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Non-Discriminatory and Fair Pricing in Insurance: Bridging Research with Practice

Fei Huang

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Today's Focus

Practical Applications

1. How can you price a product when you are entering the Market?
2. Pricing a unique product to market
3. Challenges:
   - Sparse Data & Different data
   - Anti-Discrimination
   - Pre-existing conditions - operational
   - Price Optimization

Emerging Research

1. What are the sources of discrimination and bias for insurance pricing?
2. How to tackle data issues (sparse data and different data)?
3. Is price optimization fair?
4. How to achieve fair insurance pricing? And who pays the cost?

Practical Applications

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Industry Voice

Michael Storozhev

Has spent the last decade building customer product solutions for travel insurance problems, helping both Insurtech brands launch and incumbents obsess over new benefits and coverages for their existing customers

Currently Chief Underwriting Officer at PassportCard Travel Insurance, looking after end-to-end actuarial, underwriting, reinsurance and analytics for a newly launched travel insurance MGA in Australia

Michael's Journey to pricing a unique product to market

Travel Insurance ... But Different

Instant payouts on approved claims, anytime, anywhere.

A unique claim solution to enable instant payouts for:

- Overseas medical issues
- Delayed luggage
- Stolen cash

Challenges for pricing and product design:

- No excess on instant payouts – so claim frequency is higher than traditional products
- Claims could be different to what the market is seeing
- Instant Claims means more streamlined assessment of claims

Challenge 1: Sparse Data & Different Data

What if you have a lack of historical data and experience

Using Market Premiums

- Unique product means competitor deconstructions are less relevant
- Large differences in prices between existing Australian Travel Insurers

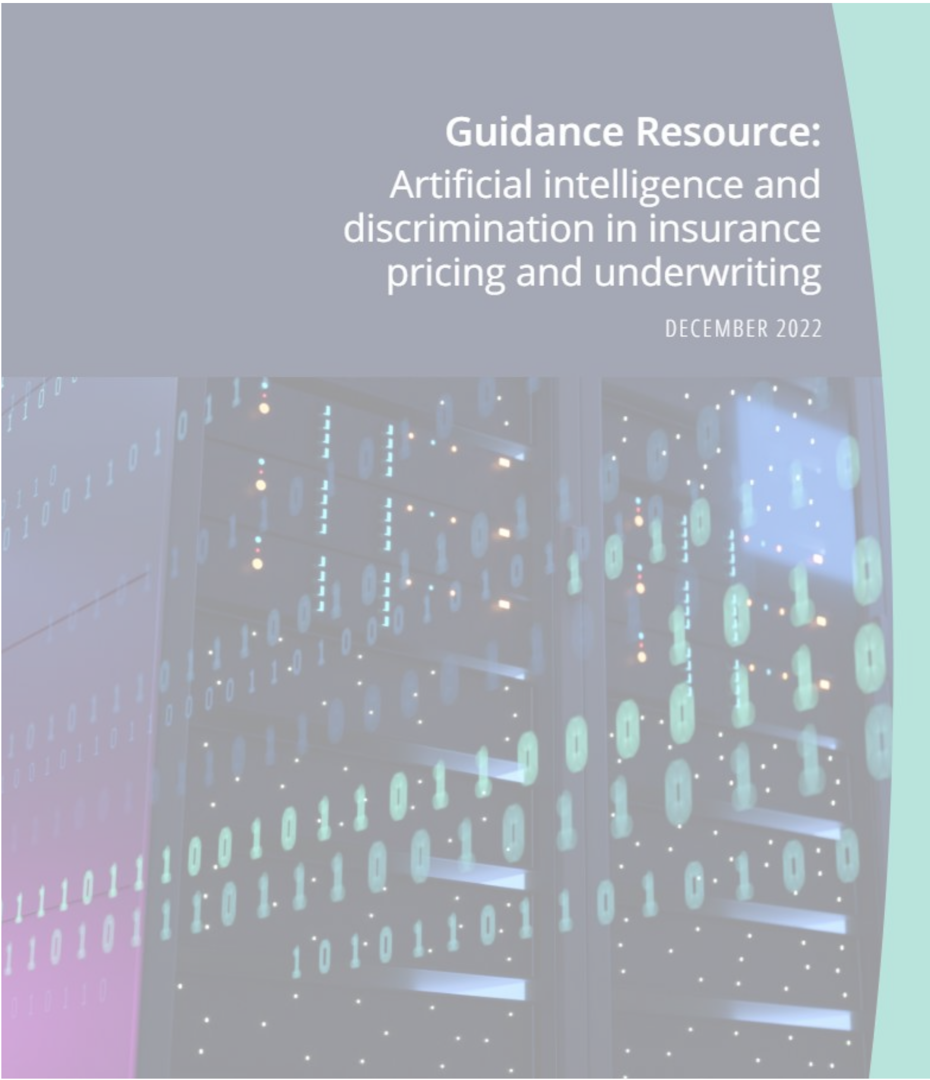
Historical Data

- Pre-Covid experience was less relevant due to emerging risks
- Travel insurance premiums had increased 70% between 2020 and 2023

Overseas Data

- Behavior very different to overseas markets
- Australians travel 1 every 2.5 years vs Europeans travelling multiple times a year

Challenge 2: Anti-Discrimination
How can we age rate without sufficient data?



Health risk increases with age, but how do you rate travelers over 80 years old when you have very little, or sparse claims data for those age groups?

> **"a sharp discontinuity at age 90 to a much higher 'average' rate might be argued as unfair by someone aged 91"** (Guidance Resource p34)

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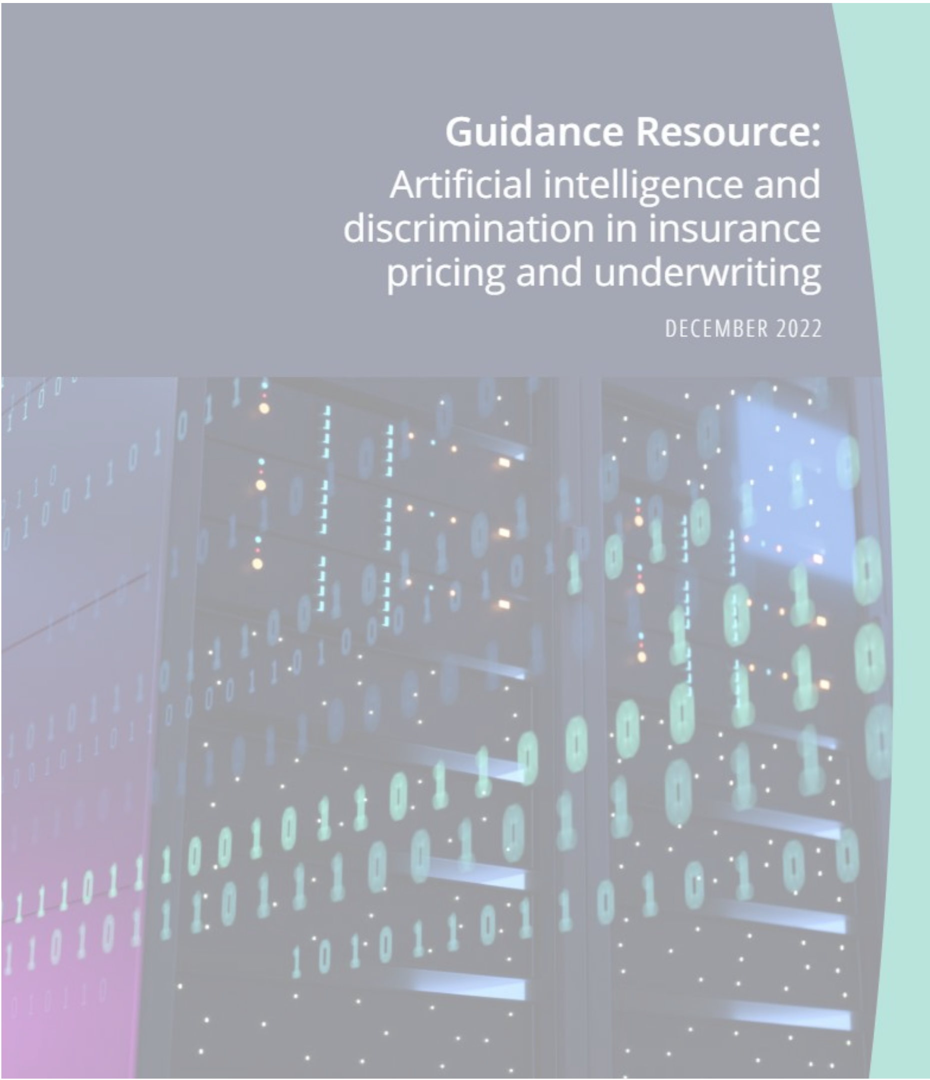

