

Optimal Rating Design Under Moral Hazard

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SITE: Market Design

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Introduction

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 - security rating, eBay, college grades, Google Ranking

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 - Ratings often lead to window dressing: ESG Ratings, USNews, Google, ...
- Ratings are information structure
- How should we think about information design when it provides incentives for the rated?

Related Literature

- Bayesian Persuasion: Kamenica and Gentzkow (2011), Dworczak and Martini (2019), Duval and Smolin (2023), ...
- Falsification and muddled information: Perez-Richet and Skreta (2020), Frankel and Kartik (2020), Ball (2020)
- Optimal communications in the presence of incentives: Boleslavsky and Kim (2023), Mahzoon, Shourideh, Zetlin-Jones (2023), Best, Quigley, Saeedi, Shourideh (2023)

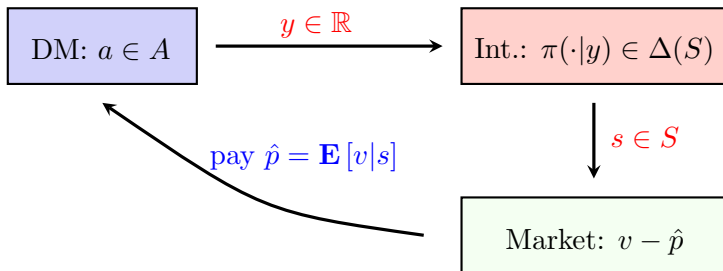
Roadmap

- The General Model
- General characterization of optimal rating system
- An Application:
 - Optimal Ratings in a Multi-tasking model a la Holmstrom and Milgrom

THE GENERAL MODEL

The Model

- DM chooses an action $a \in A \subset \mathbb{R}^N$
- Induces $(y, v) \in \mathbb{R}^2$
 - y : indicator observed by intermediary
 - v : value for the market
 - $(y, v) \sim \sigma(y, v|a)$
- Intermediary observes y and sends a signal to the market:
 - Commits to $(S, \pi(\cdot|y))$ with $\pi(\cdot|y) \in \Delta(S)$



The Model

- Payoff of DM

$$\int_Y \int_S \mathbb{E}[v|s] d\pi(s|y) dG(y|a) - c(a)$$

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- **Equilibrium:** $\phi \in \Delta (A)$ is a PBNE

- Given π and market beliefs, a maximizes DM's payoff, a.e. $-\phi$
- Market beliefs are consistent with π , ϕ , and prior according to Bayes' rule

Feasible Outcomes

- What efforts, a , can be supported in some equilibrium?
- Incentive compatibility

$$a \in \arg \max_{a' \in A} \int_Y \underbrace{\int_S \mathbb{E}[v|s] d\pi(s|y)}_{p(y)} dG(y|a') - c(a')$$

Feasible Efforts

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- $p(y) = \mathbb{E}[\mathbb{E}[v|s] | y]$: interim prices

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- $p(y) = \mathbb{E}[\mathbb{E}[v|s] | y]$: interim prices

Proposition. If $p(\cdot)$ is an interim price function, then $p \preccurlyeq_{\text{maj}} \mathbb{E}[v|y]$.

Moreover, if $p(\cdot)$ is co-monotone with $\mathbb{E}[v|y]$, i.e., $p(y) > p(y') \Rightarrow \mathbb{E}[v|y] > \mathbb{E}[v|y']$, and $p \preccurlyeq_{\text{maj}} \mathbb{E}[v|y]$, then $p(\cdot)$ is an interim price function.

Recap

- Assuming that $\mathbb{E}[v|y]$ are comonotone allows us to significantly simplify the problem
 - Textbook moral hazard with an extra majorization constraint
 - interim prices play the role of transfers
- Given co-monotonicity, WLOG

Assumption. Full-info market values, $\mathbb{E}[v|y]$, are increasing in y .

GENERAL CHARACTERIZATION OF OPTIMAL RATINGS

Optimal Ratings

- Notion of optimality: objective

$$\int W(a) d\phi + \int p(y) \alpha(y) dG(y|a) d\phi$$

with $\alpha(y) \geq 0$.

