

Good Data and Bad Data: The Welfare Effects of Price Discrimination

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Effects of Price Discrimination

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- Common folk wisdom: personalized pricing hurts consumers
 - Also: Pigou (1920), Joan Robinson (1969), etc.
- Bergemann, Brooks and Morris (2015) or BBM:
 - It can go either way
 - Every rationalizable CS-PS pair is feasible!

A Modified Version of Pigou's Logic ---

- Two types of consumers

$$D(p, \theta_1) = \theta_1 - p < \theta_2 - p = D(p, \theta_2)$$

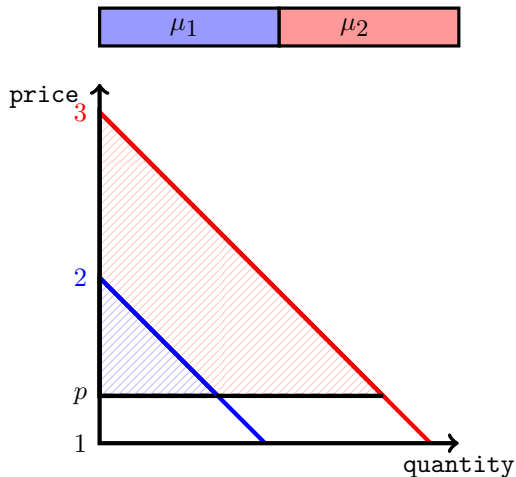
- Any market segment with distribution: $\mu_1 + \mu_2 = 1$
- Optimal price:

$$p = \frac{\mu_1 \theta_1 + \mu_2 \theta_2}{2}$$

- Total quantity

$$Q = \frac{\mathbb{E}\theta}{2}$$

Pigou's Logic: Example

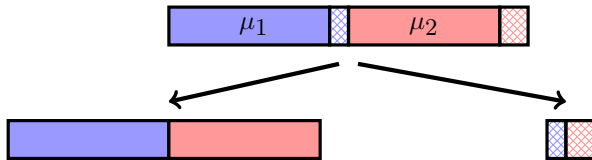


$$CS = \frac{3}{4}\text{var}[\theta] + \frac{1}{4}\mathbb{E}[\theta^2]$$

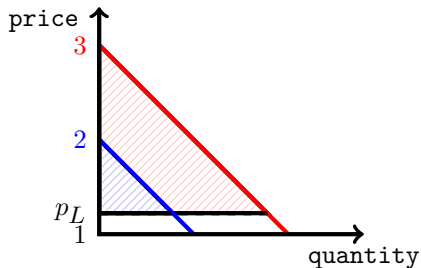
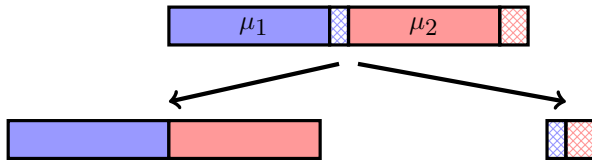
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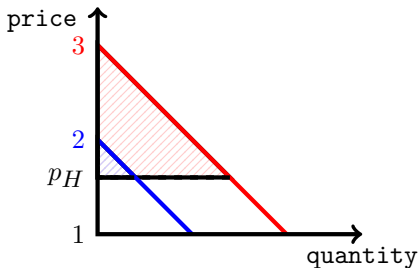
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$$CS_L = \frac{3}{4}\text{var}_L[\theta] + \frac{1}{4}\mathbb{E}_L[\theta^2]$$



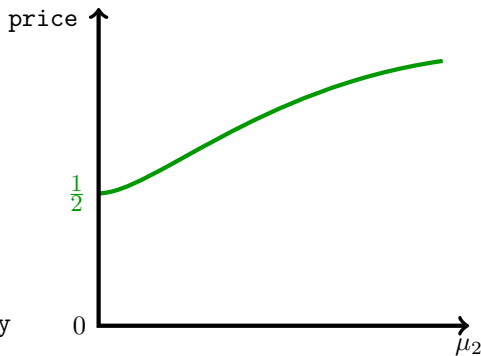
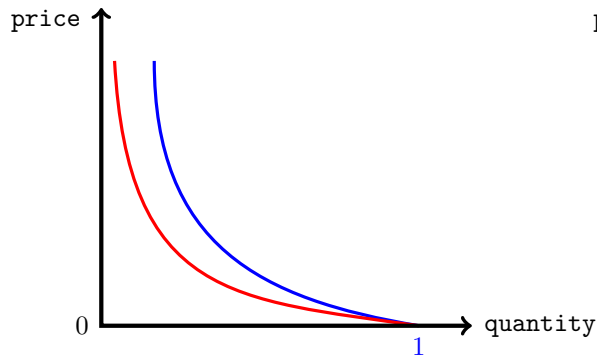
$$CS_H = \frac{3}{4}\text{var}_H[\theta] + \frac{1}{4}\mathbb{E}_H[\theta^2]$$

