

Partial Identification Under Iterated Strict Dominance

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Section 1

Motivation

Structural Estimation of Static Games

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- Without an Equilibrium Selection Mechanism, $P(y)$ is not always defined.
- Theory provides little guidance on what an Equilibrium Selection Mechanism should look like.
- In complicated environments, the “equilibrium play” assumption itself may be suspect.

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- Apply to games with any informational structure.
- For binary choice games, the identified set is sharp.

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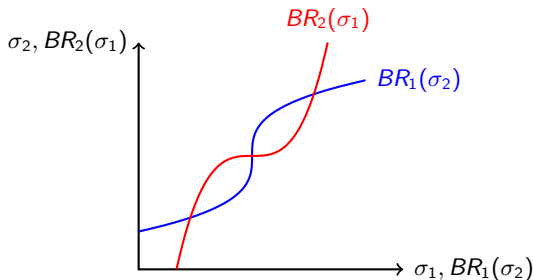
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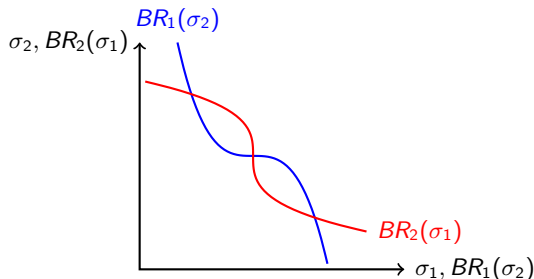


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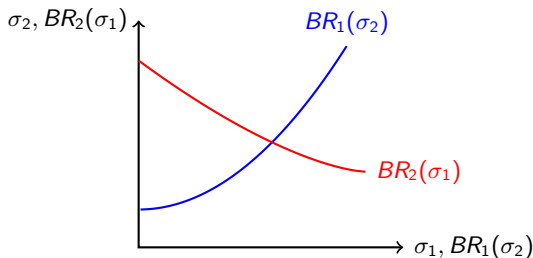


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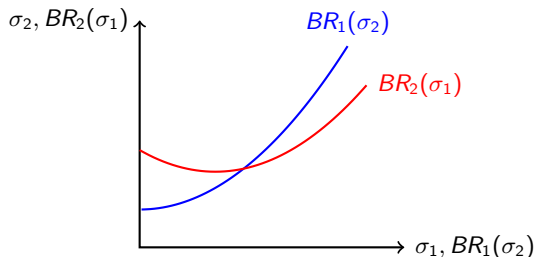


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 - ▶ **but not...**



(Very Incomplete) Literature

Set identification in games:

- **Bounds:** Tamer '03; Ciliberto, Tamer '09; Ciliberto, Murry, Tamer '21; Fan, Yang '22; Aradillas-Lopez, Tamer '08; Aradillas-Lopez '10; Pakes, Porter, Ho, Ishii '15; Aradillas-Lopez, Rosen '22, Magnolfi, Roncoroni '22.

Supermodular Games:

- **Theory:** Milgrom, Roberts '90; Van Zandt, Vives '07.
- **Empirics:** Akerberg, Gowrinsankaran '06; Molinari, Rosen '08; Jia '08; Uetake, Watanabe '13, Uetake, Watanabe '20.

Static games:

- Berry '92; Mazzeo '02; Jia '06; Ellickson, Houghton, Timmins '18; Wollman '18, Ciliberto, Jäkel '21, Schaumans, Verboven '08, Verboven, Schaumans '15; Seim '06; Draganska et al '08; Molinari, Rosen '08; Uetake, Watanabe '13, Uetake, Watanabe '20.

Outline

- 1 Motivation
- 2 Entry Game Example
 - Game Setup
 - ISD in SMSGs
- 3 Identified Set
- 4 Identification Power of ISD Bounds
- 5 Montecarlo
- 6 Conclusion

Section 2

Entry Game Example

2×2 Incomplete Information Entry Game

Two firms simultaneously decide whether to enter a market.

