Recursivity and the Estimation of Dynamic Games with Continuous Controls

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Introduction

We revisit the estimation of **dynamic games with continuous controls** (DGCCs)

- Investments in R&D, quality, capacity, advertising; political campaign spending . . .

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We start from **two observations**:

- If observed policies are a **MPE**, solving Bellman eqs must return the same policy.
- $\widehat{\text{Transitions}} + \widehat{\text{Continuation}}(\boldsymbol{\theta}) \Rightarrow$ can solve "empirical" Bellman equations

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We **propose** estimators based on the intuition above.

- *Recursive Estimators* (REs).

$$\min_{\theta} d\Big(\text{Observed Policy}, \text{(Pseudo) Model-Implied Policy}\Big)$$

This Paper 1/2

We **evaluate** REs' relative to Bajari, Benkard, and Levin (2007) (BBL) ▸ List of applications.

- $V(\text{State} \mid \textbf{Observed Policy}) \geq V(\text{State} \mid \textbf{Deviation}) \ \forall$ Deviation.
- **Q**: Which deviations? We deploy multiple implementations.
- "Empirically-relevant" Monte Carlos based on Hashmi and van Biesebroeck (2016).

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1. REs are computationally tractable.
2. They substantially outperform BBL in terms of finite sample bias and precision.
    - Indeed, we struggle to obtain reasonable estimates with BBL.

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Bonus (very little on it today)

- These ideas lead to a semi-parametric (SP) estimator for DGCCs.
- Preliminary: common parametric restrictions lead to large biases; SP estimator works well.

Related Literature and Contributions

Estimation of DGCCs

- Bajari et al. (2007), Jofre-Bonet and Pesendorfer (2003), Schrimpf (2011), Srisuma (2013)
- Applications: Ryan (2012), Hashmi and van Biesebroeck (2016), Fowlie, Reguant, and Ryan (2016), Liu and Siebert (2022), Egan, Hortaçsu, Kaplan, Sunderam, and Yao (2025).

Estimation of Dynamic Discrete Games

- Aguirregabiria and Mira (2007), Pakes, Ostrovsky, and Berry (2007), Pesendorfer and Schmidt-Dengler (2008).

Contributions.

- REs are **computationally tractable** in empirically realistic settings.
- And **outperform** the main available alternative.

Roadmap

- A **model** of entry, exit, and quality upgrading.
  - Introduce estimators based on recursive equilibrium conditions.
  - A review of the Bajari et al. (2007) inequality estimator.
  - Monte Carlo simulations.
  - Semi-parametric estimation of DGCCs.

Market Structure and Profits

A variant of Pakes and McGuire (1994)

$\bar{N}$ **single-product firms** in the market

- N active firms, $N \leq \bar{N}$; N endogenous.
- $\bar{N} - N$ inactive firms.

Firms are described by a **characteristic** $\xi_j \in \Xi \subset \mathbb{R} \cup \{-\infty\}$

- Quality, capacity, technology, consumer "goodwill", ...
- $\xi_j = -\infty$ indicates being inactive.

The **industry state** is $\boldsymbol{\xi} = (\xi_1, \ldots, \xi_{\bar{N}})$.

Firms earn **flow profits** that depend on their qualities: $\pi_j(\boldsymbol{\xi})$.

- $\pi_j(\boldsymbol{\xi})$ are *symmetric* – Doraszelski and Satterthwaite (2010):

Quality Transitions & Investment

Transitions:

- Firms can invest to affect the evolution of their qualities.
- Quality transitions are conditionally independent and there are no spillovers:

$$F(\boldsymbol{\xi}'|\boldsymbol{\xi},\boldsymbol{x}) = \prod_{j=1}^{\bar{N}} F(\xi_j'|\xi_j, x_j) \ ,$$

  - Straightforward to accommodate an aggregate shock.
  - This specification includes almost all models in the literature.

Investment is costly: $c(x,\nu)$

- $\nu \sim F_\nu$ is an investment cost shock.
  - F_ν is *known* to the econometrician.

Timing and Solution Concept

1	2	3	4	5	6
Incumbents earn $\pi_j(\boldsymbol{\xi})$	$\rho \sim F_\rho$ $\phi \sim F_\phi$	Entry/exit decisions	$\nu \sim F_\nu$ (active firms)	Investment decisions	Transitions $\xi' \sim F(\xi' \mid \xi, x)$

Definition (Symmetric MPE)

A **Symmetric Markov Perfect Equilibrium** (SMPE) is a tuple

$$\sigma(\boldsymbol{\xi}, \varepsilon) = (\alpha^E(\boldsymbol{\xi}, \phi), \alpha^I(\boldsymbol{\xi}, \rho), \sigma^x(\boldsymbol{\xi}, \nu))$$

such that, given that all firms behave according to this tuple,

1. $\alpha^E(\boldsymbol{\xi}, \phi) \in \{0, 1\}$ maximizes the potential entrant's ENPV of profits;
2. $\alpha^I(\boldsymbol{\xi}, \rho) \in \{0, 1\}$ maximize the incumbent's ENPV of profits.
3. $\sigma^x(\boldsymbol{\xi}, \nu)$ maximizes the ENPV of profits of a firm that chooses to be active in $t + 1$.

A Modicum of Characterization

The firm's investment problem can be written as

$$\max_{x \in \mathbb{R}_+} \left\{ -c(x,\nu) + \beta \int_{\xi_1'} W(\xi_1' \mid \boldsymbol{\xi}, F^\sigma)\, \mathrm{d}F(\xi_1' \mid \xi_1, x) \right\},$$

where

- $W(\xi_1' \mid \boldsymbol{\xi}, F^\sigma) := \int_{\xi_2'} \cdots \int_{\xi_{\bar{N}}'} \bar{V}_I(\xi_1', \boldsymbol{\xi}_{-1}')\, \mathrm{d}F^\sigma(\xi_{\bar{N}}' \mid \boldsymbol{\xi}_{\bar{N}}) \ldots \mathrm{d}F^\sigma(\xi_2' \mid \boldsymbol{\xi}_2)$;
- $\bar{V}_I(\boldsymbol{\xi}) := \int_\rho V_I(\boldsymbol{\xi}, \rho)\, \mathrm{d}F_\rho$.
- $F^\sigma(\xi_j' \mid \boldsymbol{\xi}_j) := \int_{\varepsilon_j} F(\xi_j' \mid \xi_j, \sigma_j(\boldsymbol{\xi}_j, \varepsilon_j))\, \mathrm{d}G_{\varepsilon_j}$;

We would like the problem above to have a **unique solution**

- Computing equilibria.
- Estimation based on solving this problem.

Unique Optimal Investments

Definition (Doraszelski and Satterthwaite (2010))

The distribution $F(\xi' \mid \xi, x)$ is UIC-admissible if, for all $\xi', \xi \in \Xi$, and $x \in \mathbb{R}_+$

$$F(\xi' \mid \xi, x) = L(\xi', \xi) + K(\xi', \xi) Q(\xi, x) \; ,$$

where $Q(\xi, x)$ is $\mathcal{C}^2$ in x for all $\xi \in \Xi$ and satisfies

$$\frac{\partial Q(\xi, x)}{\partial x} > 0 \quad \text{and} \quad \frac{\partial^2 Q(\xi, x)}{\partial x^2} < 0 \; .$$

Proposition

If $F(\xi' \mid \xi, x)$ is **UIC-admissible***, then there is a* **unique optimal investment** *for all* $(\boldsymbol{\xi}, \nu) \in \Xi \times \mathrm{supp}(F_\nu)$.

Alternative conditions for uniqueness.

Existence and Equilibrium Computation

Proposition

Suppose $|\Xi| < \infty$. Then there exists a Symmetric MPE.

- Not previously established for this class of models.
- Despite the continuous controls, good old Brouwer suffices.
  - Only endogenous parameter in the investment problem is F^σ, **finite-dimensional**.
  - We prove the existence of a fixed point for F^σ and from it construct an equilibrium.
  - Akin to the *Representation Lemma* in Aguirregabiria and Mira (2007).