- Recall ϕ : distribution of action $a \in A$

Optimal Ratings

$$\int W(a) d\phi + \int p(y) \alpha(y) dG(y|a) d\phi$$

- Examples:

- **Correcting an externality :** $\alpha(y) = 0$ and $W(a) \neq \underbrace{V(a) = \mathbb{E}[v|a] - c(a)}_{\text{total surplus}}$

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 - Correcting an externality: $\alpha(y) = 0$ and $W(a) \neq V(a) = \mathbb{E}[v|a] - c(a)$
 - **Learning Externality a la Holmstrom (1999):** $\alpha(y) = 0, W(y) = V(y)$
 - Under full information: market's belief about v , $\mathbb{E}[v|y]$, does not vary with DM's choice of a
 - Externality when $\frac{\partial}{\partial a} \mathbb{E}[v|y] \neq 0$.

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 - **Distributional concerns:** $\alpha(y)$ varies with y

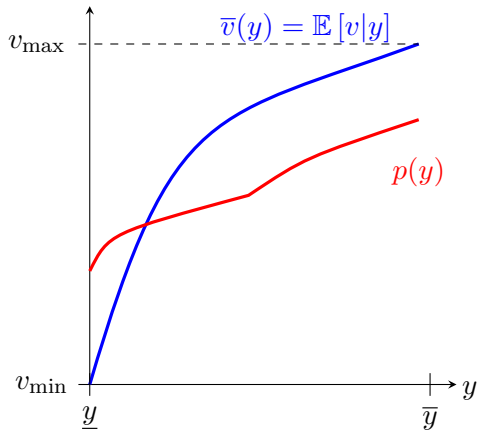
Optimality under Majorization

- Suppose mathematical problem of finding optimal interim prices was of the form (For now trust me that it is!!!):

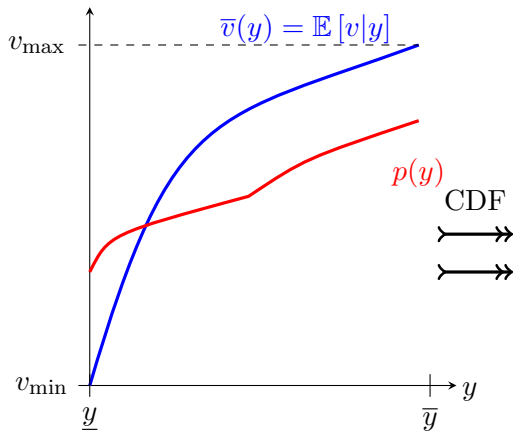
$$\max_{p(y): \mathbb{E}[v|y] \succ_{\text{maj}} p(y)} \int h(y) p(y) dG(y)$$

