Fairness Issues in Long-Term Care Insurance via AI-Inspired Methods

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20th Longevity Conference
Sept 8 – 9, 2025, Singapore

Topic Coverage

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Background

Insurance Ratemaking → Group policyholders into homogeneous risk classes

Anti-Discrimination Regulations → Restrict use of protected attributes

TENSION:
Ratemaking seeks to use detailed risk factors, but regulations prohibit the use of protected variables (e.g., race, gender)

- A common compliance method is to exclude protected variables from models
- However, this is often inadequate due to the presence of proxy variables

Gaps in the literature

- Actuarial methods have been proposed to remove both direct and indirect effects of discriminatory variables
  - Discrimination-free premium, pioneered by Lindholm et al. (2022)
  - Group fairness constraints (see Pessach and Shmueli, 2022, for a review)
- Most existing work assumes expected losses can be modeled using linear or generalized linear models (GLMs)
- Some lines of insurance require more complex pricing approaches while still demanding fairness considerations
- A notable example is long-term care insurance (LTCI)

Challenges in applying discrimination-free pricing to LTCI

- Pricing LTCI products often relies on multi-state Markov models that track transitions between health states
- Premiums are not directly output by these models, but derived through several intermediate steps
- Many discrimination-free pricing methods assume the model output is the premium, which can be adjusted for fairness
- In contrast, LTCI requires a multi-step derivation:

$$\text{transition intensities} \rightarrow \text{transition probabilities} \rightarrow \text{expected present value} \rightarrow \text{premium}$$

- It is unclear whether existing fairness methods extend naturally to this framework

Research objectives

- Propose a framework for estimating transition intensities in multi-state models which allows fair pricing methods readily
- Illustrate fair pricing in LTCI using Lindholm et al. (2022)
- Investigate demographic discrepancies in public survey data, and whether these can be reduced using fair pricing methods

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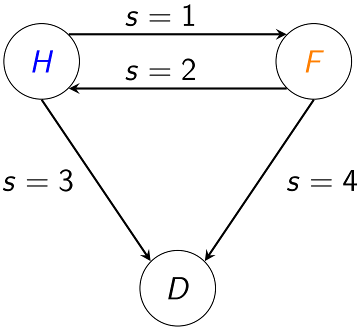
Multi-state Markov model



- H: healthy; F: functionally disabled or simply disabled
- s: type of transitions

- The health state is determined by a person's ability to perform activities of daily living (ADLs), such as bathing, toileting, and dressing
- Two or more ADL limitations indicate functional disability, in line with long-term care insurers' practice.

Poisson-survival connection

- For illustration, assume λ_s constant across lifetime
- Let T denote the time of transition/censoring

$$L(\theta) = \prod_{s=1}^{S} \exp\left(-T\lambda_s\right)\left(\lambda_s\right)^{\delta_s} \propto \prod_{s=1}^{S} \frac{\exp\left(-T\lambda_s\right)\left(T \cdot \lambda_s\right)^{\delta_s}}{\left(T\lambda_s\right)!}$$

- Likelihood is product of S independent Poisson processes
  - Mean: $T\lambda_s$
  - Count: $\delta_s = 0$ or 1
- Motivate modeling a given multi-state model as a product of independent Poisson regressions
  - Need to relax stringent assumptions on λ_s

Incorporating covariates into λ_s

- We assume an underwriting/pricing setting
  - Non-age covariates $\mathbf{z}$ observed only at entry
  - For the same individual, only age x (last birthday) changes over time
- $\lambda_s(x, \mathbf{z})$ constant within each year, up to the point of transition
- Fractional times: incorporate exposure τ_x

Multi-state regression model as product of Poisson regressions

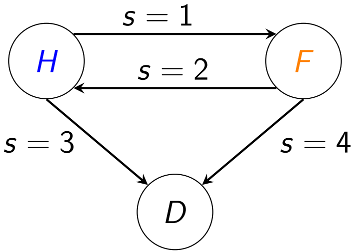
Let T denote the time of transition/censoring

$$L(\theta) = \prod_{s \in S} \prod_{x \le T} \exp(-\tau_x \lambda_s(x, \mathbf{z}))(\lambda_s(x, \mathbf{z}))^{\delta_s}$$

$$\propto \prod_{s \in S} \prod_{x \le T} \frac{\exp(-\tau_x \lambda_s(x, \mathbf{z}))(\tau_x \lambda_s(x, \mathbf{z}))^{\delta_s}}{(\tau_x \lambda_s(x, \mathbf{z}))!}$$

where

$$S = \begin{cases} \{1, 3\}, & \text{current state is } H \\ \{2, 4\}, & \text{current state is } F \end{cases}$$