Computation

- Looks for a fixed point for F^σ.
- Not dissimilar to Pakes and McGuire (1994).

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The Estimation Problem

The econometrician observes a panel of M markets over T periods

- For each of the N_{mt} active firms, the data include
  - the firm's characteristic ξ_{jmt};
  - the firm's investment x_{jmt};

Flow profits and transitions

- Can be estimated "offline".
  - I.e., without imposing dynamic equilibrium conditions.

What remains to be estimated

- Investment cost parameters $\boldsymbol{\theta}_x$ in $c(x, \nu; \boldsymbol{\theta}_x)$.
- Scrap value parameters $\boldsymbol{\theta}_\rho$ in $F_\rho(\rho; \boldsymbol{\theta}_\rho)$.
- Entry cost parameters $\boldsymbol{\theta}_\phi$ in $F_\phi(\phi; \boldsymbol{\theta}_\phi)$.

Recursive Estimator

- Assume (as in BBL) we have estimates of
  - $\hat{F}(\xi' \mid \xi, x)$
  - $\hat{F}^{\sigma}(\xi' \mid \boldsymbol{\xi})$
  - $\widehat{\bar{V}_I}(\boldsymbol{\xi}; \hat{\sigma}, \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho)$ of $\bar{V}_I(\boldsymbol{\xi}; \sigma, \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho)$

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Then we can set up and solve the RHS of firms' Bellman equations for any ν:

$$\max_{x \in \mathbb{R}_+} \left\{ -c(x, \nu; \boldsymbol{\theta}_x) + \beta \int_{\xi_1'} W(\xi_1' \mid \boldsymbol{\xi}, \hat{F}^{\sigma}; \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho) \, \mathrm{d}\hat{F}(\xi_1' \mid \xi_1, x) \right\}$$

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$\Rightarrow$ Predicted levels of investment $T_{\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}, \nu; \hat{\Phi})$, where $\hat{\Phi} = (\widehat{\bar{V}_I}(\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}), \hat{F}, \hat{F}^{\sigma})$

- Use $T_{\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}, \nu; \hat{\Phi})$ in estimation.
- E.g., **Indirect inference**, MLE, MD, NNLS, etc.

Recursive Estimator: Indirect Inference

Investment

Run

$$T_{\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}_i, \nu_i; \hat{\Phi}) = \sum_{k=1}^{B} \lambda_k^x \Psi_k^x(\boldsymbol{\xi}_i) + \zeta_i^x \quad \Rightarrow \quad \hat{\boldsymbol{\lambda}}_{\text{Investment}}(\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}; \hat{\Phi})$$

for draws $\nu_i \sim F_\nu$ and the analogous regression on observed investment.

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Entry/Exit

Solving the investment problems yields $\widehat{\bar{V}}_I^A(\boldsymbol{\xi}; \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho) \Rightarrow \hat{\mathbb{P}}(\text{ Exit} \mid \boldsymbol{\xi}; \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho)$.

- Run regressions of these probabilities on functions of $\boldsymbol{\xi}$.
- Run analogous regressions on observed exit decisions.
- Similarly for entry decisions.

Recursive Estimator: Indirect Inference

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The II estimator solves

$$\min_{\boldsymbol{\theta}} \left[\hat{\boldsymbol{\lambda}}(\boldsymbol{\theta};\hat{\Phi}) - \hat{\gamma}\right]^\top \boldsymbol{\Omega}\left[\hat{\boldsymbol{\lambda}}(\boldsymbol{\theta};\hat{\Phi}) - \hat{\gamma}\right]$$

Indirect Inference Details
Other Recursive Estimators

How to Estimate Continuation Values?

We show that

$$[I - \beta \boldsymbol{M}(\boldsymbol{P})] \bar{\boldsymbol{V}}_I = \boldsymbol{\pi} - \boldsymbol{K}(\boldsymbol{\theta}_x) + \boldsymbol{\Sigma}(\boldsymbol{\theta}_\rho) \ . \tag{1}$$

Details

- $\bar{V}_I$ estimable up to $\boldsymbol{\theta}$; no simulation error.
- Similar calculations in Jofre-Bonet and Pesendorfer (2003) and Pakes et al. (2007).

Is it feasible to repeatedly solve (12)**?**

- Some models have special structure that makes it very fast (more below).
- O.w., use e.g. Chen (2025).
- Alternatively, simulate $W(\xi\prime \mid \boldsymbol{\xi}; \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho)$

Roadmap

- ◦ A model of entry, exit, and quality upgrading.
- ◦ Introduce estimators based on recursive equilibrium conditions.
- ▶ A review of the Bajari et al. (2007) inequality estimator.
- ◦ Monte Carlo simulations.
- ◦ Semi-parametric estimation of DGCCs.

Bajari et al. (2007)

If σ is a SMPE then $\forall\ \boldsymbol{\xi}, \sigma'$

$$\bar{V}_I(\boldsymbol{\xi}; \sigma, \sigma, \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho) \geq \bar{V}_I(\boldsymbol{\xi}; \sigma', \sigma, \boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho);$$

- Analogous condition holds for $\bar{V}_E$.

Define

$$g_s(\boldsymbol{\xi}, \sigma'; \sigma, \boldsymbol{\theta}) := \bar{V}_s(\boldsymbol{\xi}; \sigma, \sigma, \boldsymbol{\theta}) - \bar{V}_s(\boldsymbol{\xi}; \sigma', \sigma, \boldsymbol{\theta}) \ , \quad s \in \{I, E\} \ .$$

The **BBL estimator** is

$$\hat{\boldsymbol{\theta}}_{BBL} = \arg\min_{\boldsymbol{\theta}} \hat{Q}(\boldsymbol{\theta}, \hat{\sigma}) = \frac{1}{n_I} \sum_{i=1}^{n_I} \left(\min\left\{ \hat{g}_{s_i}(\boldsymbol{\xi}_i, \sigma'_i; \hat{\sigma}, \boldsymbol{\theta}), 0 \right\} \right)^2$$

- Estimates are a function of the chosen **deviations** σ'.
  - How to choose deviations σ'?
  - Choice does matter: Srisuma (2013) and simulations below.

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We specialize the framework above.

- Adding entry and exit to the **Hashmi and van Biesebroeck (2016)** model.

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  - Single-product firms facing nested logit demand.
  - Constant marginal cost $mc(\xi)$.
  - Nash-Bertrand competition.
  - Flow Profit Derivation

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- Transitions
  - $\xi' \in \{\xi - \delta, \xi, \xi + \delta\}$.
  - $P(\xi + \delta \mid \xi, x)$: $\uparrow x, \downarrow \xi$.
  - Computational payoff of local transitions + absorbing exit

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  - Computational payoff of local transitions + absorbing exit
- $c(x, \nu) = \theta_{x1} x + \theta_{x2} x^2 + \theta_{x3} \nu x$.
- $\bar{N} = 5$.

Monte Carlo Setup

Parameter	Value
Data Structure	
Number of Markets	100
Number of Periods	40
Maximum Number of Firms	5
Own State Space	[$-\infty$, -1.4, -1.2, ... , 1.2, 1.4]
Model Parameters	
Discount Factor	0.925
Investment Cost Parameters	[2.625, 1.624, 0.5096]
Scrap Value Distribution	$\log N(-1.0, 0.75)$
Entry Cost Distribution	$\log N(0.625, 0.5)$
II Estimator	
Number of Investment Repetitions	5
Weight Matrix	Bootstrap
Number of Bootstrap Samples	1000
BBL Estimators	
Number of Inequalities	5000
Number of Simulated Paths	500
Simulation Horizon	80

Two-parameter F_ρ, F_ϕ, as opposed to common exponential.