subject to monotonicity and given a ϕ

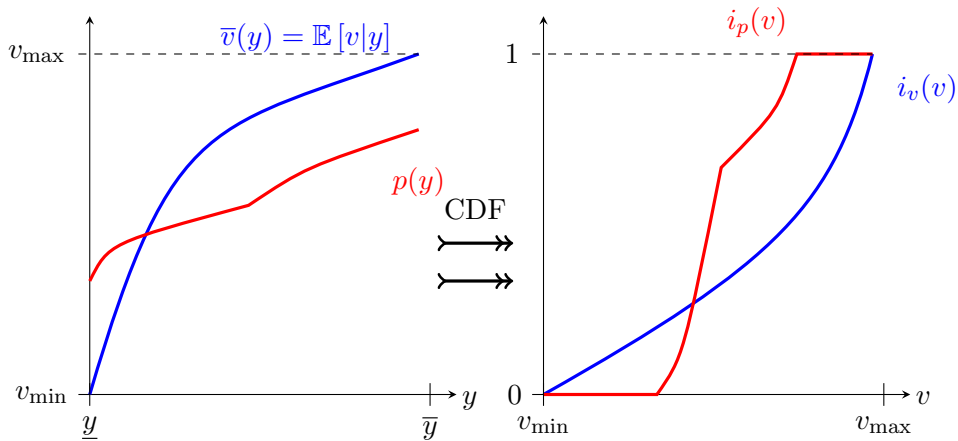
Majorization: A Reformulation



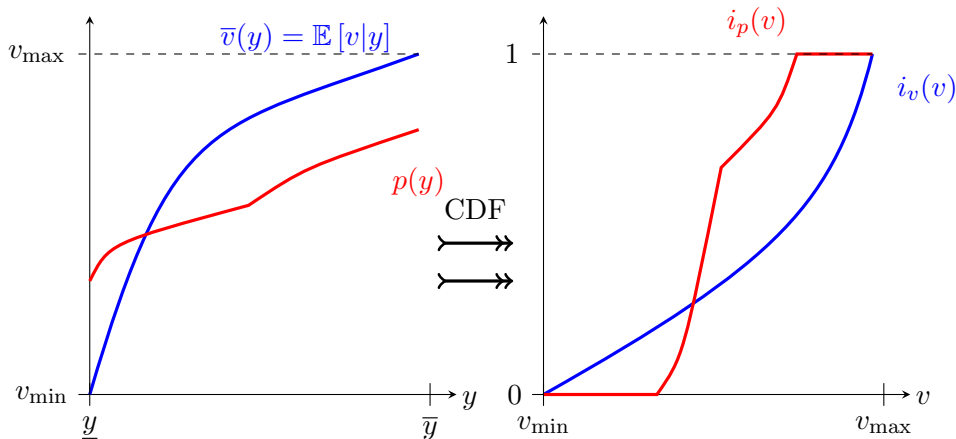
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Majorization: A Reformulation



$$\mathbb{E}[v|y] \succ_{\text{maj}} p(y) \Leftrightarrow i_p(v) \succ_{\text{maj}} i_v(v)$$

Majorization: A Reformulation

$$\max_{p(y)} \int h(y) p(y) dG(y)$$

subject to

$$\mathbb{E}[v|y] \succ_{\text{maj}} p(y)$$

=

$$\int \text{cav} H(i) dv_Q(i)$$

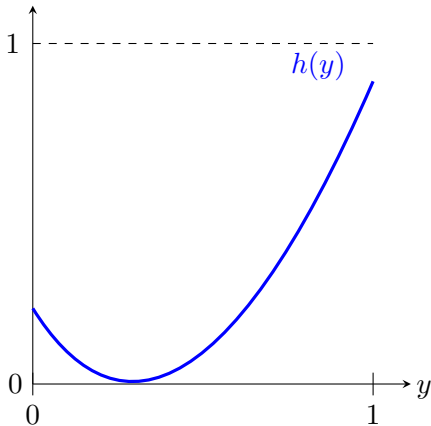
with

$$v_Q(i) = i_v^{-1}(i) \quad \text{Quantiles } \bar{v}(y)$$

$$H(i) = \int \mathbf{1}[\{y : \bar{v}(y) > v_Q(i)\}] h(y) dG \quad \text{Cumulative weight above } i$$

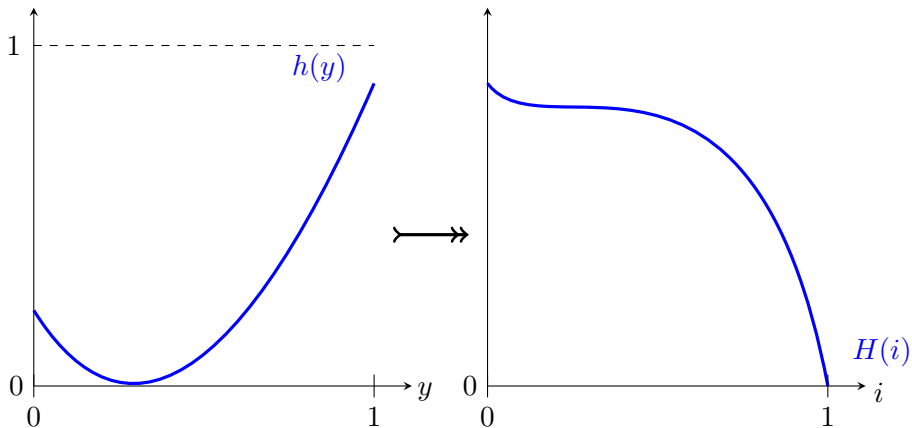
Majorization: A Reformulation

- **Example:** $v = y \in [0, 1]$, $i_v(v) = v$, $v_Q(i) = i$; v, y : uniformly distributed



