

# Identification and Estimation of Sequential Games of Incomplete Information with Multiple Equilibria

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## Introduction

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# Introduction

## ***A sequential game with finite players***

- ▶ Sequential Entry Games, Bargaining games between groups
- ▶ Different order of actions leads to different strategic behavior
- ▶ Researchers may not observe the “*true*” order of actions

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- ▶ Different order of actions leads to different strategic behavior
- ▶ Researchers may not observe the “*true*” order of actions
- ▶ *Incomplete information*
  - ▶ Player knows her own payoff, not the rival’s payoff
  - ▶ The former player may not know a lot about the later player’s payoff

# Introduction

## ***A sequential game with finite players***

- ▶ Sequential Entry Games, Bargaining games between groups
- ▶ Different order of actions leads to different strategic behavior
- ▶ Researchers may not observe the “*true*” order of actions
- ▶ *Incomplete information*
  - ▶ Player knows her own payoff, not the rival’s payoff
  - ▶ The former player may not know a lot about the later player’s payoff
- ▶ *Order of actions / Multiple equilibria*
  - ▶ Observable to players, Unobservable to researchers
  - ▶ The misspecified equilibrium type / order of actions may lead to inaccurate estimates on structural parameters

# Contribution

1. First theoretical approach to empirical models for sequential games considering:
  - 1.1 Incomplete information game
  - 1.2 Multiple Perfect Bayesian Nash Equilibria
  - 1.3 Unknown distribution of the order of actions
  
2. Semiparametric identification, estimation, and inference on structural parameters:
  - 2.1 Payoff function parameters
  - 2.2 Equilibrium selection mechanism
  - 2.3 Distribution of the order of actions
  
3. Empirical application on the sequential entry game between Walmart and Kmart

# Motivating Example

*Entry Games between Walmart and Kmart (Jia (2008))*

$$U_W = \begin{cases} X'_{W,m}\beta_W - S_{K,m}\delta_W - e_{W,m} & \text{if } S_{W,m} = 1 \\ 0 & \text{if } S_{W,m} = 0 \end{cases}$$

$$U_K = \begin{cases} X'_{K,m}\beta_K - S_{W,m}\delta_K - e_{K,m} & \text{if } S_{K,m} = 1 \\ 0 & \text{if } S_{K,m} = 0 \end{cases}$$

for  $W$  (Walmart),  $K$  (Kmart), and market  $m$

- ▶  $S_{i,m}$ : entry decision of player  $i \in \{W, K\}$  in market  $m$
- ▶  $X_{i,m}$ : observable covariates
- ▶  $e_{i,m}$ : unobservable characteristics (to econometrician)
- ▶  $\delta_W, \delta_K$ : strategic interaction parameters

# Motivating Example

Sequential Entry Games (*Walmart* plays first)

$$U_W = \begin{cases} X'_{W,m} \beta_W - S_{K,m} \delta_W - e_{W,m} & \text{if } S_{W,m} = 1 \\ 0 & \text{if } S_{W,m} = 0 \end{cases}$$

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- ▶ Assume  $\beta_W = \beta_K = 0$ , unique equilibrium
- ▶ Stage 2:  $P(S_{K,m} = 1 | X_m, S_{W,m}) = F_{e_K}(-S_{W,m} \delta_K)$
- ▶ Stage 1:  $P(S_{W,m} = 1 | X_m) = F_{e_W}(-P(S_{K,m} = 1 | X_m, S_{W,m} = 1) \delta_W) = F_{e_W}(-F_{e_K}(-\delta_K) \delta_W)$
- ▶  $P(S_{W,m} = 1, S_{K,m} = 1 | X_m) = F_{e_K}(-\delta_K) F_{e_W}(-F_{e_K}(-\delta_K) \delta_W)$



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$$U_W = \begin{cases} X'_{W,m} \beta_W - S_{K,m} \delta_W - e_{W,m} & \text{if } S_{W,m} = 1 \\ 0 & \text{if } S_{W,m} = 0 \end{cases}$$