First Stage: II and BBL

- $\boldsymbol{\pi}(\boldsymbol{\xi})$
  - Treated as known.
- $\sigma^x(\boldsymbol{\xi}, \nu)$
  - $\sigma^x(\boldsymbol{\xi}, \nu) = F_X^{-1}(1 - F_\nu(\nu) \mid \boldsymbol{\xi})$
  - We estimate evenly spaced **quantile regressions** of investment on functions of $\boldsymbol{\xi}$.
  - Commonly used $\mathbb{E}[x \mid \boldsymbol{\xi}]$ ignores dependence on ν.
- $P(\xi' \mid \xi, x)$
  - MLE, parametric structure imposed above.
- $P(\xi' \mid \boldsymbol{\xi}) \approx \sum_k \omega_k P(\xi' \mid \xi, \sigma(\boldsymbol{\xi}, \nu_k))$
  - Combine previous two steps.
- Probabilities of entry and exit.
  - Logit on functions of $\boldsymbol{\xi}$.

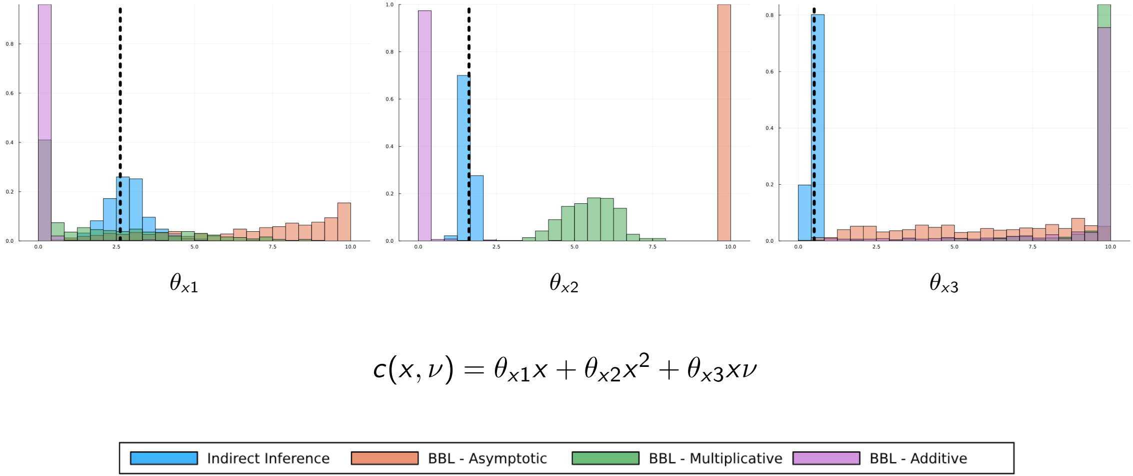
Monte Carlo Results

	Value	Indirect Inference	BBL		
			Asymptotic	Multiplicative	Additive
θ_{x1}	2.625	2.872	6.888	1.944	0.08
		0.734	2.635	2.21	0.442
θ_{x2}	1.624	1.581	10.0	5.481	0.055
		0.148	0.004	0.813	0.335
θ_{x3}	0.5096	0.466	5.714	9.611	9.067
		0.097	2.694	1.142	2.003
μ_ρ	-1.0	-1.127	-1.329	-1.103	-2.0
		0.39	0.101	0.081	0.001
σ_ρ	0.75	0.746	0.69	0.589	1.038
		0.13	0.036	0.031	0.167
μ_ϕ	0.625	0.864	1.809	1.851	1.898
		0.616	0.074	0.063	0.268
σ_ϕ	0.5	0.735	2.998	2.998	3.0
		0.468	0.015	0.019	0.0

- Qualitatively similar results with sample size as in Ryan (2012).

Policy and Deviation Details

Investment Cost Parameters Estimates

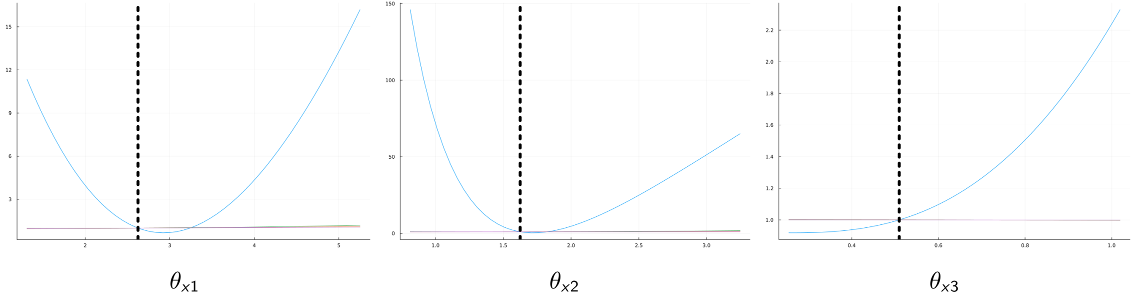


$$c(x,\nu) = \theta_{x1}x + \theta_{x2}x^2 + \theta_{x3}x\nu$$

Indirect Inference Only

F_ρ and F_ϕ Estimates

Objective Function: Investment Cost Parameters



$$c(x, \nu) = \theta_{x1} x + \theta_{x2} x^2 + \theta_{x3} x \nu$$

θ^{II}_{x3} is minimized away from zero in this sample.

▸ Objective Function: F_ρ and F_ϕ

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Semi-parametric Estimation

☠ This is very preliminary.

Model + data + $\boldsymbol{\theta}$ induce an operator $T_{\boldsymbol{\theta}} : \mathcal{F}_\nu \to \mathcal{F}_\nu$ as follows:

$$F_\nu \mapsto \sigma^x(\boldsymbol{\xi}, \nu) \mapsto \bar{V}_I \mapsto W(\xi' \mid \boldsymbol{\xi}, F^\sigma) \mapsto F_\nu$$

▸ Integrated Value Function Details

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If $T_{\boldsymbol{\theta}}$ has a unique fixed point $F_\nu(\boldsymbol{\theta})$ for all $\boldsymbol{\theta}$,

Then, we can estimate $\boldsymbol{\theta}$ by solving

$$\min_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, F_\nu(\boldsymbol{\theta}))$$

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- In the example below, $\sum_\xi d\left(\hat{F}_X(\cdot \mid \xi), F_X(\cdot \mid \xi, \boldsymbol{\theta})\right)$, where $d(F, G) = \|F^{-1} - G^{-1}\|_\infty$

Semi-parametric Estimation: Example

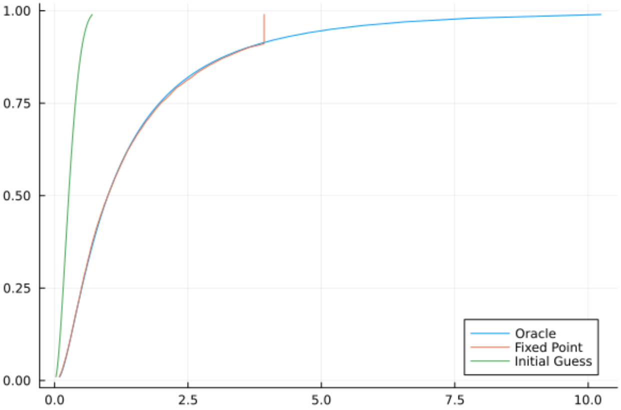
We test the feasibility of the idea above in a very simple setting.

- A monopolist solving a dynamic decision problem.
- $D(p;\xi) = \xi - p \Rightarrow \pi(\xi)$.
- $\xi \in \{\xi_L, \xi_H\}$.
- Monopolist controls dynamics of ξ via $P(\xi_L \mid \xi, x)$.

This is a rather difficult DGP:

- Only two states.
- Stationary distribution has $P(\xi_H) = 0.9$.
- And still ...

Semi-parametric Estimation: T_θ



T_θ seems rather stable in this example.

- Looks like a contraction with a rather low contraction modulus.
- We have found convergence for all $\boldsymbol{\theta}$ and F_ν^0.