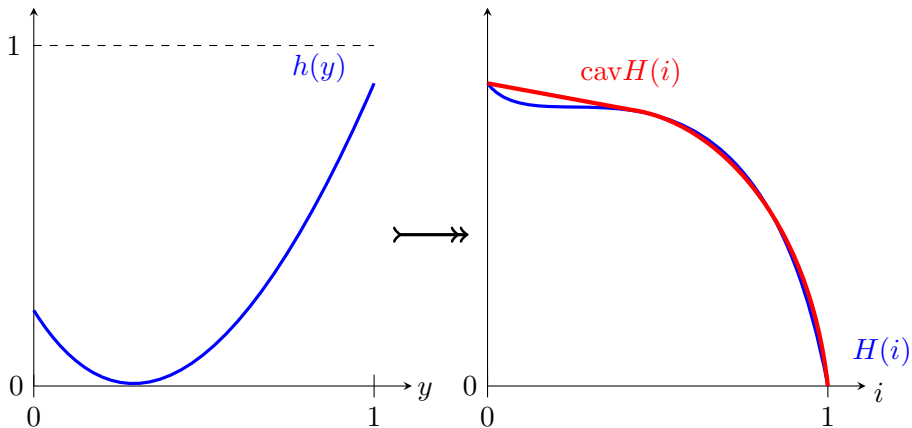
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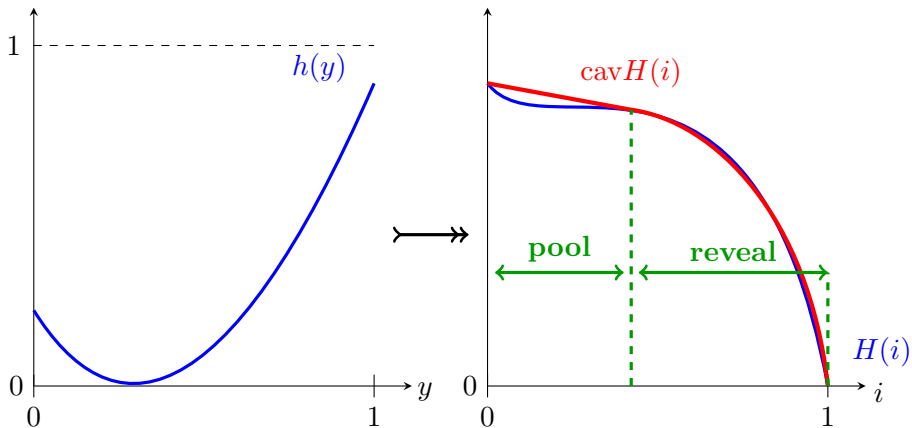
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Optimal Ratings

Theorem 1. The problem of optimal rating design is solved by solving the following

$$\min_{\Lambda} \max_{\phi, v_Q} \int W(a) d\phi + \int \text{cav} H(i; \Lambda, \phi) dv_Q(i)$$

where

$$\begin{aligned} H(i; \Lambda, \phi) &= \int \mathbf{1}[\{y : \bar{v}(y) > v_Q(i)\}] \alpha(y) dG + \int \int_{\hat{a} \in A} [F(i|\hat{a}) - i] d\Lambda d\phi \\ &\quad + \int \int [c(\hat{a}) - c(a)] d\Lambda d\phi \end{aligned}$$

and

$$F(i|\hat{a}) = \int \mathbf{1}[y : \bar{v}(y) \leq v_Q(i)] dG(y|\hat{a})$$

Optimal Ratings

- Theorem 1 is a mouthful!
- Some unpacking:
 - Identifies the function to concavify:
 - changes in quantile distribution from binding deviation weighted by their shadow value

$$\int \int_{\hat{a} \in A} [F(i|\hat{a}) - i] d\Lambda d\phi$$

- Cumulative welfare weights

$$\int \mathbf{1}[\{y : \bar{v}(y) > v_Q(i)\}] \alpha(y) dG$$

- No need for first order approach
- Proof: Uses Rockefellar-Fenchel duality
 - used also in Dworczak-Koloilin (2023), Corrao-Kolotilin-Wolitzky (2024), Farboodi-Haghpanah-Shourideh (2024)

Simple Ratings are Optimal

Assumption 1. Distribution $G(y|a)$ satisfies:

1. **Interval Support (IS):** $\forall a \in A, \text{Supp}G(\cdot|a) = I \subseteq \mathbb{R}$,
2. **Independence (I).** For any subinterval $I' \subset I$ and $a \neq a' \in A$, there exists $y_1, y_2 \in I'$ such that $G(y_1|a)/G(y_1|a') \neq G(y_2|a)/G(y_2|a')$.

