Quality Disclosure and Regulation:
Scoring Design in Medicare Advantage

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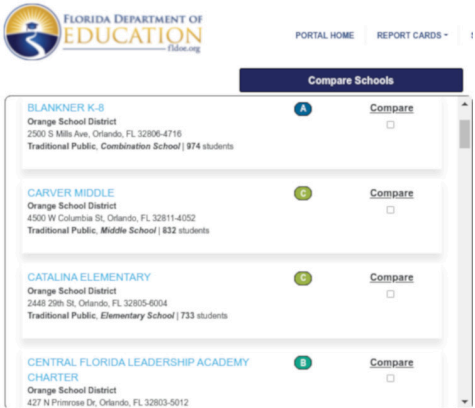
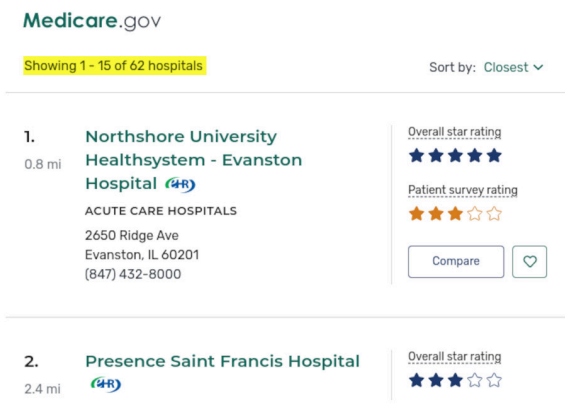
Motivation

- **Quality scores affect our everyday choices**





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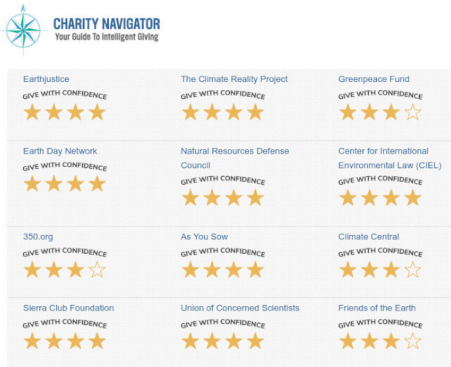

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- **Quality scores affect our everyday choices**
  - How to design them to maximize welfare?

- Two central mechanisms:
  1. Help consumers choose through added information (Dranove and Jin, 2010)
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- Scores can be powerful policy tools, however
  - No systematic guidance on how to design them
  - Poor designs can backfire (gaming) (Feng Lu, 2012)

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- Develop a general empirical scoring design methodology
  - Combine computational methods with insights from information design (Kamenica and Gentzkow, 2011)

  $\Rightarrow$ Model + method deliver a welfare-improving design for MA

Preview of Results

- **New design increases total welfare by 3.7 monthly premiums per consumer/year**
  - Uses four scores: four stars with discrete increments
  - One-star pools low and medium quality (↓ info) others partition high quality (↑ info)
  - Consumers avoid one-star plans, firms respond by increasing investments (↑ quality)
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- Delivers broad lessons about scoring policies
  - Scores are powerful mechanisms by which to regulate quality
  - Coarse, simple, scores can outperform full-information outcomes at small informational losses

Outline

1. **Institutional Details and Data**
   - Graphical representation of the scoring design problem
2. **Model, Identification, and Estimates**
   - Measurement of the frictions addressed by the scores
3. **Scoring Design**
   - Mechanisms by which optimal scores improve welfare

Three Facts About Medicare Advantage

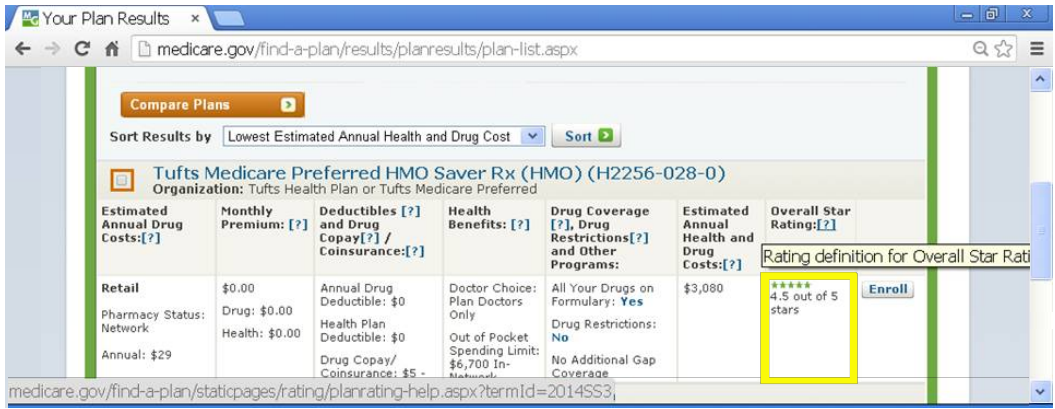
1. National regulated private health insurance market
   - All 65 million Medicare-eligible individuals can opt into MA, about half do
   - Trade-off: greater access vs. better coverage
   - Generous premium subsidies, risk-adjustments for insurers

2. Highly concentrated: 90% of average county enrollment controlled by 2 firms
   - 4 firms account for 70% of national MA enrollment

3. Quality heterogeneity affects mortality, costs billions in subsidies (Abaluck et al., 2021)
   - Challenging to assess if not for the quality scores