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Market Approach is not consistent

Age	60	65	70	75	80	85	90	95
Competitor A	100%	114%	160%	218%	343%	343%	343%	343%
Competitor B	100%	125%	131%	193%	315%	394%	613%	613%
Competitor C	100%	110%	150%	206%	314%	387%	462%	462%

Challenge 3: Other policy decisions to help with Fair Pricing in Insurance

Use of Manual Underwriting to minimize potential harms

- A customer’s pre-existing conditions are typically very unique but can lead to higher premiums, reduced coverage or a refusal of quotation
- Decision can be made to use an automated online process or a manually underwritten approach may provide fairer outcomes for customers
- With little data an offline approach may be fairer than an online automated approach

Price Optimization

- Plenty of research about price optimization
- Optimization requires wealth of conversion data to understand demand
- May not be the most appropriate for a new provider with little data
- It’s a good idea to formalize a companies expectation around price optimization within it’s pricing policy

Emerging Research

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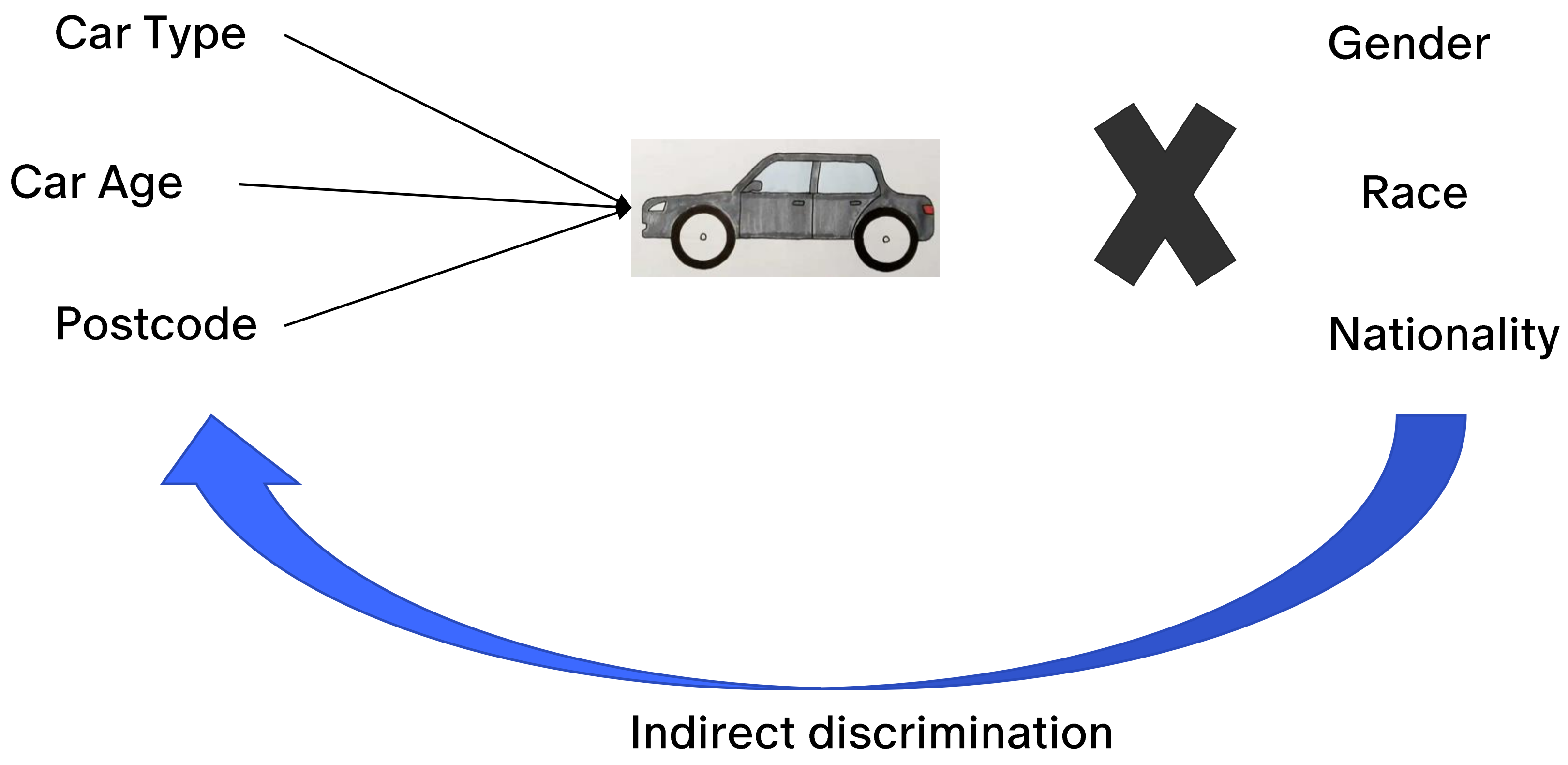
Academic Voice

Fei Huang

- Senior Lecturer in Risk and Actuarial Studies at UNSW Business School
- Her research focuses on fair pricing and ethical AI for insurance.

Example for Insurance Discrimination



Discrimination and Biases in algorithmic decision-making over the entire life cycle

- Historical Bias
- Behavioral Bias
- …

Human

Data

- Direct Discrimination
- Omitted Variable Bias
- Sampling Bias
- Representation Bias (Sparse and Different Data)
- Aggregation Bias
- …