Pigou's Logic

- Finer segmentation: two effects
 1. Market size effect: depending on how the seller reacts, total quantity can go up or down
 - 1.1 For linear demand family, it does not change
 2. Misallocation effect: finer segmentation decreases CS – inefficiency of delivering fixed quantity via multiple markets
- Linear demand: only misallocation effect

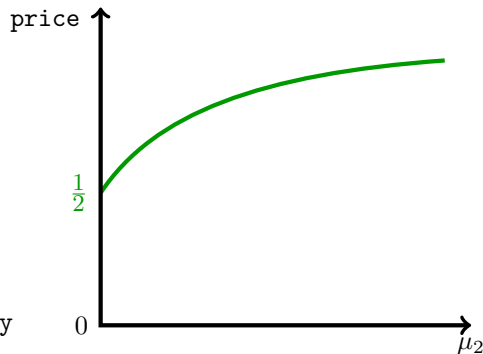
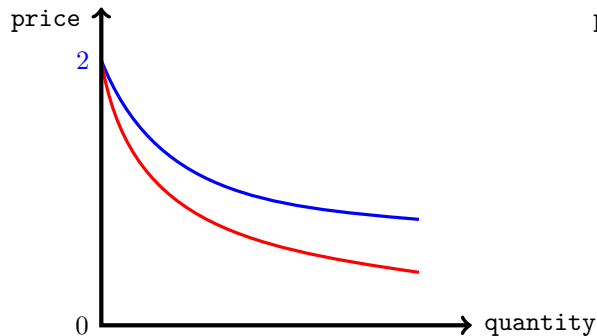
Piguo's Logic is more General

- Another example: $D(p, \theta_1) = (1 + p)^{-3}$, $D(p, \theta_2) = (1 + p)^{-2}$
 - Price is almost linear $\Rightarrow$ Misallocation effect dominates



Good Data!

- Another example: $D(p, \theta_1) = 1 - p + \frac{2}{p}$, $D(p, \theta_2) = 3 - 2p + \frac{2}{p}$
 - Price is concave in prior $\Rightarrow$ Quantity effect dominates



Our Paper

- Question: when is it that any coarsening is good? In other words, how general is Pigou's logic?
- Useful determinant for outright bans of personalized pricing
 - cannot really verify who knows what
- Alternative: banning use of specific type of data
 - standard information design
 - not this paper: but related

Two Main Results

- Key concept: IMB (or IMG): $\alpha \cdot CS + (1 - \alpha) \cdot PS$

Information is Monotonically Bad! (or Good!)

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- **Theorem 1:** Full characterization of demand systems (class of demand functions) where more data is always bad (or always good):
 - No exclusion, i.e., all types are active
 - demand functions are generated by linear combinations of two demands

Two Main Results

- Key concept: IMB (or IMG): $\alpha \cdot CS + (1 - \alpha) \cdot PS$

Information is Monotonically Bad! (or Good!)

- **Theorem 1:** Full characterization of demand systems (class of demand functions) where more data is always bad (or always good):
 - No exclusion, i.e., all types are active
 - demand functions are generated by linear combinations of two demands
- **Theorem 2:** Provide bounds for any demand system for loss/gain from more data.
 - Key idea:
 - rank of Hessian of the (KG) value function ≤ 2
 - eigenvalues!