The MA Star Ratings

- Summarize medical and service quality in 1-to-5 stars, in half-star increments



Scoring Design (simplified)

1. Measure plan's performance over five categories of quality
    1. Medical Outcomes
    2. Intermediate Medical Outcomes (chronic conditions)
    3. Access to Care
    4. Patient Experience
    5. Process Measures (preventive, diagnostic care)
2. Give a score of 1-5 to each plan and each category
3. Show consumers the rounded weighted average

Graphical Representation

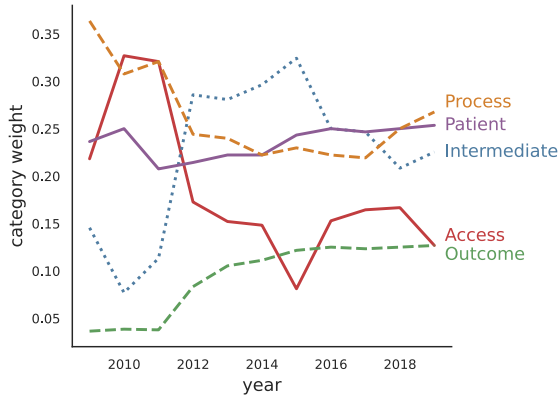
- **Design**: slope and location of hyper-planes
  - Slope = Weights, Location = Cutoffs
  - In two dimensions design is just lines ⟶

Q: Which lines to draw and how many?

- Scores reveal quality regions, not value

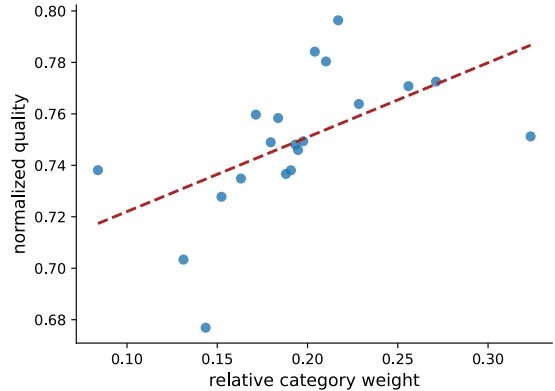
Data and Descriptive Evidence

1. Scoring rules
   - Hand collected from CMS
   - **Substantial variation in design**



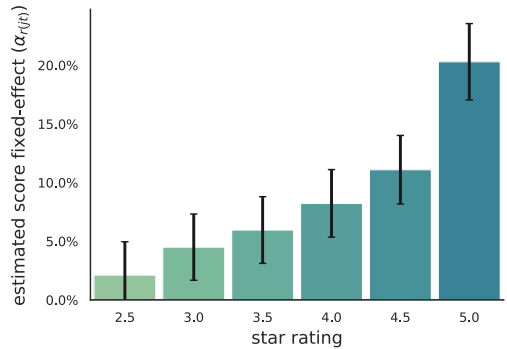
Data and Descriptive Evidence

1. Scoring rules
2. Data on all plans
   - Premiums, coverage, and benefits
   - Total investment by contract (2015 only)
   - **Quality: responds to design**



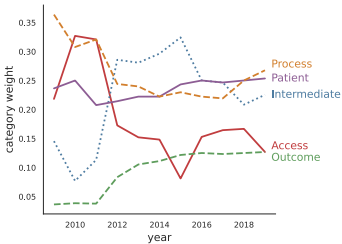
Data and Descriptive Evidence

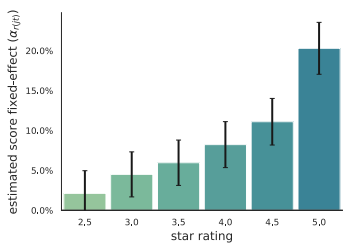
1. Scoring rules
2. Data on all plans
3. Enrollment data
   - Individual-level representative panel
   - 46,833 enrollment choices
   - Linked claims
   - **Consumers prefer higher-scoring plans**

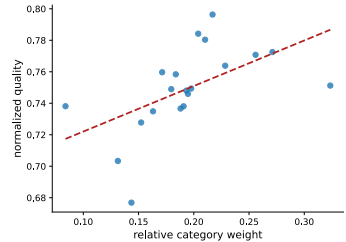


Taking Stock: The Designer's Toolkit

- Plentiful design variation reveals that scores:
  1. Shift demand across products
  2. Affect firms' quality investments
- To extrapolate to new designs, we must recover the social cost and value of quality
  - Costs: from variation in scoring incentives to invest
  - Value: from variation in WTP for scores

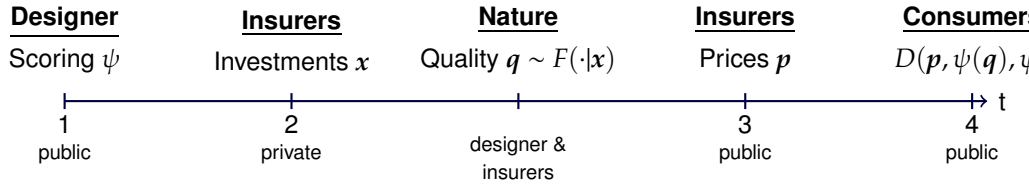




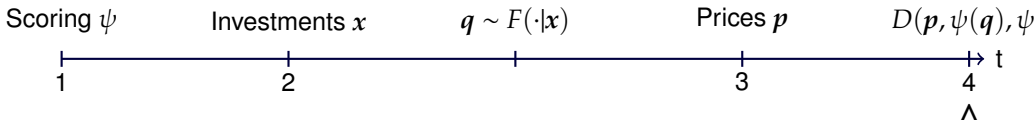


Outline

Model


Designer
Scoring ψ
Insurers
Investments $\boldsymbol{x}$
Nature
Quality $\boldsymbol{q} \sim F(\cdot|\boldsymbol{x})$
Insurers
Prices $\boldsymbol{p}$
Consumers
$D(\boldsymbol{p}, \psi(\boldsymbol{q}), \psi)$
t
1
public
2
private
designer &
insurers
3
public
4
public

