Bilateral Trade with Costly Information Acquisition

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Bilateral trade problem with information acquisition.

- Principal proposes a trading mechanism,
- Buyer and Seller privately acquire payoff-relevant information,
- Information acquisition is costly and flexible,
- Information acquisition can be arbitrarily correlated across players.

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What do we do?

- Provide implementability conditions,
- Characterize info structures consistent with allocational efficiency.
 - Application: subsidy minimization for efficient trade.

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Endogenous information acquisition can help

- Bikhchandani (2010): FSE \Rightarrow incentives to acquire info about others.
- Bikhchandani and Obara (2017): "inflexible" info \Rightarrow FSE (not always).
 - "inflexible" = finitely many conditionally independent signals.

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Flexible endogenous information acquisition addresses the challenge

- Also interesting in its own right.
- Growing literature on flexible info in fixed games.

Tractable characterization of implementabilty

• Finite dimensional system of equations and inequalities.

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Application: subsidy minimization for efficient trade

- Perfect correlation forces the designer to give up surplus.
 - Compensate for the cost of information acquisition ⇒ no gross FSE.
 - Prevent further information acquisition ⇒ no net FSE.

Model: setup

- Principal and two players: Buyer and Seller.
- Buyer and Seller can trade an indivisible good with quality $v \in V$.
 - V is finite.
 - Buyer's valuation is $u^b(v)$, Seller's valuation is $u^s(v)$ \Rightarrow Interdependent values (nests private and pure common values).
- Principal collects revenue from/subsidizes trade between the players.

Model: information

The true quality $v \in V$ is unknown to anyone at the beginning.

We need a model where players jointly determine info structrure:

State
$$v$$
 s_1^s s_2^s ... s_J^s s_1^b $\alpha_{11}(v)$ $\alpha_{12}(v)$... $\alpha_{1J}(v)$ s_2^b $\alpha_{21}(v)$ $\alpha_{22}(v)$... $\alpha_{2J}(v)$ s_I^b $\alpha_{I1}(v)$ $\alpha_{I2}(v)$... $\alpha_{IJ}(v)$

 \Rightarrow player's actions = random variables.

Commonly known to everyone at the beginning:

- Probability space $(X, \mathcal{F}, \mathbb{P})$, where $X = [0, 1] \ni x$ and \mathbb{P} is uniform.
- A random variable $\mathbf{V}: X \to V$, induces a common prior μ_0 on V.

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Players acquire info about $v \in V$ by choosing other random var's.

- Players have access to a countably infinite set of signal realizations.
- A signal of player $p \in \{b, s\}$ is a pair $\sigma^p = (S^p, \mathbf{S}^p)$, where
 - S^p is a finite non-empty subset of \mathbb{N} , $S^p: X \to S^p$ is a random variable.

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 - S^p is a finite non-empty subset of \mathbb{N} , $\mathbf{S}^p: X \to S^p$ is a random variable.
- $(\mathbf{V}, \sigma^b, \sigma^s)$ induces a joint distribution α over $V \times S^b \times S^s$.
 - Any Bayes-plausible (i.e. marg $_{V}\alpha = \mu_{0}$) α can be induced.

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Signals are costly; $C(\sigma^p)$ is posterior separable.

• **Today:** $C(\sigma^p)$ is proportional to reduction in entropy.

Model: timing

- Nature draws $x \in X$ uniformly, but nobody observes it.
- 2 Principal designs a trading mechanism (M, q, t)
 - $M = M^b \times M^s$; M^p is the message space of player p.
 - $q=(q^b,q^s);$ $q^p:M\to [0,1]$ is the allocation function of player p.• $t=(t^b,t^s);$ $t^p:M\to \mathbb{R}$ is the payment function of player p.
- **3** Each player *p* privately chooses $\sigma^p = (S^p, \mathbf{S}^p)$.
- **4** Each player p privately observes $s^p = \mathbf{S}^p(x)$ and sends $m^p \in M^p$.
- **5** Allocations and payments are determined according to (q, t); State v = V(x) is realized.