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Proposition. Suppose that IS and I hold, then the optimal rating is monotone partition.

Moreover, whenever $\text{cav}H(i; \Lambda, \phi) = H(i; \Lambda, \phi)$, optimal rating reveals the value $\bar{v} = v_Q(i)$ to the market. When $\text{cav}H(i; \Lambda, \phi) < H(i; \Lambda, \phi)$, then there exists an interval $i \in [i_1, i_2]$ such that optimal rating reveals that $\bar{v} \in [v_Q(i_1), v_Q(i_2)]$.

DISTRIBUTION INDEPENDENT OPTIMAL RATINGS

Implementable Efforts

- When $\alpha(y) = 0$, only relevant question is what subset A^* of A is implementable by some rating.
- Common case: $A \subset \mathbb{R}$, $g(y|a)$ satisfies MLRP, i.e., $g(y|a)$: log-supermodular

Proposition. Suppose that $A \subset \mathbb{R}_+$ and $G(y|a)$ satisfies IS, I and MLRP. Then, $\max A^* = a_{FI}^*$ where a_{FI}^* is the highest level of equilibrium effort when y is fully revealed.

- The change in quantile distribution is concave
- See also: Dewatripont, Jewitt and Tirole (1999)

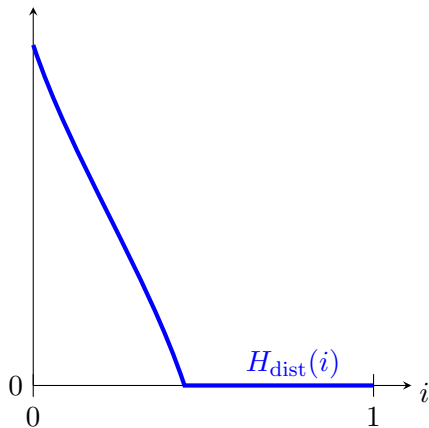
Implementable Efforts

- Other specifications:
 - $y \sim N(a, ka)$, $a \geq 0$, $\max A^* = \max a_{LS}^*$: the highest value of effort among all lower censorship policies.
 - $G(y|a) = e^{-y^{-1/a}}$, $a \leq 1/2$. $\max A^* = \max a_{HS}^*$: the highest value of effort among all upper censorship policies.
- Both among a class of distribution function where $\frac{\partial^2}{\partial a \partial y} \log g(y|a)$ switches sign only once.

