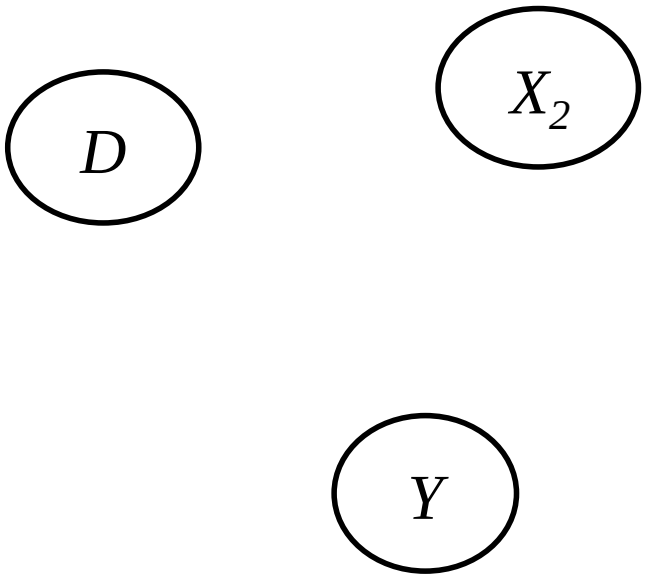
$$\mathrm{E}\left[Y \middle| D = a\right] = \mathrm{E}\left[Y \middle| D = b\right]$$

CAUSAL INFERENCE PERSPECTIVE

$D = a$ and $X_2 < 500$

- low risk aversion
- higher premium

$D = b$ and X_2



Counterfactual Fairness

Requires

If X_2

Fair premiums & causal model

Discrimination-Free Premium (DFP)

$$P(x_1, x_2, x_3) = Y\left|\{D = a, X = (x_1, x_2, x_3)\}\right. \Pr^*(D = a)$$
$$+ Y\left|\{D = b, X = (x_1, x_2, x_3)\}\right. \Pr^*(D = b)$$

If $X_2 < 500$

DFP overcharges for $D = b$

and undercharges for $D = a$

If $\boldsymbol{X}=(x_1, x_3)$ then D is irrelevant and DFP [1] UP

DFP is useful when D is a confounder

Notes

If D is not a confounder? eg

In pr… …are premium (UP) = DF

…measurement error can create spurious …ciations → UP ¸ DFP

Notes from the causal perspective

1. The DAG helps identify risk factors (causal) from other rating factors.
2. The DAG helps achieve counterfactual fairness.
3. DAGs are subjective.
4. Variable aggregation, discretization, use of proxies, will impact the reliability of causal inference.
5. Problems with high dimensions
6. Availability of Discriminatory covariate
7. Impact of telemetrics; interpretation; algorithmic fairness

CASE STUDY: WISCONSIN AUTO INSURANCE

Redlining in Milwaukee, 1964

link to Auto insurance premiums Milwaukee Redlining in Milwaukee,...

Racial distribution Milwaukee, 2010

Each dot is 25 people:

