Quality Disclosure and Regulation:Scoring Design in Medicare Advantage

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Quality scores affect our everyday choices



Medicare.gov Showing 1 - 15 of 62 hospitals Sort by: Closest > Overall star rating Northshore University 1. Healthsystem - Evanston 0.8 mi Hospital (4R) Patient survey rating ACUTE CARE HOSPITALS *** 2650 Ridge Ave Evanston II 60201 Compare (847) 432-8000 Overall star rating Presence Saint Francis Hospital **** (HR) 2.4 mi

Quality scores affect our everyday choices





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)
 - 2 Affect firms' incentives to invest in quality (Barahona et al., 2020)

Quality scores affect our everyday choices

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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)

- Q: How to design welfare-maximizing scores for Medicare Advantage (MA)?
 - > Summarize medical and service quality of insurance plans using nine scores (stars)
- Use yearly variation in scoring design between 2009 and 2015 to:
 - 1 Show that design affects demand and supply of health insurance
 - 2 Estimate a model of demand, pricing, and quality investments
 - Information asymmetries: consumers' quality information is severely limited
 - Inefficient quality provision: too low on aggregate, distorted by private incentives (Spence, 1975)
- Develop a general empirical scoring design methodology
 - > Combine computational methods with insights from information design
 - ⇒ Model + method deliver a welfare-improving design for MA

Preview of Results

New design increases surplus by 2.4 monthly premiums per consumer/year

- Uses five scores: five stars with discrete increments
- > One-star pools low and medium quality (\psi info) others partition high quality (\psi info)
- Consumers avoid one-star plans, firms respond by increasing investments (↑ quality)
- Reward more improvements in quality dimensions consumers' care about (↑ efficiency ↑ info)
- ⇒ Consumers make more informed choices over higher quality products
- 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 3|22

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

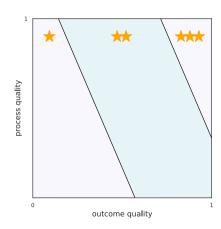
- 1 National regulated private health insurance market
 - > All 65 million Medicare-eligible individuals can opt into MA, about half do
 - > Trade-off: greater access vs. better coverage
 - > Generous premium subsidies, risk-adjustments for insurers
- 2 Highly concentrated: 90% of average county enrollment 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

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

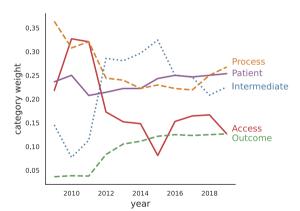


- 1 Measure plan's performance over five categories of quality
 - 1 Medical Outcomes
 - 2 Intermediate Medical Outcomes (chronic conditions)
 - 3 Access to Care
 - 4 Patient Experience
 - 5 Process Measures (preventive, diagnostic care)
- 2 Give a score of 1-5 to each plan and each category
- 3 Show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

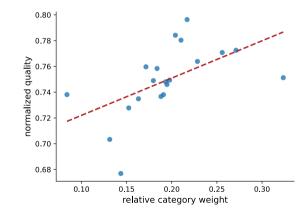
- ▶ **Design**: slope and location of hyper-planes
 - Slope = Weights, Location = Cutoffs
 - In two dimensions design is just lines →
- Q: Which lines to draw and how many?
- Scores reveal quality regions, not value



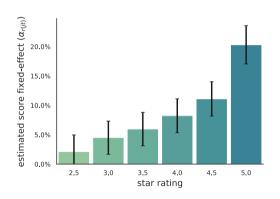
- 1 Scoring rules
 - Hand collected from CMS
 - Substantial variation in design



- Scoring rules
- 2 Data on all plans
 - > Premiums, coverage, and benefits
 - Quality: responds to design

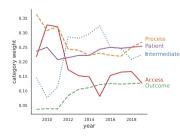


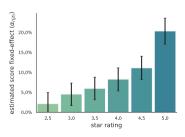
- 1 Scoring rules
- 2 Data on all plans
- 3 Enrollment data
 - Individual-level representative panel
 - > 46,833 enrollment choices
 - Consumers prefer higher-scoring plans

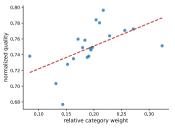


Taking Stock: The Designer's Toolkit

- 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.