REDISTRIBUTIVE OPTIMAL RATINGS

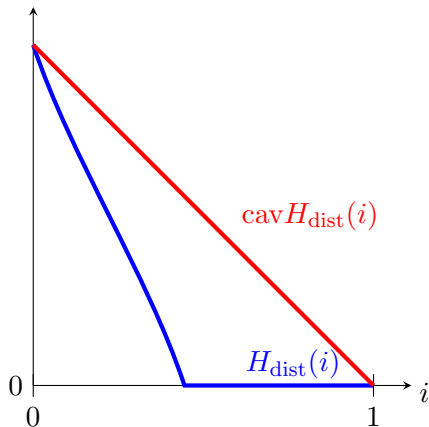
Redistributive Motives

- Suppose that $\alpha(y)$'s are positive and decreasing



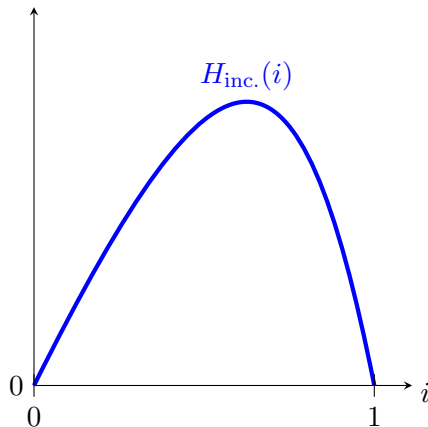
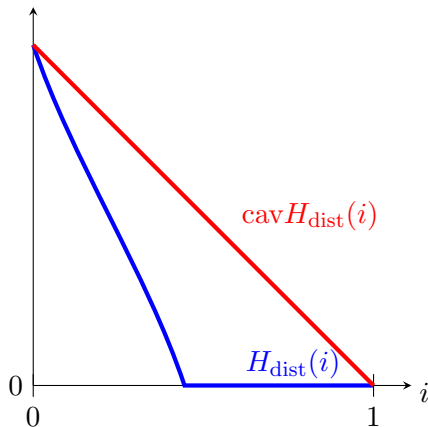
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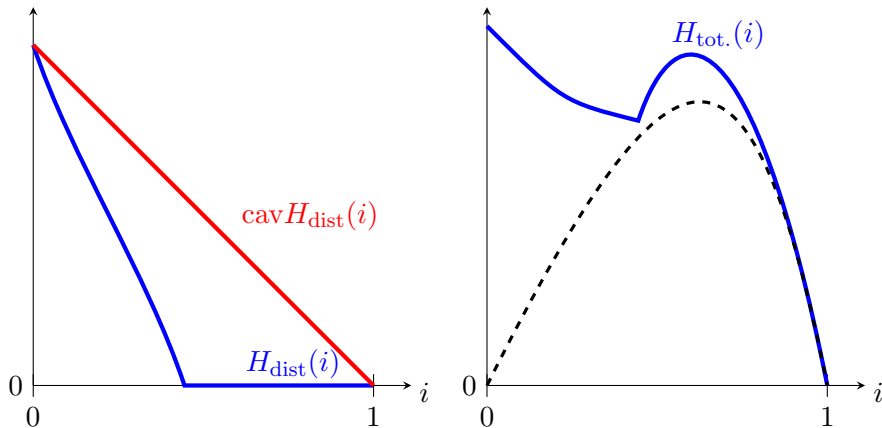
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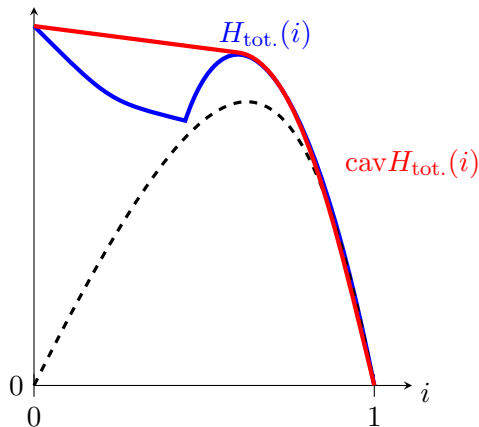
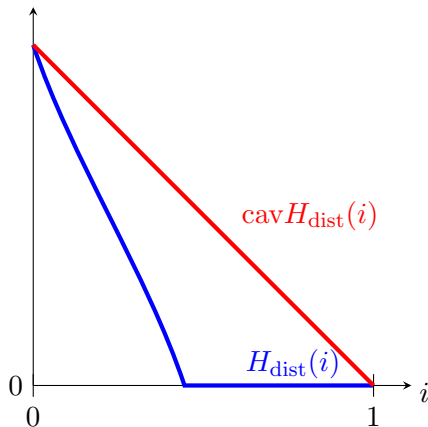
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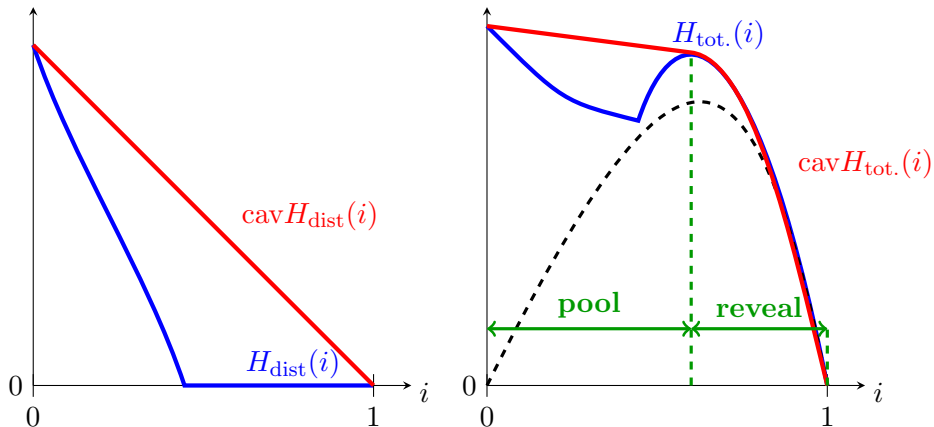
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Redistributive Motives