Algorithms

- Proxy Discrimination
- Algorithmic Bias
- Evaluation Bias
- …

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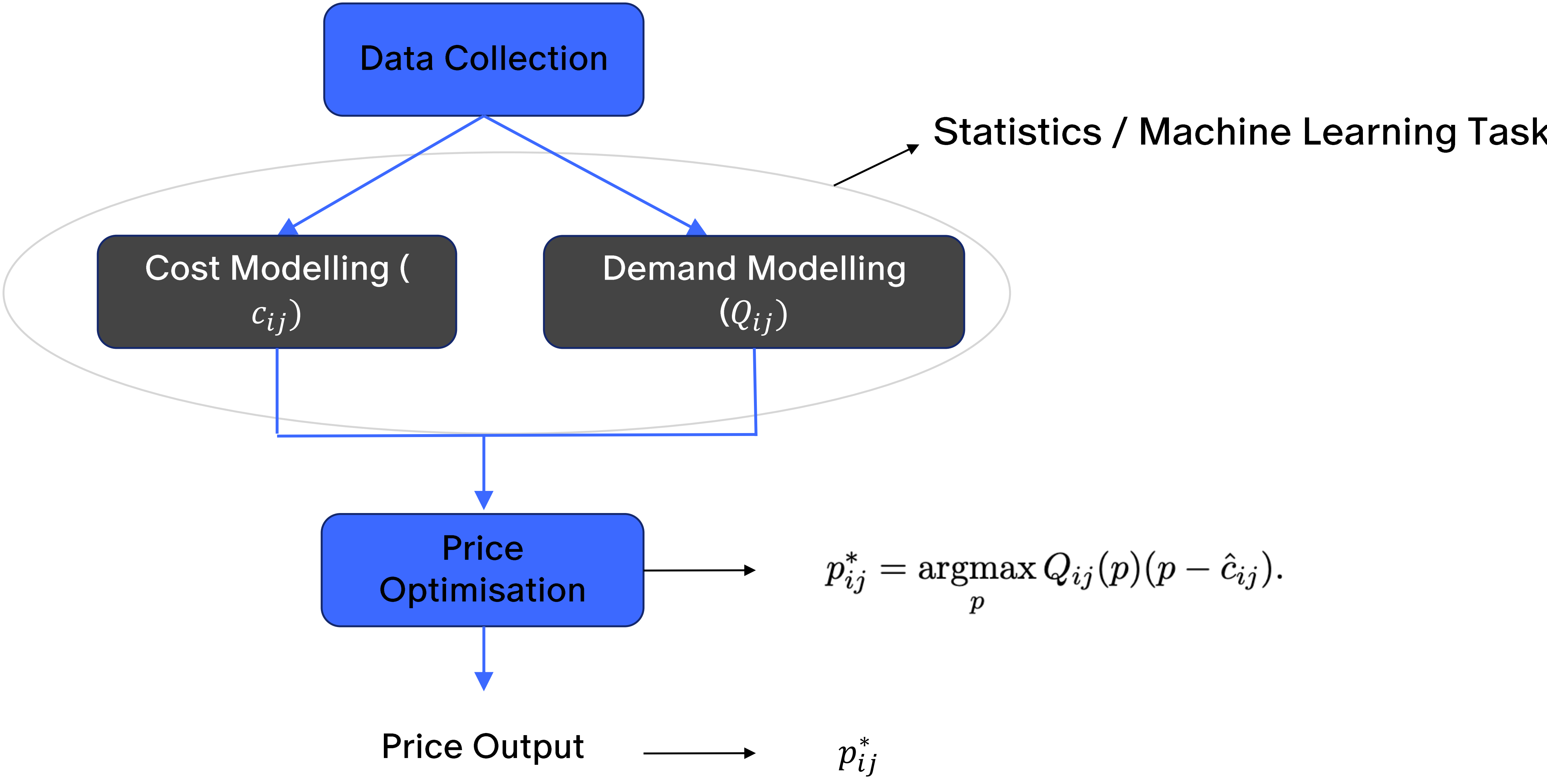
General Insurance Pricing Process



How to tackle the data quality issues (sparse data and different data)?

- Data augmentation to solve sparse data issues
  - Synthetic Data Generation

- Stable learning algorithms to solve dataset shifting problem (different training and testing data) (Subbaswamy & Saria, 2019)
  - Proactive approach: only learn information that will generalise
  - Reactive approach (when deployment/test data is available): domain adaptation algorithms using importance sampling to reweight training data

- **How to test if fairness has been achieved or not?**

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Is Price Optimisation Fair?

- From an insurer's point of view, the use of price optimization tools is simply a sound business practice that is widely used in many other industries.
  - An insurer prices two consumers differently with the same risk profile because their anticipated price sensitivity differs.

- Consumers have taken a dim viewpoint of price optimization
  - unfair penalty on customer loyalty
  - impose price increases on customers, not for their tendency to have high claims but rather for their tendency to be loyal

- Many of those less likely to shop around for a better price are low-income and minority consumers.

- Thus, although insurers may be optimizing neutral objectives, the result of their actions may result in unintentional proxy discrimination.

Regulations on Price Optimisation

- Many U.S. insurance state regulators have banned price optimization in personal lines insurance since 2015.
- In January 2022, the FCA banned home and motor insurers from engaging in price-walking -- gradually increasing premiums by quoting existing policyholders a higher price to renew their insurance than the offers available to new customers.
- **What are the welfare implications of such bans?**

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Fair insurance pricing

How to achieve it?

- Fairness in cost prediction or pricing?
- Fairness in terms of prices or markups?
- Which fairness policy/criteria to apply?

How to evaluate the cost of fairness?

- Consumer welfare v.s. Firm profit
- Welfare for males v.s. Welfare for females

Potential Fair Pricing Policies

Cost Prediction

Rule C0: unconstrained cost model

Rule CA: Cost model with accountability (formulating the predictions as base rates * relativities)

Rule CU: Cost model with unawareness

Rule CDP: Cost model with demographic parity (equalised predictions on average across different groups)

Rule CC: Cost model controlling for sensitive attribute (Lindholm et al. 2022)

Pricing

Rule P0: Unconstrained pricing

Rule PA: Accountable pricing

Rule POB: Price optimization ban (US)

Rule PDP: Pricing with demographic parity

Rule PAF: Pricing with actuarial group fairness (Dolman and Semenovich 2018)

Data and Implementation

- Cost Modeling
    - Data: A French private motor insurance drawn from the R package CASdatasets (Dutang, Charpentier, and Dutang (2015). We focus on the material damage coverage. It contains 100,000 third-party liability (TPL) policies observed from 2009 to 2010.
    - Protected attribute: gender
    - Model: GLM and XGBoost (Poisson & gamma loss)

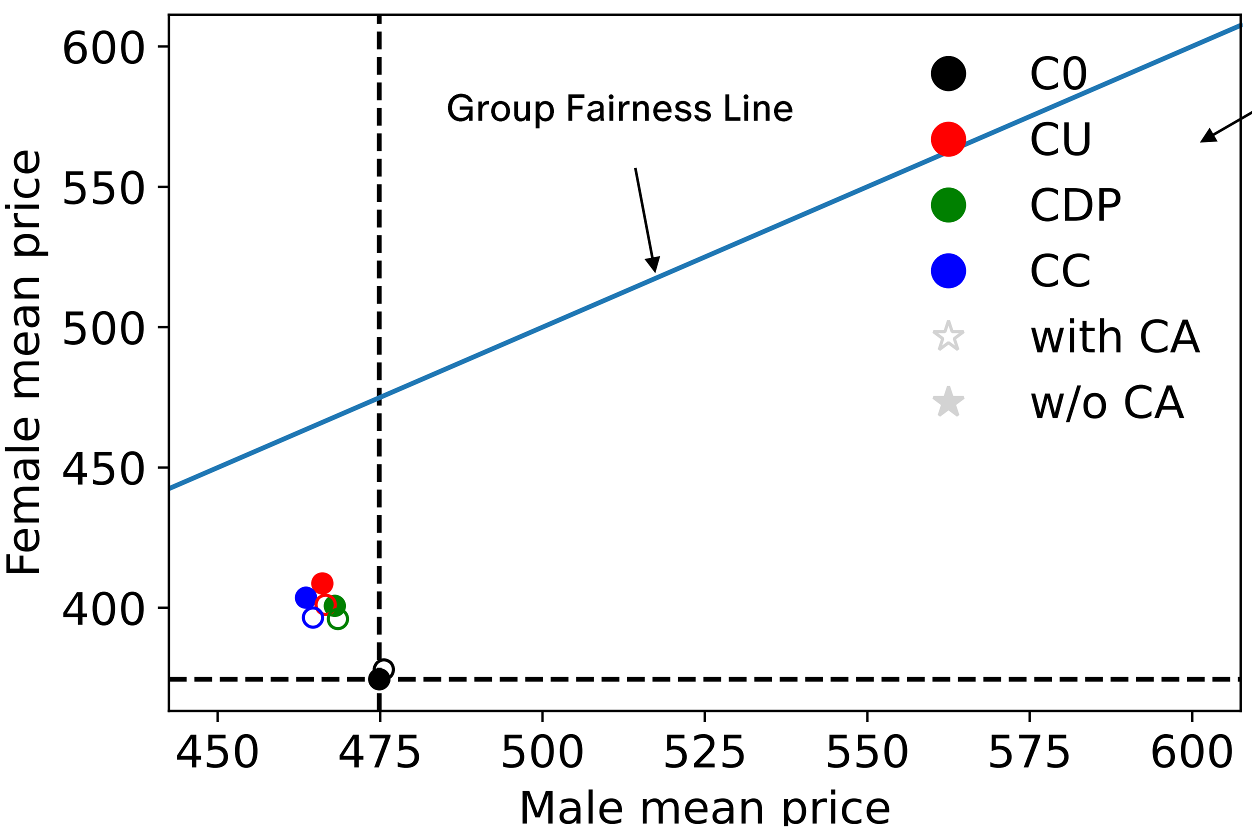
- Demand Modeling
    - We construct our simulated consumers by utilizing the claims data from Dutang et al. (2015) and the estimated demand models from Einav et al. (2010) and Jin and Vasserman (2021).