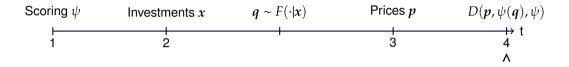
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2 Model, Identification, and Estimates

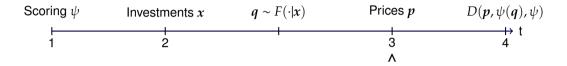
3 Scoring Design

Designer	<u>Insurers</u>	<u>Nature</u>	<u>Insurers</u>	Consumers
Scoring ψ	Investments x	Quality $q \sim F(\cdot x)$	Prices p	$D(\pmb{p},\psi(\pmb{q}),\psi)$
1	+	+	+	→ t
public	private	designer &	public	public



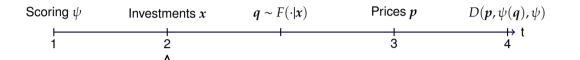
$$u_{ij} = \underbrace{\alpha_i P_j}_{\text{premium}} + \underbrace{\beta_i b_j}_{\text{coverage}} + \underbrace{\mathcal{E}_q[\gamma' q | \psi(q_j), \psi]}_{\text{quality}} + \underbrace{\lambda' z_{ij}}_{\text{obs.}} + \underbrace{\mathcal{E}_j}_{\text{unobs.}} + \underbrace{\mathcal{E}_{ij}}_{\text{~T1EV}}$$

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



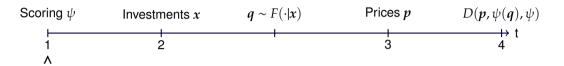
$$\pi_f(\boldsymbol{q}, \psi) = \max_{[p_j]_{j \in J_f}} \sum_{j \in J_f} \underbrace{D_j(\boldsymbol{p}, \psi(\boldsymbol{q}))}_{\text{demand}} (\underbrace{R_j(p_j)}_{\text{Mg. Revenue}} - \underbrace{C(q_j, z_j, \theta_j)}_{\text{Mg. Cost}})$$

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



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

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

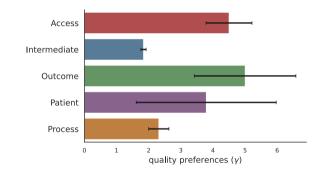


No optimality imposed on designer's experimentation

Identification 11

- Supply model identified from profit optimality conditions
- ► Revealed preferences identify consumers' WTP for scores
 - Cannot tell if WTP comes from beliefs about quality or preferences
 - 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 $\gamma = \$20$?
- Intuition: if consumers understand design, posterior beliefs are bounded
 - > Bounds on beliefs + WTP ⇒ bounds on preferences
 - Consumers knows that $\psi(q)=3\iff q\in[0.8\%,1\%)$ and $\psi(q)=4\iff q\in[0,0.3\%)$
 - Therefore $\Delta \mathcal{E}(q) \in (0.5\%, 1\%) \implies \gamma \in (100, 200)$
 - ⇒ Variation in scoring design generates additional bounds and tightens identification

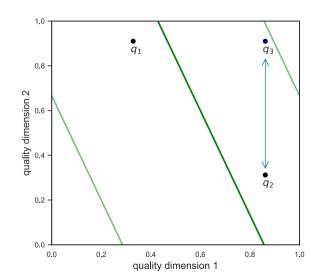
- ▶ 1 std. dev. in Outcomes ≈ \$1463 in OOP
- Incomplete info lowers surplus by \$185.9 (keeping supply fixed)
- Two sources of information asymmetry:



