Lecture 8b: Solving and Estimating STATIC Games of Incomplete Information

2019 Econometric Society Summer School in Dynamic Structural Econometrics

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Road Map for Lectures on Games

Lecture 8b: Structural Estimation of Static Games Incomplete Information (Schjerning)

- Methods: NFXP, MPEC, CCP and NPL
- Example: Simple static entry model
- Explicit focus: Multiple Equilibira

Lecture 9,10, 17 and 18: Structural Estimation of Dynamic Games Incomplete Information

- Issues and Stochastic Algorithms for Computing Equilibria to Dynamic Games (Arial Pakes)
- Identification of Firms' Beliefs and Learning in Empirical Dynamic Games of Oligopoly Competition (Victor Aguirregabiria)
- Dynamic Discrete Games in Marketing (Paul Ellickson)
- Application: Does AMD Spur Intel to Innovate More? (Brett Gordon)

Road Map for Lectures on Games

Lecture 19 and 20: Solving and estimating dynamic games with multiple equilibria (Iskhakov, Rust, Schjerning)

- New solution method: Recursive Lexicographic Search (RLS)
- Estimation method: MLE using NRLS (implemented using Branch and Bounds algorithm)
- Compare with: MPEC, CCP estimator and Nested Pseudo Likelihood
- Example: Dynamic model of Bertrand duopoly competition and cost reducing investments

Estimating Discrete-Choice Games of Incomplete Information

Estimating Discrete-Choice Games of Incomplete Information

- Aguirregabiria and Mira (2007): NPL (Recursive 2-Step)
- Bajari, Benkard and Levin (2007): 2-Step Minimum Distance Estimator
- Pakes, Ostrovsky and Berry (2007): Various 2-Step (PML, MoM, min χ^2)
- Pesendorfer and Schmidt-Dengler (2008): 2-Step Least Squares
- Pesendorfer and Schmidt-Dengler (2010): comments on AM (2007)
- Kasahara and Shimotsu (2012): Modified NPL
- Su (2013), Egesdal, Lai and Su (2015): Constrained Optimization

Example: Static Game Entry of Incomplete Information

- Two firms: a and b
- Actions: each firm has two possible actions:

$$d_a = \begin{cases} 1, & \text{if firm } a \text{ choose to enter the market} \\ 0, & \text{if firm } a \text{ choose not to enter the market} \end{cases} \tag{1}$$

$$d_b = \begin{cases} 1, & \text{if firm } b \text{ choose to enter the market} \\ 0, & \text{if firm } b \text{ choose not to enter the market} \end{cases} \tag{2}$$

Example: Static Entry Game of Incomplete Information

Utility: Ex-post payoff to firms

$$u_a(d_a, d_b, x_a, \epsilon_a) = \begin{cases} [\alpha + d_b * (\beta - \alpha)]x_a + \epsilon_{a1}, & \text{if } d_a = 1 \\ 0 + \epsilon_{a0}, & \text{if } d_a = 0 \end{cases}$$

$$u_b(d_a, d_b, x_a, \epsilon_b) = \begin{cases} [\alpha + d_a * (\beta - \alpha)]x_b + \epsilon_{b1}, & \text{if } d_b = 1 \\ 0 + \epsilon_{b0}, & \text{if } d_b = 0 \end{cases}$$

- (α, β): structural parameters to be estimated
- (x_a, x_b): firms' observed types; **common knowledge**
- $\epsilon_a = (\epsilon_{a0}, \epsilon_{a1}), \epsilon_b = (\epsilon_{b0}, \epsilon_{b1})$: firms' unobserved types, **private information**
- (ϵ_a, ϵ_b) are observed only by each firm, but not by their opponent firm nor by the econometrician

Example: Static Entry Game of Incomplete Information

- Assume the error terms (ϵ_a, ϵ_b) have a standardized type III extreme value distribution
- A Bayesian Nash equilibrium (p_a, p_b) satisfies

$$
\begin{aligned}
p_a &= \frac{\exp[p_b \beta x_a + (1 - p_b)\alpha x_a]}{1 + \exp[p_b \beta x_a + (1 - p_b)\alpha x_a]} \\
&= \frac{1}{1 + \exp[-\alpha x_a + p_b x_a(\alpha - \beta)]} \\
&\equiv \Psi_a(p_b, x_a; \alpha, \beta)
\end{aligned}
$$

$$
\begin{aligned}
p_b &= \frac{1}{1 + \exp[-\alpha x_b + p_a x_b(\alpha - \beta)]} \\
&\equiv \Psi_b(p_a, x_b; \alpha, \beta)
\end{aligned}
$$

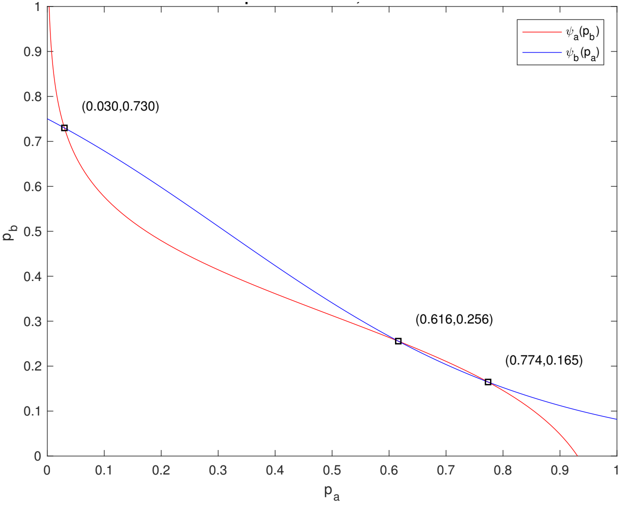
Static Game Example: Parameters

We consider a very contestable game throughout

- Monopoly profits: $\alpha * x_j = 5 * x_j$
- Duopoly profits: $\beta * x_j = -11 * x_j$
- Firm types: $(x_a, x_b) = (0.52, 0.22)$