Related Literature

- 2-demand models: Pigou (1920), Robinson(1933), Varian(1985), Aguirre, Cowan, Vickers(2010)
- All segmentations: Bergemann, Brooks, Morris (2014), ..., Strack and Yang (2025)
- Bayesian Persuasion:
 - Kamenica and Gentzkow (2011),
 - First order approach and duality: Kolotilin (2018); Dworczak, Martini (2019); Kolotilin, Corrao, Wolitzky (2023); Smolin, Yamashita (2023); Dworczak, Kolotilin (2023)

The Model

- A family of demand curves $\mathcal{D} = \{D(p, \theta)\}_{\theta \in \Theta}$, a distribution $\mu_0 \in \Delta(\Theta)$.
 - Each $D(p, \theta)$ is decreasing, C^1 , and $R(p, \theta) = pD(p, \theta)$ is st. concave
 - $D(p, \theta) : [0, \bar{p}(\theta)] \rightarrow \mathbb{R}_+$
- An interpretation:
 - unit demand but θ is the finest information
 - 1D-PD is not possible

Market Segmentation

- Segmentation: $\sigma \in \Delta\Delta\Theta$, $\mathbb{E}\mu = \mu_0$; each μ is a “market”
- Seller chooses a price for every market
 $\mu \in \text{Supp}\sigma, p^*(\mu) \in \arg \max_{p \in \mathbb{R}_+} \mathbb{E}[R(p, \theta)]$.
- (Regulator) objective

$$V^\alpha(\sigma) = \alpha \int \int CS(p^*(\mu), \theta) d\mu d\sigma + (1 - \alpha) \int \int R(p^*(\mu), \theta) d\mu d\sigma$$

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Definition. Demand system $\mathcal{D}$ is:

1. *IMB* if for all σ, σ' with $\sigma \succsim_{\text{MPS}} \sigma'$, $V^\alpha(\sigma) \leq V^\alpha(\sigma')$,
2. *IMG* if for all σ, σ' with $\sigma \succsim_{\text{MPS}} \sigma'$, $V^\alpha(\sigma) \geq V^\alpha(\sigma')$,

IMB: Information is Monotonically Bad!

THEOREM 1

Theorem 1

Theorem. For demand system $\mathcal{D}$, let D_1, D_2 be demands in $\mathcal{D}$ with lowest and highest monopoly price p_1^*, p_2^* . $\mathcal{D}$ is IMB (IMG) if and only if:

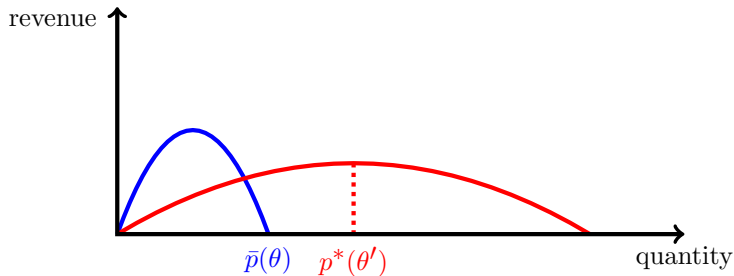
1. there is no exclusion: $p^*(\theta) \leq \bar{p}(\theta')$ for all $\theta, \theta' \in \Theta$,
2. D_1, D_2 is a basis for $\mathcal{D}$, i.e.,

$$D(p, \theta) = f_1(\theta) D_1(p) + f_2(\theta) D_2(p), \forall \theta, p \in (p_1^*, p_2^*)$$

3. $\{D_1(p), D_2(p)\}$ is IMB (IMG).

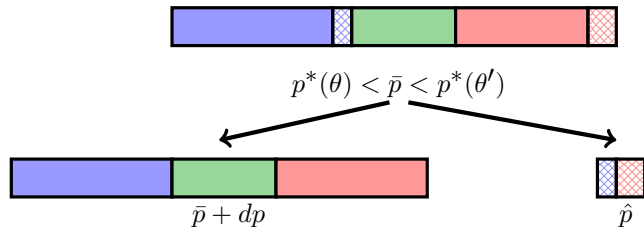
No Exclusion

- Similar to BBM



- $\Pr(\theta') \gg 0$: A segmentation that separates some θ from the rest does better.
- $\Pr(\theta) \gg 0$: A segmentation that separates some θ from the rest does worse.