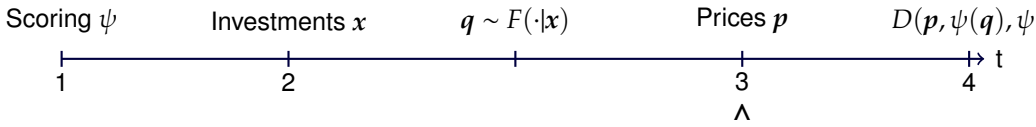
Model



$$u_{ij} = \underbrace{\alpha_i P_j}_{\text{premium}} + \underbrace{\beta_i b_j}_{\text{coverage}} + \underbrace{\mathcal{E}_q[\boldsymbol{\gamma}'\boldsymbol{q}|\psi(q_j), \psi]}_{\text{quality}} + \underbrace{\lambda' z_{ij}}_{\substack{\text{Obs.} \\ \text{attributes}}} + \underbrace{\xi_j}_{\substack{\text{unobs.} \\ \text{preferences}}} + \underbrace{\varepsilon_{ij}}_{\sim\text{T1EV}}$$

- Choose among MA plans – or – Medicare + Part D (prescription drug coverage)
- Heterogeneity in WTP for quality (γ/α_i) $\Rightarrow$ scoring granularity
- Subjective Bayesian non-parametric priors $\Rightarrow$ scoring cutoffs and weights

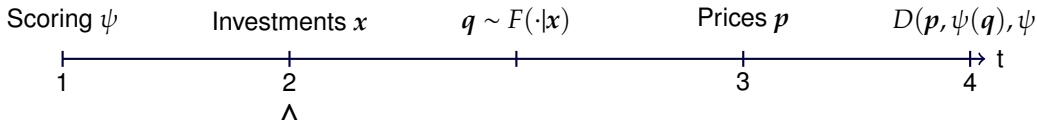
Model



$$\pi_f(\boldsymbol{q}, \psi) = \max_{\{p_j\}_{j \in J_f}} \sum_{j \in J_f} \underbrace{D_j(\boldsymbol{p}, \psi(\boldsymbol{q}))}_{\text{demand}} \Big(\underbrace{R_j(p_j)}_{\text{Mg. Revenue}} - \underbrace{C(\boldsymbol{q}_j, \boldsymbol{z}_j, \boldsymbol{\theta}_j)}_{\text{Mg. Cost}} \Big)$$

- Multiproduct oligopolistic price competition with risk adjustment
- Quality affects insurance cost:
  - Better hospitals increase claim prices ($\uparrow C$), preventive care reduces hospitalization ($\downarrow C$)

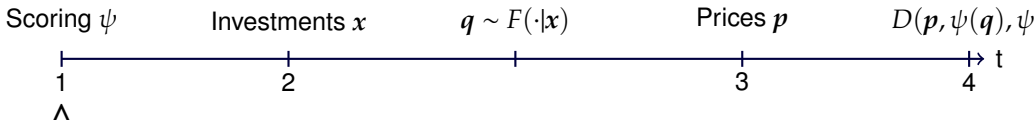
Model



$$\max_{\boldsymbol{x}_f \in \mathbb{R}^{|\mathcal{Q}| \times |J_f|}} \underbrace{\int \mathbb{E}[\pi_f(\boldsymbol{q}_f, \boldsymbol{q}_{-f}, \psi)] dF(\boldsymbol{q}_f|\boldsymbol{x}_f)}_{\text{expected insurance profit}} - \underbrace{I_f(\boldsymbol{x}_f)}_{\text{investment cost}}$$

- Choose investment for each product-category
- Rational expectations about rivals' investments based on market observables (Sweeting, 2009)
- Heterogenous convex investment costs ⇒ equilibrium quality effects

Model



- No optimality imposed on designer's experimentation

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  - Example: only readmission risk quality (scalar)
    - Consumers WTP \$100 for plan to have 4 instead of 3 stars, all else equal
    - $\Delta\mathcal{E}(q) = 1\%$ and $\gamma = \$100$ or $\Delta\mathcal{E}(q) = 5\%$ and $\gamma = \$20$?