- Price Optimization
    - Then we find the individualized profit-maximizing price of a single-product firm by solving a high-dimensional constrained optimization problem, utilizing the recent progress of optimization techniques Cotter et al. (2019).

First Finding

Fairness in machine learning (cost prediction) $\neq$ Fairness in outcome (pricing)

Machine Learning Fairness is different from Outcome Fairness



Various fairness regulations on cost prediction (statistics/machine learning)

- Females have lower prices on average.
- Fair regulations on cost modelling reduces the price gaps among groups.

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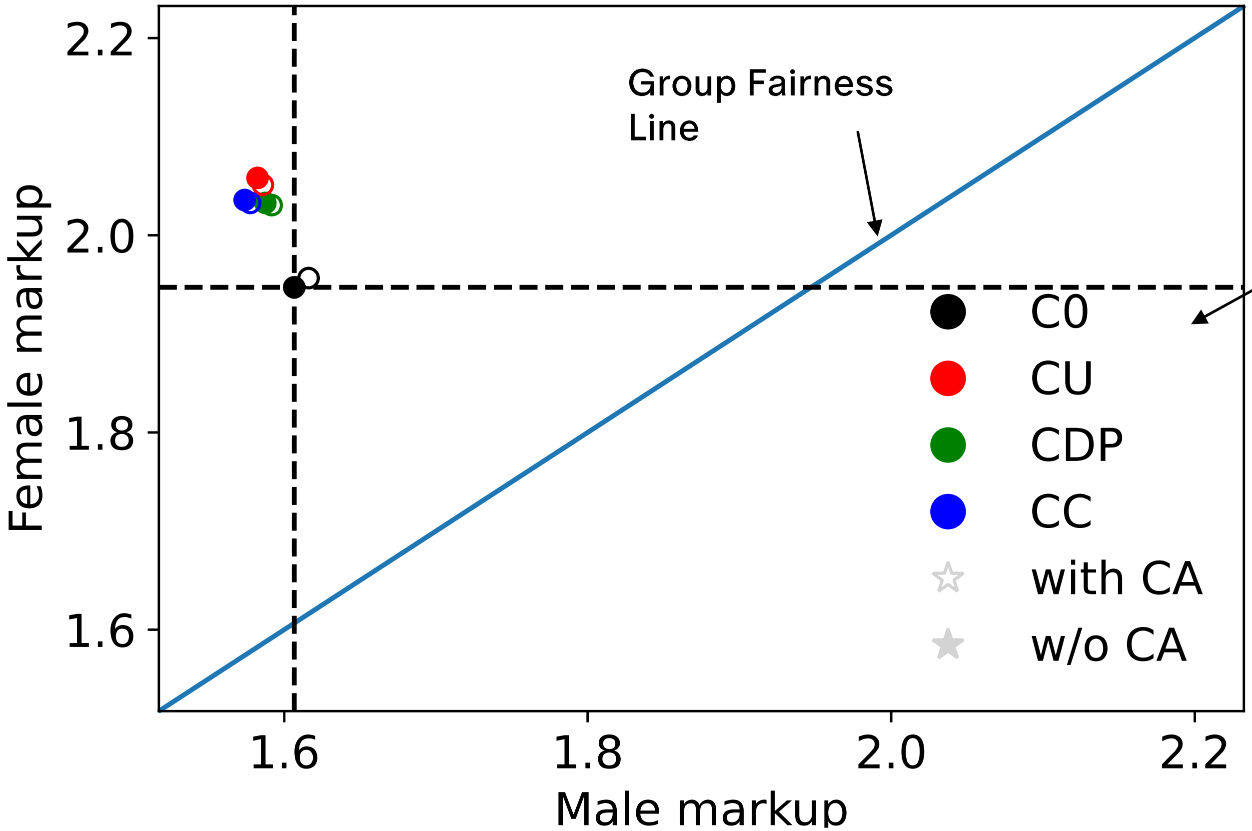
Machine Learning fairness can even make things worse...



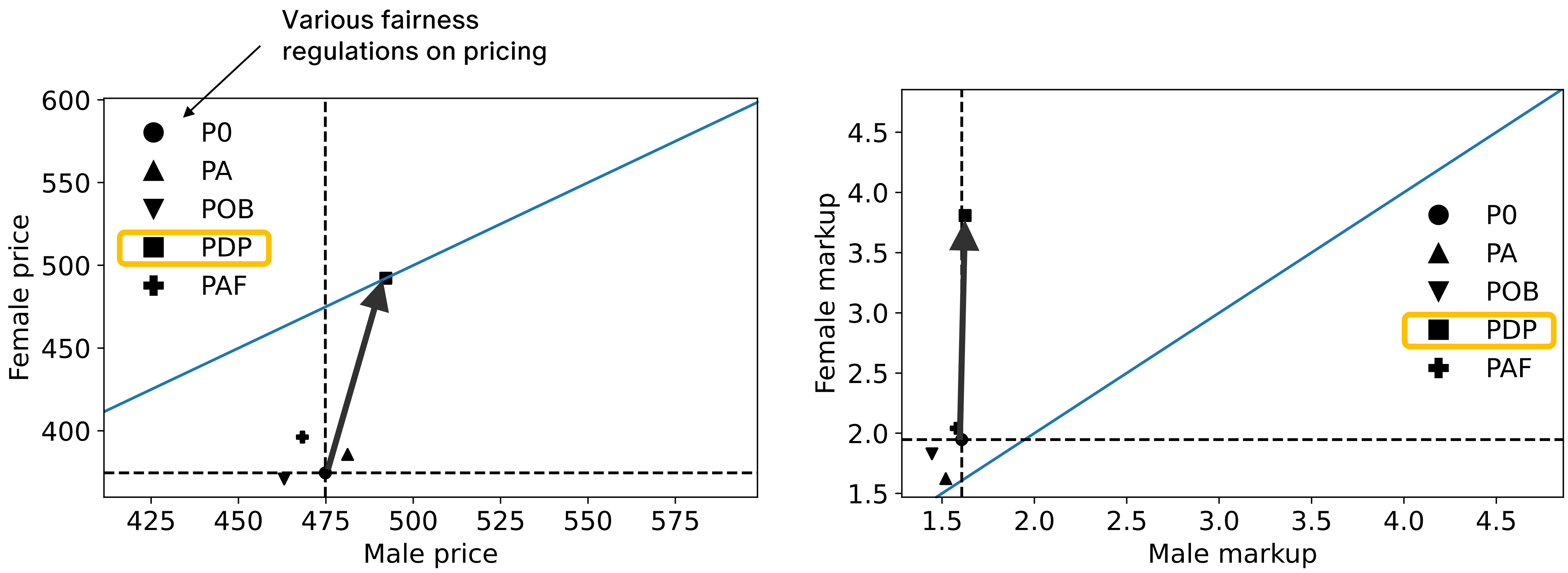
Various fairness regulations on cost prediction (statistics/machine learning)

- Females have higher markups on average.
- Fair regulations on cost modelling increases the markup gaps between gender groups.