Roadmap

- Revelation principle
- 2 Implementability
- 3 Information structures consistent with efficient trade
- 4 Application: subsidy minimization for efficient trade
- Concluding remarks

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Revelation principle

Unlike in standard mechanism design, type space is endogenous.

- Players choose signals in response to principal's mechanism.
- Players' signal realizations become their "types".
- Principal selects equilibrium ⇒ correctly anticipates players' choice of signals ⇒ can ask about their signal realizations directly.

Revelation principle

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Revelation principle: it is w.l.o.g. to consider direct mechanisms.

• Players could report one of their signal realizations or abstain:

$$M^b = S^b \cup \{m_\emptyset^b\}, \qquad M^s = S^s \cup \{m_\emptyset^s\},$$

where S^b and S^s are endogenously determined.

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Implementability lemma

Lemma (Implementability for the buyer)

 (α,q,t) is implementable for the buyer iff there are multipliers $\lambda_j^b(v)$ for all $s_i^s \in S^s$ and $\phi_{ii}^b(v)$ for all $(s_i^b,s_i^s) \in S^b \times S^s$ and all $v \in V$:

$$(\mathsf{ST}^b) \qquad \underbrace{q^b_{ij} u^b(v) - t^b_{ij}}_{\frac{\partial U^b}{\partial \alpha_{ij}(v)}} - \underbrace{\log \left(\mu^b_i(v)\right)}_{\frac{\partial C^b}{\partial \alpha_{ij}(v)}} - \lambda^b_j(v) + \phi^b_{ij}(v) = 0,$$

$$(\mathsf{DF}^b) \quad \phi_{ij}^b(v) \geq 0,$$

(CS^b)
$$\alpha_{ij}(\mathbf{v})\phi_{ij}^{\mathbf{b}}(\mathbf{v}) = 0,$$

$$(\mathsf{NA}^b) \qquad \sum_{v \in V} \exp\big(-\min_j \{\lambda_j^b(v)\}\big) \le 1.$$

Analogous conditions apply to the seller. Seller's in

Seller's implementability

Buyer's problem

Consider a candidate (α, q, t) with α induced by some (σ^b, σ^s) .

- Does Buyer have a profitable deviation $\tilde{\sigma}^b$?
- l+1 actions under $\sigma^b \Rightarrow \tilde{\sigma}^b$ with l+1 realizations are w.l.o.g.
- $(\tilde{\sigma}^b, \sigma^s)$ will induce an alternative information structure $\tilde{\alpha}$.
- Can rewrite the best deviation problem in terms of $\tilde{\alpha}$:

$$\mathcal{BD}^{b}(\alpha, q, t) = \underset{\tilde{\alpha}, \tilde{S}^{b}}{\operatorname{argmax}} \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{v \in V} \tilde{\alpha}_{ij}(v) (q_{ij}^{b} u^{b}(v) - t_{ij}^{b}) - c^{b}(\tilde{\alpha}),$$

$$(1) \quad \tilde{S}^{b} = S^{b} \cup \{s_{0}^{b}\}, \quad \tilde{\alpha} \in \Delta(\tilde{S}^{b} \times S^{s} \times V);$$

- (2) $\operatorname{marg}_{S^s \times V} \tilde{\alpha} = \operatorname{marg}_{S^s \times V} \alpha$.

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$$(1) \quad \tilde{S}^{b} = S^{b} \cup \{s_{\emptyset}^{b}\}, \quad \tilde{\alpha} \in \Delta(\tilde{S}^{b} \times S^{s} \times V);$$

(2)
$$\operatorname{marg}_{S^s \times V} \tilde{\alpha} = \operatorname{marg}_{S^s \times V} \alpha$$
.

Implementability condition for the buyer: $(\alpha, S^b) \in \mathcal{BD}^b(\alpha, q, t)$.

Solution to Buyer's problem

We split Buyer's deviations into two classes:

- Class 1: induce different $\tilde{\alpha}$'s over the same signal realizations S^b .
- Class 2: augment S^b with s_{\emptyset}^b with positive probability.