Proof: Reduction to Two Demands



- Effects:
 - Composition effect: $\varepsilon (V(\hat{p}, \theta) - V(\bar{p}, \theta)) + \varepsilon' (V(\hat{p}, \theta') - V(\bar{p}, \theta'))$
 - Behavioral response of the seller:

$$dp = \frac{\varepsilon R_p(\bar{p}, \theta) + \varepsilon' R_p(\bar{p}, \theta')}{\mathbb{E}[R_{pp}(\bar{p}, \theta)]}, \quad 0 = \varepsilon R_p(\hat{p}, \theta) + \varepsilon' R_p(\hat{p}, \theta')$$

Reduction to Two Demands

- Total Effect:

$$dV \approx \frac{\frac{\mathbb{E}V_p(\bar{p}, \theta)}{\mathbb{E}R_{pp}(\bar{p}, \theta)} R_p(\bar{p}, \theta') + V(\hat{p}, \theta') - V(\bar{p}, \theta')}{R_p(\hat{p}, \theta')} \\ - \frac{\frac{\mathbb{E}V_p(\bar{p}, \theta)}{\mathbb{E}R_{pp}(\bar{p}, \theta)} R_p(\bar{p}, \theta) + V(\hat{p}, \theta) - V(\bar{p}, \theta)}{R_p(\hat{p}, \theta)}$$

- Should always have the same sign under IMB/IMG for any two types
- At $\bar{p} = \hat{p}$, $dV = 0$, dV same sign for all $\hat{p}$

$$\left. \frac{d}{d\hat{p}} dV \right|_{\hat{p}=\bar{p}} = 0 \Rightarrow \frac{V_p(\bar{p}, \theta')}{R_p(\bar{p}, \theta')} - \frac{\mathbb{E}V_p(\bar{p})}{\mathbb{E}R_{pp}(\bar{p})} \frac{R_{pp}(\bar{p}, \theta')}{R_p(\bar{p}, \theta')} = \frac{V_p(\bar{p}, \theta)}{R_p(\bar{p}, \theta)} - \frac{\mathbb{E}V_p(\bar{p})}{\mathbb{E}R_{pp}(\bar{p})} \frac{R_{pp}(\bar{p}, \theta)}{R_p(\bar{p}, \theta)}$$

- Has to hold for all pairs at all beliefs

$$\Rightarrow D(p, \theta) \in \mathbf{span} \{D(p, \theta_1), D(p, \theta_2)\}$$

Proof: Reduction to Two Demands ---

- In the paper, use duality approach of Kolotilin, Corrao, Wolitzky (2025)

Two Types

- Curvature of KG value function

$$\begin{aligned}v''(\mu) &= (p^*(\mu))^2 \mathbb{E}[V''(p^*(\mu))] \\&\quad + 2 \frac{d}{d\mu} p^*(\mu) \left[V_2'(p^*(\mu)) - V_1'(p^*(\mu)) \right] \\&\quad + \frac{d^2}{d\mu^2} p^*(\mu) \mathbb{E}[V'(p^*(\mu))]\end{aligned}$$

- Sufficient conditions for IMB (with $V = CS$): p^* convex enough, $D_2 > D_1$
- Sufficient conditions for IMG (with $V = CS$): p^* concave, $D_2 < D_1$

CES Demand

Example. Consider two demand curves $(c+p)^{-\theta_1}, (c+p)^{-\theta_2}$ for $\theta_1 > \theta_2 > 1$ and some constant $c > 0$. Then α -IMB holds if and only if $\theta_1 \leq \theta_2 + \frac{1}{2}$ for all $\alpha \geq 1/2$.

THEOREM 2

General Demand Systems

- Theorem 1: silent on arbitrary demand systems

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- Assume finite number of types $|\Theta| = N$ – possible to make it more general
- Value of a segmentation

$$W(\sigma) = \int \int \overbrace{V(p^*(\mu), \theta)}^{\text{KG's } v(\mu)} d\mu d\sigma, v : \mathbb{R}^{N-1} \rightarrow \mathbb{R}$$

General Demand Systems

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Proposition. Hessian of v , $\nabla^2 v(\mu)$ is of rank at most 2 and satisfies

$$\nabla^2 v(\mu) = -\frac{1}{\mathbb{E}R_{pp}} \left[\left(\Delta \mathbf{V}_p - \frac{d}{dp} \frac{\mathbb{E}V_p}{\mathbb{E}R_{pp}} \Delta \mathbf{R}_p \right) \Delta \mathbf{R}_p^T + \Delta \mathbf{R}_p \left(\Delta \mathbf{V}_p - \frac{d}{dp} \frac{\mathbb{E}V_p}{\mathbb{E}R_{pp}} \Delta \mathbf{R}_p \right)^T \right]$$

$\Delta \mathbf{V}, \Delta \mathbf{R}$ is the stacked version of difference between all types (but 1) and type 1.