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    - Consumers knows that $\psi(q) = 3 \iff q \in [0.8\%, 1\%)$ and $\psi(q) = 4 \iff q \in [0, 0.3\%)$
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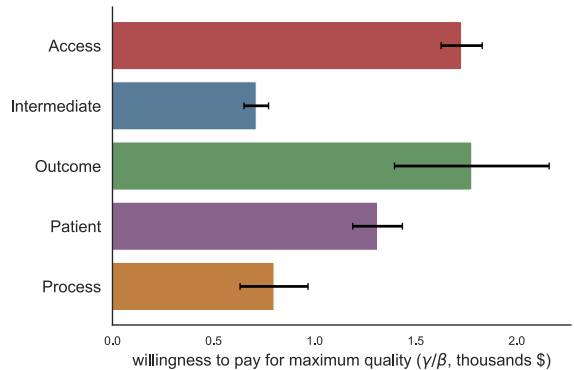
$\Rightarrow$ Variation in scoring design generates additional bounds and tightens identification

Key Estimates - Information Assymetry

- Maximum Outcome quality ≈ $4,036 in OOP
- Incomplete info lowers surplus by $199.3 (keeping supply fixed)
- Two sources of information asymmetry:



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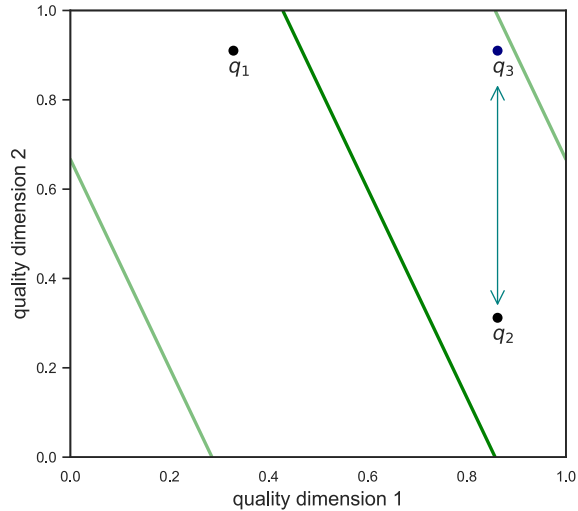

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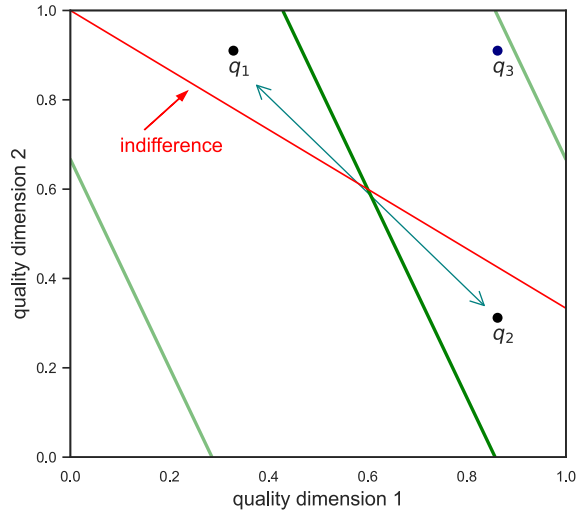

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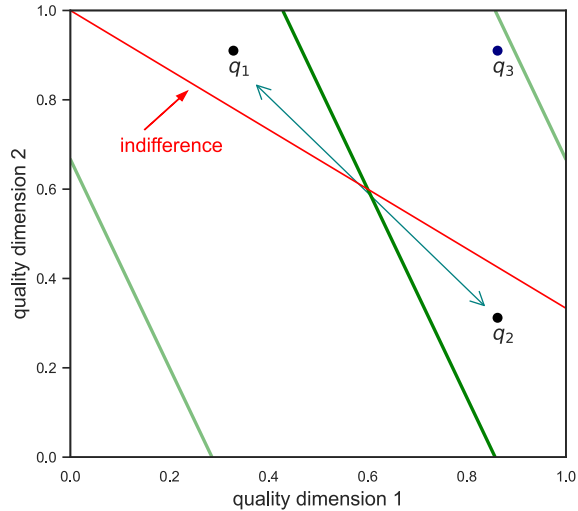
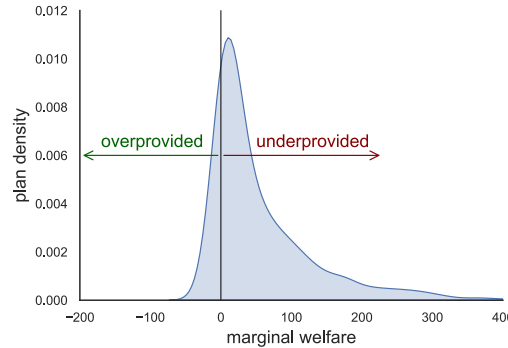
  ⇒ 94.5% of losses come from across-score



Key Estimates - Quality provision

- Avg insurance markup of 10.5%
  - For top insurers: avg marginal cost is $758
  - Curto et. al (2019): medical cost is $680
- Median investment = 12% of insurance profits
- Quality is underprovided:
  1. On average, $dTW/dq \in [17.6, 84.9]$ million/contract
  2. Less so in more competitive markets (Spencian)
  3. Less so in categories with ↑ weight (Design)



Outline

The Designer's Problem

$$\max_{\psi \in \Psi} \quad \mathbb{E}_{\boldsymbol{q}}[\underbrace{CS(\psi, \boldsymbol{q})}_{\text{Consumer surplus}} + \underbrace{\sum_f V_f(\psi, \boldsymbol{q}) - I(\boldsymbol{x}_f^*(\psi), \mu_f) \,|\boldsymbol{x}^*(\psi)}_{\text{Insurer profit}}]$$

- Subject to equilibrium behavior:
  - Firms update investments, prices, beliefs about rivals
  - Consumers update beliefs given design and realized scores
- Focus on deterministic, monotone, finite designs
  - Includes MA, school letter grades, food labeling, ...