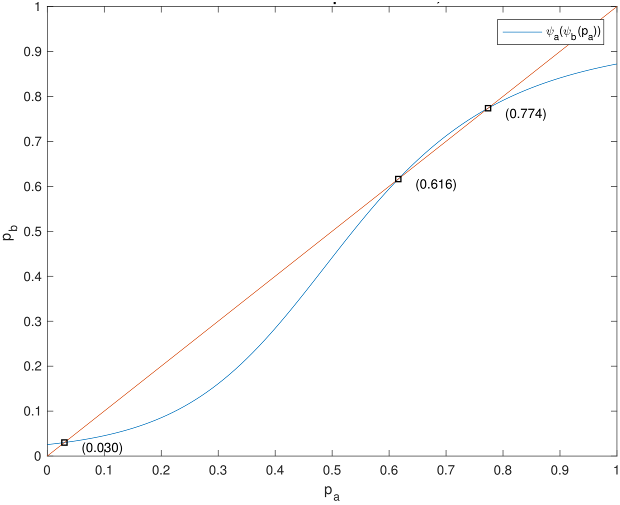
Static Game Example: Three Bayesian Nash Equilibria

Figure: Equilibria at intersections of best response functions



Static Game Example: Solving for Equilibria

Figure: Fixed points on second order best response function



Static Game Example: Solving for Equilibria

Solution method: Combination of succesive approximations and bisection algorithm

Succesive approximations (SA)

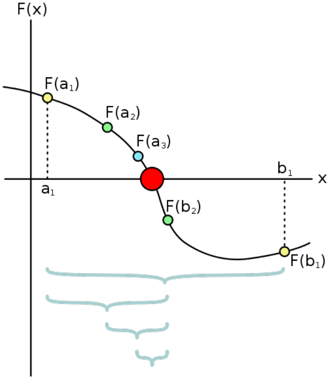
- Converge to nearest stable equilibrium.
- Start SA at $p_a = 0$ and $p_a = 1$.
- Unique equilibrium (K=1): SA will converge to it from anywhere.
- Three equilibria (K=3): Two will be stable, and one will be unstable.
- More equilibria (K>3): Not in this model.

Bisection method

- Use this to find the unstable equilibrium (if K=3).
- The bisection method that repeatedly bisects an interval and then selects a subinterval in which the fixed point (or root) must lie.
- The two stable equilibria, defines the initial interval to search over.
- The bisection method is a very simple and robust method, but it is also relatively slow.

Static Game Example: Solving for Equilibria

Figure: Bisection method



A few steps of the bisection method applied over the starting range [a1;b1]. The bigger red dot is the root of the function.

Static Game Example: Data Generation and Identification

- Data Generating Process (DGP): the data are generated by a single equilibrium
- The two players use the same equilibrium to play 1000 times
- Data: $X = \{(d_a^i, d_b^i)_{i=1}^{1000}, (x_a, x_b) = (0.52, 0.22)\}$
- Given data X, we want to recover structural parameters α and β

Static Game Example: Maximum Likelihood Estimation

- Maximize the likelihood function

$$\begin{aligned}\max_{\alpha,\beta} \quad \log \quad & \mathcal{L}(p_a(\alpha,\beta);X) \\ = \quad & \sum_{i=1}^{N} \left(d_a^i * \log(p_a(\alpha,\beta)) + (1-d_a^i*)\log(1-p_a(\alpha,\beta)) \right) \\ + \quad & \sum_{i=1}^{N} \left(d_b^i * \log(p_b(\alpha,\beta)) + (1-d_b^i*)\log(1-p_b(\alpha,\beta)) \right)\end{aligned}$$

- $p_a(\alpha,\beta)$ and $p_a(\alpha,\beta)$ are the solutions of the Bayesian-Nash Equilibrium equations

$$\begin{aligned} p_a &= \frac{1}{1+\exp[-\alpha x_a + p_b x_a(\alpha-\beta)]} \equiv \Psi_a(p_b, x_a; \alpha, \beta) \\ p_b &= \frac{1}{1+\exp[-\alpha x_b + p_a x_b(\alpha-\beta)]} \equiv \Psi_b(p_a, x_b; \alpha, \beta)\end{aligned}$$

Static Game Example: MLE via NFXP

- Outer Loop
  - Choose (α, β) to maximize the likelihood function

$$\log \mathcal{L}(p_a(\alpha, \beta), p_b(\alpha, \beta); X)$$

- Inner loop:
  - For a given (α, β), solve the BNE equations for **ALL** equilibria: $(p_a^k(\alpha, \beta), p_b^k(\alpha, \beta)), k = 1, ..., K$
  - Choose the equilibrium that gives the highest likelihood value:

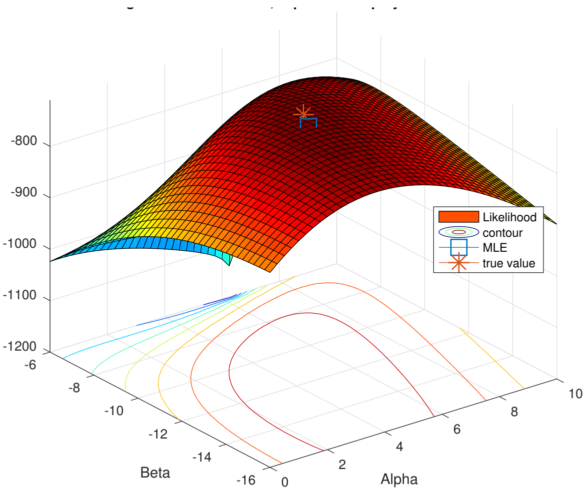
$$k^* = \arg \max_{k=1,\ldots,K} \log \mathcal{L}(p_a^k(\alpha, \beta), p_b^k(\alpha, \beta); X)$$

    such that

$$(p_a(\alpha, \beta), p_b(\alpha, \beta)) = (p_a^{k*}(\alpha, \beta), p_b^{k*}(\alpha, \beta))$$