Theorem 2

- $\underline{\lambda}(\mu)$ and $\bar{\lambda}(\mu)$ are the lowest and the highest eigenvalues of $\nabla^2 v(\mu)$

Theorem 2. Suppose $\mathcal{D}$ is finite and there is no exclusion. For any two $\sigma \succ_{MPS} \sigma'$,

$$\frac{1}{2} \min_{\mu \in \Delta\Theta} \underline{\lambda}(\mu) \leq \frac{V^\alpha(\sigma) - V^\alpha(\sigma')}{\text{var}_\sigma(\|\mu\|_2) - \text{var}_{\sigma'}(\|\mu\|_2)} \leq \frac{1}{2} \max_{\mu \in \Delta\Theta} \bar{\lambda}(\mu).$$

The bounds are tight.

A CES example

Implications of the first result:

1. $\frac{1}{2}$ -IMB holds for $\{(c+p)^{-1.5}, (c+p)^{-2}\}$.
2. $\frac{1}{2}$ -IMB does not hold for $\{(c+p)^{-1.5}, (c+p)^{-2}, (c+p)^{-\theta}\}$, $1.5 < \theta < 2$.

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Implication of the second result for total surplus:

θ	Lower bound	Upper bound
1.9	-0.460	4.6×10^{-5}
1.8	-0.395	1.47×10^{-4}
1.7	-0.332	2.19×10^{-4}
1.6	-0.282	1.48×10^{-4}

IMPLICATIONS

Example: The class $aD + b$ _____

Proposition. Consider $\mathcal{D} = \{a(\theta)D(p) + b(\theta)\}_{\theta}$. α -IMB (α -IMG) holds if and only if

$$(2\alpha - 1)p + \alpha \frac{pD'(p)}{R''(p)}$$

is increasing (decreasing) over $[\min_{\theta} p^*(\theta), \max_{\theta} p^*(\theta)]$.

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- $\alpha = 1/2$, $V^{\alpha} = TS$:
 - 1/2-IMB holds if and only if $-p^2 D'(p)$ is log-concave.
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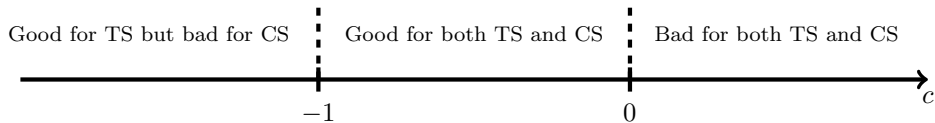
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- Three cases for how information affects CS and TS. $D'(p) = -p^{-2}(1 + cp)^c$

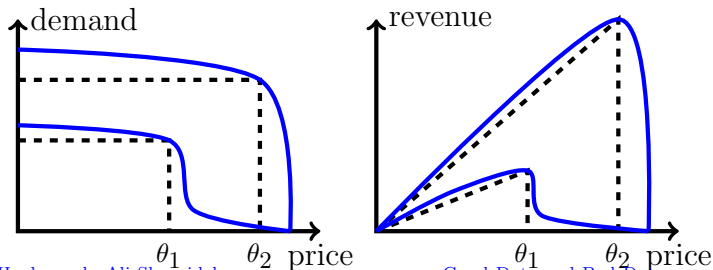


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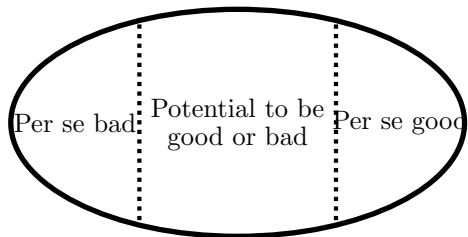
What if we approach unit-demand curves without violating no exclusion? _____

Corollary. Consider $\mathcal{D}^\epsilon$ that uniformly converges to a family of unit-demand curves as $\epsilon \rightarrow 0$ and revenue is concave for every $\epsilon > 0$. For small enough ϵ , the partial-inclusion condition is violated and therefore information is neither monotonically good nor bad.



Conclusion

A characterization of:



- More examples in the paper
- Methodologically:
 - We apply modern tools (concavification and duality) to study a classical problem
 - Bounds

THANK YOU!