Second Finding

Fairness in prices $\neq$ Fairness in markups

Fairness in terms of prices or markups?



- PDP (demographic parity) can perfectly equalize the price between different gender groups but creates a huge markup gap.

Third Finding

Welfare

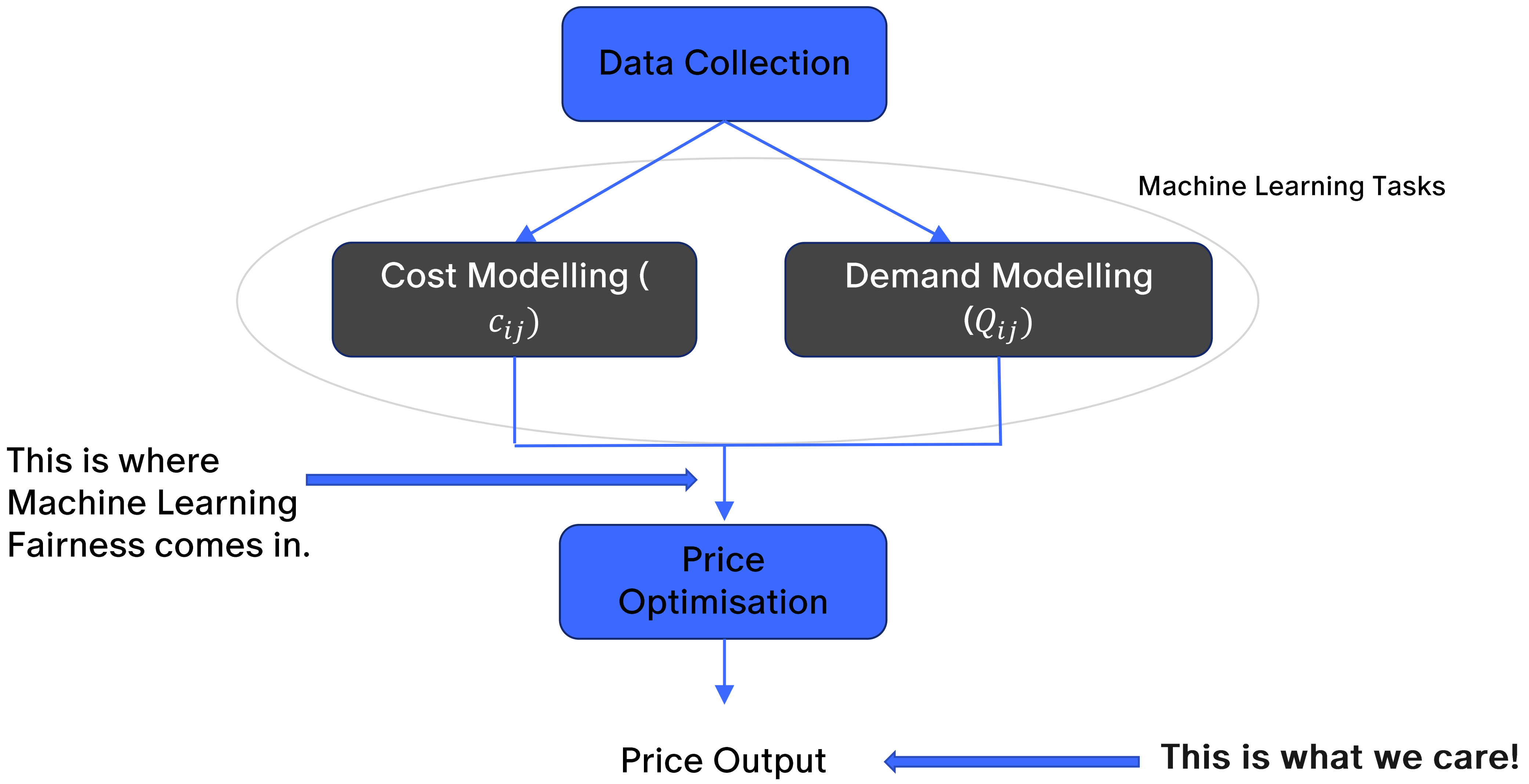
Fairness-~~**Accuracy**~~ Trade-off

Our empirical results show that

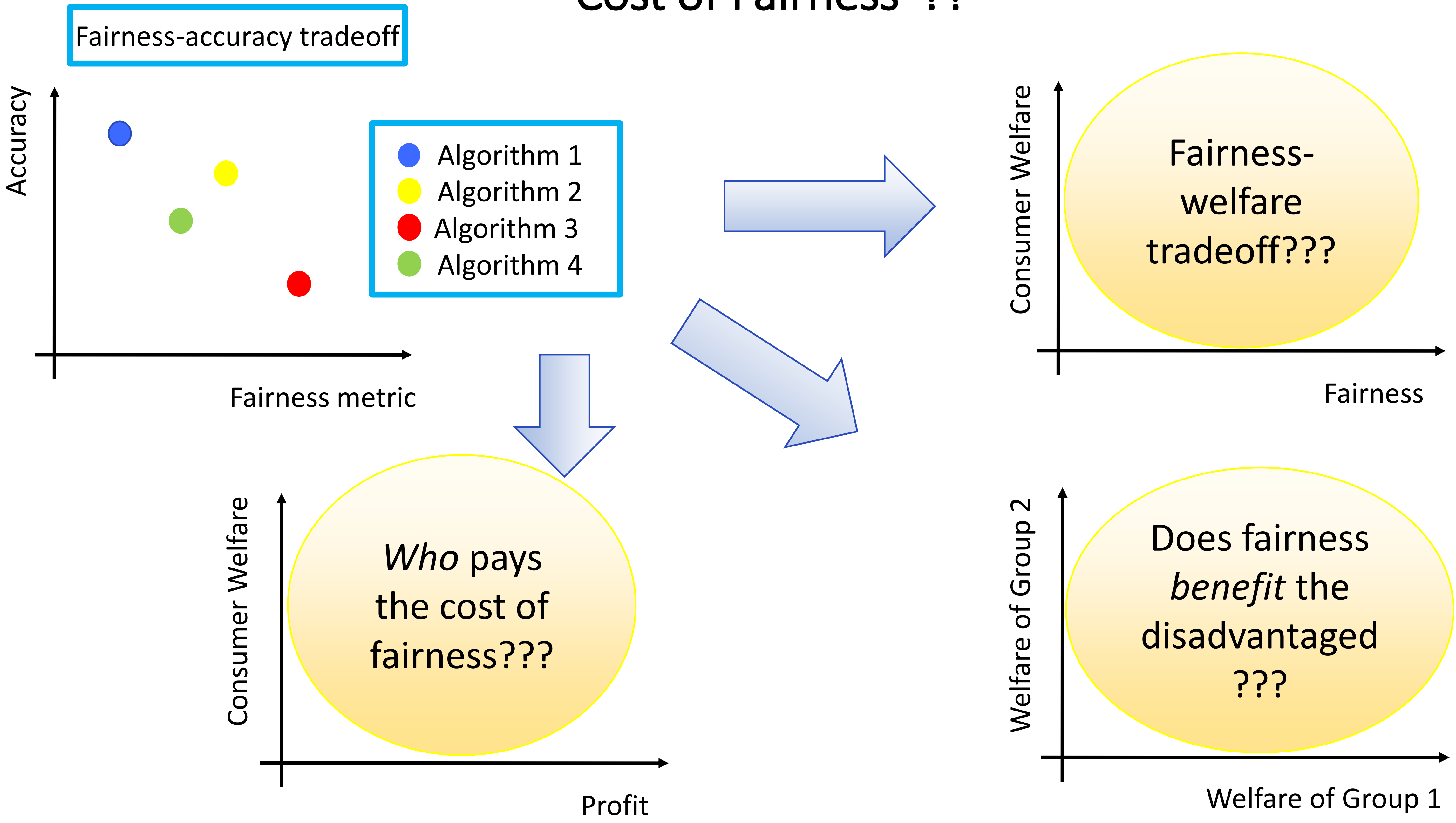
- Decrease machine learning accuracy by only 0.5% can decrease 5% of profit and consumer welfare.