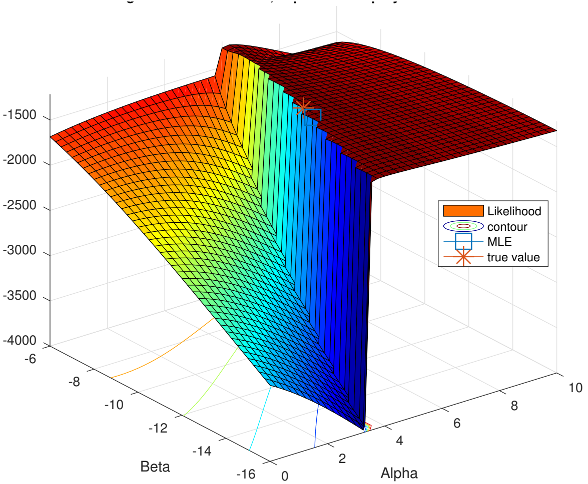
NFXP's Likelihood as a Function of (α, β) - Eq 1

Figure: Data generated from equilibrium 1



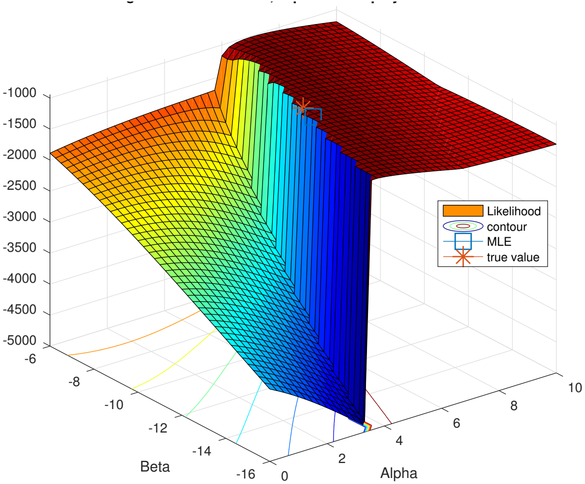
NFXP's Likelihood as a Function of (α, β) - Eq 2

Figure: Data generated from equilibrium 2



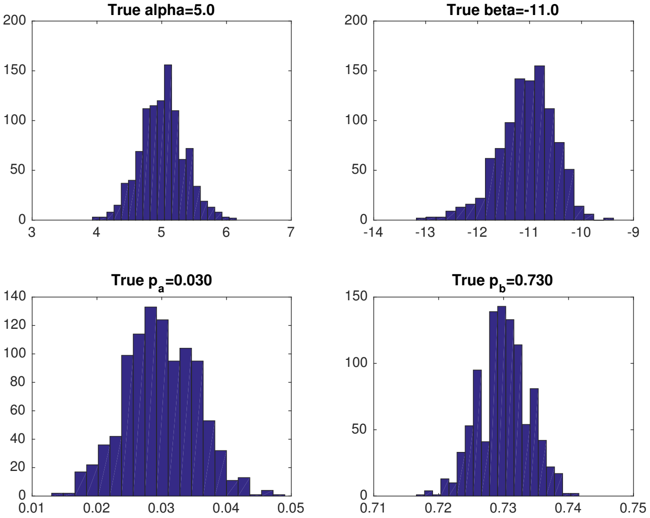
NFXP's Likelihood as a Function of (α, β) - Eq 3

Figure: Data generated from equilibrium 3



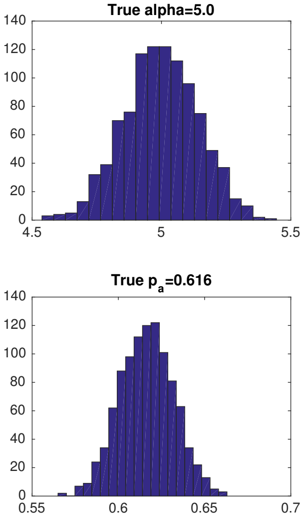
Monte Carlo Results: NFXP with Eq1

Figure: Data generated from equilibrium 1



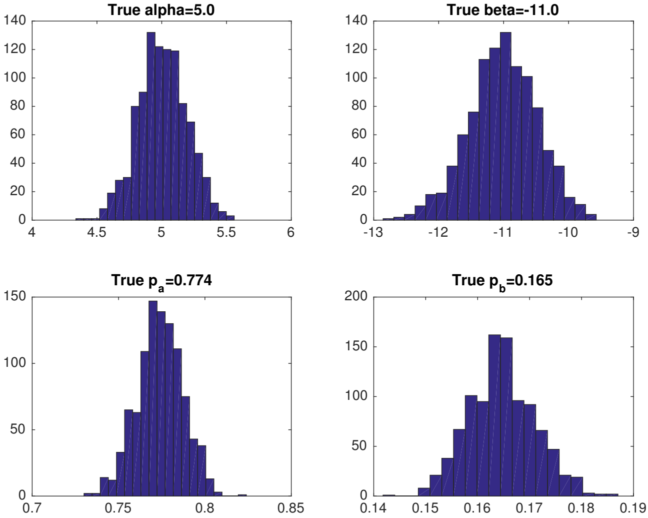
Monte Carlo Results: NFXP with Eq2

Figure: Data generated from equilibrium 2



Monte Carlo Results: NFXP with Eq3

Figure: Data generated from equilibrium 3



Constrained Optimization Formulation for Maximum Likelihood Estimation

- Maximize the likelihood function

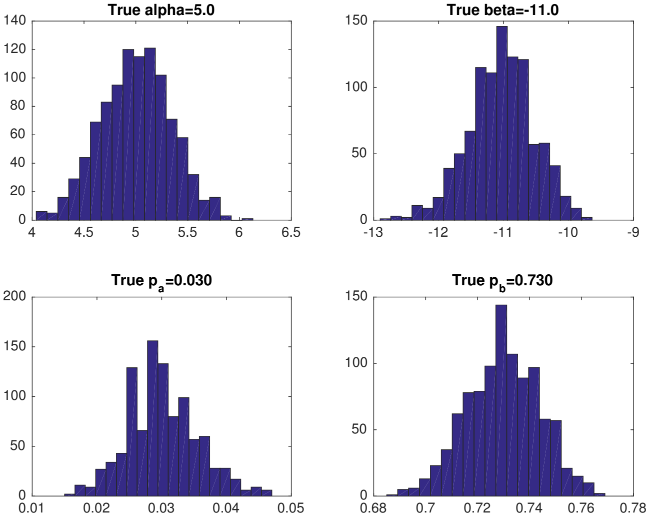
$$
\begin{aligned}
\max_{\alpha,\beta,p_a,p_b} \quad \log \quad & \mathcal{L}(p_a; X) \\
= \quad & \sum_{i=1}^{N} \left(d_a^i * \log(p_a) + (1 - d_a^i *) \log(1 - p_a) \right) \\
+ \quad & \sum_{i=1}^{N} \left(d_b^i * \log(p_b) + (1 - d_b^i *) \log(1 - p_b) \right)
\end{aligned}
$$

