

# Buyer-Optimal Demand and Monopoly Pricing

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## Model

- there is a seller (of a single object) and a buyer
- buyer's value,  $v$ ,  $\sim$  CDF  $F$  on  $[0, 1]$
- seller sets price  $p$
- buyer observes  $v$  ( $\sim F$ )
- and accepts  $p \Leftrightarrow v \geq p$
- seller's profit is  $p$ , buyer's payoff is  $v - p$

## Model I

- there is a seller (of a single object) and a buyer
- buyer chooses a CDF  $F$  supported on  $[0, 1]$
- seller observes  $F$  and sets price  $p$
- buyer observes  $v (\sim F)$
- and accepts  $p \Leftrightarrow v \geq p$
- seller's profit is  $p$ , buyer's payoff is  $v - p$

## Model II

- there is a seller (of a single object) and a buyer
- buyer's value,  $v$ ,  $\sim$  CDF  $F$  on  $[0, 1]$
- buyer observes signal  $s$  about  $v$
- seller sets price  $p$
- and accepts  $p \Leftrightarrow E(v|s) \geq p$
- seller's profit is  $p$ , buyer's payoff is  $v - p$

## Notations

$D(F, p) = 1 - F(p) + \Delta(F, p)$  : demand at  $p$

$\Delta(F, v)$  : atom at  $v$

$\Pi(F) = \max_p pD(F, p)$

$P(F) = \arg \max_p pD(F, p)$  : profit maximizing prices

$U(F, p) = \int_p^1 v - pdF(v)$ .

## Reduce the problem to a one-dimensional one

1. For each  $p$ , find  $F_p$  which maximizes  $U$  s.t.  $p \in P(F_p)$ .
2. Find  $p^*$  s.t.  $F_{p^*}$  maximizes  $U$  in the class  $\{F_p\}_p$ .

## Equal-revenue distributions

For each  $\pi \in (0, 1]$ , let  $F_\pi$  be defined as follows:

$$F_\pi(v) = \begin{cases} 0 & \text{if } v \in [0, \pi], \\ 1 - \frac{\pi}{v} & \text{if } v \in (\pi, 1), \\ 1 & \text{if } v = 1. \end{cases}$$

**Note:**

$$(1) \quad pD(F_\pi, p) = p[1 - F_\pi(p)] = p(\pi/p) = \pi$$

$$(2) \quad \Pi(F_\pi) = \pi \text{ and } P(F_\pi) = [\pi, 1].$$

## Lemma

Suppose  $G \in \mathcal{F}$  and  $p \in P(G)$ . Then

(i)  $F_p(v) \leq G(v)$  for all  $v$ .

(ii)  $U(F_p, p) \geq U(G, p)$  and the inequality is strict if  $F_p \neq G$



Proof of (i)

Since  $p \in P(G)$ ,

$$vD(G, v) = v(1 - G(v) + \Delta(G, v)) \leq pD(G, p).$$

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$\Delta(G, p) \in [0, 1]$  and  $D(G, p) \leq 1$ , so

$$1 - \frac{p}{v} = F_{\pi}(v) \leq G(v).$$

Proof of (ii)

$$\begin{aligned} U(F_p, p) &= \int_p^1 v - p dF_p(v) \\ &\geq \int_p^1 v - p dG(v) = U(G, p) \end{aligned}$$

## Theorem

In the unique equilibrium outcome,

- $F^* = F_{1/e}$
- $p^* = U(F^*, p^*) = \Pi(F^*) = 1/e.$

## Proof

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(2) Buyer's payoff:

$$\begin{aligned} U(F_\pi, \pi) &= \int_\pi^1 v - \pi dF_\pi(v) = \int_\pi^1 v f_\pi(v) dv + \Delta(F_\pi, 1) - \pi \\ &= \int_\pi^1 \frac{\pi}{v} dv = -\pi \log \pi, \end{aligned}$$

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- ▶  $-\pi \log \pi$  is maximized at  $1/e$
- ▶  $U(F_{1/e}, 1/e) = -1/e \log 1/e = 1/e$
- ▶  $\Pi(F_{1/e}) = 1/e$ .



## Welfare

- first-best total surplus: 1
- equilibrium total surplus:  $2/e (\approx 0.73)$

⇒ welfare loss:  $\approx 27\%$

## Literature Review

### **Information rent in hold-up problems:**

Lau (2008) and Hermalin and Katz (2009).

### **Equal-Revenue Distribution:**

Bergemann and Schlag (2008): min-max regret criterion

Neeman (2003) minimizes profit/ expected value in auctions

Hart and Nisan (2012) approximate the seller's maximum revenue in a multiple-item auction.

## An extension

- What if  $Ev \leq \mu$ ?