- $y_f \in \{0 \text{ (No Entry)}, 1 \text{ (Entry)}\}$.
- ϵ_f : iid private shock. $V[\epsilon_f] = 1$.
- R : variable profit, $R^{mon} > R^{duo}$

$$\pi_f = \begin{cases} R^{mon}(x_f) - \theta_{ec} + \theta_{sc}\epsilon_f & \text{if } y_f = 1 \text{ and } y_{-f} = 0 \\ R^{duo}(x_f) - \theta_{ec} + \theta_{sc}\epsilon_f & \text{if } y_f = 1 \text{ and } y_{-f} = 1 \\ 0 & \text{if } y_f = 0 \end{cases}$$

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Given (x, θ) the goal is to build bounds around $Pr(y_f = 1|x, \theta)$.

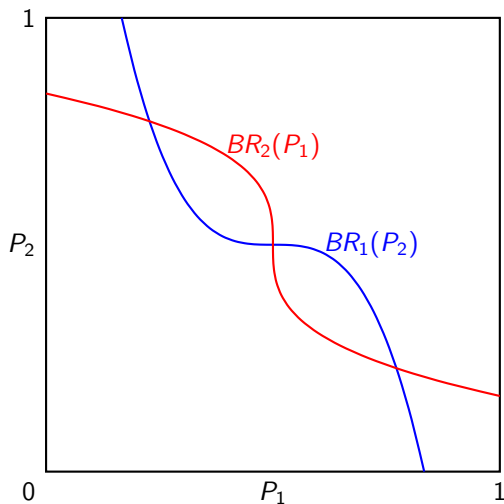
Best Responses in Probabilities

Fix a game, (x, θ) , and let ρ_2 be 1's belief about $Pr(y_2 = 2)$.

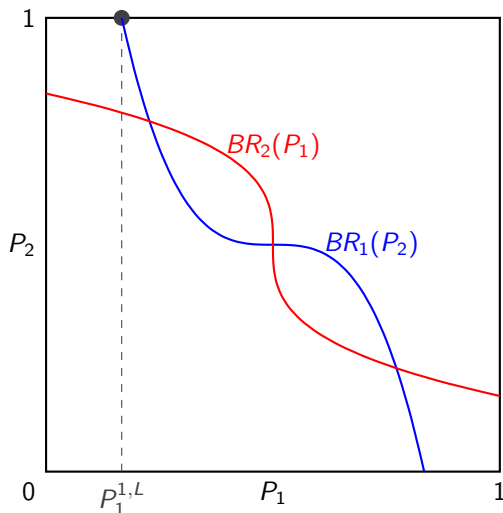
Given ρ_2 , firm 1's optimal entry probability is:

$$BR_1(\rho_2) = Pr\left(\rho_2 R^{duo} + (1 - \rho_2) R^{mon} - \theta_{ec} + \theta_{sc} \epsilon_1 > 0\right)$$

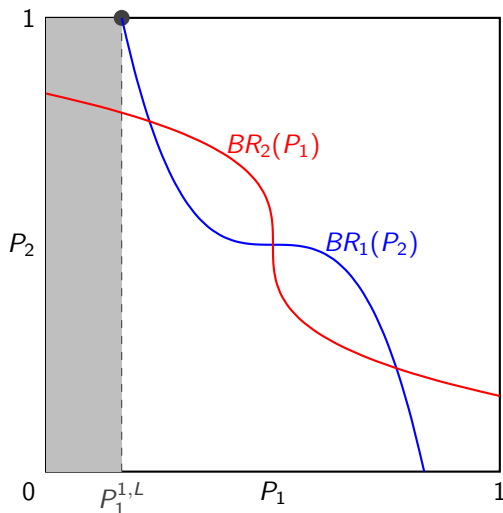
Applying ISD (in probability space)