White

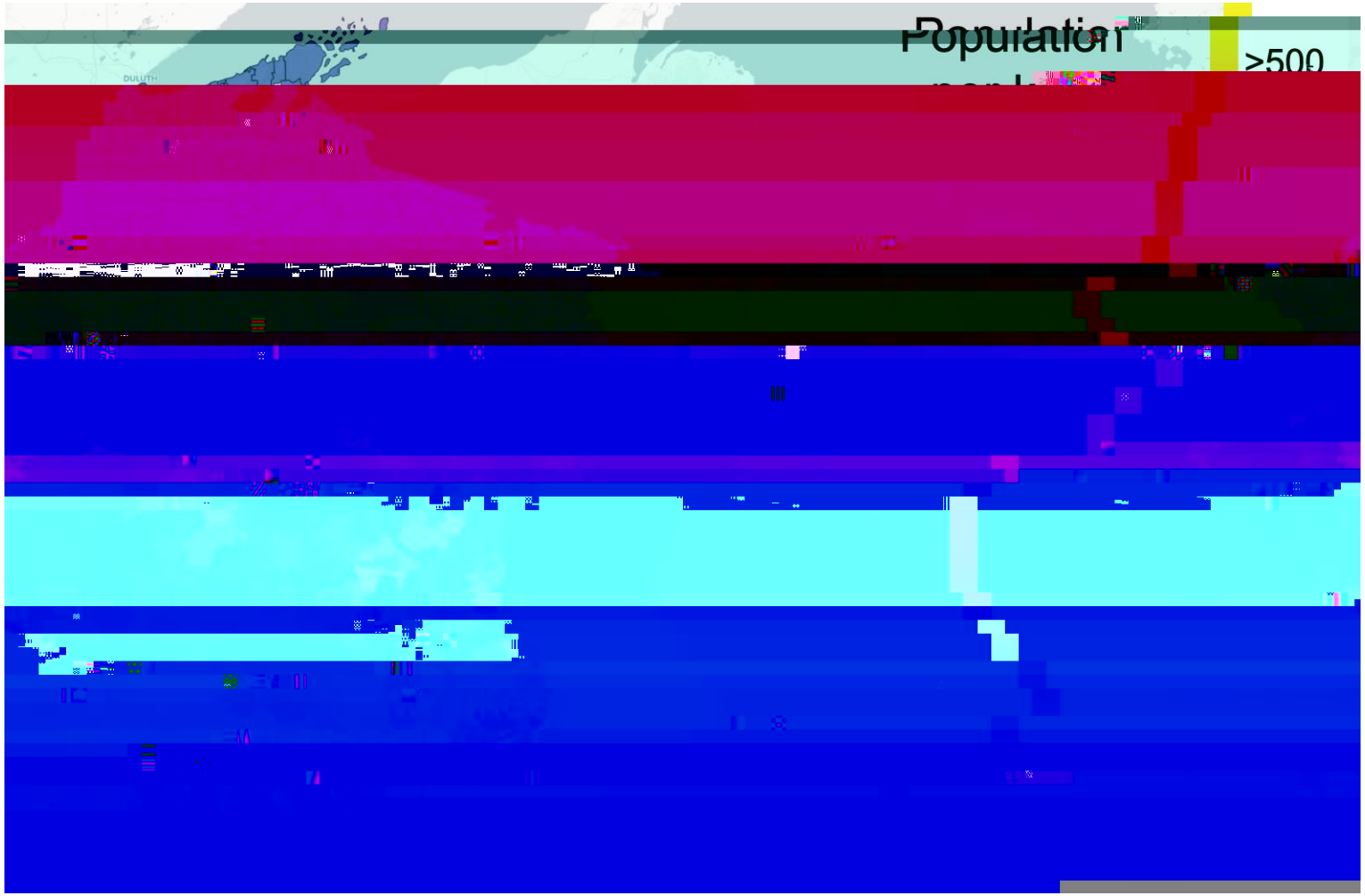
Questions

Are there ongoing effects of the redlining era on auto insurance premiums?