- Subject to p_a and p_a are the solutions of the Bayesian-Nash Equilibrium equations

$$
\begin{aligned}
p_a &= \frac{1}{1 + \exp[-\alpha x_a + p_b x_a(\alpha - \beta)]} \\
p_b &= \frac{1}{1 + \exp[-\alpha x_b + p_a x_b(\alpha - \beta)]} \\
0 &\le p_a, p_b \le 1
\end{aligned}
$$

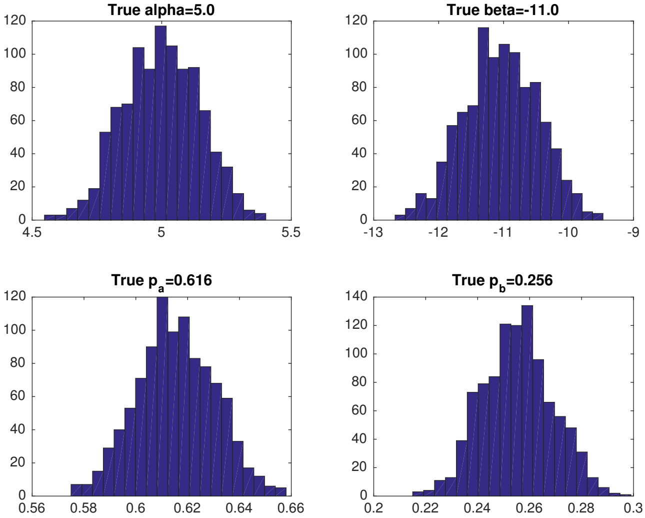
Monte Carlo Results: MPEC with Eq1

Figure: Data generated from equilibrium 1



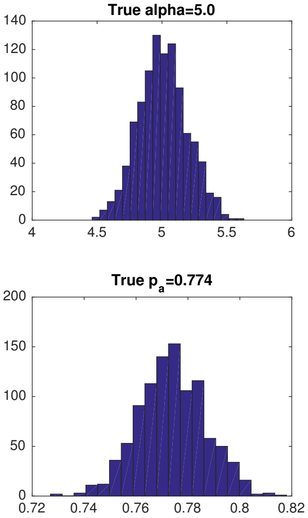
Monte Carlo Results: MPEC with Eq2

Figure: Data generated from equilibrium 2



Monte Carlo Results: MPEC with Eq3

Figure: Data generated from equilibrium 3



Static Game Example: Maximum Likelihood Estimation

- Maximize the likelihood function

$$
\begin{aligned}
\max_{\alpha,\beta} \quad \log \quad & \mathcal{L}(p_a(\alpha,\beta);X) \\
= \quad & \sum_{i=1}^{N} \left(d_a^i * \log(p_a(\alpha,\beta)) + (1-d_a^i*)\log(1-p_a(\alpha,\beta)) \right) \\
+ \quad & \sum_{i=1}^{N} \left(d_b^i * \log(p_b(\alpha,\beta)) + (1-d_b^i*)\log(1-p_b(\alpha,\beta)) \right)
\end{aligned}
$$

- $p_a(\alpha,\beta)$ and $p_a(\alpha,\beta)$ are the solutions of the Bayesian-Nash Equilibrium equations

$$
\begin{aligned}
p_a &= \frac{1}{1+\exp[-\alpha x_a + p_b x_a(\alpha-\beta)]} \equiv \Psi_a(p_b, x_a; \alpha, \beta) \\
p_b &= \frac{1}{1+\exp[-\alpha x_b + p_a x_b(\alpha-\beta)]} \equiv \Psi_b(p_a, x_b; \alpha, \beta)
\end{aligned}
$$

Discussion

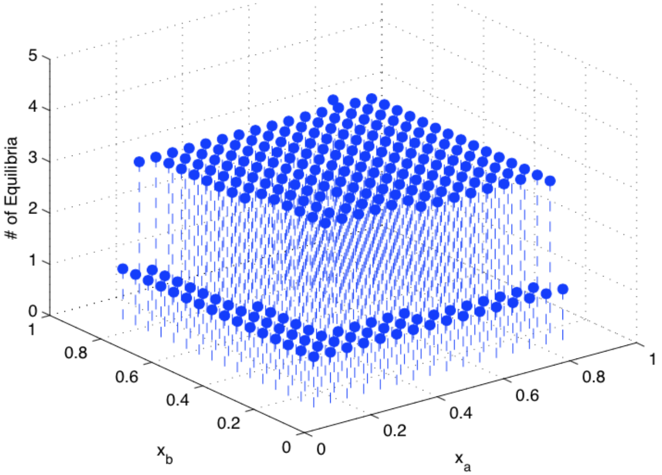
- Is the likelihood function smooth in α and β for NFXP? What about MPEC - is objective function and constraints smooth in parameters, $\theta = (\alpha, \beta, p_a, p_b)$?
- Sensitivity to starting values?
- Can we identify what equilibrium is played in the data, i.e. the equilibrium selection rule?
- Can we use standard theorems for inference? Is true value in interior of parameter space? Is it differentiable? Is objective function continuous?
- This problem is extremely simple. p_a and p_b are scalars. How would you solve for p_b and p_b when they are solutions to players Bellman equations?
- Can we be sure to find all equilibria by iterating on player's Bellman equations? Why/why not?