Pricing formulae for LTCI

- Let h_t denote the health status of a person at time t
- Once transition rates λ_s for a person are available, transition probabilities such as $\Pr(h_t = H \mid H_0 = H)$ and $\Pr(h_t = F \mid H_0 = H)$ can be calculated
- Pricing formulae depend on product design
  - e.g. for a product which collects premiums each year when the person is healthy, and pays out 1 for each year the person is functionally disabled

$$P = \frac{\sum_t v^t \Pr(h_t = F \mid h_0 = H)}{\sum_t v^t \Pr(h_t = H \mid h_0 = H)}$$

Data

- We use the `RAND HRS Data` 1998-2020 from the U.S. Health and Retirement Study (HRS), a nationally representative longitudinal panel survey
- The HRS is a biennial survey that began in 1992 and follows up with interviews of initially non-institutionalized Americans aged 50 and above
    - Use only post-1998 data since questions on ADLs are inconsistent pre-1998

List of variables

C: categorical; N: numeric

Demographic	Health	Finance
Age (N)	Self-rated health (C)	Net total assets (N)
Gender (C)	Diabetes (C)	Total investments (N)
Race (C)	Lung disease (C)	
Ethnicity (C)	Heart disease (C)	
Ed. yrs (C)	Stroke (C)	
Cens. region (C)	BMI (N)	
Marital status (C)	Drink (C)	
# household members (N)	Smoke (C)	

Model specification

- For illustration purposes, we consider
  - Sensitive attribute: race (White, Black, Other); denoted D
  - Non-sensitive attributes: other variables $(x, \mathbf{z})$
- Consider a log-linear form for λ_s, $s = 1, 2, 3, 4$:

$$\text{Race-unaware:}\;\; \ln \lambda_s(x, \mathbf{z}) = \beta_s + \gamma_s' \begin{pmatrix} x \\ \mathbf{z} \end{pmatrix}$$

$$\text{Best-estimate:}\;\; \ln \lambda_s(d, x, \mathbf{z}) = \beta_s + \gamma_s' \begin{pmatrix} d \\ x \\ \mathbf{z} \end{pmatrix}$$

  - In general, Poisson regression framework allows extensions to more flexible forms

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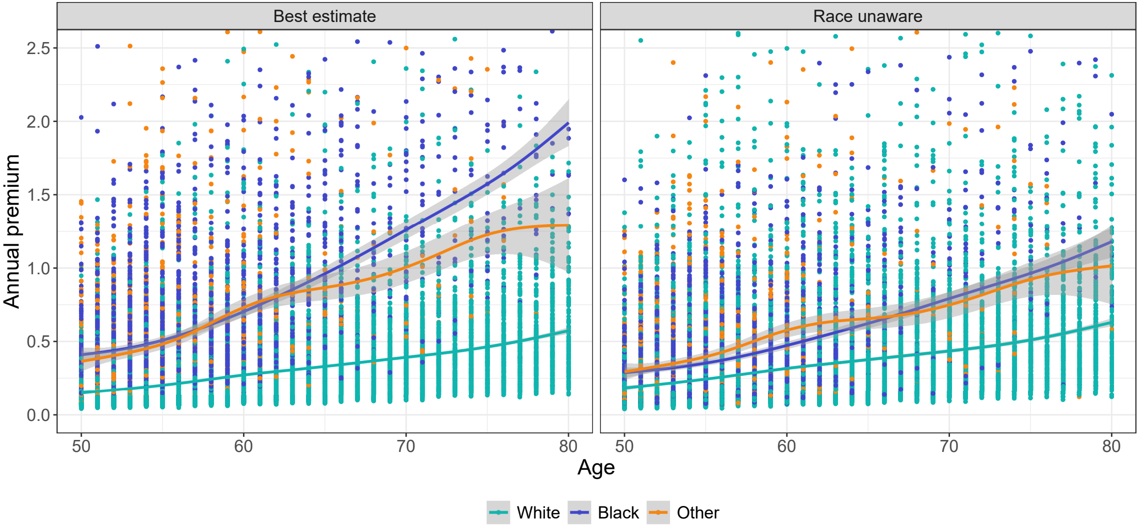
Naive adjustment

- Naive approach to enforce fairness: remove sensitive attribute D
  - Fit Poisson regressions with D omitted
- In reality, does **not** eliminate effect of D if other non-sensitive attributes (X) are associated with D
  - Lindholm et al. (2022) observed that race-unaware prediction $E[Y|X=x]$ is related to the best estimate $E[Y|X=x,D=d]$ by

$$\mathbb{E}[Y|X=x] = \int_s \mathbb{E}[Y|X=x,D=d]\mathrm{d}\mathbb{P}(d|X=x)$$

- This means predictions only utilizing X still indirectly depend on D through its dependence with X

Annual premium by race: best estimate vs. race unaware



Adapting Lindholm et al. (2022) to LTCI

- Lindholm et al. (2022): choose a probability measure that is independent of X

$$\mu^*(x) = \int_d \mathbb{E}[Y \mid X = x, D = d] \mathrm{d}\mathbb{P}^*(d)$$

- Choices to make
  - What should $\mathbb{E}[Y \mid X = x, D = d]$ be?
  - What should $\mathbb{P}^*(d)$ be?