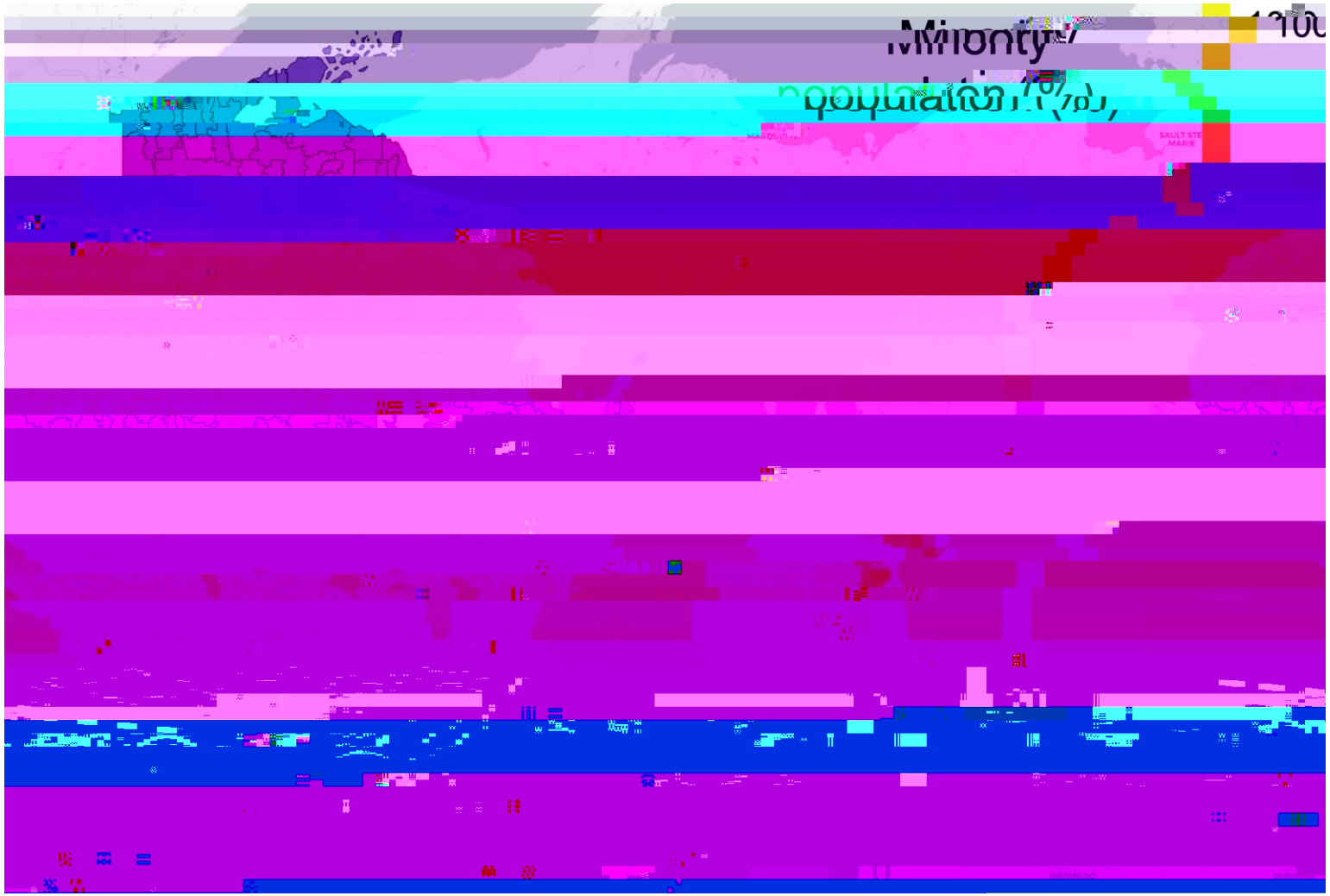
Could actuarial models, assumptions and policy design be perpetuating systemic discrimination?

Should insurers and regulators take historic inequality into consideration?

Population density Wisconsin



Minority population Wisconsin



Maybe Milwaukee is an outlier?

We examined an extensive database on accidents attended by police, 2001-2020.

Link

Notes

Premiums are ~ 50%-100% higher in the predominantly Black/Hispanic neighbourhoods.

Population density does not appear to

A MICROSIMULATION STUDY

Microsimulation Experiment

Simulate a portfolio of policyholders

Calibrated to Wisconsin 2020 population data.

Calibrated to Wisconsin premiums

Calibrated to Dept of Transport data on accident frequency and severity

Simulated Variables

Age, gender, marital status, education, driving record, car, mileage, zip code — **Rating Factors**

Income ← **Proxied Rating Factor**

Risk aversion, driving ability, driving type ← **Latent variables**

Race ← **Discriminatory covariate**

Insurance frequency / severity ← **Response Variables**

Simulation results - summary

	White	Black	Asian	Hispanic	Total
Policyholders	83%	6%	3%	7%	100%
- urban	24%	86%	53%	63%	31%
- rural	48%	5%	12%	19%	42%
Claim freq.	0.187	0.200	0.189	0.190	0.188
Ave severity	6,536	5,282	6,207	5,803	6,388
Ave pure premium	1,227	1,058	1,158	1,115	1,206

Link

What does the insurer see?