Small prediction accuracy drop can lead to big profit and welfare loss.

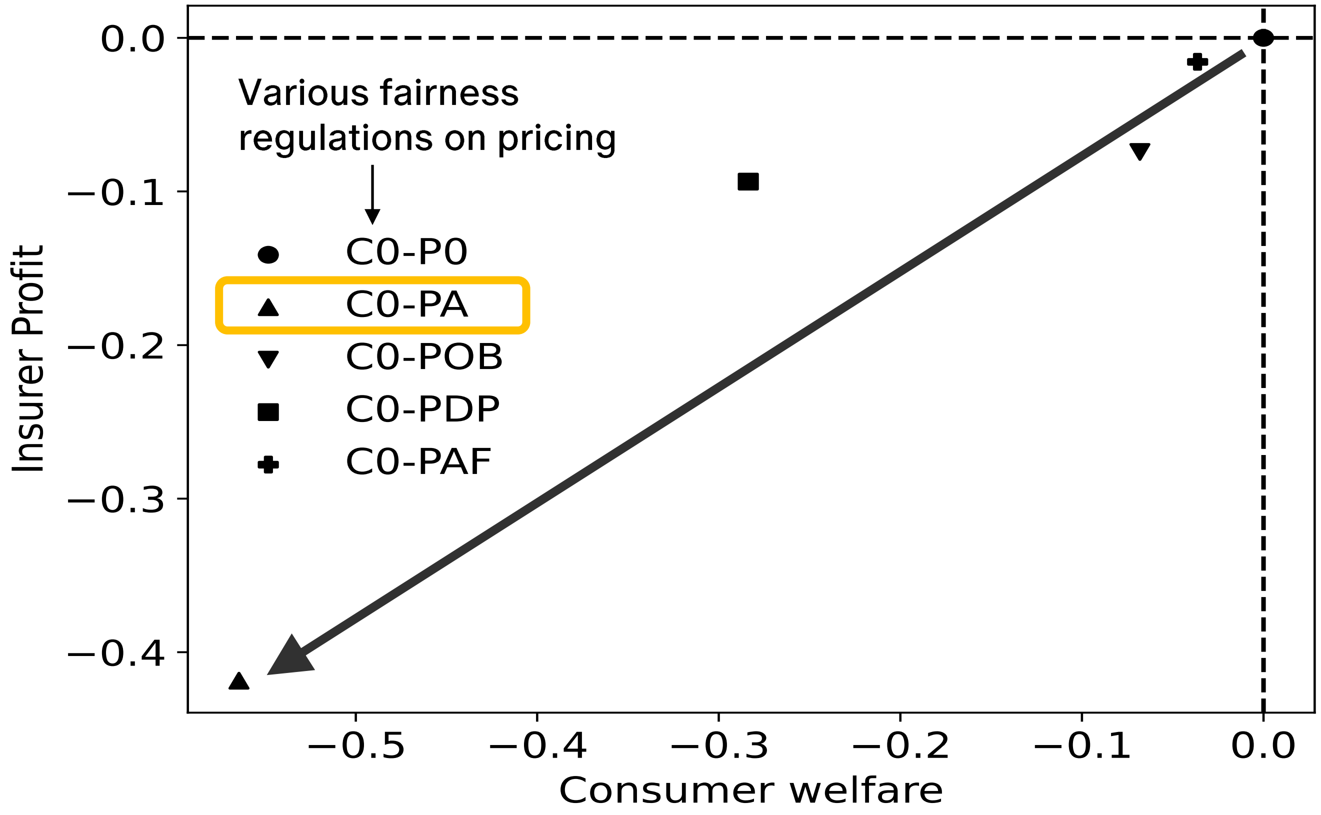
Insurance Pricing Process



“Cost of Fairness”??



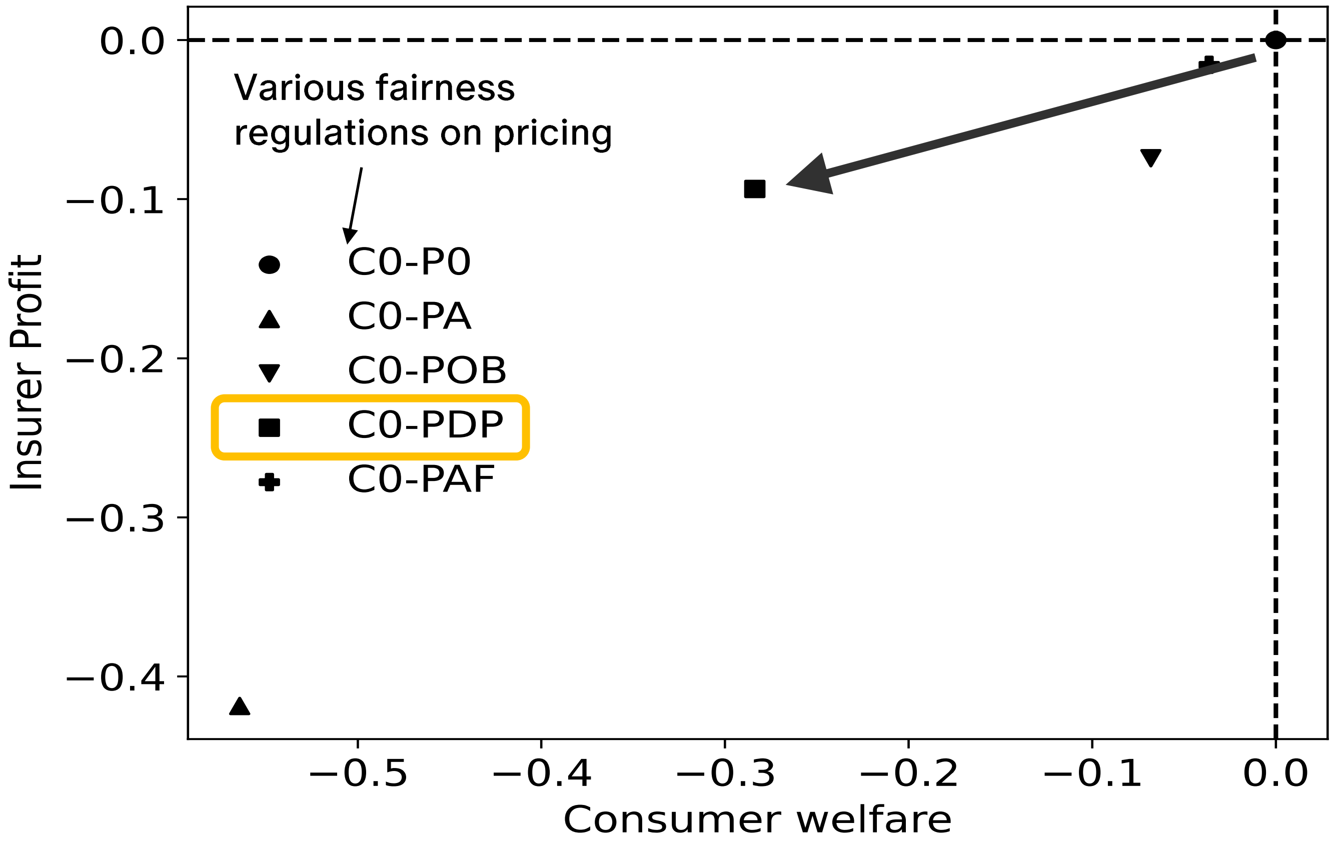
Consumer Welfare v.s Firm Profit (Monopoly Market)



- Large negative impact of accountability (PA) regulation on both insurer and consumers.