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## Motivating Example

- ▶ “. . . . . the northern regions had been Kmart’s backyard until recently, while Wal-Mart started its business from the south and has expertise in serving the southern population.” - Jia (2008)
- ▶ The observed joint conditional choice probability is

$$\begin{aligned} & P(S_{W,m} = 1, S_{K,m} = 1 | X_m) \\ &= \lambda P(S_{W,m} = 1, S_{K,m} = 1 | X_m, \text{Walmart first}) \\ &\quad + (1 - \lambda) P(S_{W,m} = 1, S_{K,m} = 1 | X_m, \text{Kmart first}) \\ &= \lambda F_{e_K}(-\delta_K) F_{e_W}(-F_{e_K}(-\delta_K) \delta_W) \\ &\quad + (1 - \lambda) F_{e_W}(-\delta_W) F_{e_K}(-F_{e_W}(-\delta_W) \delta_K) \end{aligned}$$

where  $\lambda$  is the proportion of markets in which Walmart moves first

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## Previous Literature

- ▶ Simultaneous Games with Incomplete Information

Seim (2006), Sweeting (2009), Aradillas-lopez (2010), Bajari, Hong, Krainer, and Nekipelov (2010), De Paula and Tang (2012), Wan and Xu (2014), Lewbel and Tang (2015), **Aguirregabiria and Mira (2019)**

- ▶ Sequential Games with Complete / Incomplete Information

Jia (2008), **Einav (2010)**, Blevins (2015), Gayle and Luo (2015), Wagner (2016)

- ▶ Nonparametric Estimation of Conditional Moment Models

**Ai and Chen (2003)**, Newey and Powell (2003), Chen and Pouzo (2009, 2012, 2015)

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# Model

- ▶ The game consists of  $N$  players:  $\{1, \dots, N\}$
- ▶ The action set is  $\{a_0, a_1, \dots, a_L\}$ : each player has  $L + 1$  actions
- ▶ The order of actions is  $O = (o(1), \dots, o(N))$ :
  - ▶  $o(1) = 1, o(2) = 2$  means that player 1 is the first mover and player 2 is the later mover
  - ▶  $o(1) = o(2) = 1$  implies a simultaneous game
- ▶ The payoff of player  $i$  is

$$u_i = \pi_i(s, X, O; \beta_0) + \epsilon_i$$

where  $s = (s_1, \dots, s_N)$  is the market outcome,  $X = (X_1, \dots, X_N)$  are covariates

- ▶ The distribution of  $\epsilon_i$  is known to players and researchers

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# Perfect Bayesian Nash Equilibria

A *Perfect Bayesian Nash Equilibrium (PBNE)* is a set of strategies  $\{S_i(\mathcal{J}_{o(i)}, \epsilon_i)\}_{i=1}^N$  such that for each player  $i$ ,

$$S_i(\mathcal{J}_{o(i)}, \epsilon_i) = \arg \max_{a \in \{a_0, \dots, a_L\}} \Pi_i(a, \mathcal{J}_{o(i)}, \epsilon_i)$$

- ▶  $\Pi_i(a, \mathcal{J}_{o(i)}, \epsilon_i)$ : expected payoff with information set  $\mathcal{J}_{o(i)} \equiv \{X, O, s_-^{o(i)}\}$

$$\begin{aligned} \Pi_i(a, \mathcal{J}_{o(i)}, \epsilon_i) &= \bar{\pi}_i(a, \mathcal{J}_{o(i)}; \beta_0) + \epsilon_i \\ &= \sum_{a_+^{o(i)}} \pi_i\left(\left(s_-^{o(i)}, a, a_+^{o(i)}\right), X, O; \beta_0\right) P\left(a_+^{o(i)} \mid \mathcal{J}_{o(i)}\right) + \epsilon_i \end{aligned}$$

- ▶  $s_-^{o(i)}$ : actions played **before** player  $i$
- ▶  $a_+^{o(i)}$ : actions played **after** player  $i$



# Perfect Bayesian Nash Equilibria: Logit

- ▶ If  $\epsilon_i$  follows an i.i.d. Type-I extreme distribution,

$$P(s_i = a | \mathcal{J}_{o(i)}) = \frac{\exp(\bar{\pi}_i(\mathbf{a}, \mathcal{J}_{o(i)}; \beta_0))}{\sum_{a' \in \{a_0, \dots, a_L\}} \exp(\bar{\pi}_i(\mathbf{a}', \mathcal{J}_{o(i)}; \beta_0))}$$

and

$$\bar{\pi}_i(\mathbf{a}, \mathcal{J}_{o(i)}; \beta_0) = \sum_{a_+^{o(i)}} \pi_i\left(\left(s_-^{o(i)}, a, a_+^{o(i)}\right), X; \beta_0\right) P\left(a_+^{o(i)} \mid \mathcal{J}_{o(i)}\right)$$

- ▶ By Hotz and Miller (1993), there is one-to-one correspondence between the equilibrium probabilities and expected payoffs
- ▶ The equilibrium probabilities  $P(s_i = a | \mathcal{J}_{o(i)})$  are identified up to the payoff parameters  $\beta_0$
- ▶ The equilibrium may not be unique but finite