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Our approach:

- **1** Solve **Class 1**-problem, characterize solution in terms of λ , ϕ .
- Show the following:

Lemma

If α solves Class 1-problem, then (α, S^b) solves Class 2-problem iff

$$(\mathsf{NA}^b) \qquad \sum_{v \in V} \exp \big(- \min_j \{ \lambda_j^b(v) \} \big) \leq 1.$$

Class 1-problem

$$\alpha \in \operatorname{argmax} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{v \in V} \tilde{\alpha}_{ij}(v) (q_{ij}^{b} u^{b}(v) - t_{ij}^{b}) - c^{b}(\tilde{\alpha}),$$

(1)
$$\tilde{\alpha}_{ij}(v) \geq 0;$$
 $\phi_{ij}^b(v)$

(2)
$$\sum_{i=1}^{l} \tilde{\alpha}_{ij}(v) = \sum_{i=1}^{l} \alpha_{ij}(v). \qquad \lambda_{j}^{b}(v)$$

Convex optimization problem (concave objective + affine constraints) \Rightarrow KKT conditions are necessary and sufficient.

Class 2-lemma

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Proof sketch: illustrate the proof using a $2 \times 2 \times 2$ example.

State <u>v</u>	s_1^s	s_2^s
s_1^b	$\underline{\alpha}_{11} - \epsilon \underline{\beta}_{11}$	$\underline{\alpha}_{12} - \epsilon \underline{\beta}_{12}$
s_2^b	$\underline{\alpha}_{21} - \epsilon \underline{\beta}_{21}$	$\underline{\alpha}_{22} - \epsilon \underline{\beta}_{22}$
s_\emptyset^b	$\epsilon \sum_{i=1}^{2} \underline{\beta}_{i1}$	$\epsilon \sum_{i=1}^{2} \underline{\beta}_{i2}$

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 $G_{\alpha}(\epsilon\beta)$ is the gain from deviation in direction $\epsilon\beta$ from α .

 $MG_{\alpha}(\beta) \equiv \lim_{\epsilon \to 0} \frac{1}{\epsilon} G_{\alpha}(\epsilon \beta)$ is the marginal gain.

Proof of Class 2 lemma

We prove the contrapositive statement:

- Suppose there is a deviation with a positive gain $G_{\alpha}(\beta) > 0$.
- Convexity of cost function $\Rightarrow [G_{\alpha}(\beta) > 0 \Rightarrow MG_{\alpha}(\beta) > 0]$.
- $MG_{\alpha}(\beta)$ can be computed in closed form:

$$\begin{split} MG_{\alpha}(\beta) &= -\sum_{i,j,v} \overbrace{\beta_{ij}(v)}^{0 \text{ if } \alpha_{ij}(v) = 0} \times \left[\underbrace{q_{ij}^b u^b(v) - t_{ij}^b - \log\left(\mu_i^b(v)\right)}_{=\lambda_j^b(v) \text{ as long as } \alpha_{ij}(v) > 0, \text{ by KKT}} \right] + F(\beta) \\ &= -\sum_{i,j,v} \beta_{ij}(v) \lambda_j^b(v) + F(\beta). \end{split}$$

• Let $\beta^* = \operatorname{argmax}_{\beta} MG_{\alpha}(\beta; \lambda^b)$, then $MG_{\alpha}(\beta^*; \lambda^b) > 0 \Rightarrow \neg (NA^b)$

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Information structures consistent with efficient trade

 $V = \{\underline{v}, \overline{v}\}$ and gains from trade at every quality level: $u^b(v) > u^s(v)$.

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Proposition (Efficiency \Rightarrow Essentially perfect correlation)

If α is consistent with efficient trade, then α has the following form:

State v	s_1^s		s_k^s		$s_{I-\ell}^s$		s_l^s
s_1^b	α_{11}		α_{1k}		0		0
:	:	٠.	:	٠	:	٠	: :
s_k^b	α_{k1}		$\alpha_{\it kk}$		0		0
:	:	٠	:	٠	:	٠	:
$s_{I-\ell}^b$	0		0		$\underline{\alpha}_{I-\ell,I-\ell}$		$\underline{\alpha}_{I-\ell,I}$
:	:	٠	:	٠	:	٠	:
s_l^b	0		0		$\underline{\alpha}_{I,I-\ell}$		$\underline{\alpha}_{II}$

and the posteriors within each block are equal to each other.