Key Estimates - Information Assymetry

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- Two sources of information asymmetry:
 - 1 Within-scores:

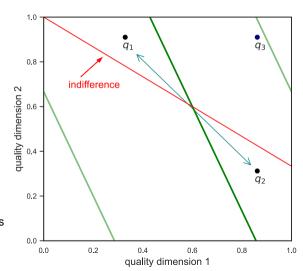
Best 4-star worth \$257.1 more than worst



Key Estimates - Information Assymetry

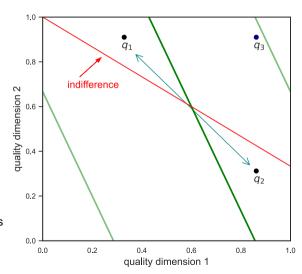
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 Best 4-star worth \$257.1 more than worst
 - 2 Across-scores:22.4% of plans ranked opposite to preferences

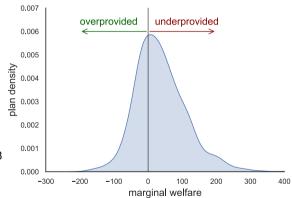


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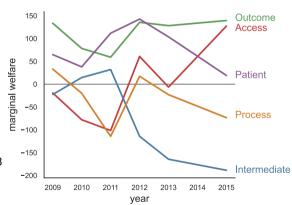
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- Two sources of information asymmetry:
 - 1 Within-scores: 5%
 Best 4-star worth \$257.1 more than worst
 - Across-scores: 95%22.4% of plans ranked opposite to preferences



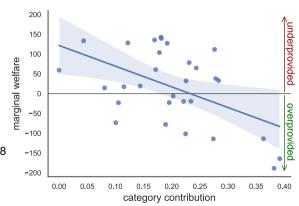
- Avg insurance markup of 11.2%
 - > For top insurers: avg marginal cost is \$771
 - > Curto et. al (2019): medical cost is \$680
- ► Median investment = 24% of insurance profits
- Quality is inefficiently provided:
 - 1 On aggregate: underprovided dTW/dq = \$42.8



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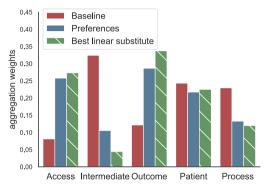
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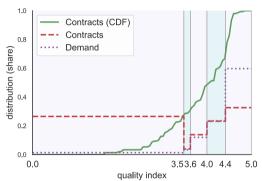
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$$\max_{\psi \in \Psi} \quad \mathbb{E}_{\boldsymbol{q}}[\underbrace{CS(\psi, \boldsymbol{q})}_{\substack{\text{Consumer} \\ \text{surplus}}} + \underbrace{\sum_{f} V_f(\psi, \boldsymbol{q}) - I(\boldsymbol{x}_f^*(\psi), \mu_f) \, |\boldsymbol{x}^*(\psi)|}_{\substack{\text{Insurer}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

- Subject to equilibrium behavior:
 - > Firms update investments, prices, beliefs about rivals
 - Consumers update beliefs given design and realized scores
- Empirical scoring design methodology:
 - 1 Represent scores as composition of aggregator and cutoffs
 - 2 Use equivalence of scores to distribution over posterior beliefs (Aumann and Maschler, 1995)

Solution: Best Linear Design

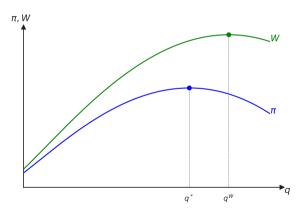




- 1 Pooling at the bottom: first score pools all low qualities
- 2 Aggregator: optimal weighting scheme, increase reward on dimensions consumers value
- 3 Limited granularity: use only five scores; four partition higher quality

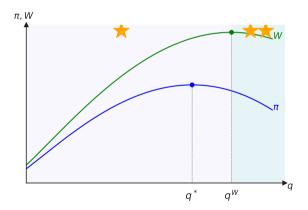
Decomposing the Design: Pooling at the Bottom