- Suppose that $\alpha(y)$'s are positive and decreasing
- Typical case: optimality of lower censorship
- Has implications for the design of tests for admission into college

APPLICATION: A MULTI-TASKING MODEL
A LA HOLMSTROM AND MILGROM (1991)

A Multi-Tasking Model

- Holmstrom and Milgrom (1991)
- Two tasks: $a = (e_1, e_2)$
 - e_1 : value generating
 - e_2 : window dressing
 - cost: $k_1 e_1^2/2 + k_2 e_2^2/2$
- Market values and indicators:
 - values: $v = \beta \cdot e_1 + \varepsilon_v$
 - indicator: $y = \alpha_1 e_1 + \alpha_2 e_2 + \varepsilon_y$

$$\begin{pmatrix} \varepsilon_v \\ \varepsilon_y \end{pmatrix} \sim N(0, \Sigma(a))$$

- $\alpha_i, \beta > 0$

A Multi-Tasking Model

- Inefficient action: window dressing
- Conditional expectation of v :

$$\mathbb{E}[v|y] = \beta e_1 + \frac{\sigma_{yv}(a)}{\sigma_v(a)^2} (y - \alpha_1 e_1 - \alpha_2 e_2)$$

- **Holmstrom and Milgrom (1991):** Assuming linear wage contracts, a decline in k_2 leads to lower power incentives.

A Multi-Tasking Model

Proposition. Suppose that $\frac{\partial}{\partial a}\Sigma(a) = 0$, then total surplus maximizing rating is always full information.

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Proposition. 1. Suppose that FOA holds, then total surplus maximizing rating is either lower censorship or higher censorship.

2. If $\frac{\partial}{\partial e_1}\sigma_y = 0$, $\frac{\partial}{\partial e_2}\sigma_y > 0$, HM's result holds: as k_2 goes down, optimal rating becomes less informative.

Conclusion

- Studied optimal rating design in presence of incentives
- General Characterization of optimal ratings
- Our Techniques can be used to shed light on several design questions of interest:
 - HM's result on changes in window dressing costs
 - Possible to think about the redistributive design of exams and tests

Majorization

Definition. For a r.v. $y \sim H$, satisfy $f(y) \succ_{\text{maj}} g(y)$ (equivalently, $g(y) \succ_{\text{cv}} f(y)$ or $f(y) \succ_{\text{cx}} g(y)$) if and only if

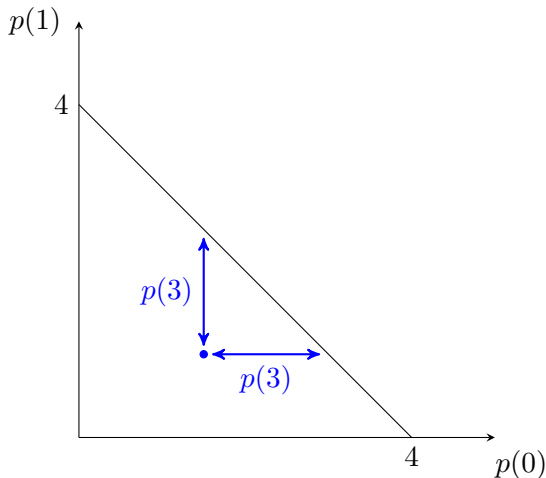
$$\int u(f(y)) dH \geq \int u(g(y)) dH, \forall u : \text{convex}, u : X \rightarrow \mathbb{R}$$

or equivalently

$$\int u(g(y)) dH \geq \int u(f(y)) dH, \forall u : \text{concave}, u : X \rightarrow \mathbb{R}.$$