Source: Shimao and Huang (2023)

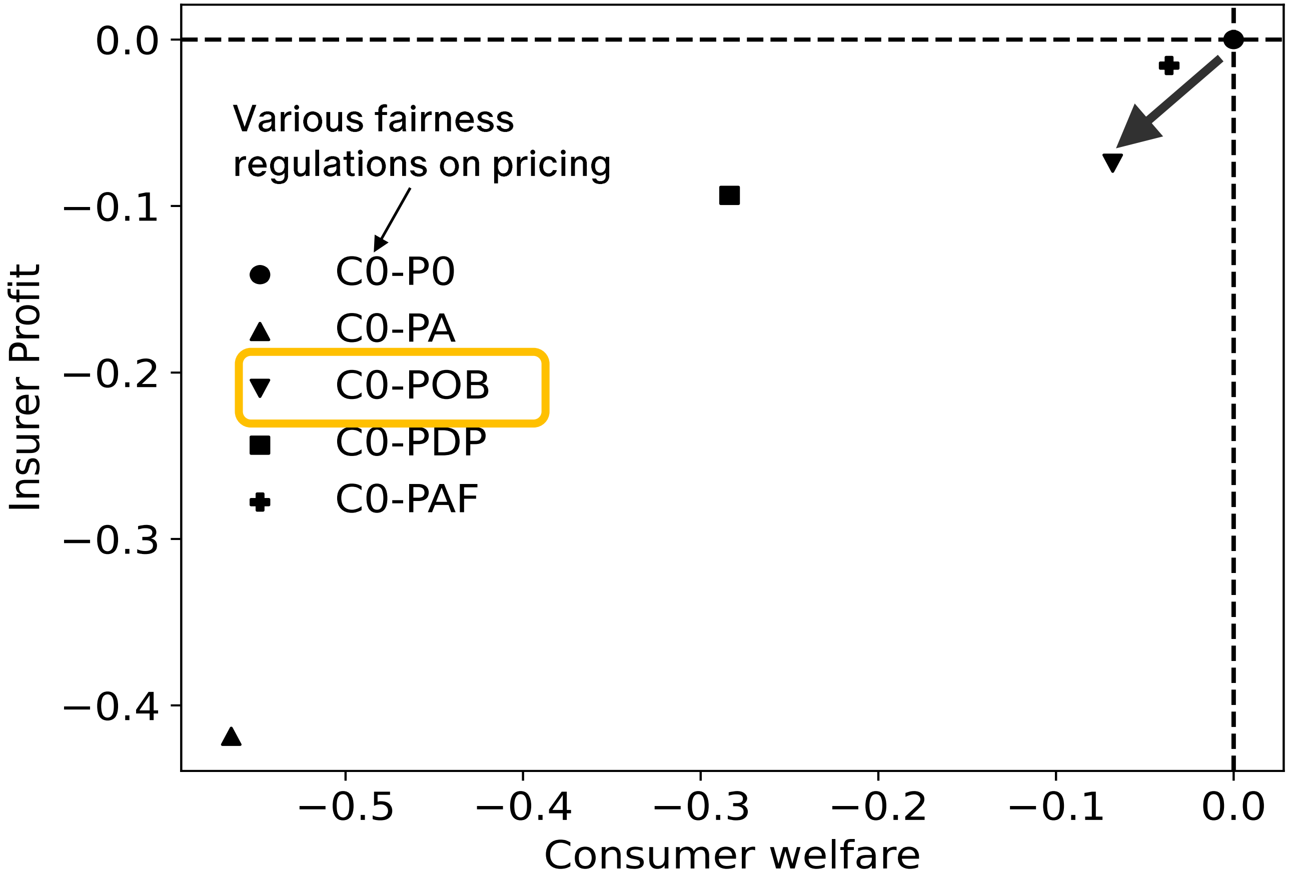
Consumer Welfare v.s Firm Profit (Monopoly Market)



- Similar but less magnitude impact for PDP (Equalised prices of both genders).

Source: Shimao and Huang (2023)

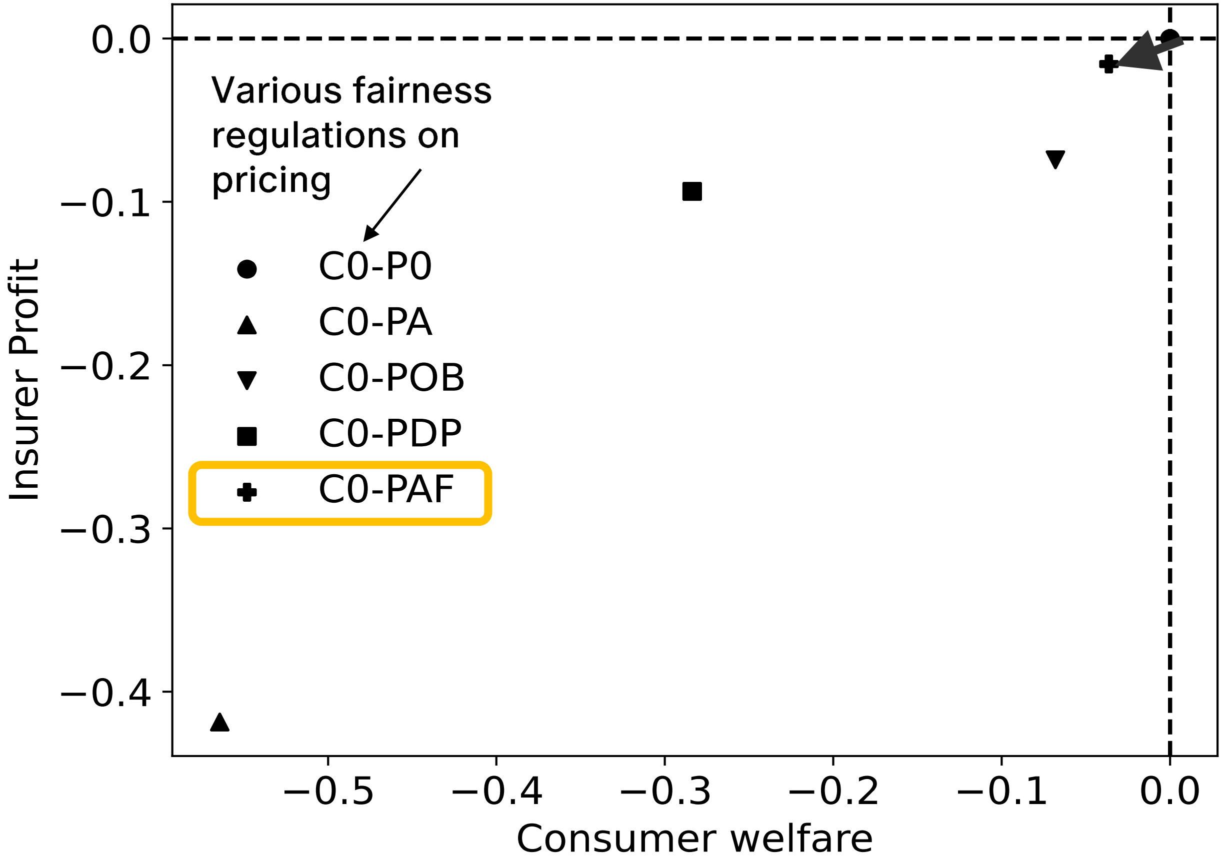
Consumer Welfare v.s Firm Profit (Monopoly Market)



- POB (Price optimization ban) decreases consumer welfare and firm profit .