Choices for Lindholm et al. (2022) for LTCI

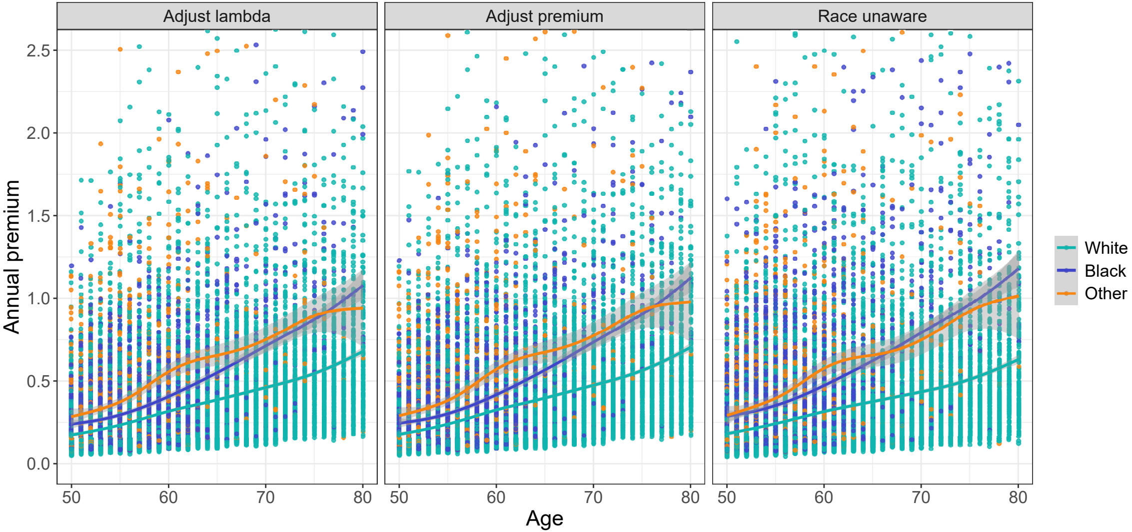
- Recall: How is unawareness price calculated?
  - D is omitted in each of the Poisson regressions
  - Induces indirect dependence on transition rates, and hence of price, on D
- Hence makes the most sense to apply Lindholm et al. (2022) to each of the four transition intensities separately

$$\mathbb{P}^*(d) : \text{person-year exposure in a given state with sensitive variable } D = d$$

- For comparison, also apply to annual premium
  - Key stakeholder goal: reduce inequality in premiums

$$\mathbb{P}^*(d) : \text{number of policyholders with sensitive variable } D = d$$

Adjusted annual premium



Discussion of results

- Resulting prices are similar whether the adjustment is applied to transition rates or to prices
- Changes from race-unaware prices
  - Prices for the Black group are visibly closer to the White (majority) group
  - Prices for Other (individuals not classified as White or Black) appear to be roughly the same
  - Suggests covariates are informative for membership in Black, but less so for Other

Limitations

- Adjustment reduces but does not eliminate inequalities
  - Adjustment eliminates the ability to infer the effects of D through X
  - Remaining inequalities reflect legitimate group differences due to allowable covariates
- This is the extent possible through statistical adjustment
  - Eliminating residual inequalities requires concrete action such as policy interventions

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Conclusion

- Introduce a Poisson-based framework for estimating transition intensities in multi-state models that readily accommodates fair pricing methods
- Removing sensitive attribute of race does not eliminate its effect on LTCI premium
- Applying the fair pricing method of Lindholm et al. (2022) reduces demographic disparities between White and Black groups; however, its impact on individuals classified as Other is limited

References I

- Lindholm, M., Richman, R., Tsanakas, A., and Wüthrich, M. V. (2022) Discrimination-free insurance pricing. *ASTIN Bulletin*, **52**(1), 55–89.
- Pessach, D. and Shmueli, E. (2022) A review on fairness in machine learning. *ACM Comput. Surv.*, **55**(3), 51:1–51:44.