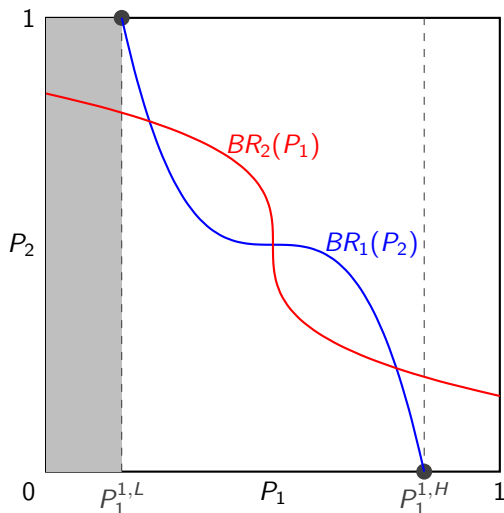
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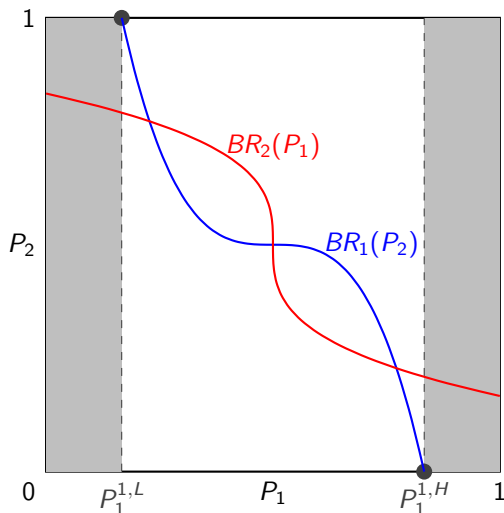
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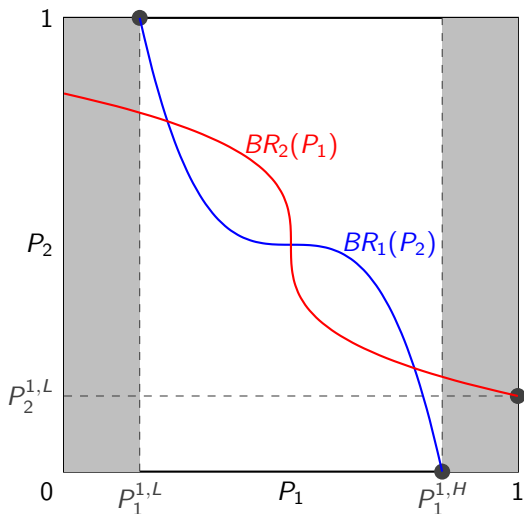
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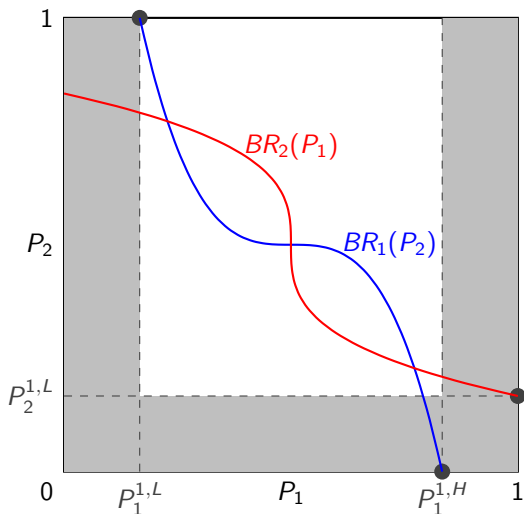
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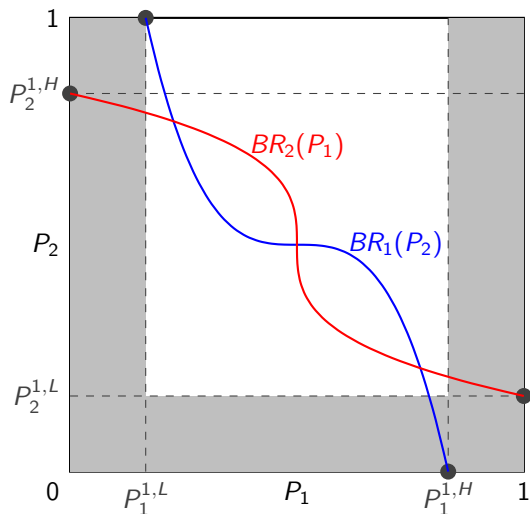
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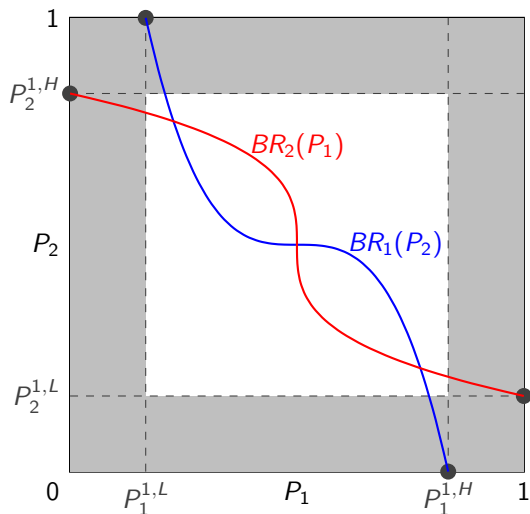
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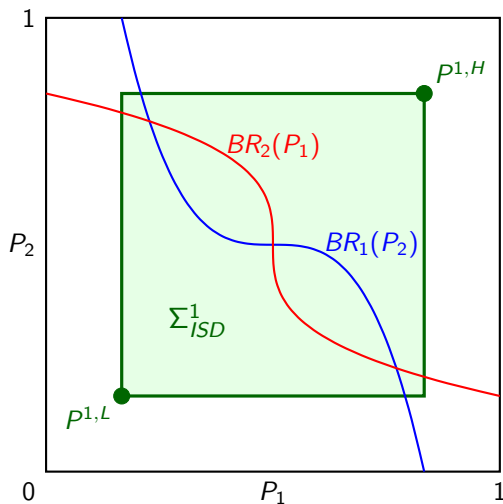
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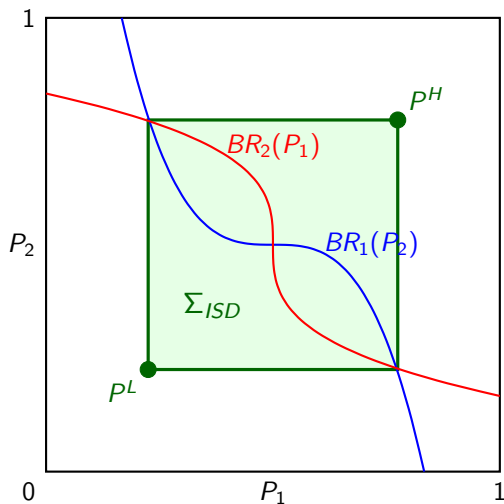
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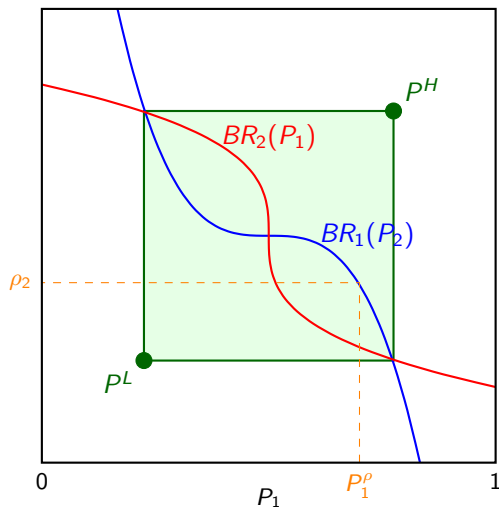
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ISD Bounds