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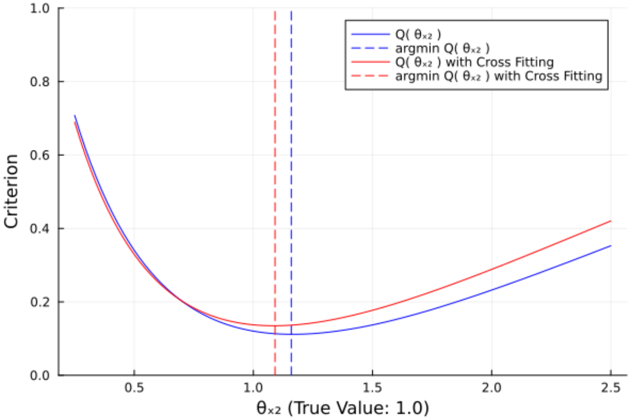
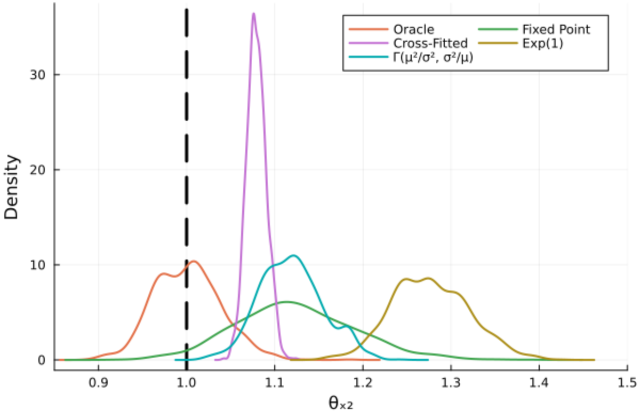


Semi-parametric Estimation: Monte Carlo with Misspecification



Conclusion

Many of the decisions we want to model are most naturally treated as **continuous**.

Yet, applications of DGCCS are not as plentiful as one might expect. **Why?**

- Many barriers to estimating a DGCC.
- An important one, we hypothesize, is the performance of available estimators.

We **show** that estimators of DGCCs based on firms' optimality conditions

- Are sufficiently **cheap** to compute in an empirically-relevant setting.
- Deliver substantial **performance gains** relative to the most popular alternative.

We have also given a preliminary rough outline of a **semi-parametric** estimator for DGCCs.

- They perform reasonably well in a simple example.
- We show that misspecification of F_ν can impart significant bias on $\hat{\boldsymbol{\theta}}$.

Thank you!

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Value Functions: The Incumbent's Investment Problem

The expected net present value (ENPV) to the incumbent entering the period is

$$\bar{V}_I(\boldsymbol{\xi}) = \int_\rho V_I(\boldsymbol{\xi}, \rho) dF_\rho = \int_\rho \max\left\{\pi(\boldsymbol{\xi}) + \rho, \int V_I^A(\boldsymbol{\xi}, \nu) dF_\nu\right\} dF_\rho$$

where $V_I^A(\boldsymbol{\xi}, \nu)$ is the ENPV of having chosen to be active next period, i.e.

$$V_I^A(\boldsymbol{\xi}, \nu) = \max_{x \in \mathbb{R}_+} \left\{\pi(\boldsymbol{\xi}) - c(x, \nu) + \beta \mathbb{E}[V_I(\boldsymbol{\xi}', \rho) \mid \boldsymbol{\xi}, x, \sigma]\right\} \qquad \text{(Investment)}$$

and the continuation value is

$$\mathbb{E}[V_I(\boldsymbol{\xi}', \rho) \mid \boldsymbol{\xi}, x, \sigma] = \int_{\boldsymbol{\varepsilon}_{-1}} \int_{\boldsymbol{\xi}'} \bar{V}_I(\boldsymbol{\xi}) \mathrm{d}F(\boldsymbol{\xi}' \mid \boldsymbol{\xi}, x, \sigma_{-1}(\boldsymbol{\xi}, \boldsymbol{\varepsilon}_{-1})) \mathrm{d}G_{\boldsymbol{\varepsilon}_{-1}}$$

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and the continuation value is , by indep. of ε_j

$$\mathbb{E}[V_I(\boldsymbol{\xi}',\rho) \mid \boldsymbol{\xi}, x, \sigma] = \int_{\varepsilon_2}\cdots\int_{\varepsilon_{\bar{N}}}\int_{\boldsymbol{\xi}'} \bar{V}_I(\boldsymbol{\xi})\mathrm{d}F(\boldsymbol{\xi}' \mid \boldsymbol{\xi}, x, \sigma_{-1}(\boldsymbol{\xi},\boldsymbol{\varepsilon}_{-1}))\mathrm{d}G_{\varepsilon_{\bar{N}}}\ldots\mathrm{d}G_{\varepsilon_2}$$

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and the continuation value is , by indep. of ε_j and by conditional indep. of $\boldsymbol{\xi}' \mid \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{x}$

$$\mathbb{E}[V_I(\boldsymbol{\xi}', \rho) \mid \boldsymbol{\xi}, x, \sigma] = \int_{\xi_1'} \int_{\xi_{\bar{N}}'} \cdots \int_{\xi_2'} \bar{V}_I(\boldsymbol{\xi}) \prod_{j=2}^{\bar{N}} \int_{\varepsilon_j} \mathrm{d}F(\xi_j' \mid \xi_j, \sigma_j(\boldsymbol{\xi}_j, \varepsilon_j)) \mathrm{d}G_{\varepsilon_j} \mathrm{d}F(\xi_1' \mid \xi_1, x)$$

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and the continuation value is , by indep. of ε_j and by conditional indep. of $\boldsymbol{\xi}' \mid \boldsymbol{\xi}, \boldsymbol{\alpha}, \boldsymbol{x}$

$$\mathbb{E}[V_I(\boldsymbol{\xi}', \rho) \mid \boldsymbol{\xi}, x, \sigma] = \int_{\xi_1'} W(\xi_1' \mid \boldsymbol{\xi}; F^\sigma) \mathrm{d}F(\xi_1' \mid \xi_1, x) \qquad \text{(Continuation)}$$

$$W(\xi_1' \mid \boldsymbol{\xi}; F^\sigma) = \int_{\xi_{\bar{N}}'} \cdots \int_{\xi_2'} \bar{V}_I(\boldsymbol{\xi}) \mathrm{d}F^\sigma(\xi_2' \mid \boldsymbol{\xi}_2) \ldots \mathrm{d}F^\sigma(\xi_{\bar{N}}' \mid \boldsymbol{\xi}_{\bar{N}})$$

Value Functions: The Incumbent's Investment Problem

Value Functions: Exit

Incumbents must commit to exiting before knowing ν. Their ENPV given ρ is

$$V_I(\boldsymbol{\xi}, \rho) = \max\left\{\pi(\boldsymbol{\xi}) + \rho, \int V_I^A(\boldsymbol{\xi}, \nu) dF_\nu\right\} \tag{Exit}$$

Hence the conditional probability of exiting is

$$\mathbb{P}(\alpha^I(\boldsymbol{\xi}, \rho) = 1 | \boldsymbol{\xi}) = 1 - F_\rho\left(\int V_I^A(\boldsymbol{\xi}, \nu) dF_\nu - \pi(\boldsymbol{\xi})\right)$$

Value Functions: Entry

Entrants are short-lived: they either enter or perish. Their ENPV given ϕ is

$$V_E(\boldsymbol{\xi}_{-1}, \phi) = \max \left\{ 0, \bar{V}_E^A(\boldsymbol{\xi}_{-1}) - \phi \right\} \tag{Entry}$$

where

$$\bar{V}_E^A(\boldsymbol{\xi}_{-1}) = \int_\nu \max_{x \in \mathbb{R}_+} \left\{ -c(x,\nu) + \beta \int_{\xi_1'} W(\xi_1' | (-\infty, \boldsymbol{\xi}_{-1}), F^\sigma) \mathrm{d}F(\xi_1' | \xi_E, x) \right\} \mathrm{d}F_\nu$$

where $\xi_E \in \Xi$ is an exogenously specified quality for the entrant.
Hence the conditional probability of entering is

$$\mathbb{P}(\alpha^E(\boldsymbol{\xi}_{-1}, \phi) = 1 | \boldsymbol{\xi}_{-1}) = F_\phi(\bar{V}_E^A(\boldsymbol{\xi}_{-1}))$$

