Addressing Strategic Uncertainty with Incentives and Information

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Principal contracts with set of agents

Can provide information about fundamentals

Can provide information on others' contracts and information

Optimal scheme to uniquely implement desired action profile?

## CONTRIBUTION

ADDRESSING STRATEGIC UNCERTAINTY

- 1. Incentive design
  - Segal (2003), Winter (2004), Bernstein-Winter (2012), Chassang-Del Carpio-Kapon (2020), Halac-Kremer-Winter (2020, 2021), Camboni-Porcellacchia (2021), Halac-Lipnowski-Rappoport (2021)
- 2. Information design
  - Hoshino (2019), Moriya-Yamashita (2019), Mathevet-Perego-Taneva (2020), Morris-Oyama-Takahashi (2020), Inostroza-Pavan (2021), Li-Song-Zhao (2021)

Today: Methodology to jointly study both instruments

# Model

## Environment

Parameters:

Agents	:	$N = \{1, \ldots, N\}$
Fundamental states	:	$p_0 \in \Delta \Omega$
Allocations	:	$(X_i)_{i\in N}$
Agent preferences	:	$u_i: \{0,1\}^N \times X_i \times \Omega \to \mathbb{R}$

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Timeline:

- Principal designs contracts + information (see next slide)
- ► Then, agents simultaneously choose from {0,1}

Want to maximize  $\mathbb{E} \sum_{i} v_i$  subject to everyone choosing 1.

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Want to maximize  $\mathbb{E} \sum_{i} v_i$  subject to everyone choosing 1.

**Assumption:** Some  $\bar{x}_i \in X_i$  makes 1 dominant for *i* 

Before play, principal designs **incentive scheme**  $\sigma = \langle T, q, \chi \rangle$ :

• 
$$T = \prod_i T_i$$
, where each  $T_i$  is finite

• 
$$q \in \Delta(T \times \Omega)$$
 with marg <sub>$\Omega$</sub>  $q = p_0$ 

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Principal's problem:

$$\sup_{\sigma} \quad \mathbb{E} \sum_{i} v_i(\chi_i(t_i), \omega)$$
  
s.t.  $\sigma$  is UIF

Solving the principal's problem

Say 
$$t = (t_i^R, t_i^S)_i \in T$$
 has no ties if  $t_i^R \neq t_j^R$  for distinct  $i, j \in N$ 

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Let  $\Pi$  be the set of permutations on N

Given such *t*, the **ranking state** is  $\pi(t) \in \Pi$  induced by  $(t_i^R)_i$ 

The total state is  $(\pi(t), \omega) \in \Pi \times \Omega$ 

Each type has **belief**  $\mu_i^q(\cdot|t_i) \in \Delta(\Pi \times \Omega)$ 

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Ranking-consistent behavior  $A_{-i}(\pi) \subseteq A_i$  where

$$I_i(x_i, \pi, \omega) = \min_{a_{-i} \in A_{-i}(\pi)} [u_i(1, a_{-i}, x_i, \omega) - u_i(0, a_{-i}, x_i, \omega)]$$
  
$$\mathcal{X}_i^*(\mu_i) = \{x_i : \mathbb{E}I_i(x_i, \cdot) > 0\} \text{ allocations uniquely incentivizing 1}$$

#### RANKING SCHEMES

#### $\sigma = \langle T, q, B \rangle$ is a (strict) ranking scheme if

- 1. Every supported *t* has no ties
- 2. Every *i* and  $t_i$  have  $\chi_i(t_i) \in \mathcal{X}_i^*(\mu_i^q(\cdot|t_i))$

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#### Lemma:

- 1. Every ranking scheme is UIF
- 2. Any UIF scheme is payoff-equivalent to a ranking scheme