Insurer's analysis of frequency data

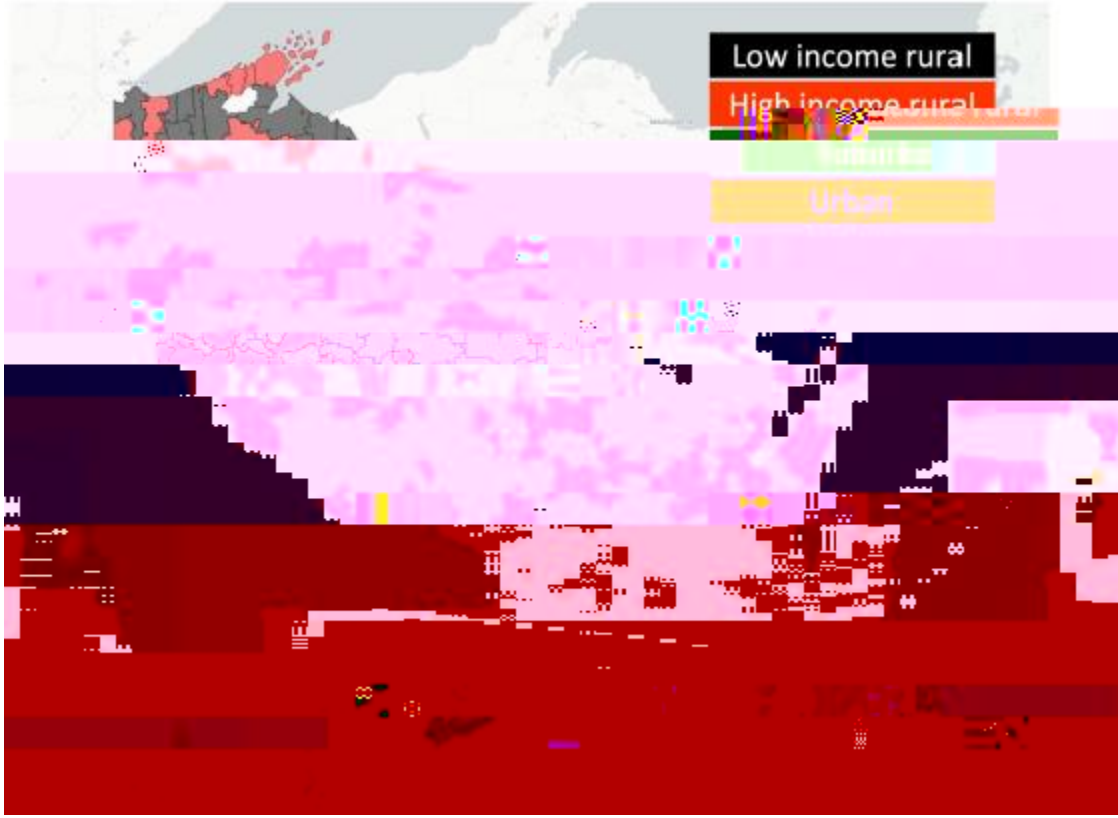
Insurer's analysis of severity data

Model 1: Independent of all covariates

Model 2: Dependent on car make/model/year

Model 3: GLM, area income proxy for zip code, all other rating factors

Model 3:
income → zip code proxy



Discrimination metrics

Relative bias tests:

- Relative bias for Model *j*: $f_j(d) = \frac{m_j(d)}{m(d)} - 1$
- where is the Model *j* estimated average pure premium for group $d \in D$
- and $m(d)$ is the true average pure premium for group $d \in D$

Why use relative bias?

- Better generalization to different input lengths
- Inductive bias of model

Discrimination metrics

1. Frequency or severity parameters ^ race?
2. Relative bias ratio:

$$\frac{f(d = \text{White})}{f(d = \text{Black/Asian/Hispanic})} <> 0.8$$

3. Pairwise comparison of relative bias
   - 14 mostly minority ZC vs 48 mostly White

Proxy discrimination sample

Discrimination Results

	Direct	Indirect (1)	Indirect (2)	Indirect (3)
Frequency	**No**	**No**	**No**	**Yes**
Model 1	**No**	**Yes**	**Yes**	**Yes**
Model 2	**No**	**Yes**	**Yes**	**Yes**
Model 3	**No**	**No**	**No**	**Yes**
Model 4	**No**	**No**	**No**	**No**

Other issues

Would demographic parity be appropriate here?

Would the Discrimination-Free Premium be appropriate here?

How might counterfactual fairness be taken into consideration?

Causal inference requires subjective judgement – might this introduce more bias?

Summary

The causal framework can illuminate sources of unfairness.

Discrimination can arise from a common actuarial model of frequency/severity.

Our results are consistent with empirical evidence in terms of premiums and insurance losses.

Using causal rating factors can mitigate discrimination.

Rating systems (underwriting, NCB, rating factors) can exacerbate unfairness

References

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