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# Identification with Multiple Equilibria / Order of Actions

- ▶ Consider the following example:

$$P(s = \alpha | X) \\ = \sum_{l=1}^2 \sum_{b=1}^3 \prod_{i=1}^N P^{(b)}(s_i = \alpha_i | X, s_{-i}^{o_l(i)}, O_l; \beta_0) \lambda_{\tau | X, O}(\tau_b) \rho_{O | X}(O_l)$$

if there are 3 PBNE ( $b = 1, 2, 3$ ) and 2 order of actions ( $l = 1, 2$ )

- ▶  $P^{(b)}(s = \alpha | X, O; \beta_0)$ : equilibrium probability of type  $b$
- ▶  $\beta_0 \in \mathcal{B} \subseteq \mathbb{R}^{d_\beta}$ : payoff function parameters
- ▶  $\lambda_{\tau | X, O}$ : equilibrium selection mechanism
- ▶  $\rho_{O | X}$ : distribution of the order of actions

# Identification Strategy

- ▶ It is a special case of the finite mixture model:

$$\begin{aligned} & P(s = \alpha | X) \\ &= \sum_{l=1}^2 \sum_{b=1}^3 \prod_{i=1}^N P^{(b)}(s_i = \alpha_i | X, s_{-}^{o_l(i)}, O_l; \beta_0) \lambda_{\tau | X, O}(\tau_b) \rho_{O | X}(O_l) \\ &= \sum_{k=1}^6 P^{(k)}(s = \alpha | X, O_k; \beta_0) h_{0,k}(X) \end{aligned}$$

such that  $\sum_{k=1}^6 h_{0,k}(X) = 1$

- ▶  $P(s = \alpha | X)$  is identified from data
- ▶  $P^{(k)}(s = \alpha | X, O_k; \beta_0)$  is identified up to  $\beta_0$  by model
- ▶ The **mixture weights**  $h_{0,k}(X)$  are nonparametric functions of  $X$

## Identification of $\lambda_{\tau|X,O}$ and $\rho_{O|X}$

- ▶ Suppose  $\{\beta_0, h_{0,1}(X), \dots, h_{0,6}(X)\}$  is identified
- ▶ For the previous example with 3 PBNE ( $b = 1, 2, 3$ ) and 2 order of actions ( $l = 1, 2$ )

$$h_{0,1}(X) = \lambda_{\tau|X,O}(\tau_1)\rho_{O|X}(O_1)$$

$$h_{0,2}(X) = \lambda_{\tau|X,O}(\tau_2)\rho_{O|X}(O_1)$$

$$h_{0,3}(X) = \lambda_{\tau|X,O}(\tau_3)\rho_{O|X}(O_1)$$

implies that

$$\rho_{O|X}(O_1) = \sum_{k=1}^3 h_{0,k}(X), \quad \lambda_{\tau|X,O}(\tau_1) = \frac{h_{0,1}(X)}{\sum_{k=1}^3 h_{0,k}(X)}$$

# Identification of Structural Parameters

- ▶ The structural parameters  $\{\beta_0, \lambda_{\tau|X,O}, \rho_{O|X}\}$  are **identified** if there is a unique solution  $\{\beta_0, \{h_{0,k}(X)\}_{k=1}^{N_k}\}$  of the equations

$$P(s = \alpha|X) = \sum_{k=1}^{N_k} P^{(k)}(s = \alpha|X, O_k; \beta_0) h_{0,k}(X)$$

for  $X$ -a.s. and all joint actions  $\alpha$

- ▶  $N_k$  is the number of types for unobserved heterogeneity ( $\tau$  and  $O$ )

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for  $X$ -a.s. and all joint actions  $\alpha$

- ▶  $N_k$  is the number of types for unobserved heterogeneity ( $\tau$  and  $O$ )
1. **Sufficient Rank condition:** (by Rouché–Capelli) the solution of the linear system is unique only at  $\beta_0 \in \mathcal{B}$
  2. **Necessary Order condition:**  $(L + 1)^N \geq N_k$

## Remarks

- ▶ The maximum number of  $N_k$  depends on the number of players  $N$  and the number of actions  $L$
- ▶ The possible orders of actions  $O$  increase in  $N$ 
  - ▶ 3 orders for two players:  $O = (1, 2), (2, 1), (1, 1)$
  - ▶ 13 orders for three players:  $O = (1, 1, 1), (1, 1, 2), \dots, (1, 2, 3)$
  - ▶ 75 orders for four players:  $O = (1, 1, 1, 1), \dots, (1, 2, 3, 4)$
- ▶ The possible joint actions increase in  $L$ 
  - ▶  $(L + 1)^N$  joint actions for  $N$  players