Estimation with Multiple Markets

- There 25 different markets, i.e., 25 pairs of observed types $(x_a^m, x_b^m), m = 1, ..., 25$
- The grid on x_a has 5 points equally distributed between the interval $[0.12, 0.87]$, and similarly for x_b
- Use the same true parameter values: (α_0, β_0)
- For each market with (x_a^m, x_b^m), solve BNE conditions for (p_a^m, p_b^m).
- There are multiple equilibria in most of 25 markets
- For each market, we (randomly) choose an equilibrium to generate 1000 data points for that market
- The equilibrium used to generate data can be different in different markets - we flip a coin at each market.

of Equilibria with Different (x_a^m, x_b^m)

Figure: Number of equilibria



NFXP - Estimation with Multiple Markets

Inner loop:

$$\max_{\alpha,\beta} \quad \log \mathcal{L}(p_a^m(\alpha,\beta), p_b^m(\alpha,\beta); X)$$

Outer loop: For a given values of (α,β) solve BNE equations for ALL equilibria, $k = 1,..,K$ at each market, $m = 1,..,M$: That is, $p_a^{m,k}(\alpha,\beta)$ and $p_a^{m,k}(\alpha,\beta)$ are the solutions to

$$\begin{aligned} p_a^m &= \Psi_a(p_b^m, x_a^m; \alpha, \beta) \\ p_b^m &= \Psi_b(p_a^m, x_b^m; \alpha, \beta) \\ m &= 1, ..., M \end{aligned}$$

where we again choose the equilibrium, that gives the highest likelihood value at each market m

$$k^* = \arg \max_{k=1,\dots,K} \log \mathcal{L}(p_a^{m,k}(\alpha,\beta), p_b^{m,k}(\alpha,\beta); X)$$

such that

$$(p_a^m(\alpha,\beta), p_b^m(\alpha,\beta)) = (p_a^{m,k*}(\alpha,\beta), p_b^{m,k*}(\alpha,\beta))$$

Estimation with Multiple Markets - MPEC

Constrained optimization formulation

$$\max_{\alpha,\beta,p_a^m,p_b^m} \quad \log \mathcal{L}(p_a^m, p_b^m; X)$$

subject to

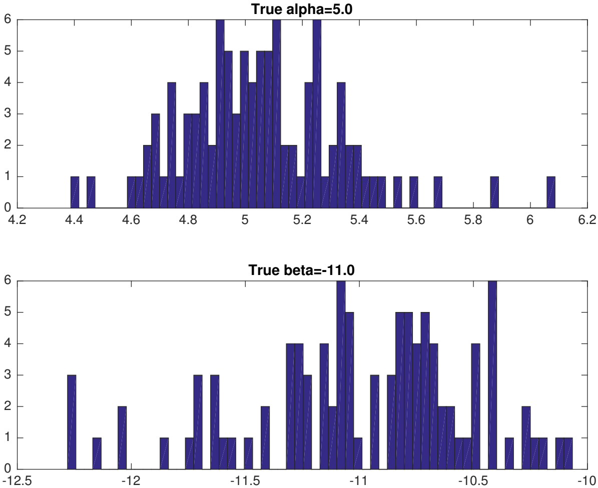
$$\begin{aligned} p_a^m &= \Psi_a(p_b^m, x_a^m; \alpha, \beta) \\ p_b^m &= \Psi_b(p_a^m, x_b^m; \alpha, \beta) \\ 0 &\leq p_a^m, p_b^m \leq 1, m = 1, ..., M \end{aligned}$$

- MPEC does not explicitly solve the BNE equations to find ALL equilibria at each market - for every trial value of parameters.
- But the number of parameters is much larger.
- Both MPEC and NFXP are based on Full Information Maximum Likelihood (FIML) estimators.

NFXP: Monte Carlo - Multiple Markets (M=25, T=50)

Starting values $\alpha_0 = \alpha$, $\beta_0 = \beta$

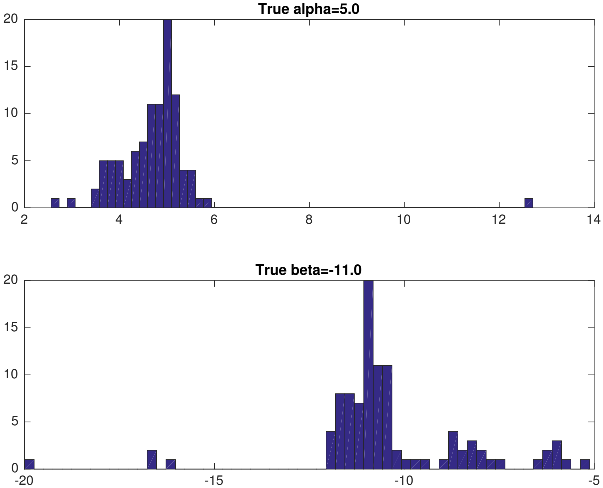
Random equilibrium selection in different markets



MPEC: Monte Carlo - Multiple Markets (M=25, T=50)

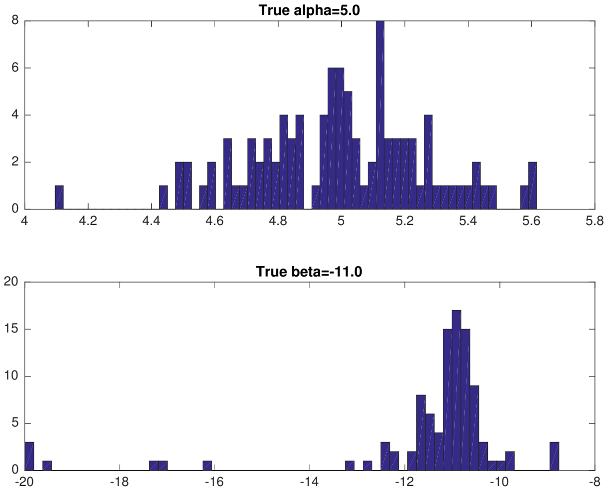
Starting values $\alpha_0 = \alpha$, $\beta_0 = \beta$

Random equilibrium selection in different markets



MPEC: Monte Carlo - Multiple Markets (M=2, T=625)