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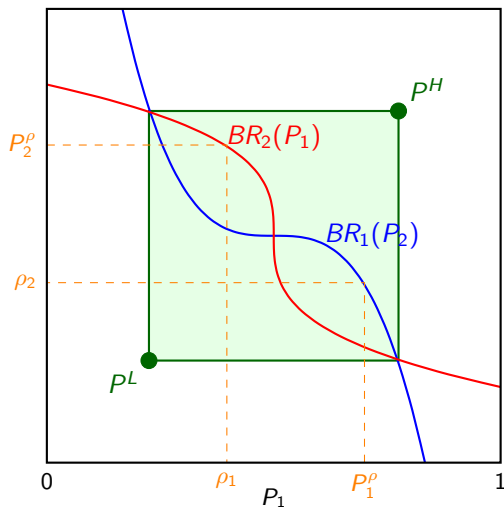
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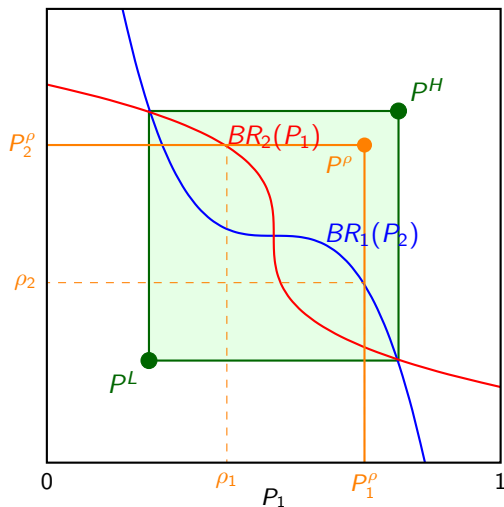
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ISD Bounds Result