Market power over quality (Spence, 1975; Crawford et al., 2019): firms under-invest even under full info



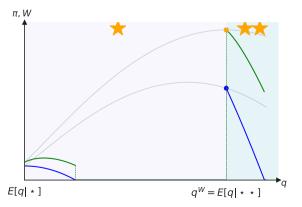
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Decomposing the Design: Pooling at the Bottom

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- ▶ Delegation equivalence (Zapechelnyuk, 2020) : certification $\iff q^w$ or 0

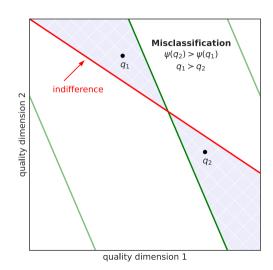


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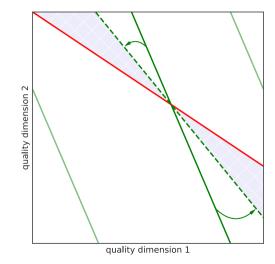
- Market power over quality (Spence, 1975; Crawford et al., 2019): firms under-invest even under full info
- **Delegation equivalence** (Zapechelnyuk, 2020) : certification $\iff q^w$ or 0
- ► Penalizes underprovision with ↓ demand: 35% of welfare gain (certification)
 - > 62.6% of contract would receive 1 star in baseline, only 26.5% in equilibrium
 - Serve only 1.3% of consumers
 - Quality is 4.3% higher in equilibrium

Aggregation produces two problems:

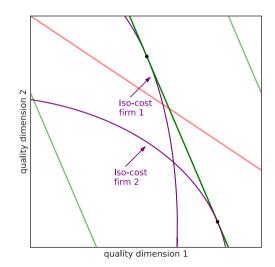
1 Across-scores information asymmetry:



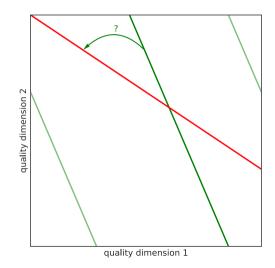
- 1 Across-scores information asymmetry:
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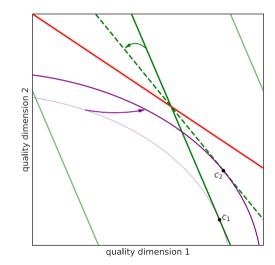
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- 2 Multitasking moral hazard (Holmstrom and Milgrom, 1991)
 - > Firms' allocations ignore preferences



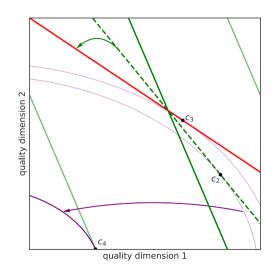
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- 1 Across-scores information asymmetry:
 - > Reduced by 97.1% under new weights
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- 3 Solution accounts for cost heterogeneity
 - Convex costs vs. (mostly) concave demand gains



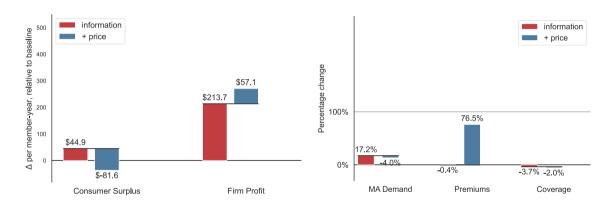
- Pooling at the bottom + optimal aggregator account for 94% of welfare gains
 - Pooling increases overall investment
 - > Optimal aggregation improves informativeness and allocative efficiency of investments
 - ⇒ High welfare value from optimal certification