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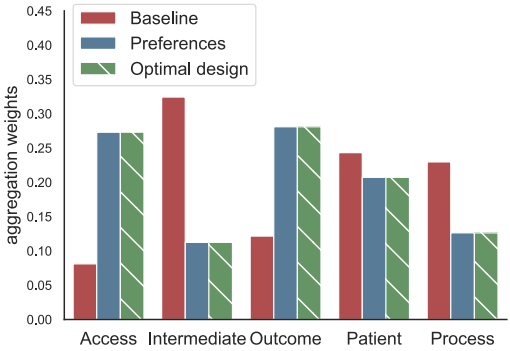
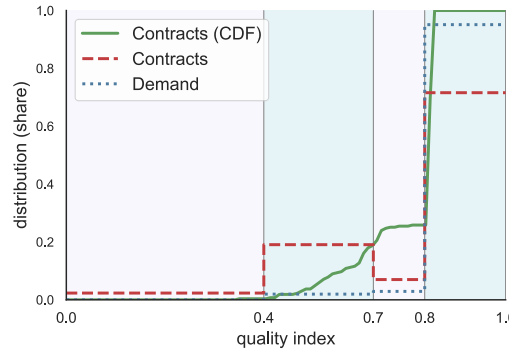
     - ψ induces a distribution over state-space, requires costly integration for every guess
   - **Solution**: computation in Belief Space (Aumann and Maschler, 1995)
     - Drastically reduces dimensionality of state-space and integration costs

     $\Rightarrow$ Solve large grid of independent equilibria, identify value of each score as a distribution over grid

Solution: Best Linear Design

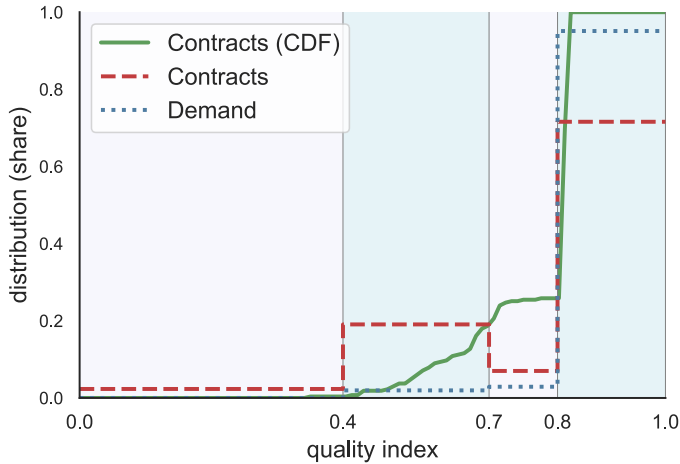




1. Pooling at the bottom: first score pools all low qualities
2. Aggregator: optimal weighting scheme aligned with preferences
3. Limited granularity: use only four scores; three partition higher quality

Decomposing the Design: Pooling at the Bottom

- Creates demand penalty for under-investment: ↑ quality



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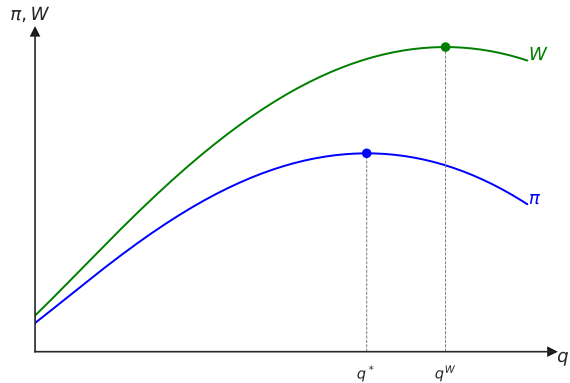

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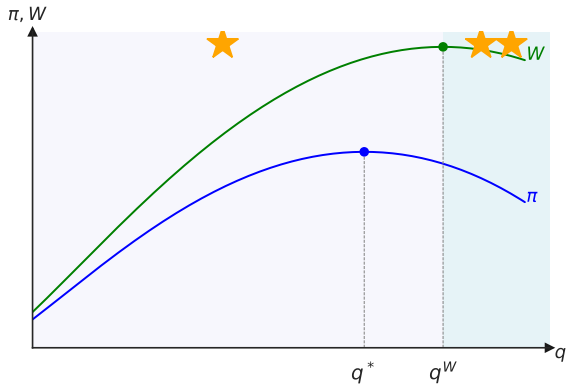

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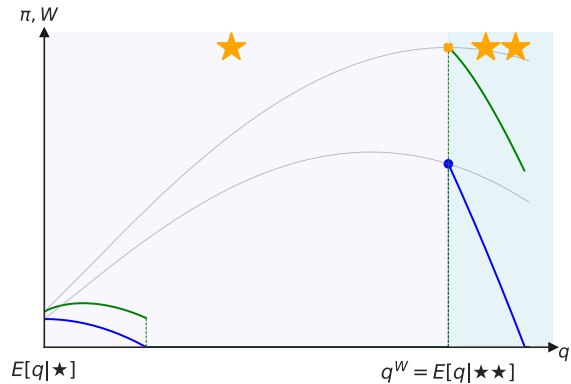