Back

Investment: First Order Condition

Consider firm 1's problem (wlog given symmetry and anonymity). Then

$$-\partial_x c(x,\nu) + \beta \partial_x \left(\int_{\xi_1'} W(\xi_1' \mid \boldsymbol{\xi}, F^\sigma) dF(\xi_1' \mid \xi_1, x) \right) \leq 0 \tag{2}$$

where recall

$$W(\xi_1' \mid \boldsymbol{\xi}; F^\sigma) := \int_{\xi_2'} \cdots \int_{\xi_{\bar{N}}'} \bar{V}_I(\xi_1', \boldsymbol{\xi}_{-1}') dF(\xi_{\bar{N}}' \mid \xi_{\bar{N}}, x) \dots dF(\xi_2' \mid \xi_2, x)$$

and

$$\bar{V}_I(\boldsymbol{\xi}) = \int_\rho V_I(\boldsymbol{\xi}, \rho) dF_\rho = \int_\rho \max \left\{ \pi(\boldsymbol{\xi}) + \rho, \int V_I^A(\boldsymbol{\xi}, \nu) dF_\nu \right\} dF_\rho$$

and

$$V_I^A(\boldsymbol{\xi}, \nu) = \max_{x \in \mathbb{R}_+} \left\{ \pi(\boldsymbol{\xi}) - c(x,\nu) + \beta \mathbb{E}[V_I(\boldsymbol{\xi}', \rho) \mid \boldsymbol{\xi}, x, \sigma] \right\}$$

Back to model.

Assumption (A1)

Let Ξ be a compact subset of the real line, and denote its minimum and maximum by ξ_m and ξ_M. Let Ξ° be the interior of Ξ. The family of distributions $F(\cdot \mid \xi, x)$ is such that

(a) *$F(\xi' \mid \xi, x)$ is strictly decreasing and strictly convex in x, for all $\xi \in \Xi$ and $\xi' \in \Xi^\circ$;*

(b) *$F(\xi_m \mid \xi, x)$ is decreasing and convex in x, , for all $\xi \in \Xi$.*

Proposition

Assume

(a) *$c(x, \nu)$ is convex in x;*

(b) *$F(\xi' \mid \xi, x)$ is twice continuously differentiable in x for all ξ', ξ;*

(c) *$W(\xi' \mid \boldsymbol{\xi}, F^\sigma)$ is increasing in ξ' for all $\boldsymbol{\xi}$.*

(d) *A1 holds.*

Then the incumbent's investment problem is strictly concave in x.

Back to UIC.

Computing Markov Perfect Equilibria

1. Guess $\bar{V}_I(\boldsymbol{\xi})$ and $F^\sigma(\xi' \mid \boldsymbol{\xi})$.
2. Solve incumbents' investment problem at all $\boldsymbol{\xi}$ and judiciously chosen ν.
    - Gives $\bar{V}_I^A := \int V_I^A(\boldsymbol{\xi}, \nu)\, \mathrm{d}F_\nu$.
3. Compute incumbents' optimal exit decisions.
4. Use incumbents' optimal choices to update $\bar{V}_I(\boldsymbol{\xi})$.
5. Solve potential entrants' investment problems at all $\boldsymbol{\xi}_{-1}$ and judiciously chosen ν to obtain $\bar{V}_E^A := \int V_E^A(\boldsymbol{\xi}_{-1}, \nu)\, \mathrm{d}F_\nu$.
6. Compute potential entrants' optimal entry decisions.
7. Iterate to convergence in $\bar{V}_I$ and F^σ.

N.B.:

- We need only compute $\bar{V}_I$.
    - Potential entrants' decisions depend on $\bar{V}_I$.
    - There is no continuation value conditional on not entering: short-lived PEs assumption.
    - Symmetry reduces the computational burden significantly: Pakes and McGuire (1994).

Back to model.

Indirect Inference I: Investment

Predicted investment $T_{\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}, \nu; \hat{\Phi})$ can be used in multiple ways.

Our preferred estimator is based on Indirect Inference:

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1. Compute $\{T_{\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}_i, \nu_i; \hat{\Phi})\}_{i=1}^{MK}$ for K randomly drawn ν per observation.

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2. Estimate

$$T_{\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}_i,\nu_i;\hat{\Phi}) = \sum_{k=1}^{B} \lambda_k^x \Psi_k^x(\boldsymbol{\xi}_i) + \zeta_i^x \quad \Rightarrow \quad \hat{\boldsymbol{\lambda}}_{\text{Investment}}(\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\};\hat{\Phi})$$

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3. Estimate

$$x_m = \sum_{k=1}^{B} \gamma_k^x \Psi_k^x(\boldsymbol{\xi}_m) + \eta_m^x \quad \Rightarrow \quad \hat{\boldsymbol{\gamma}}_{\text{Investment}} := \left[\hat{\gamma}_1^x,\ldots,\hat{\gamma}_B^x,\hat{S}_\eta^x\right]$$

Indirect Inference IIa: Exit

1. Compute

$$\widehat{\mathbb{P}}(\text{Exit} \mid \boldsymbol{\xi}; \{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}) = 1 - F_\rho\left(\int_\nu \widehat{V}_I^A(\boldsymbol{\xi}; \{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}) \mathrm{d}F_\nu - \pi(\boldsymbol{\xi}); \boldsymbol{\theta}_\rho \right)$$

2. Estimate, as in Collard-Wexler (2013),

$$\widehat{\mathbb{P}}(\text{Exit} \mid \boldsymbol{\xi}; \{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}) = \sum_{k=1}^{B} \lambda_k^E \Psi_k^E(\boldsymbol{\xi}_i) + \zeta_i^E \quad \Rightarrow \quad \hat{\boldsymbol{\lambda}}_{\text{Exit}}(\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}; \hat{\Phi})$$

3. Estimate

$$\mathbb{1}\{\xi'_m = -\infty\} = \sum_{k=1}^{B} \gamma_k^E \Psi_k^E(\boldsymbol{\xi}_m) + \eta_m^E \quad \Rightarrow \quad \hat{\boldsymbol{\gamma}}_{\text{Exit}} := \left[\hat{\gamma}_1^E, \ldots, \hat{\gamma}_B^E\right]$$

Indirect Inference IIb: Entry

1. Compute

$$\widehat{\mathbb{P}}(\text{Entry} \mid \boldsymbol{\xi}; \{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho, \boldsymbol{\theta}_\phi\}) = F_\phi\left(\int_\nu \widehat{V}_E^A(\boldsymbol{\xi}_{-1}; \{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho\}) \mathrm{d}F_\nu; \boldsymbol{\theta}_\phi \right)$$

2. Estimate, as in Collard-Wexler (2013),

$$\widehat{\mathbb{P}}(\text{Entry} \mid \boldsymbol{\xi}; \{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho, \boldsymbol{\theta}_\phi\}) = \sum_{k=1}^{B} \lambda_k^N \Psi_k^N(\boldsymbol{\xi}_i) + \zeta_i^N \quad \Rightarrow \quad \hat{\boldsymbol{\lambda}}_{\text{Entry}}(\{\boldsymbol{\theta}_x, \boldsymbol{\theta}_\rho, \boldsymbol{\theta}_\phi\}; \hat{\Phi})$$

3. Estimate

$$\mathbb{1}\{\xi_m' > -\infty | \xi_m = -\infty\} = \sum_{k=1}^{B} \gamma_k^N \Psi_k^N(\boldsymbol{\xi}_m) + \eta_m^N \quad \Rightarrow \quad \hat{\boldsymbol{\gamma}}_{\text{Entry}} := \left[\hat{\gamma}_1^N, \ldots, \hat{\gamma}_B^N\right]$$

Indirect Inference III: Estimator

Let

$$\hat{\boldsymbol{\lambda}}(\boldsymbol{\theta};\hat{\Phi}) = \left[\hat{\boldsymbol{\lambda}}_{\text{Investment}}(\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho;\hat{\Phi}) \quad \hat{\boldsymbol{\lambda}}_{\text{Entry}}(\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho,\boldsymbol{\theta}_\phi;\hat{\Phi}) \quad \hat{\boldsymbol{\lambda}}_{\text{Exit}}(\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho;\hat{\Phi})\right]$$

and

$$\hat{\gamma} = \left[\hat{\gamma}_{\text{Investment}} \quad \hat{\gamma}_{\text{Entry}} \quad \hat{\gamma}_{\text{Exit}}\right]$$