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For any (x, θ) , and any ISD Consistent beliefs ρ :

- 1 There are strategies $P^L \leq P^H$ such that for all f :

$$P_f^L(x, \theta) \leq P_f^\rho(x, \theta) \leq P_f^H(x, \theta)$$

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This is a specific instance of a general result that applies to games with many firms, multidimensional y_f , and (in)complete information, as long as:

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Section 3

Identified Set

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ISD Identified Set

The ISD Identified Set is:

$$\Theta_{ISD} = \{\theta \in \Theta : P_f^L(x, \theta) \leq P_f^0(x) \leq P_f^H(x, \theta) \text{ for all } x \text{ and } f\}$$

Section 4

Identification Power of ISD Bounds

Trivial ISD Bounds

► Identification at Infinity

We say θ generates trivial bounds if for all x and all f :

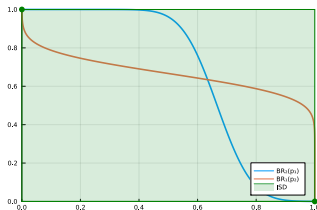
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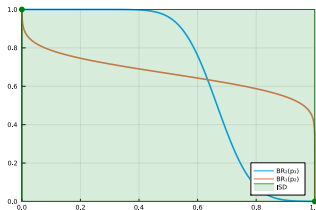


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Theorem: Non-Trivial Bounds

No $\theta \in \Theta$ generates trivial bounds *iff* there exist x, x' such that:

$$R^{mon}(x) < R^{duo}(x')$$

What generates trivial bounds?

[▶ Details.](#)

Say $R^{duo}(x') < R^{mon}(x), \forall x, x'$. There is a θ_{ec} such that $\forall x$:

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Hence:

$$P_f^L(x, \theta) = Pr \left(R^{duo}(x) - \theta_{ec} + \theta_{sc} \epsilon_f > 0 \right) \rightarrow 0 \text{ as } \theta_{sc} \rightarrow 0$$

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We get, $P_f^L(x, \theta) \rightarrow 0, P_f^H(x, \theta) \rightarrow 1$, for all x , so $\theta \in \Theta_{ISD}$.

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Hence:

$$P_f^L(x, \theta) = Pr(R^{duo}(x) - \theta_{ec} + \theta_{sc}\epsilon_f > 0) \rightarrow 0 \text{ as } \theta_{sc} \rightarrow 0$$

$$P_f^H(x, \theta) = Pr(R^{mon}(x) - \theta_{ec} + \theta_{sc}\epsilon_f > 0) \rightarrow 1 \text{ as } \theta_{sc} \rightarrow 0$$

We get, $P_f^L(x, \theta) \rightarrow 0, P_f^H(x, \theta) \rightarrow 1$, for all x , so $\theta \in \Theta_{ISD}$.

Take away: Non-trivial ISD Bounds require variables that shift profits uniformly, e.g. *market size*, so that:

$$R^{mon}(x) < R^{duo}(x')$$

for some x, x'

Section 5

Montecarlo

Monte Carlo Set Up

Consider a **imperfect information** entry game with payoffs:

$$\pi_f = y_f \left(\overbrace{\frac{x_f}{(1 + \sum_{f'} y_{f'})^2}}^{R(x): \text{Cournot Prof.}} - \theta_{ec} + \theta_{sc} \left(\sqrt{0.5} \xi_f + \sqrt{0.5} \epsilon_f \right) \right)$$

with $F \in \{2, 3\}$.

Monte Carlo Set Up

Consider a **imperfect information** entry game with payoffs:

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- $x_f \sim \text{Uniform}\{0.5, 1.5, \dots, 4.5\}$: observables.

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with $F \in \{2, 3\}$.

- $x_f \sim \text{Uniform}\{0.5, 1.5, \dots, 4.5\}$: observables.
- $(\theta_{ec}^0, \theta_{sc}^0) = (1, 1)$: parameters.
- $\xi_f \sim N(0, 1)$: common knowledge unobservables.
- $\epsilon_f \sim N(0, 1)$: private information.