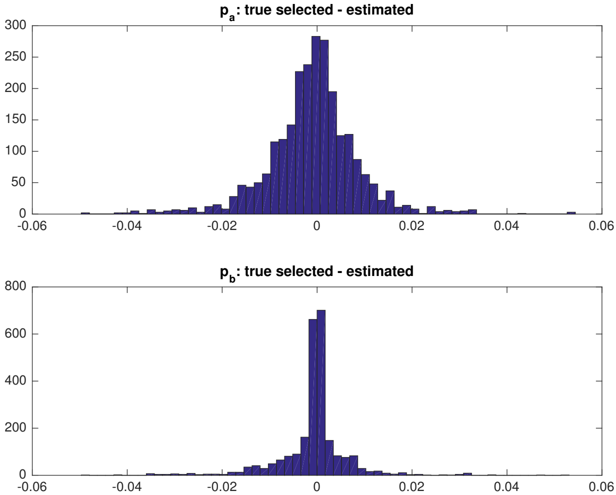
Figure: Random equilibrium selection in different markets



NFXP: Monte Carlo - Multiple Markets (M=25, T=50)

Starting values $\alpha_0 = \alpha$, $\beta_0 = \beta$

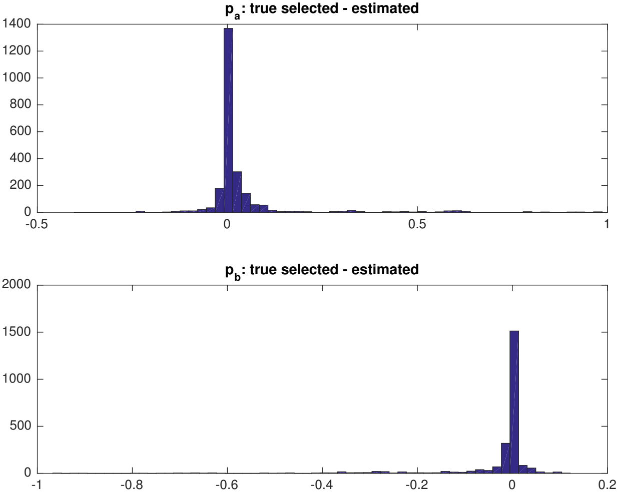
Random equilibrium selection in different markets



MPEC: Monte Carlo - Multiple Markets (M=25, T=50)

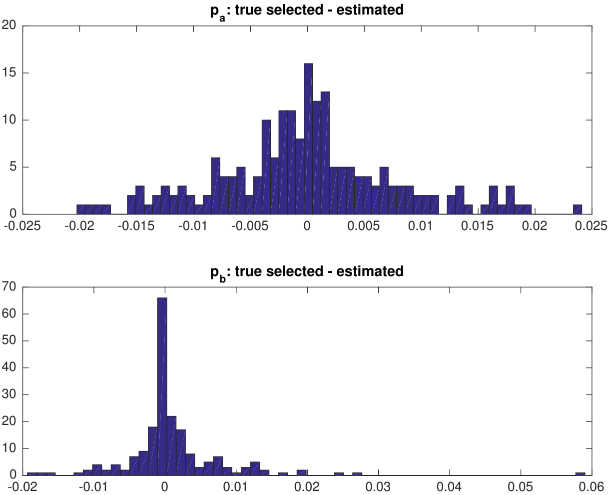
Starting values $\alpha_0 = \alpha$, $\beta_0 = \beta$

Random equilibrium selection in different markets



MPEC: Monte Carlo - Multiple Markets (M=2, T=625)

Figure: Random equilibrium selection in different markets



MPEC and NFXP: multiple markets

NFXP:

- 2 parameters in optimization problem
- we can estimate the equilibrium played in the data, $p_a^{m,k*}$ and $p_b^{m,k*}$ (but in models with observationally equivalent equilibria it may not be possible to obtain joint identification of structural parameters and equilibrium probabilities)
- Needs to find ALL equilibria at each market (very hard in more complex problems)
- Good full solution methods required

MPEC:

- $2 + 2M$ parameters in optimization problem
- Does not always converge towards the equilibrium played in the data, although NFXP indicates that $p_a^{m,k*}$ and $p_b^{m,k*}$ are actually identifiable
- Local minima with many markets.
- Disclaimer: Quick and dirty implementation of MPEC. Use AMPL/Knitro

2-Step Methods

Recall the constrained optimization formulation for FIML is

$$\max_{\alpha,\beta,p_a^m,p_b^m} \quad \log \mathcal{L}(p_a^m, p_b^m; X)$$

subject to

$$\begin{aligned} p_a^m &= \Psi_a(p_b^m, x_a^m; \alpha, \beta) \\ p_b^m &= \Psi_b(p_a^m, x_b^m; \alpha, \beta) \\ 0 &\leq p_a^m, p_b^m \leq 1, m = 1, ..., M \end{aligned}$$

- Denote the solution as $(\alpha^*, \beta^*, p_a^*, p_b^*)$
- Suppose we know (p_a^*, p_b^*), how do we recover (α^*, β^*)?

2-Step Methods: Recovering (α^*, β^*)

- Idea 1: Solve the BNE equations for (α^*, β^*)

$$
\begin{aligned}
p_a^* &= \Psi_a(p_b^*, x_a; \alpha, \beta) \\
p_b^* &= \Psi_b(p_a^*, x_b; \alpha, \beta)
\end{aligned}
$$

- Idea 2: Choose (α, β) to

$$
\max_{\alpha,\beta} \log \mathcal{L}(\Psi_a(p_b^*, x_a; \alpha, \beta), \Psi_b(p_a^*, x_b; \alpha, \beta); X)
$$

2-Step Methods: Recovering (α^*, β^*)

- Idea 1:
  - Step 1: Estimate $\hat{p} = (\hat{p}_a, \hat{p}_b)$ from the data
  - Step 2: Solve

$$\begin{aligned} \hat{p}_a &= \Psi_a(\hat{p}_a, x_a; \alpha, \beta) \\ \hat{p}_b &= \Psi_b(\hat{p}_b, x_b; \alpha, \beta) \end{aligned}$$

- Idea 2
  - Step 1: Estimate $\hat{p} = (\hat{p}_a, \hat{p}_b)$ from the data
  - Step 2: : Choose (α, β) to

$$\max_{\alpha,\beta} \log \mathcal{L}(\Psi_a(\hat{p}_b, x_a; \alpha, \beta), \Psi_b(\hat{p}_a, x_b; \alpha, \beta); X)$$