The Indirect Inference estimator solves

$$\min_{\boldsymbol{\theta}} \left[\hat{\boldsymbol{\lambda}}(\boldsymbol{\theta};\hat{\Phi}) - \hat{\gamma}\right]^\top \boldsymbol{\Omega} \left[\hat{\boldsymbol{\lambda}}(\boldsymbol{\theta};\hat{\Phi}) - \hat{\gamma}\right]$$

Consistency conditions (dependence on $\hat{\Phi}$ omitted):

- $B_{MK}(\boldsymbol{\lambda},\boldsymbol{\theta}) \to \mathcal{B}(\boldsymbol{\lambda},\boldsymbol{\theta})$ uniformly in $\boldsymbol{\lambda},\boldsymbol{\theta}$.
- For any $\boldsymbol{\theta}$, $\mathcal{B}(\boldsymbol{\lambda},\boldsymbol{\theta})$ has a unique optimum in $\boldsymbol{\lambda}$, $\boldsymbol{\lambda}(\boldsymbol{\theta})$.
- $\lim_{n\to\infty} \hat{\boldsymbol{\lambda}}(\boldsymbol{\theta}) = \boldsymbol{\lambda}(\boldsymbol{\theta})$.
- $\gamma = \boldsymbol{\lambda}(\boldsymbol{\theta})$ has a unique solution, i.e. $\boldsymbol{\lambda}^{-1}$ is well-defined.

Back to Indirect Inference.

Alternative Recursive Estimators

Other objective functions could be considered:

- Nonlinear Least Squares:

$$\min_{\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\}} \sum_{i=1}^{N} \left(x_i - \mathbb{E}_\nu[T_{\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}_i,\nu;\hat{\Phi}) \mid \boldsymbol{\xi}]\right)^2$$

- Based on Asymptotic Least Squares:

$$\min_{\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\}} \sum_{\boldsymbol{\xi}} \left(\hat{\mathbb{E}}[\sigma(\boldsymbol{\xi},\nu) \mid \boldsymbol{\xi}] - \mathbb{E}_\nu[T_{\{\boldsymbol{\theta}_x,\boldsymbol{\theta}_\rho\}}(\boldsymbol{\xi}_i,\nu;\hat{\Phi}) \mid \boldsymbol{\xi}]\right)^2$$

Indirect Inference:

- Performed better than NLLS/ALS in early experimentation.
- Is cheaper to compute (NLLS and ALS solve as many problems as ν nodes)
- ALS + entry/exit moments $\approx$ BBL "moment matching" estimator

MLE on the to do list.

Back to Indirect Inference.

Integrated Value Function

$$[I - \beta \boldsymbol{M}(\boldsymbol{P})]\bar{\boldsymbol{V}}_I = \boldsymbol{\pi} - \boldsymbol{K}(\boldsymbol{\theta}_x) + \boldsymbol{\Sigma}(\boldsymbol{\theta}_\rho) \ .$$

where

$$\boldsymbol{K}(\boldsymbol{\theta}_x) = \left[\mathbb{P}(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi}) \int c(\sigma^x(\boldsymbol{\xi},\nu),\nu;\boldsymbol{\theta}_x)\,\mathrm{d}F_\nu\right]_{\{\boldsymbol{\xi}\in\Xi_I\}}$$

$$\boldsymbol{\Sigma}(F_\rho) = \left[\left[1 - \mathbb{P}(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi})\right]\mathbb{E}\left[\rho \mid F_\rho(\rho) > \mathbb{P}(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi})\right]\right]_{\{\boldsymbol{\xi}\in\Xi_I\}}$$

$$\boldsymbol{M}(\boldsymbol{P}) = \left[\prod_{j=1}^{\bar{N}} F^\sigma(\xi_j' \mid \boldsymbol{\xi}) : \boldsymbol{\xi}', \boldsymbol{\xi} \in \Xi_I\right]$$

- $\bar{V}_I$ estimable up to $\boldsymbol{\theta}$ given $\hat{\mathbb{P}}(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi})$, $\hat{F}^\sigma(\xi_j' \mid \boldsymbol{\xi})$, and $\hat{\sigma}^x(\boldsymbol{\xi},\nu)$.
- $\sigma^x(\boldsymbol{\xi},\nu) = F_X(1 - F_\nu(\nu) \mid \boldsymbol{\xi})$.
- Similar calculations in Jofre-Bonet and Pesendorfer (2003) and Pakes et al. (2007).

Back to integrated VF. Back to semi-parametric estimation.

Computational Considerations

- $[I - \beta \boldsymbol{M}(\boldsymbol{P})]\bar{\boldsymbol{V}}_I = \boldsymbol{\pi} - \boldsymbol{K}(\boldsymbol{\theta}_x) + \boldsymbol{\Sigma}(F_\rho)$ must be solved for each $\boldsymbol{\theta}$.
- *However*, the matrix $I - \beta \boldsymbol{M}(\boldsymbol{P})$ is *banded*:

- The LU decomposition of a banded matrix has banded components.
  - Speeds up computation considerably.
  - Decomposition computed once and stored in memory.

Back to Monte Carlo Setup.

Bajari et al. (2007): Non-Linearity in $\boldsymbol{\theta}$

Note the model is not linear in parameters:

$$\bar{V}_I(\boldsymbol{\xi}) = \int_\rho \max\left\{\pi(\boldsymbol{\xi}) + \rho, \int V_I^A(\boldsymbol{\xi}, \nu) dF_\nu\right\} dF_\rho$$

Back to BBL.

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Note the model is not linear in parameters:

$$\bar{V}_I(\boldsymbol{\xi}) = \pi(\boldsymbol{\xi}) + \int_\rho \max\left\{\rho, \int V_I^A(\boldsymbol{\xi}, \nu) dF_\nu - \pi(\boldsymbol{\xi})\right\} dF_\rho$$

Back to BBL.

Bajari et al. (2007): Non-Linearity in $\boldsymbol{\theta}$

Note the model is not linear in parameters:

$$\bar{V}_I(\boldsymbol{\xi}) = \pi(\boldsymbol{\xi}) + \int_{\int V_I^A(\boldsymbol{\xi},\nu)\mathrm{d}F_\nu - \pi(\boldsymbol{\xi})}^{\infty} \rho \mathrm{d}F_\rho + F_\rho\left(\int V_I^A(\boldsymbol{\xi},\nu)\mathrm{d}F_\nu - \pi(\boldsymbol{\xi})\right)\left[\int V_I^A(\boldsymbol{\xi},\nu)\mathrm{d}F_\nu - \pi(\boldsymbol{\xi})\right]$$

Back to BBL.

Bajari et al. (2007): Non-Linearity in $\boldsymbol{\theta}$

Note the model is not linear in parameters:

$$\bar{V}_I(\boldsymbol{\xi}) = \pi(\boldsymbol{\xi}) + \int_{F_\rho^{-1}[\mathbb{P}(\alpha^I(\boldsymbol{\xi},\rho)=1|\boldsymbol{\xi})]}^{\infty} \rho \mathrm{d}F_\rho + \mathbb{P}\left(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi}\right) F_\rho^{-1}\left[\mathbb{P}\left(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi}\right)\right]$$

$\int_a^\infty \rho \mathrm{d}F_\rho$ is not generally linear in parameters (e.g. exponential is, lognormal isn't).

Back to BBL.

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Nonetheless, forward simulation can still be performed once.

- Draw $u \sim U[0,1]$
- Exit: $\mathbb{1}\{u \leq \mathbb{P}(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi})\} \Leftrightarrow \mathbb{1}\{F_\rho^{-1}(u) \leq \int V_I^A(\boldsymbol{\xi},\nu)\mathrm{d}F_\nu - \pi(\boldsymbol{\xi})\}$

Back to BBL.

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Nonetheless, forward simulation can still be performed once.