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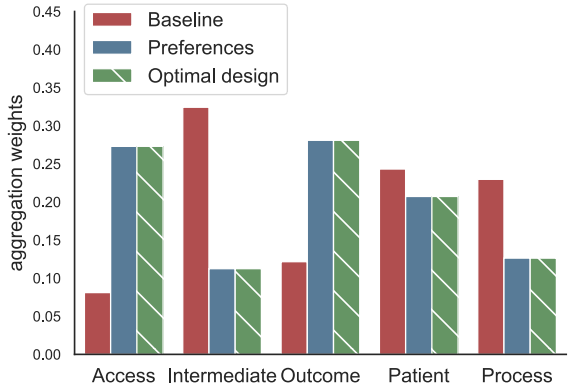
- **Accounts for 71.8% of welfare gain** (certification)
  - 57% of contracts would receive <2 star in baseline, only 21% in equilibrium
  - Serve only 1.9% of consumers
  - Quality is 4% higher in equilibrium, investment nearly triples

Decomposing the Design: Aggregator

- New weights align with consumer preferences



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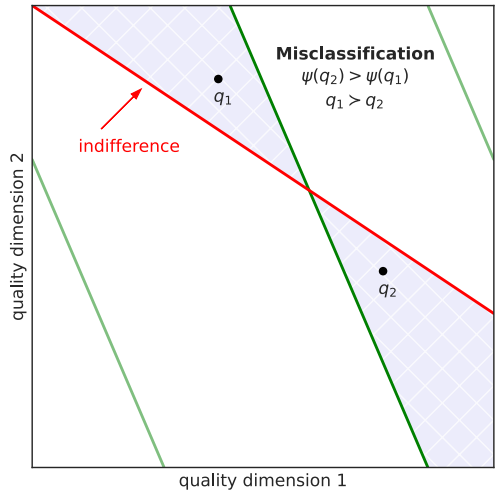

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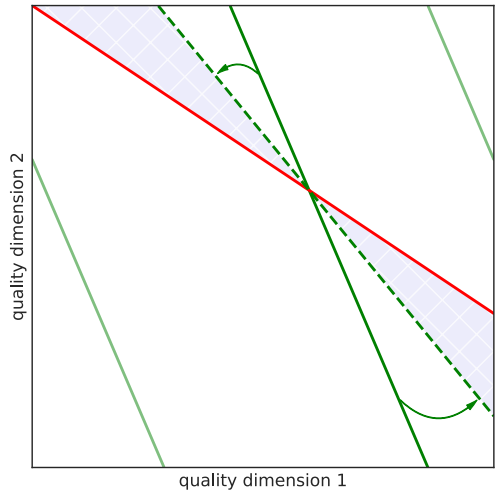

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Aggregation produces two problems:

1. Across-scores information asymmetry:
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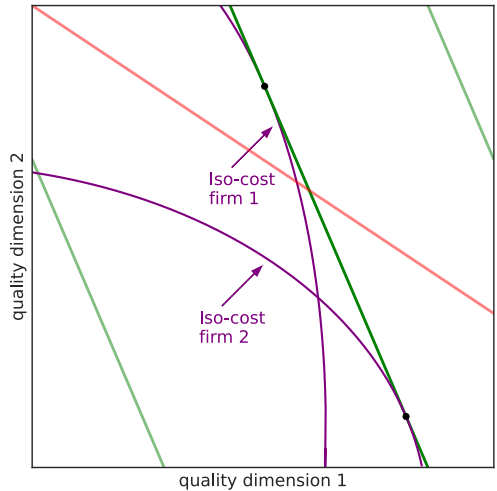
2. Multitasking moral hazard (Holmstrom and Milgrom, 1991)
   - Firms' allocations ignore preferences



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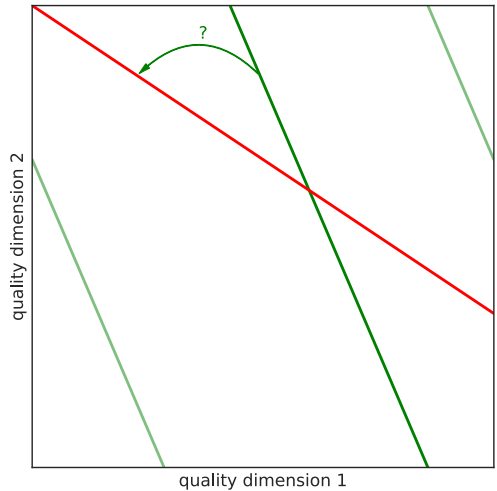

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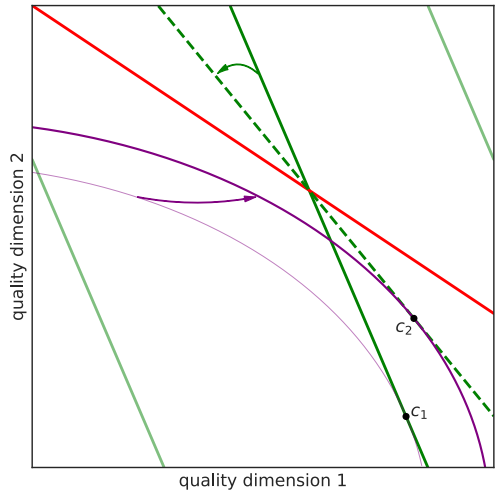