Simulations:

- $MC = 100$ simulated samples.
- $N = 2000$ sample size.

Inference:

- Follow Chernozukov, Chetverikov, Kato '18.
- $H_0 : \theta = \theta_0$.

Coverage Probability: $F = 2$ (top), $F = 3$ (bottom)

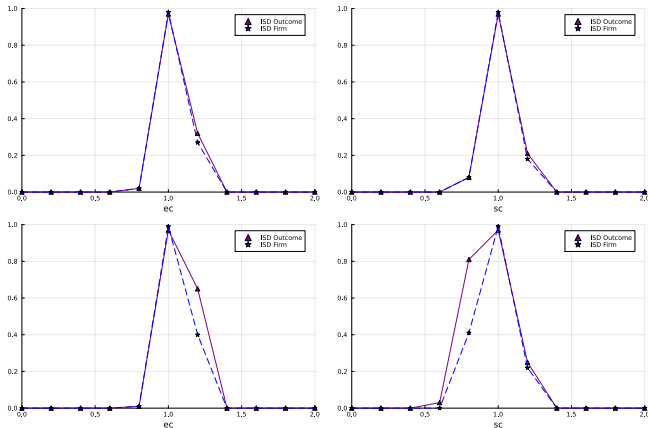


Figure: Monte Carlo simulations for two-firm (top) three-firm (bottom) games.

Section 6

Conclusion

Closing Remarks

I propose ISD bounds for set identification. The bounds:

- ① Are robust to multiple equilibria/non-equilibrium play.
- ② Allow for discrete/continuous choice variables.
- ③ Allow for arbitrary informational structures.

For a large class of games, i.e., SMSGs, I argue that:

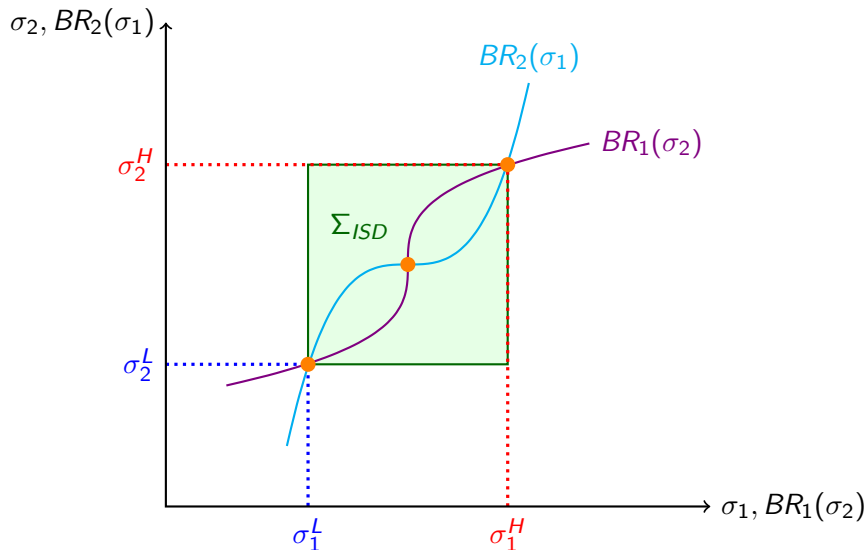
- ① Bounds have bite.
- ② They are easy to compute.
- ③ Many (most?) empirical games literature fall under this category!

In the paper:

- ① Results on sharpness and point identification for binary games.
- ② Application to the airline industry with a focus on the Spirit/JetBlue merger.

Thanks!

Games with Strategic Complements

[▶ back](#)

Games with Strategic Substitutes

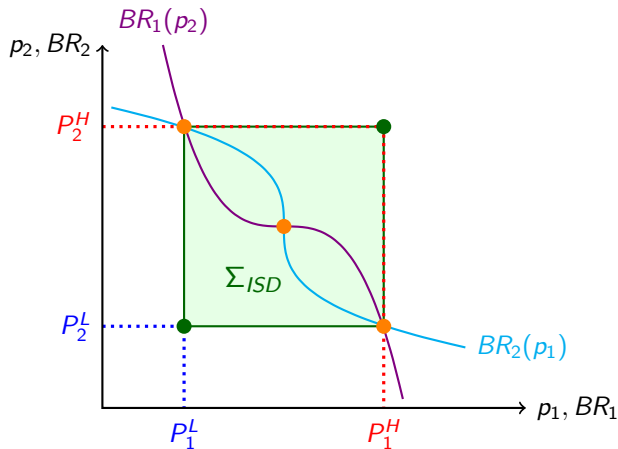
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Figure: ISD in Games of Strategic Substitution