2-Step Methods: Potential Issues to be Addressed

- How do we estimate $\hat{p} = (\hat{p}_a, \hat{p}_b)$?
- Different methods give different $\hat{p}$
- One method is the frequency estimator:

$$\begin{aligned} \hat{p}_a &= \frac{1}{N}\sum_i^N I_{\{d_a^i=1\}} \\ \hat{p}_b &= \frac{1}{N}\sum_i^N I_{\{d_b^i=1\}} \end{aligned}$$

- if $(\hat{p}_a, \hat{p}_b) \neq (p_a^*, p_b^*)$ then $(\hat{\alpha}, \hat{\beta}) \neq (\alpha^*, \beta^*)$
- For a given $(\hat{p}_a, \hat{p}_b)$, there might not be a solution to the BNE equations

$$\begin{aligned} \hat{p}_a &= \Psi_a(\hat{p}_a, x_a; \alpha, \beta) \\ \hat{p}_b &= \Psi_b(\hat{p}_b, x_b; \alpha, \beta) \end{aligned}$$

2-Step Methods: Pseudo Maximum Likelihood

In 2-step methods

- Step 1: Estimate $\hat{p} = (\hat{p}_a, \hat{p}_b)$ from the data
- Step 2: Solve

$$\max_{\alpha,\beta,p_a,p_b} \quad \log \mathcal{L}(p_a, p_b; X)$$

subject to

$$\begin{aligned} p_a &= \Psi_a(\hat{p}_a, x_a; \alpha, \beta) \\ p_b &= \Psi_b(\hat{p}_b, x_b; \alpha, \beta) \\ 0 &\leq p_a^m, p_b^m \leq 1, m = 1, ..., M \end{aligned}$$

Or equivalently

- Step 1: Estimate $\hat{p} = (\hat{p}_a, \hat{p}_b)$ from the data
- Step 2: Solve

$$\max_{\alpha,\beta} \quad \log \mathcal{L}(\Psi_a(\hat{p}_b, x_a; \alpha, \beta), \Psi_b(\hat{p}_a, x_b; \alpha, \beta); X)$$

Least Square Estimators

Pesendofer and Schmidt-Dengler (2008)

- Step 1: Estimate $\hat{p} = (\hat{p}_a, \hat{p}_b)$ from the data
- Step 2: Solve

$$\min_{\alpha,\beta} \left\{ (\hat{p}_a - \Psi_a(\hat{p}_b, x_a; \alpha, \beta))^2 + (\hat{p}_b - \Psi_b(\hat{p}_a, x_b; \alpha, \beta); X))^2 \right\}$$

For dynamic games, Markov perfect equilibrium conditions are characterized by

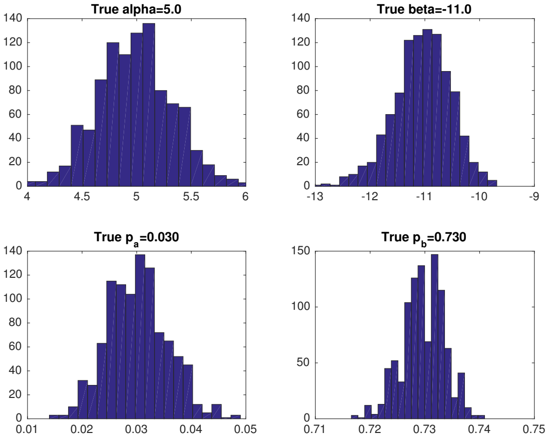
$$p = \Psi(p, \theta)$$

- Step 1: Estimate $\hat{p}$ from the data
- Step 2: Solve

$$\min_{\alpha,\beta} [\hat{p} - \Psi(\hat{p}; \theta)]' W [\hat{p} - \Psi(\hat{p}; \theta)]'$$

Static Game Example: 2-Step PML

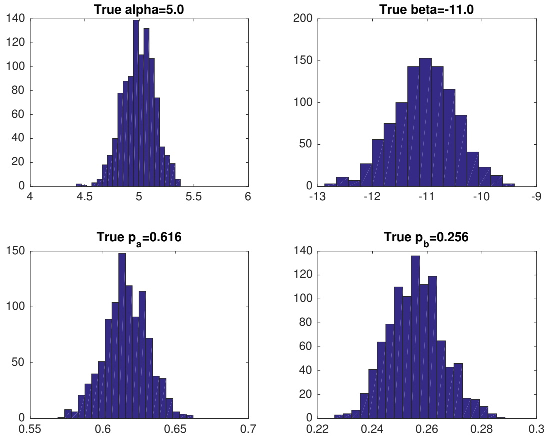
Figure: Data generated from equilibrium 1



- Pakes, Ostrovsky, and Berry (2007): PML 2-step estimator and can lead to large bias in finite samples.
- In this example, however, it seems to work pretty OK. Why?

Static Game Example: 2-Step PML

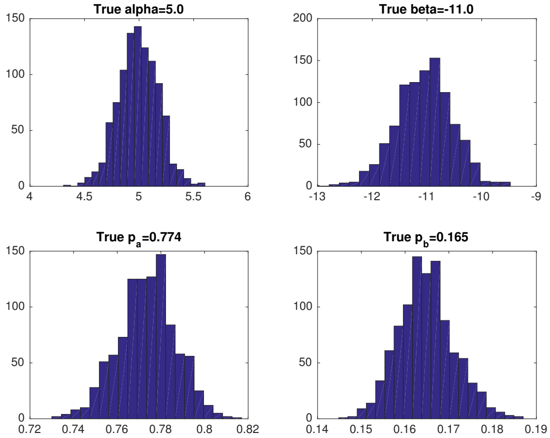
Figure: Data generated from equilibrium 2



- Pakes, Ostrovsky, and Berry (2007): PML 2-step estimator and can lead to large bias in finite samples.
- In this example, however, it seems to work pretty OK. Why?