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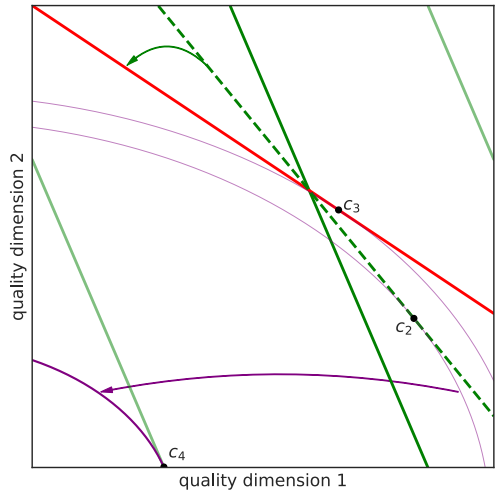
3. Firm cost heterogeneity crucial for solution
   - Otherwise, alignment leads to quality losses



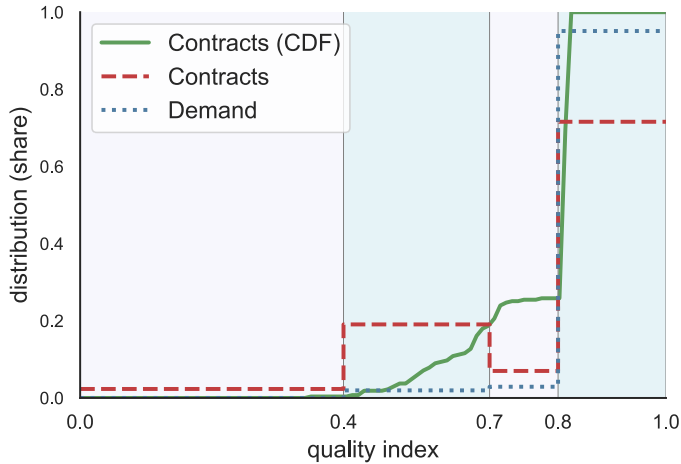
Decomposing the Design: Aggregator

- New weights align with consumer preferences
- **Pooling at the bottom + optimal aggregator account for 98.2% of welfare gains**
  - Pooling increases overall investment
  - Optimal aggregation improves informativeness and allocative efficiency of investments

  $\Rightarrow$ High welfare value from optimal certification

Decomposing the Design: Granularity

- Why only three scores at the top?



Decomposing the Design: Granularity

- Why only three scores at the top?
- Trade-off: efficiency vs. product variety
  - More scores allow more investment actions for firms (delegation equivalence)
  - More actions allow for more heterogeneity: lower quality at lower prices
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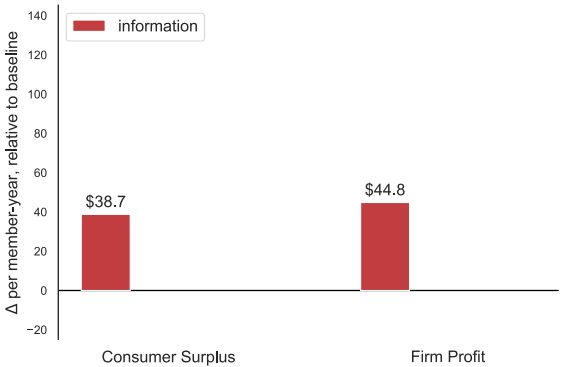
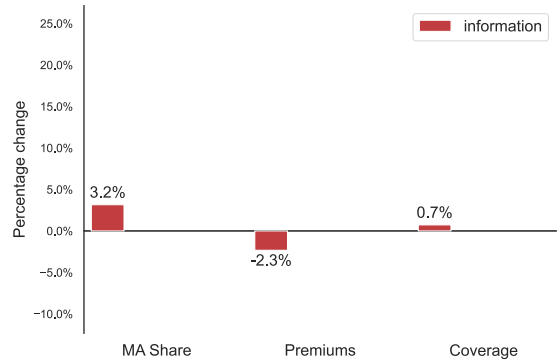
- Granularity governed by:
  1. Value: consumers' heterogeneity in WTP for quality
  2. Cost: ability to generate separating choices for firms

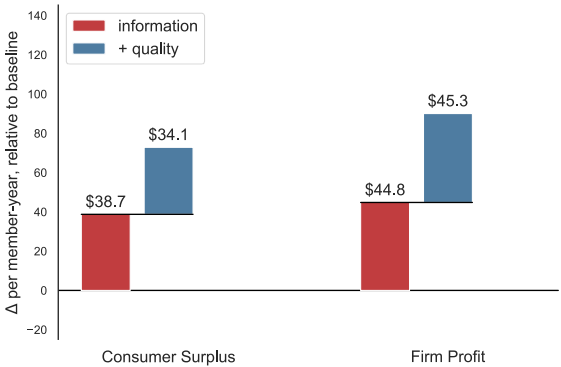
Welfare

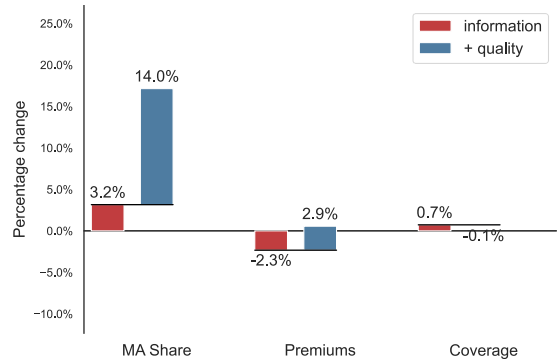




- Holding prices and quality change information:
  - Products are easier to choose, fewer mistakes
  - MA expansion: Consumers select quality that offsets systematic preferences