Proof sketch

Lemma (Sets of equal posteriors for the buyer)

For all $j \in S^s$ there exists $\mathcal{I}^*(j) \subseteq S^b$ s.t. $\underline{\alpha}_{ij} = 0$ for all $i > \max \mathcal{I}^*(j) \equiv \overline{i}^*(j)$, and $\overline{\alpha}_{ij} = 0$ for all $i < \min \mathcal{I}^*(j) \equiv \underline{i}^*(j)$. Moreover, for any $i, i' \in \mathcal{I}^*(j)$ we get $\underline{\mu}^b_i = \underline{\mu}^b_{i'}$ and $\overline{\mu}^b_i = \overline{\mu}^b_{i'}$.

<u>v</u>	s_1^s s_j^s	s ^s	\overline{v}	s ₁ ^s	s;	 s ^s
s_1^b	$\underline{\alpha}_{1j}$		s_1^b		0	
:	:		:		:	
$s_{\overline{i}^*(j)-1}^b$	$\overline{\underline{lpha}}_{ar{i}^*(j)-1,j}$		$s^b_{ar{i}^*(j)-1}$		0	
$s_{\underline{i}^*(j)}^b$			$s_{\underline{i}^*(j)}^b$			
:			÷			
$s_{\overline{i}^*(j)}^b$			$s_{i^*(j)}^b$			
$s_{\overline{i}^*(j)+1}^b$	0		$s_{\bar{i}^*(j)+1}^b$		$\overline{\alpha}_{\overline{i}^*(j)+1,j}$	
:	<u>:</u>		:		:	
s_I^b	0		s_I^b		\overline{lpha}_{Ij}	

- Define $\overline{i}^*(j) \equiv \max\{i | \underline{\alpha}_{ij} > 0\}, \ \mathcal{I}^*(j) \equiv \{i | \overline{\mu}_i^b = \overline{\mu}_{\overline{i}^*(j)}^b\}.$
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<u>v</u>	$\left \begin{array}{cccccccccccccccccccccccccccccccccccc$	\overline{v}	$ s_1^s \ldots s_j^s \ldots s_j^s $
s_1^b	\underline{lpha}_{1j}	s_1^b	???
:	÷	:	:
$s_{ar{i}^*(j)-1}^b$	$\alpha_{\bar{i}^*(j)-1,j}$	$s_{\overline{i}^*(j)-1}^b$????
$s_{\underline{i}^*(j)}^b$		$s_{\underline{i}^*(j)}^b$	
:		:	
$s_{ar{i}^*(j)}^b$		$s_{\overline{i}^*(j)}^b$	
$s_{i^*(j)+1}^b$	0	$s_{ar{i}^*(j)+1}^b$	$\overline{lpha}_{l}^{ aust}(j)+1,j$
:	<u>:</u>	:	:
s_I^b	0	s_I^b	\overline{lpha}_{lj}

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<u>v</u>	$s_1^s \dots s_j^s \dots s_J^s$	\overline{v}	$s_1^s \dots s_j^s \dots s_J^s$
s_1^b	\underline{lpha}_{1j}	s_1^b	???
:	<u>:</u>	:	<u>:</u>
$s_{\overline{i}^*(j)-1}^b$	$\underline{\alpha}_{\overline{i}^*(j)-1,j}$	$s_{ar{i}^*(j)-1}^b$????
$\frac{s_{\bar{i}^*(j)-1}^b}{s_{\underline{i}^*(j)}^b}$		$s_{\underline{i}^*(j)}^b$	
:		:	
$s_{\overline{i}^*(j)}^b$		$s_{\overline{i}^*(j)}^b$	
$s_{\overline{i}^*(j)+1}^b$	0	$s_{\overline{i}^*(j)+1}^b$	$\overline{lpha}_{ec{l}}^{-*}(j){+}1{,}j$
:	<u> </u>	:	<u>:</u>
s_I^b	0	s_I^b	\overline{lpha}_{lj}

• Suppose for a contradiction that $\exists i < \underline{i}^*(j)$ such that $\overline{\alpha}_{ij} > 0$.