- Draw $u \sim U[0,1]$
- Exit: $\mathbb{1}\{u \leq \mathbb{P}(\alpha^I(\boldsymbol{\xi},\rho) = 1 \mid \boldsymbol{\xi})\} \Leftrightarrow \alpha^I(\boldsymbol{\xi}, F_\rho^{-1}(u))$
- Forward simulate, storing exit u_{τ_e}. As $\boldsymbol{\theta}_\rho$ changes, only recompute $F_\rho^{-1}(u_{\tau_e}; \boldsymbol{\theta}_\rho)$.
- Generalizes to investment, entry choices if wanted.

Back to BBL.

Flow Profit Specification

Demand

- Nested Logit:

$$u_{ij} = \begin{cases} \epsilon_i^{\text{out}} + (1-\varsigma)\varepsilon_{ij} & \text{if } j = 0 \\ \alpha p_j + \xi_j + \epsilon_i^{\text{in}} + (1-\varsigma)\varepsilon_{ij} & \text{if } j = 1, \dots, N \end{cases},$$

- Inside and Outside good nests; $\epsilon_i^{g} + (1-\varsigma)\varepsilon_{ij} \sim T1EV, g = \{\text{in, out}\}$.

Pricing

- Marginal cost: $\mu(\xi_j) = \exp(\theta_{c1} + \theta_{c2}\xi_j)$.
- Firms compete à la Bertrand
  - Caplin and Nalebuff (1991) $\Rightarrow \exists!$ Eqm $\Rightarrow \pi_j(\boldsymbol{\xi})$ well-defined.

Back to Monte Carlo setup.

Monte Carlo: First Stage and Deviation Details

- Empirical policy functions:

$$\hat{\sigma}^x(\xi, \nu_\tau) = f^x(\xi)^\top \hat{\chi}^x_\tau \qquad \hat{\mathbb{P}}^E(\xi_{-1}) = \Lambda\big(f^E(\xi)^\top \hat{\chi}^E\big) \qquad \hat{\mathbb{P}}^I(\xi) = \Lambda\big(f^I(\xi)^\top \hat{\chi}^I\big).$$

- BBL deviations: asymptotic,

We draw $\tilde{\boldsymbol{\chi}}_i \sim \mathrm{N}(\hat{\chi}, \hat{\boldsymbol{\Sigma}}_\chi)$ for each deviation i. We then form deviations as

$$\tilde{\sigma}^x_i(\xi, \nu_\tau) = f^x(\xi)^\top \hat{\chi}^x_{i\tau}; \quad \tilde{\mathbb{P}}^E_i(\xi_{-1}) = \Lambda\big(f^E(\xi)^\top \hat{\chi}^E_i\big); \quad \tilde{\mathbb{P}}^I_i(\xi) = \Lambda\big(f^I(\xi)^\top \hat{\chi}^I_i\big).$$

Back to Monte Carlo Results.

Monte Carlo: First Stage and Deviation Details

- Empirical policy functions:

$$\hat{\sigma}^x(\boldsymbol{\xi}, \nu_\tau) = f^x(\boldsymbol{\xi})^\top \hat{\chi}^x_\tau \qquad \hat{\mathbb{P}}^E(\boldsymbol{\xi}_{-1}) = \Lambda\big(f^E(\boldsymbol{\xi})^\top \hat{\chi}^E\big) \qquad \hat{\mathbb{P}}^I(\boldsymbol{\xi}) = \Lambda\big(f^I(\boldsymbol{\xi})^\top \hat{\chi}^I\big).$$

- BBL deviations: multiplicative,

We draw $\iota_i \in \{.95, .975, 1.025, 1.05, 1.075\}$ for each deviation i. We then form deviations as

$$\tilde{\sigma}^x_i(\boldsymbol{\xi}, \nu_\tau) = \iota_i f^x(\boldsymbol{\xi})^\top \hat{\chi}^x_\tau; \quad \tilde{\mathbb{P}}^E_i(\boldsymbol{\xi}_{-1}) = \Lambda\big(\iota_i f^E(\boldsymbol{\xi})^\top \hat{\chi}^E\big); \quad \tilde{\mathbb{P}}^I_i(\boldsymbol{\xi}) = \Lambda\big(\iota_i f^I(\boldsymbol{\xi})^\top \hat{\chi}^I\big),$$

Back to Monte Carlo Results.

Monte Carlo: First Stage and Deviation Details

- Empirical policy functions:

$$\hat{\sigma}^x(\boldsymbol{\xi}, \nu_\tau) = f^x(\boldsymbol{\xi})^\top \hat{\chi}^x_\tau \qquad \hat{\mathbb{P}}^E(\boldsymbol{\xi}_{-1}) = \Lambda\big(f^E(\boldsymbol{\xi})^\top \hat{\chi}^E\big) \qquad \hat{\mathbb{P}}^I(\boldsymbol{\xi}) = \Lambda\big(f^I(\boldsymbol{\xi})^\top \hat{\chi}^I\big).$$

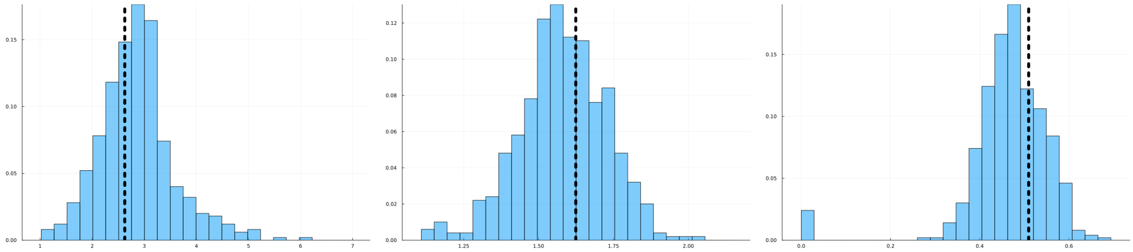
- BBL deviations: and additive.

We draw $o_{is} \sim N(0, 0.5)$ for each deviation i and simulated decision s.
We then form deviations as

$$\tilde{\sigma}^x_{is}(\boldsymbol{\xi}, \nu_\tau) = f^x(\boldsymbol{\xi})^\top \hat{\chi}^x_\tau + o^x_{is}; \quad \tilde{\mathbb{P}}^E_{is}(\boldsymbol{\xi}_{-1}) = \Lambda\big(f^E(\boldsymbol{\xi})^\top \hat{\chi}^E + o^{\text{Exit}}_{is}\big); \quad \tilde{\mathbb{P}}^I_{is}(\boldsymbol{\xi}) = \Lambda\big(f^I(\boldsymbol{\xi})^\top \hat{\chi}^I + o^{\text{Entry}}_{is}\big).$$

Back to Monte Carlo Results.