Decomposing the Design: Granularity

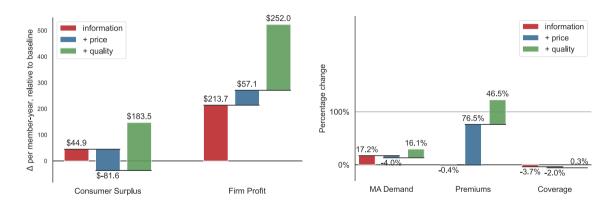
- Why only five scores at the top?
- Trade-off: efficiency vs. product variety
 - More scores allow more investment actions for firms (delegation equivalence)
 - > More actions allow for more heterogeneity: lower quality at lower prices
 - > But also more deviations away from efficient production and towards profit maximization
- Limiting factor: ability to generate separating choices for heterogenous firms



- Holding prices and quality changes information:
 - Products are easier to choose, fewer mistakes
 - Large MA expansion: Consumers select quality that offsets switching costs

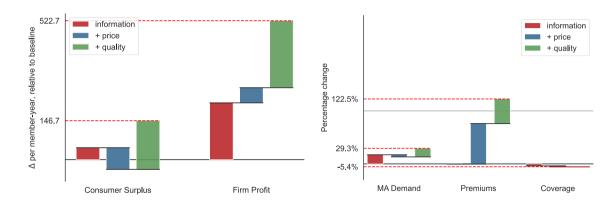


- ► Holding quality, change information and prices:
 - > New information reveals vertical differentiation across products
 - > Firms exert market power over prices capturing surplus

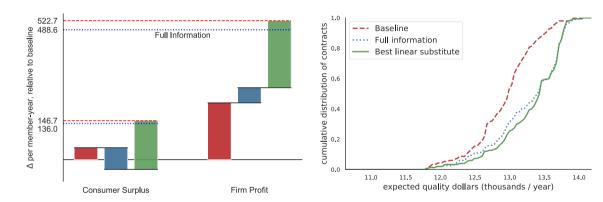


Full equilibrium changes:

- > Total welfare increases by 285%, firms' benefit from additional expansion
- > Welfare gains primarily driven by quality regulation effect

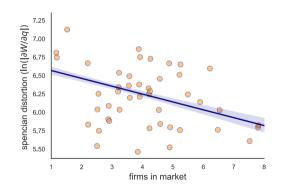


- ► Total welfare is \$669.3 per member per year
- ► Surplus gain ≈ 2.4 total monthly premiums

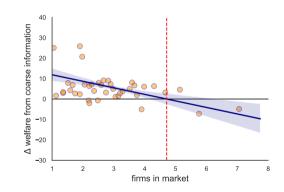


- Full information allows exercise of market power over quality, reduces welfare
- New scores dominate only because of equilibrium quality effects

- Markups increase by 37.2% under new design
 - ↑ vertical differentiation
 ⇒ ↓ 7.3% semi-elasticity of substitution across
- Additional competing firm associated with:
 - > 1 0.3pp markup increase
 - > 1.8pp quality increase
 - > 1 5.4% spencian distortion in full information



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- Additional competing firm associated with:
 - \$\d\ 0.3pp markup increase
 - > 1.8pp quality increase
 - > 1 5.4% spencian distortion in full information
- Gains from coarse information vanish at 5 firms
 - > 9.9% of consumers better under full info



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:
 - ⇒ would have to value 10% reallocation of quality by \$14 billion, orders of magnitude above cost
- 2 CMS might be risk averse to misrepresenting consumers' preferences
 - > Medicare plays a delicate political and social role, objective might be $\max_{\psi \in \Upsilon} \min_{\gamma \in \Gamma} TW(\psi, \gamma)$
 - CMS's weight nearly optimal for robust design
 - \Rightarrow optimal robust design improves upon CMS by using the same economic forces as before

Conclusions 22 | 22

- Scores are powerful quality regulation policies:
 - Adapting MA's design to equilibrium effects increases welfare by \$43 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

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Thank You!

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