Static Game Example: 2-Step PML

Figure: Data generated from equilibrium 3



- Pakes, Ostrovsky, and Berry (2007): PML 2-step estimator and can lead to large bias in finite samples.
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Nested Pseudo Likelihood (NPL): Aguirregabiria and Mira (2007)

NPL iterates on the 2-step methods

1. Step 1: Estimate $\hat{p}^0 = (\hat{p}_a^0, \hat{p}_b^0)$ from the data, set $k = 0$
2. Step 2:
   REPEAT
   1. Solve

      $$\alpha^{k+1}, \beta^{k+1} = \arg\max_{\alpha,\beta} \quad \log \mathcal{L}(\Psi_a(\hat{p}_b^k, x_a; \alpha, \beta), \Psi_b(\hat{p}_a^k, x_b; \alpha, \beta); X)$$

   2. One best-reply iteration on $\hat{p}^k$

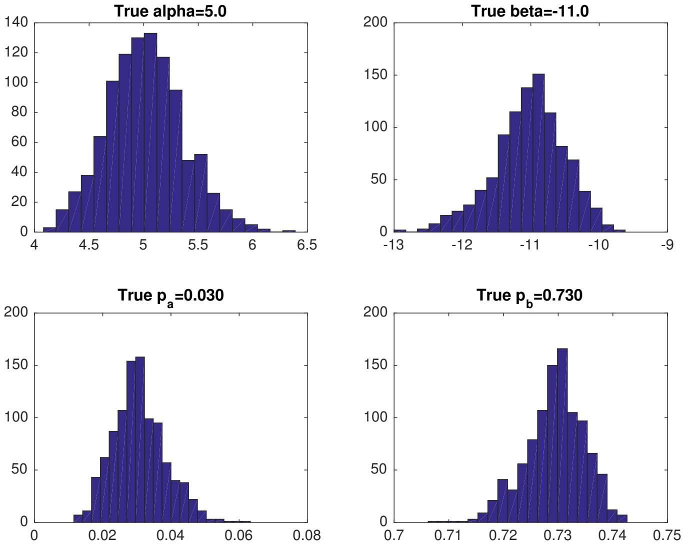
      $$\begin{aligned} \hat{p}_a^{k+1} &= \Psi_a(\hat{p}_a^k, x_a; \alpha^{k+1}, \beta^{k+1}) \\ \hat{p}_a^{k+1} &= \Psi_b(\hat{p}_b^k, x_b; \alpha^{k+1}, \beta^{k+1}) \end{aligned}$$

   3. Let k:=k+1;

   UNTIL convergence in (α^k, β^k) and $(\hat{p}_a^k, \hat{p}_b^k)$

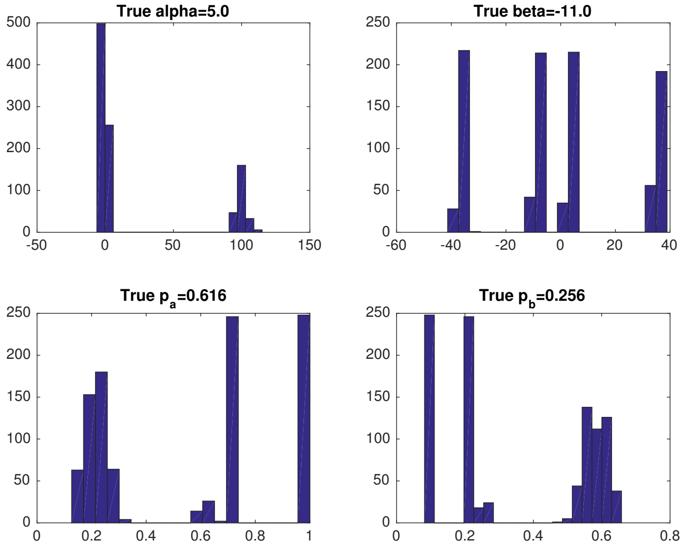
Monte Carlo Results: NPL with Eq 1

Figure: Equilibrium 1 - $\hat{p}_j = 1/N \sum_i I(d_j = 1)$



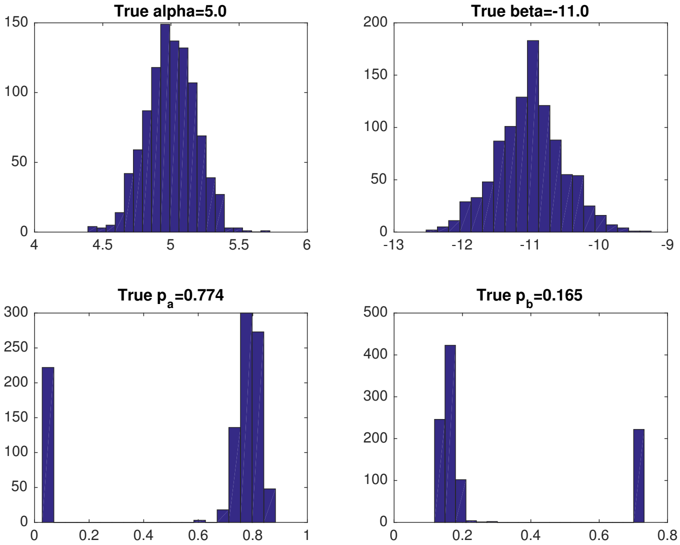
Monte Carlo Results: NPL with Eq 2

Figure: Equilibrium 2 - $\hat{p}_j = 1/N \sum_i I(d_j = 1)$



Monte Carlo Results: NPL with Eq 3

Figure: Equilibrium 3 - $\hat{p}_j = 1/N \sum_i I(d_j = 1)$



Conclusions

- NFXP/MPEC implementations of MLE is statistically efficient, but computational daunting.
- Two step estimators - computationally fast, but inefficient and biased in small samples.
- NPL (Aguirregabiria and Mira 2007) should bridge this gab, but can be unstable when estimating estimating games with multiple equilibria.
- Estimation of dynamic games is an interesting but challenging computational optimization problem
    - Multiple equilibria leads makes likehood function discontinuous $\rightarrow$ non-standard inference and computational complexity
    - Multiple equilibria leads to indeterminacy problem and identification issues.
- All these problems are amplified by orders of magnitude when we move to Dynamic models

NEXT

Estimation of dynamic games of incomplete information

- Estimation dynamic game with NPL: Agurregabiria and Mira (2012)
- Estimation of dynamic discrete choice games of incomplete information using MPEC - Egesdal, Lai and Su (2015)
- All solution algorithms necessary for NFXP: Development of all solution algorithms for solving games with Multiple Equilibria (Iskhakov et al. 2016)