Source: Shimao and Huang (2023)

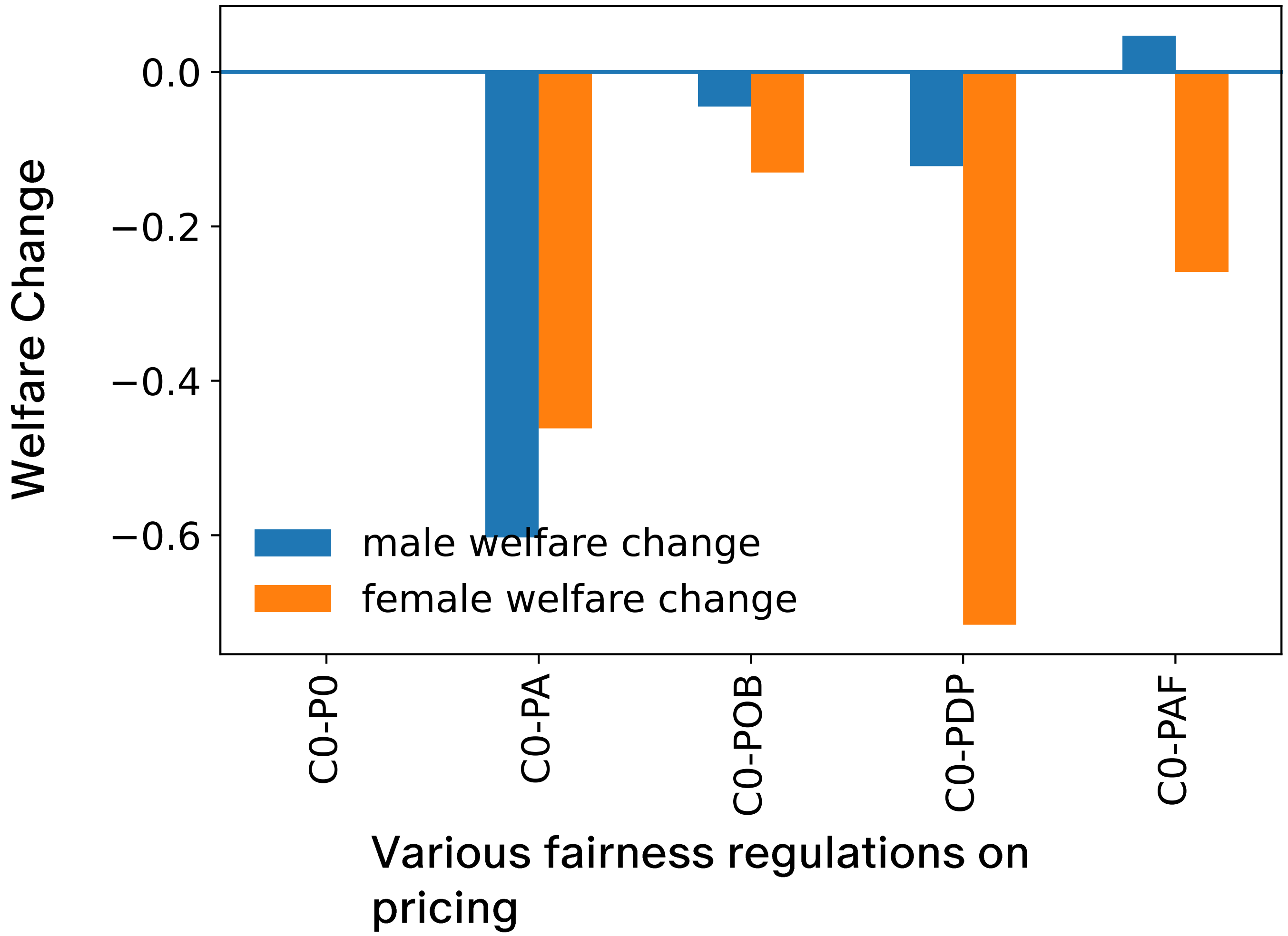
Consumer Welfare v.s Firm Profit (Monopoly Market)



- PAF (Actuarial group fairness) has small negative effect on both firms and consumers.

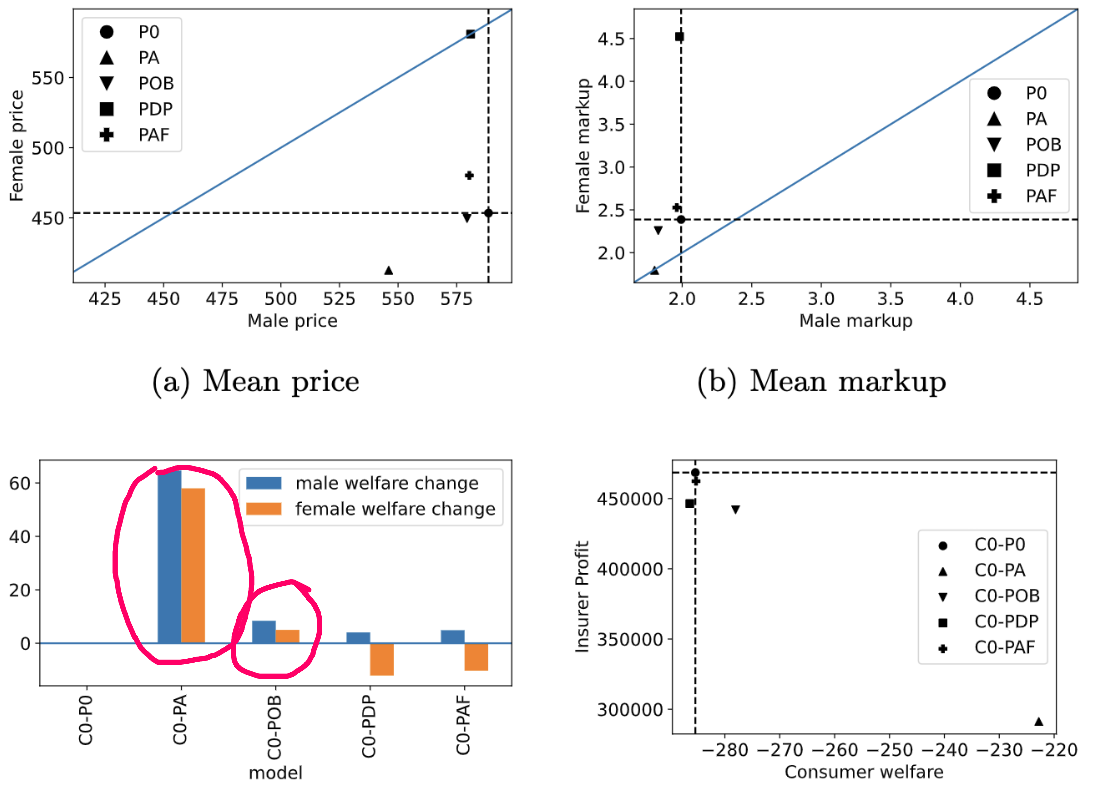
Source: Shimao and Huang (2023)

The welfare cost of fairness can be high on both genders (monopoly market)



Source: Shimao and Huang (2023)

Consumer Welfare v.s Firm Profit (Competitive Market Assumption)



(a) Mean price
(b) Mean markup
(c) Welfare change
(d) Mean consumer welfare and profit

Figure D.4: Pricing regulations under scenario 3.

- PA (accountability) and POB (price optimisation ban), can improve the welfare of both males and females.

Source: Shimao and Huang (2023)

Takeaways:

- Consider discrimination and bias over the entire decision-making life cycle.
- Address data quality via data augmentation and stable learning techniques.
- Fair machine learning techniques cannot guarantee fairness in outcomes.
- Focus on the ultimate objectives of stakeholders.

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Open Questions and Future Research

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1. More research and broader research beyond insurance and pricing.

2. Regulators and supervisors define supervisory expectations relating to fairness and unfair discrimination.

3. Develop guidelines that support informed decision-making regarding fairness criteria tailored for application contexts.

4. **Call for industry-academia collaboration and good datasets!**

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