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- $\overline{\mu}_i^b > \overline{\mu}_{\overline{i}^*(j)}^b$ since $i > \min \mathcal{I}^*(j)$ and posteriors are the same in $\mathcal{I}^*(j)$.
- Stationarity (combined with CS and DF) is given by:

$$(\mathsf{ST}^b_{ij}) \ \underline{u}^b - \log\left(\underline{\mu}^b_i\right) - \underline{\lambda}^b_j \le t^b_{ij}, \quad (\mathsf{ST}^b_{\overline{i}^*(j),j}) \ \underline{u}^b - \log\left(\underline{\mu}^b_{\overline{i}^*(j)}\right) - \underline{\lambda}^b_j = t^b_{\overline{i}^*(j),j},$$

$$\overline{u}^b - \log\left(\overline{\mu}^b_i\right) - \overline{\lambda}^b_j = t^b_{ij}. \qquad \overline{u}^b - \log\left(\overline{\mu}^b_{\overline{i}^*(j)}\right) - \overline{\lambda}^b_j \le t^b_{\overline{i}^*(j),j}.$$

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• $(ST^b_{ij}) + (ST^b_{\overline{i}^*(j),j}) \Rightarrow \overline{\mu}^b_i \leq \overline{\mu}^b_{\overline{i}^*(j)}.$

Proof sketch

Lemma (Sets of equal posteriors for the seller)

For all $i \in S^b$ there exists $\mathcal{J}^*(i) \subseteq S^s$ s.t. $\underline{\alpha}_{ij} = 0$ for all $j > \max \mathcal{J}^*(i) \equiv \overline{j}^*(i)$, and $\overline{\alpha}_{ij} = 0$ for all $j < \min \mathcal{J}^*(i) \equiv \underline{j}^*(i)$. Moreover, for any $j, j' \in \mathcal{J}^*(i)$ we get $\underline{\mu}_i^b = \underline{\mu}_{i'}^b$ and $\overline{\mu}_i^b = \overline{\mu}_{i'}^b$.

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• Introduce $\hat{\mathcal{J}}_1 \equiv \{j | \overline{\mu}_j = \overline{\mu}_1^b \}$ and $\tilde{\mathcal{I}}_1 \equiv \{i | \mathcal{J}^*(i) = \hat{\mathcal{J}}_1 \}$.

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Lemma: $\hat{\mathcal{I}}_1 = \tilde{\mathcal{I}}_1$ and $\hat{\mathcal{J}}_1 = \tilde{\mathcal{J}}_1$.

Corollary

- For all $i \in \hat{\mathcal{I}}_1$ and $j \notin \hat{\mathcal{J}}_1$ we have $\underline{\alpha}_{ii} = \overline{\alpha}_{ij} = 0$.
- ② For all $i \notin \hat{\mathcal{I}}_1$ and $j \in \hat{\mathcal{J}}_1$ we have $\underline{\alpha}_{ii} = \overline{\alpha}_{ij} = 0$.

Roadmap

- Revelation principle
- 2 Implementability
- 3 Information structures consistent with efficient trade
- 4 Application: subsidy minimization for efficient trade
- Concluding remarks

Subsidy minimization \Rightarrow perfect correlation is w.l.o.g.

Corollary (Perfect correlation)

If $(\alpha', I', J'; t'; \phi', \lambda')$ is feasible in the subsidy minimization problem, then there is $(\alpha, I, J; t; \phi; \lambda)$, which is also feasible and achieves the same objective value, but I = J and $\alpha_{ij} = \overline{\alpha}_{ij} = 0$ for $i \neq j$.