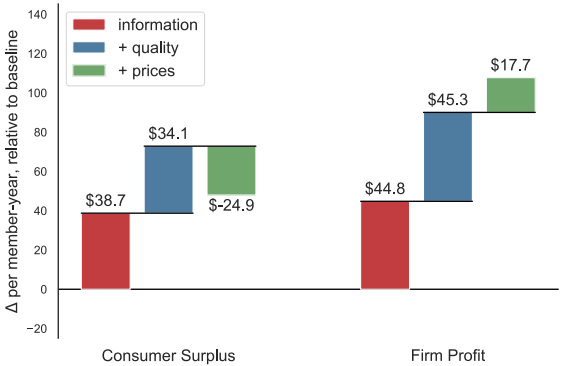
Welfare

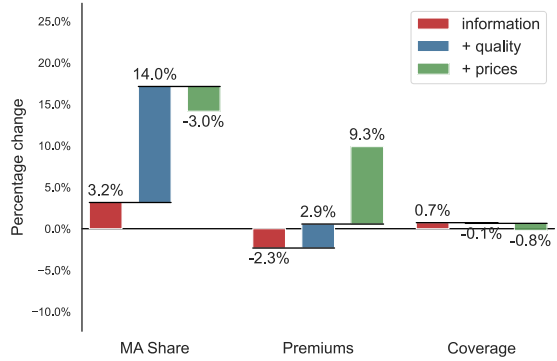




- Holding quality, change information, and prices:
  - New information reveals vertical differentiation across products
  - Firms exert market power over prices, capturing surplus

Welfare

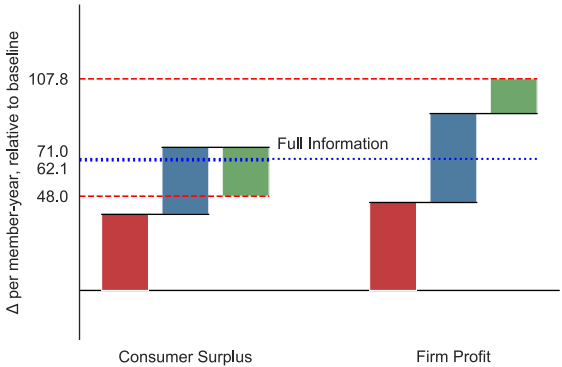


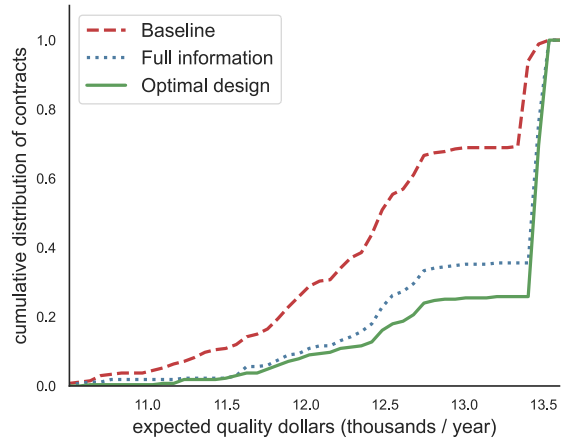


- Full equilibrium changes:
  - Total welfare increases by $155.7 per beneficiary/year, firms' benefit from coordination effect
  - Compensating variation of: quality = $90.14 > $70.45 = information

⇒ Quality regulation is key driver of welfare gains

Welfare





- Full information allows exercise of market power over quality, reduces welfare
- New scores dominate only because of equilibrium quality effects

Explaining the Differences in Designs

Why is CMS's design systematically different than the optimal?

1. Strong preferences for quality chronic care (Intermediate) and lower-cost hospitals (Outcome)
   - Paternalism or dynamic considerations for future subsidized care
   - Nudging the market with scores is enormously costly:

     $\Rightarrow$ Outperformed by a subsidy that generated 8 cents of investments per dollar spent

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2. CMS might be risk averse to misrepresenting consumers' preferences
   - CMS might also believe that consumers are naive (ignorant of policy changes)
   - Medicare plays a delicate political and social role, objective might be $\max_{\psi \in \Psi} \min_{\gamma \in \Gamma} TW(\psi, \gamma)$

   $\Rightarrow$ CMS's design outperforms best (linear) monotone partitional design
   - Assumptions of the setting are rejected by the data, yet presents credible rationale for status quo

Policy Implications Beyond MA

1. New methodology delivers aggregators that offset multitasking moral hazard
   - "Gaming" has been documented extensively in nursing homes, energy, schooling (Feng Lu, 2012; Clay et al., 2021; Neal and Schanzenbach, 2010)

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   - Quality promoting initiatives exist alongside scores in healthcare, schooling, electric appliances,...
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2. Scores should be designed with quality goals in mind, not only informativeness
   - Quality promoting initiatives exist alongside scores in healthcare, schooling, electric appliances,...
   - Properly designed scores can enhance these efforts; poorly designed ones, counteract

3. Coarse, simple scores can improve welfare at small informational cost
   - Longstanding concern about ability of consumers to process complex quality data
   - Inherent value for simplicity in quality disclosure policies

Conclusions

- Scores are powerful quality regulation policies:
  - Adapting MA's design to equilibrium effects increases welfare by $8.8 billion
- Suggests potential for redesigning scores using theory and empirical work
  - Challenges policy focus on granularity, (ex-ante) informativeness, cognitive bias considerations

  $\Rightarrow$ A simple, well-designed sticker can outperform full information outcomes
- **Empirical Scoring Design** methodology for disclosure policies
  - Data-driven solution for an extensive policy problem

Thank You!

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