Game with General Strategic Monotonicity

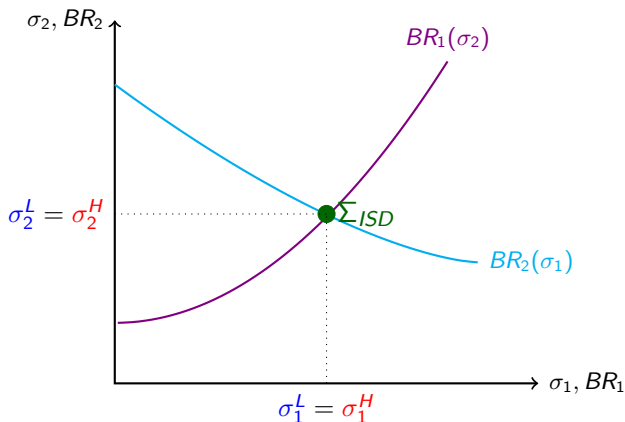
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Figure: ISD in Games Strategic Monotonicity

Ciliberto and Tamer '09 (CT)

For a given (x, θ, ξ) and rational expectations ρ :

- $\{y\} = NE(x, \theta, \xi) \Rightarrow \sigma^\rho = y$
- $\sigma^\rho = y \Rightarrow y \in NE(x, \theta, \xi).$

$$P(\{y\} = NE(x, \theta, \xi)) \leq P(\sigma^\rho = y) \leq P(y \in NE(x, \theta, \xi))$$

Fan and Yang '22 (FY)

For a given (x, θ, ξ) and any ρ

- $\{y_f\} = \Sigma_{f, ISD}^1(x, \theta, \xi) \Rightarrow \sigma^\rho = y$
- $\sigma^\rho = y \Rightarrow y \in \Sigma_{f, ISD}^1(x, \theta, \xi).$

$$P(\{y\} = \Sigma_{f, ISD}^1(x, \theta, \xi)) \leq P(\sigma^\rho = y) \leq P(\{y\} \in \Sigma_{f, ISD}^1(x, \theta, \xi))$$

Test for Confidence Set [▶ Back to Monte Carlo](#)

Let $(h_l(X))_l$ be a collection of $l = 1, \dots, L$ non-negative functions.

Moment inequalities are:

$$\overline{\psi}_{fml}(\theta) \equiv \left(Y_{fm} - P_f^L(X_m, \theta) \right) h_l(X_m) \leq 0$$

$$\underline{\psi}_{fml}(\theta) \equiv \left(P_f^H(X_m, \theta) - Y_{fm} \right) h_l(X_m) \leq 0$$

Letting \hat{E} and \widehat{SD} be the cross-market mean and s.d. operators.

$$T_{CCK}(\theta) = \sqrt{M} \max_{f,k,l} \left\{ \max \left\{ \frac{\hat{E}[\overline{\psi}_{fml}(\theta)]}{\widehat{SD}[\overline{\psi}_{fml}(\theta)]}, \frac{\hat{E}[\underline{\psi}_{fml}(\theta)]}{\widehat{SD}[\underline{\psi}_{fml}(\theta)]} \right\} \right\}$$

And test $\theta = \theta_0$ using Chernozhukov, Chetverikov, Kato '18 (CCK):

$$T_{CCK}(\theta; y) \leq CCK(\alpha)$$

Instruments

I choose h_l 's to capture the relative relative profitability of a player.
Let:

$$\tilde{X}_{fm} = \frac{X_{fm}}{(\prod_{g \neq f} X_{gm})^{1/|\mathcal{F}|}}$$

and

$$\tilde{X}_q = \{q\text{'th percentile of } (\tilde{X}_{fm})_{fm}\}$$

Letting $l(f, q)$ be the index associated to (f, q) I define:

$$h_{l(f, q)}(X_m) = \mathbb{1} \left\{ \tilde{X}_{fm} \in [\tilde{X}_q, \tilde{X}_{20+q}] \right\}$$

where $q \in \{0, 20, 40, 60, 80\}$.