State \underline{v}	s_1^s	s_2^s		s;	State \overline{v}	s_1^s	s_2^s		s;
s_1^b	$\underline{\alpha}_1$	0		0	s_1^b	$\overline{\alpha}_1$	0		0
s_2^b	0	$\underline{\alpha}_2$		0	s_2^b	0	\overline{lpha}_{2}		0
:	:	:	٠.	:		:	:	٠	:
								•	
s_l^b	0	0		$\underline{\alpha}_{I}$	s_l^b	0	0		$\overline{\alpha}_I$

Proof: merge signal realizations with equal posteriors.

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State \underline{v}	s_1^s	s_2^s		s;		State \overline{v}	s_1^s	s_2^s		s _l s
s_1^b	$\underline{\alpha}_1$	0		0	_	s_1^b	$\overline{\alpha}_1$	0		0
s_2^b	0	$\underline{\alpha}_{2}$		0		s_2^b	0	\overline{lpha}_{2}		0
:	:	:	٠	:		:	:	:	٠	į
s_l^b	0	0		α_I		s_l^b	0	0		$\overline{\alpha}_I$

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Two design concerns for the principal: IC and total cost of info.

- IC: More correlated signals \Rightarrow easier to incentivize truthful reporting.
- Total cost: Less correlated signals ⇒ more info at lower cost.

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State \underline{v}	s_1^s	s_2^s		s _l s	State \overline{v}	s_1^s	s_2^s		s _l s
s_1^b	$\underline{\alpha}_1$	0		0	s_1^b	$\overline{\alpha}_1$	0		0
s_2^b	0	$\underline{\alpha}_2$		0	s_2^b	0	\overline{lpha}_2		0
:	:	:	٠.	:	:	:	:		:
•		•	•	•	•			•	•
s_l^b	0	0		$\underline{\alpha}_I$	s_l^b	0	0		$\overline{\alpha}_I$

Proof: merge signal realizations with equal posteriors.

Two design concerns for the principal: IC and total cost of info.

- IC: More correlated signals ⇒ easier to incentivize truthful reporting.
- Total cost: Less correlated signals ⇒ more info at lower cost.

IC overwhelmingly dominates \Rightarrow pay for the same info twice!

Subsidy minimization as Bayesian persuasion

$$\max_{\{\tau,\mu;I;\Lambda\}} \sum_{i=1}^{I} \tau_{i} T(\underline{\mu}_{i}, \overline{\mu}_{i}; \Lambda^{b}, \Lambda^{s})$$

$$(\mathsf{BP}) \qquad \sum_{i=1}^{I} \tau_{i} \underline{\mu}_{i} = \underline{\mu}_{0}, \qquad \sum_{i=1}^{I} \tau_{i} \overline{\mu}_{i} = \overline{\mu}_{0};$$

$$(\mathsf{NA}^{b}) \qquad \exp\left(-\underline{\Lambda}^{b}\right) + \exp\left(-\overline{\Lambda}^{b}\right) = 1,$$

$$(\mathsf{NA}^{s}) \qquad \exp\left(-\underline{\Lambda}^{s}\right) + \exp\left(-\overline{\Lambda}^{s}\right) = 1.$$

$$\overline{\alpha}_{i} \quad \text{and} \quad \Lambda^{p} = \min\left\{\lambda^{p}\right\} \text{ and } \overline{\Lambda}^{p} = \min\left\{\overline{\lambda}^{p}\right\}$$

where $\underline{\tau_i} = \underline{\alpha}_i + \overline{\alpha}_i$, and $\underline{\Lambda}^p = \min_i \left\{ \underline{\lambda}_i^p \right\}$ and $\overline{\Lambda}^p = \min_i \left\{ \overline{\lambda}_i^p \right\}$.

For a fixed Λ , this is a Bayesian persuasion problem \Rightarrow look at concave closure of T. Concave closure of T

Example: symmetric problem

Definition (Symmetric subsidy minimization problem)

A subsidy minimization problem is symmetric if the prior is uniform, i.e.

$$\mu_0 = \overline{\mu}_0 = 0.5$$
, and $\overline{u}^b - \underline{u}^b = \overline{u}^s - \underline{u}^s \equiv \Delta u$.