## Model II

- there is a seller (of a single object) and a buyer
- buyer's value,  $v$ ,  $\sim$  CDF  $F$   $[0, 1]$ ,  $Ev = \mu$
- buyer observes signal  $s$  about  $v$
- seller sets price  $p$
- and accepts  $p \Leftrightarrow E(v|s) \geq p$
- seller's profit is  $p$ , buyer's payoff is  $v - p$

without loss:  $E(v|s) = s \sim G [0, 1]$

$\Leftrightarrow v = s + \varepsilon_s$  for some  $\varepsilon_s$  s.t.  $E(\varepsilon_s|s) = 0$

$\Leftrightarrow F$  is a mean-preserving spread of  $G$

$$\mathcal{G}_F = \left\{ G \in \mathcal{G} : \int_0^x F(v) dv \geq \int_0^x G(s) ds \text{ for all } x \in [0, 1], \int_0^1 s dG(s) = \mu \right\}.$$

## Buyer's Problem

$$\max_{G \in \mathcal{G}_F} \int_p^1 s - p dG(s)$$

$$\text{s.t. } p \in \arg \max_s s D(G, s).$$

## Truncated Pareto

$$G_q^B(s) = \begin{cases} 0 & \text{if } s \in [0, q), \\ 1 - \frac{q}{s} & \text{if } s \in [q, B), \\ 1 & \text{if } s \in [B, 1]. \end{cases}$$

## Lemma

For all  $G \in \mathcal{G}_F$ ,  $p \in P(G) \exists! B \in [\pi(G), 1]$  such that

(i)  $G$  is a mean-preserving spread of  $G_\pi^B$ ,

(ii)  $G_\pi^B \in \mathcal{G}_F$ ,

(iii)  $\int_\pi^1 s - \pi dG_\pi^B(s) \geq \int_p^1 s - p dG(s)$ , strict if  $D(G, p) < 1$ .



## Proof

Step 1:  $\exists! B$  s.t.  $\int s dG_{\pi}^B(s) = \mu$ .

$p \in P(G)$ , so  $sD(G, s) \leq \pi$  for all  $s \in [0, 1]$ :

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$$1 - \frac{\pi}{s} + \Delta(G, s) \leq G(s) \Rightarrow G_{\frac{1}{\pi}}(s) \leq G(s).$$

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$$1 - \frac{\pi}{s} + \Delta(G, s) \leq G(s) \Rightarrow G_{\pi}^1(s) \leq G(s).$$

Hence

$$\int_0^1 sdG_{\pi}^1(s) \geq \int_0^1 sdG(s) = \mu \geq pD(G, p) = \pi = \int_0^1 sdG_{\pi}^{\pi}(s).$$

$\int_0^1 sdG_{\pi}^B(s)$  is strictly increasing  $\Rightarrow B \in [\pi, 1]$  s.t.  $\int_0^1 sdG_{\pi}^B(s) = \mu$ .

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If  $s \geq B$  then

$$\begin{aligned} \int_0^s G(x) dx &= [1 - \mu] - \int_s^1 G(x) dx \\ &\geq [1 - \mu] - (1 - s) \\ &= [1 - \mu] - \int_s^1 G_{\pi}^B(x) dx = \int_0^s G_{\pi}^B(x) dx. \end{aligned}$$

Part (ii):  $G_{\pi}^B \in \mathcal{G}_F$

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Part (iii):

$$\text{WHTS: } \int_{\pi}^1 s - \pi dG_{\pi}^B(s) \geq \int_p^1 s - pdG(s), \text{ strict if } D(G, p) < 1$$



Part (iii):

WHTS:  $\int_{\pi}^1 s - \pi dG_{\pi}^B(s) \geq \int_p^1 s - pdG(s)$ , strict if  $D(G, p) < 1$

$$\int_{\pi}^1 s - \pi dG_{\pi}^B(s) = \mu - \pi \geq \int_p^1 s - pdG(s)$$

## Lemma

For all  $G \in \mathcal{G}_F$ ,  $p \in P(G) \exists! B \in [\pi(G), 1]$  such that

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- We can restrict attention to  $\{G_\pi^B\}$
- Buyer's payoff if  $G_\pi^B$ :  $\mu - \pi$
- $p^* = \min \{ \pi : \exists B \in [\pi, 1] \text{ s.t. } G_\pi^B \in \mathcal{G}_F \}$

## Theorem

$(G_{p^*}^{B^*}, p^*)$  is buyer-optimal. If  $(G, p)$  is buyer-optimal, then

(i)  $p = p^*$ ,

(ii)  $D(G, p) = 1$  and

(iii)  $G$  is a MPS of  $G_{p^*}^{B^*}$ .

$$\pi = pD(G, p)$$

By the Lemma

$$\begin{aligned} \int_p^1 s - pdG(s) &\leq \int_\pi^1 s - \pi dG_\pi^B(s) = \mu - \pi \\ &\leq \mu - p^* = \int_{p^*}^1 s - p^* dG_{p^*}^{B^*}(s). \end{aligned}$$

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The second inequality is strict unless  $\pi = p^* \Rightarrow$  (i).

Since  $\pi = p^*$ , part (i) of Lemma  $\Rightarrow$  (iii).

**Observation.**

Suppose that  $G$  is a signal distribution. Then  $\Pi(G) \geq p^*$ .

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## Proof.

By the lemma,  $\exists B \in [\Pi(G), 1]$  s.t.

(i)  $G_{\Pi(G)}^B$  is a signal distribution and

(ii)  $\Pi(G) \in P\left(G_{\Pi(G)}^B\right)$ .

Hence,  $\Pi(G) \geq p^*$ .

Example:  $F(v) = v$

**perfect learning:**  $p = 0.5$ ,  $D(F, p) = 0.5$ ,  $U(F, p) = 0.125$ ,  $DWL = 0.125$

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## Related Questions

1. Optimal Distributions in the Moussa-Rosen model
2. Intermediation
3. Costly Learning