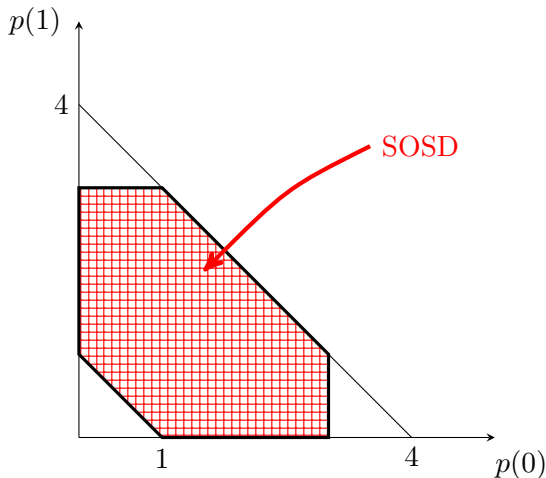
Example

- $Y = A = \{0, 1, 3\}$, $v = y$, prior: $\mu(\{y\}) = 1/3$
- Interim prices: $\frac{p(0)+p(1)+p(3)}{3} = \frac{4}{3}$



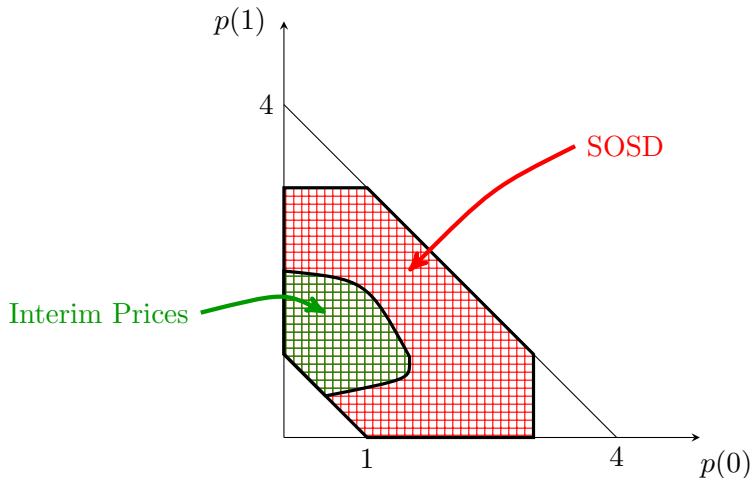
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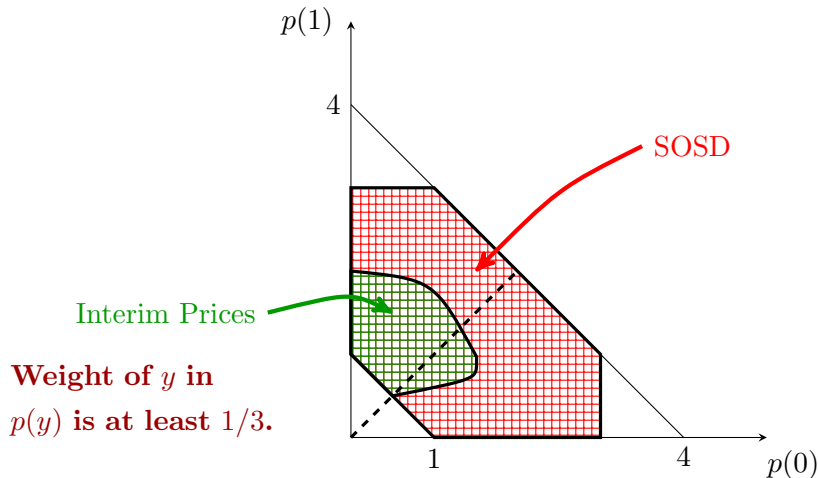
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Idea of Proof

- Steps:
 - Assume support y 's, Y , is finite,
 - Use induction to construct π ,
 - Approximate compact Y 's
- Suppose Y is finite, Market values $\{\bar{v}_1 < \cdots < \bar{v}_n\}$.
- Co-monotonicity: $p_1 \leq \cdots \leq p_n$

Idea of Proof

- A class of signal structures: for a given $i : 1 \leq i \leq n - 1$

$$\pi(\{s\} | y) = \begin{cases} \lambda & s = y \\ (1 - \lambda) \hat{\pi}(\{s\} | y) & s \in \hat{S} \end{cases}, \hat{\pi}(\{s\} | y_i) = \hat{\pi}(\{s\} | y_{i+1}), \forall s \in \hat{S}$$

- Reveals the state with probability $\lambda \in [0, 1]$; otherwise pools i and $i + 1$.
- Can always choose i and λ so that the implied interim price for $\hat{\pi}$ is co-monotone and satisfies SOSD
 - Use induction hypothesis