Example: symmetric problem

Definition (Symmetric subsidy minimization problem)

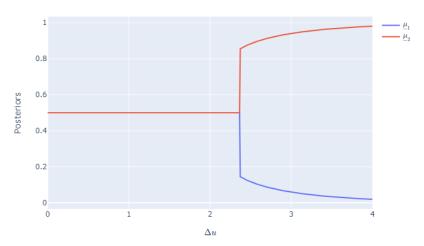
A subsidy minimization problem is symmetric if the prior is uniform, i.e. $\underline{\mu}_0 = \overline{\mu}_0 = 0.5$, and $\overline{u}^b - \underline{u}^b = \overline{u}^s - \underline{u}^s \equiv \Delta u$.

Symmetric solution:

$$1-\underline{\mu}_1^* = \underline{\mu}_2^* = \begin{cases} \underline{\underline{\mu}_0} = 0.5 & \text{for } 0 < \underline{\Delta} \underline{u} \leq \underline{\Delta} \underline{u}^*, \\ \frac{3}{4} + \frac{1}{4}\sqrt{9 + 8\frac{\exp(\underline{\Delta} \underline{u})}{1 - \exp(\underline{\Delta} \underline{u})}} & \text{for } \underline{\Delta} \underline{u} > \underline{\Delta} \underline{u}^*, \end{cases}$$

where Δu^* is obtained numerically.

Symmetric solution, illustration



Roadmap

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Concluding remarks

- Bilateral trade problem with information acquisition.
- Information acquistion is costly and flexible.
- Tractable characterization of implementability.
- Characterization of info structures consistent with efficient trade.
- Solution to subsidy minimization problem.

Appendix

- 6 Implementability for the seller
- Proof of Class 2 lemma

8 Subsidy minimization as Bayesian persuasion: solution

Implementability for the seller

Lemma (Implementability for the seller)

 (α, q, t) is globally implementable for the seller iff there are multipliers $\lambda_i^s(v)$ for all $s_i^s \in S^s$ and $\phi_{ii}^s(v)$ for all $(s_i^b, s_i^s) \in S^b \times S^s$ and all $v \in V$:

$$(\mathsf{ST}^s) \qquad \underbrace{t^s_{ij} - q^s_{ij}u^s(v)}_{\frac{\partial U^s}{\partial \alpha_{ij}(v)}} - \underbrace{\log\left(\mu^s_j(v)\right)}_{\frac{\partial C^s}{\partial \alpha_{ij}(v)}} - \lambda^s_i(v) + \phi^s_{ij}(v) = 0,$$

(DF)
$$\phi_{ij}^{s}(v) \geq 0$$
,

(CS)
$$\alpha_{ij}(\mathbf{v})\phi_{ij}^{s}(\mathbf{v}) = 0,$$

$$(\mathsf{NA}) \quad \sum_{v \in V} \exp \left(- \min_{i} \{ \lambda_{i}^{s}(v) \} \right) \leq 1.$$

Analogous conditions apply to the buyer.

Appendix

- 6 Implementability for the seller
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8 Subsidy minimization as Bayesian persuasion: solution

• $MG_{\alpha}(\beta)$ can be computed in closed form:

$$\begin{split} MG_{\alpha}(\beta) &= -\sum_{i=1}^{2} \sum_{j=1}^{2} \sum_{v \in \{\underline{v}, \overline{v}\}}^{0 \text{ if } \alpha_{ij}(v) = 0} \times \left[\underbrace{q_{ij}^{b} u^{b}(v) - t_{ij}^{b} - \log\left(\mu_{i}^{b}(v)\right)}_{=\lambda_{j}^{b}(v) \text{ as long as } \alpha_{ij}(v) > 0, \text{ by KKT}} \right] \\ &- \left[\underline{B} \log\left(\underline{\frac{B}{B+B}} \right) + \overline{B} \log\left(\underline{\frac{B}{B+B}} \right) \right], \end{split}$$
 where $\underline{B} \equiv \sum_{i=1}^{2} \sum_{j=1}^{2} \underline{\beta}_{ij}$ and $\overline{B} \equiv \sum_{i=1}^{2} \sum_{j=1}^{2} \overline{\beta}_{ij}.$