So principal can optimize over ranking schemes

THE OPTIMAL VALUE

$$\begin{aligned} v_i^*(\mu_i) &= \sup_{x_i \in \mathcal{X}_i^*(\mu_i)} \mathbb{E}_{\mu_i} v_i(x_i, \omega) \\ \hat{v}_i^*(\mu) &= \sup_{\tau_i \in \Delta \Delta(\Pi \times \Omega): \mathbb{E}_{\tau_i} \mu_i = \mu} \mathbb{E}_{\tau_i} v_i^*(\mu_i) \\ \mathcal{M}(p_0) &= \{\mu \in \Delta(\Pi \times \Omega): \operatorname{marg}_{\Omega} \mu = p_0\} \end{aligned}$$

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Theorem: The principal's optimal value is

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**Theorem:** The principal's optimal value is

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Proof idea

- Upper bound immediate from Lemma
- Can approximate arbitrary  $\mu \in \mathcal{M}(p_0)$  and give no info
- Augment types to convey any info about total state

## WHAT DOES THE THEOREM BUY US?

Multi-agent setting

- Agents' actions affect others' incentives
- Public information may be suboptimal
- *i* and *j*'s information on  $\omega$  (and  $x_k$ ) has joint restrictions

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Theorem says you can

- Enrich the fundamental state to the total state
- Choose distribution (s.t. marginal on fundamentals)
- Design information one agent at a time

Example: team production

## MORAL HAZARD IN TEAMS

Special case in which

$$N = \{1, 2\}$$
  

$$\Omega = \{1, 2\}$$
  

$$p_0 = \text{uniform}$$
  

$$X_i = \mathbb{R}_+$$
  

$$v_i(x_i, \omega) = -x_i$$

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$$u_i(a, x_i, \omega) = P_{a_1+a_2}x_i - a_ic_i(\omega)$$

where

$$\bullet \quad 0 \le P_0 < P_1 < P_2 \le 1$$

$$\bullet \quad P_2 - P_1 > P_1 - P_0$$

$$\bullet \quad c_i : \Omega \to \mathbb{R}_{++}$$

#### FIRM'S PROBLEM

Given belief  $\mu_i$  with marginals  $\mu_i^{\Pi}, \mu_i^{\Omega}$ :

- Let  $\iota_i(\mu_i^{\Pi})$  be *i*'s expected marginal product if coworker
  - Works if ranked ahead of *i*
  - Shirks if ranked behind *i* (supermodularity)

• Then 
$$\mathcal{X}_i^*(\mu_i) = \left\{ x_i : x_i \iota_i(\mu_i^{\Pi}) > c_i(\mu_i^{\Omega}) \right\}$$

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• Then 
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• Hence, 
$$v_i^*(\mu_i) = -\frac{c_i(\mu_i^{\Omega})}{\iota_i(\mu_i^{\Pi})}$$

$$\min_{\mu \in \mathcal{M}(p_0)} \sum_{i=1,2} \min_{\tau_i \in \Delta \Delta(\Pi \times \Omega)} \int \frac{c_i(\mu_i^{\Omega})}{\iota_i(\mu_i^{\Pi})} d\tau_i(\mu_i)$$
s.t. 
$$\int \mu_i d\tau_i(\mu_i) = \mu$$

# EXPLICITLY CHARACTERIZED OPTIMUM

**Propositions:** For optimal  $(\mu, \tau_1, \tau_2)$ :

- 1. If  $c_1(1) = c_1(2)$  and  $c_2(1) = c_2(2)$ , **no information**: neither agent learns anything about the total state
- 2. If  $c_1(1) = c_2(2) > c_2(1) = c_1(2)$ , **public information**: both agents learn the fundamental state
- 3. If  $c_1(1) > c_2(2) = c_2(1) = c_1(2)$ , private information: only agent 1 learns the fundamental state

Note: Higher-order belief features sometimes come for free

## CONCLUDING REMARKS

Joint incentive + information design under strategic uncertainty

Methodology (for binary actions) that

- Identifies the appropriate total state variable
- Reduces information design problem to be agent-by-agent

Flexible framework can be applied to varied settings

# Thanks!