Investment Cost Parameters II Estimates



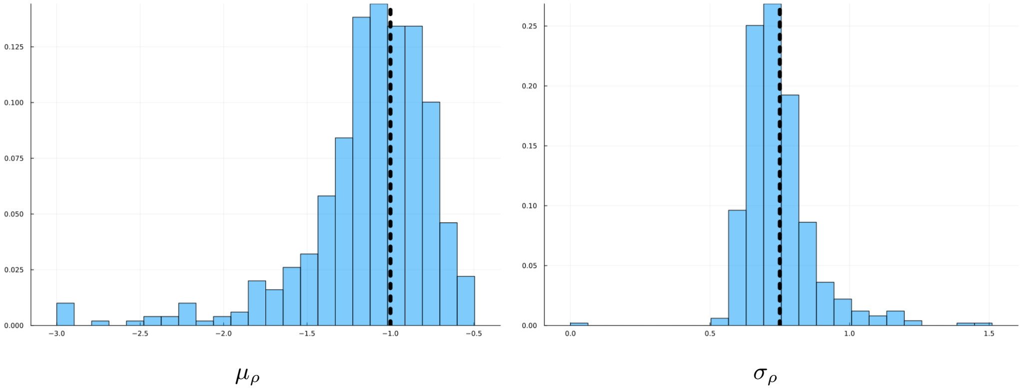
θ_{x1} θ_{x2} θ_{x3}

$$c(x, \nu) = \theta_{x1} x + \theta_{x2} x^2 + \theta_{x3} x \nu$$

Indirect Inference BBL - Asymptotic BBL - Multiplicative BBL - Additive

Back to Investment Cost Parameters Estimates

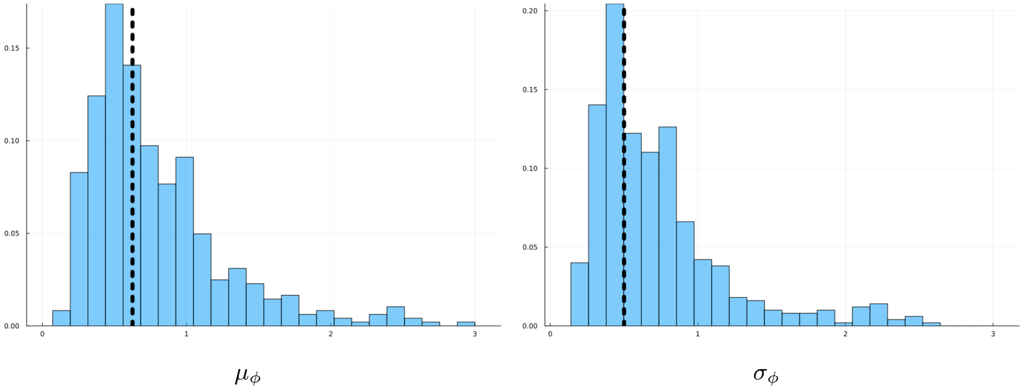
Scrap Value Parameters II Estimates



$$\rho \sim \log N(\mu_\rho, \sigma_\rho)$$

Back to Investment Cost Parameters Estimates

Entry Cost Parameters II Estimates

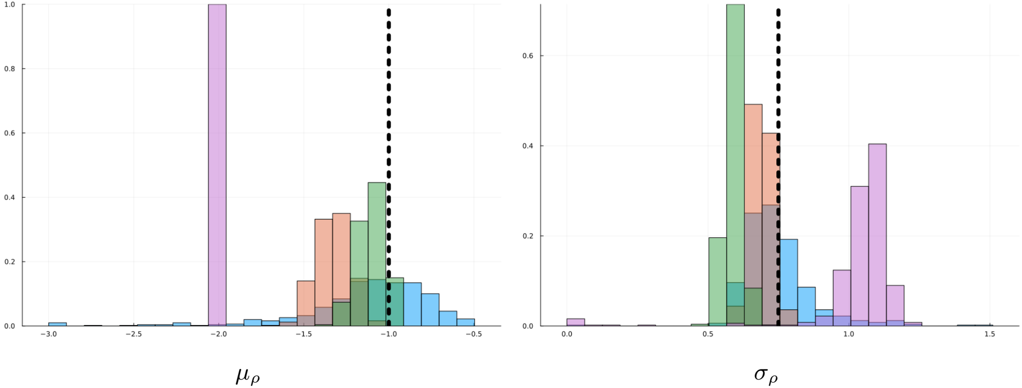


$$\phi \sim \log N(\mu_\phi, \sigma_\phi)$$

Indirect Inference | BBL - Asymptotic | BBL - Multiplicative | BBL - Additive

▸ Back to Investment Cost Parameters Estimates

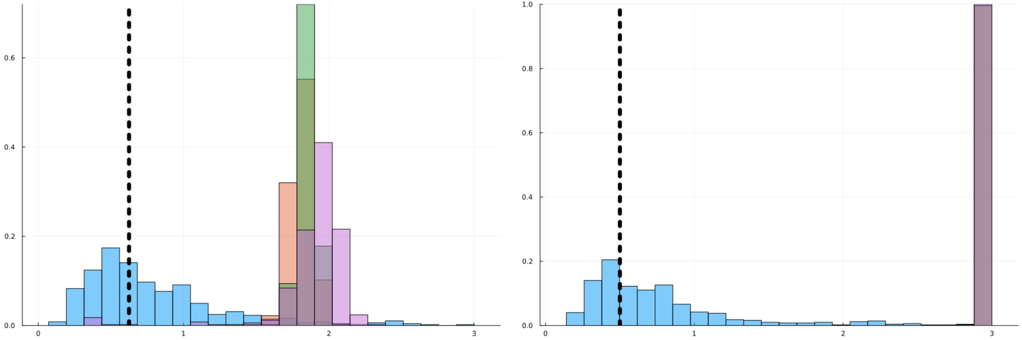
Scrap Value Parameters Estimates



$$\rho \sim \log N(\mu_\rho, \sigma_\rho)$$

Back to Investment Cost Parameters Estimates

Entry Cost Parameters Estimates



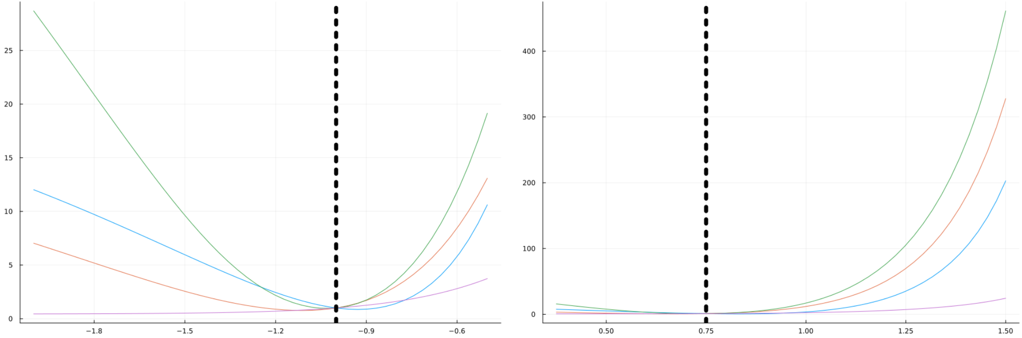
μ_ϕ σ_ϕ

$$\phi \sim \log N(\mu_\phi, \sigma_\phi)$$

Indirect Inference | BBL - Asymptotic | BBL - Multiplicative | BBL - Additive

Back to Investment Cost Parameters Estimates

Objective Function: Scrap Value Parameters



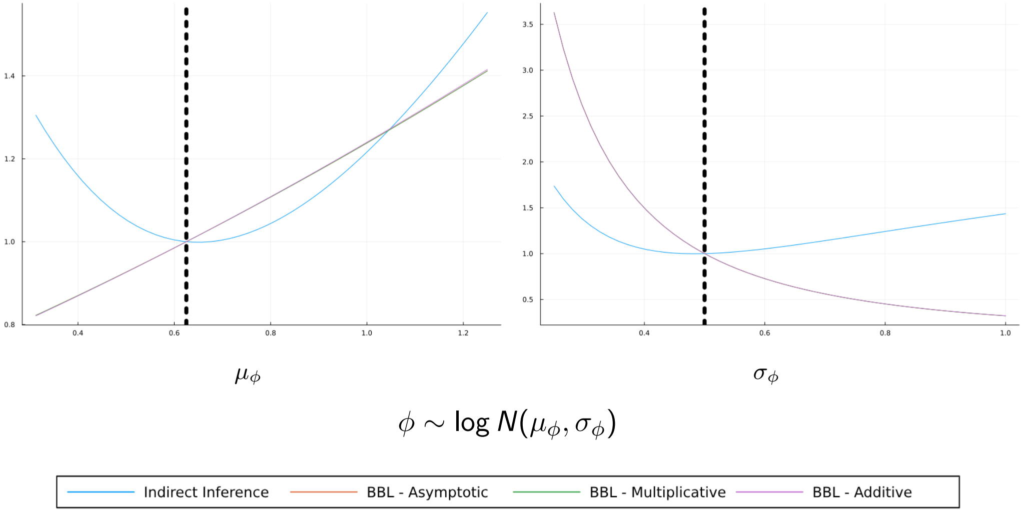
μ_ρ σ_ρ

$$\rho \sim \log N(\mu_\rho, \sigma_\rho)$$

Indirect Inference | BBL - Asymptotic | BBL - Multiplicative | BBL - Additive

Back to Objective Function

Objective Function: Entry Cost Parameters



$$\phi \sim \log N(\mu_\phi, \sigma_\phi)$$

Back to Objective Function