$$MG_{\alpha}(\beta) = -\sum_{i=1}^{2} \sum_{j=1}^{2} \left[\underline{\beta}_{ij} \underline{\lambda}_{j}^{b} + \overline{\beta}_{ij} \overline{\lambda}_{j}^{b} \right] - \left[\underline{B} \log \left(\underline{\underline{B}} + \underline{B} \right) + \overline{B} \log \left(\underline{\overline{B}} + \underline{B} \right) \right].$$

$$MG_{\alpha}(\beta) = -\sum_{i=1}^{2} \sum_{j=1}^{2} \left[\underline{\beta}_{ij} \underline{\lambda}_{j}^{b} + \overline{\beta}_{ij} \overline{\lambda}_{j}^{b} \right] - \left[\underline{B} \log \left(\underline{\underline{B}} + \underline{B} \right) + \overline{B} \log \left(\underline{\overline{B}} + \underline{B} \right) \right].$$

• If $MG_{\alpha}(\beta) > 0$, then a better direction is also strictly profitable:

$$-\underline{\underline{B}} \min_j \{\underline{\lambda}_j^b\} - \overline{\underline{B}} \min_j \{\overline{\lambda}_j^b\} - \left[\underline{\underline{B}} \log \left(\underline{\underline{\underline{B}}} + \underline{\underline{B}}\right) + \overline{\underline{B}} \log \left(\underline{\overline{\underline{B}}} + \underline{\underline{B}}\right)\right] > 0.$$

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• Divide through by $\underline{B} + \overline{B}$ and define $P \equiv \frac{\underline{B}}{B + \overline{B}}$ to get:

$$-P\min_j\{\underline{\lambda}_j^b\}-(1-P)\min_j\{\overline{\lambda}_j^b\}-P\log(P)-(1-P)\log(1-P)>0.$$

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• Divide through by $\underline{B} + \overline{B}$ and define $P \equiv \frac{\underline{B}}{B + \overline{B}}$ to get:

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• Maximizing over P, can find the best direction, profitable if and only if

$$\exp\left(-\min_{j}\{\underline{\lambda}_{j}^{b}\}\right) + \exp\left(-\min_{j}\{\overline{\lambda}_{j}^{b}\}\right) > 1.$$

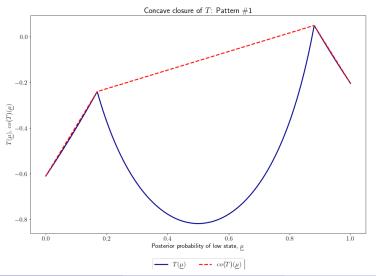
Appendix

6 Implementability for the seller

Proof of Class 2 lemma

8 Subsidy minimization as Bayesian persuasion: solution

Concave closure of $T(\underline{\mu}, 1 - \underline{\mu}; \Lambda^b, \Lambda^s)$



Optimality conditions

Proposition (Optimality conditions)

If the subsidy minimization problem achieves a minimum, then we can set $I=2\ w.l.o.g.$, and moreover the optimal posteriors satisfy

$$\begin{array}{ll} (\mathsf{Opt}^b) & \underline{u}^b - \log(\underline{\mu}_1) - \underline{\Lambda}^b = \overline{u}^b - \log(\overline{\mu}_1) - \overline{\Lambda}^b, \\ \\ (\mathsf{Opt}^s) & \underline{u}^s + \log(\mu_2) + \underline{\Lambda}^s = \overline{u}^s + \log(\overline{\mu}_2) + \overline{\Lambda}^s. \end{array}$$

Combine (Opt) with (NA) to solve for Λ and plug into the objective \Rightarrow unconstrained problem for posteriors.