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  - ▶ 75 orders for four players:  $O = (1, 1, 1, 1), \dots, (1, 2, 3, 4)$
- ▶ The possible joint actions increase in  $L$ 
  - ▶  $(L + 1)^N$  joint actions for  $N$  players
- ▶ The *exclusion restriction* is helpful to attain the order condition:  
there exists  $X_s \subseteq X$  s.t.  $\rho_{O|X}(\cdot|X) = \rho_{O|X}(\cdot|X_s)$
- ▶  $X_v = X \setminus X_s$  are instruments:  $P(s = \alpha|X)$  varies with  $X_v$  but  $\rho_{O|X}(\cdot|X)$  does not

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# Conditional Moment Restrictions

- ▶ Observe  $Z^m = (s^m, X^m)$  for  $m = 1, \dots, n$
- ▶ Parameter of interest:  $\theta_0 = (\beta_0, h_{0,1}, \dots, h_{0,N_K}) \in \Theta = \mathcal{B} \times \mathcal{H}$
- ▶ Conditional moments:

$$E[\ell_j(Z^m, \theta_0) | X^m] = 0$$
$$E\left[1 - \sum_{k=1}^{N_K} h_{0,k}(X^m) \mid X^m\right] = 0$$

where

$$\ell_j(Z^m, \theta) = 1\{s^m = \alpha^j\} - \sum_{k=1}^{N_K} P^{(k)}(s^m = \alpha^j | X^m, O_k; \beta) h_k(X^m)$$

for  $j = 1, \dots, (L+1)^N - 1$

# The Sieve Minimum Distance Estimator

- ▶ The SMD estimator  $\hat{\theta}_n = (\hat{\beta}_n, \hat{h}_{1,n}, \dots, \hat{h}_{N_k,n}) \in \Theta_n = \mathcal{B} \times \mathcal{H}_n$  solves

$$\min_{\theta \in \mathcal{B} \times \mathcal{H}_n} \mathcal{G}_n(Z^m, \theta)' \left( I \otimes \left( P^{J_n} P^{J_n} \right)^{-1} \right) \mathcal{G}_n(Z^m, \theta)$$

where

$$\mathcal{G}_n(Z^m, \theta) = \sum_{m=1}^n \ell(Z^m, \theta) \otimes p^{J_n}(X^m)$$

$$p^{J_n}(X) = (p_1(X), \dots, p_{J_n}(X))' \text{ (sieve basis)}$$

$$P^{J_n} = \left( p^{J_n}(X^1), \dots, p^{J_n}(X^n) \right)' \text{ (sieve basis)}$$

- ▶  $\hat{h}_{k,n}(x) = \sum_{j=1}^{K_n} c_j p_j(x) \in \mathcal{H}_{k,n}$  and  $\mathcal{H}_n = \prod_{k=1}^{N_k} \mathcal{H}_{k,n}$

# Asymptotic Properties of the Estimator

## ► Assumptions for Consistency

1.  $\{Z^m\}_{m=1}^n$  i.i.d.,  $\mathcal{X} \subseteq \mathbb{R}^{d_x}$  compact,  $f_X$  bounded
2. CCPs  $P(s = \alpha | X)$  and  $h_{0,k}(X)$  are smooth functions (Hölder space with  $\gamma > d_x/2$ )
3. Equilibrium probability  $\{P^{(k)}(s_i = \alpha_i | \mathcal{J}_{o_k(i)}; \beta)\}_{k=1}^{N_k}$  is continuously differentiable on  $\mathcal{X}$  and  $\mathcal{B}$
4. Smoothing parameters satisfy  $(L+1)^N J_n \geq d_\beta + N_\kappa K_n$ ,  $K_n \rightarrow \infty$ ,  $J_n/n \rightarrow 0$  as  $n \rightarrow \infty$

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4. Smoothing parameters satisfy  $(L+1)^N J_n \geq d_\beta + N_k K_n$ ,  $K_n \rightarrow \infty$ ,  $J_n/n \rightarrow 0$  as  $n \rightarrow \infty$

► **Consistency:**  $\|\hat{\theta}_n - \theta_0\|_s = o_p(1)$  where

$$\|\theta\|_s = \|\beta\|_E + \max_{k=1, \dots, N_k} \sup_{x \in \mathcal{X}} |h_k(x)|$$

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# Asymptotic Properties of the Estimator

- ▶ Define the sieve variance components:

$$D_n = E [\Delta_n (X)' \Delta_n (X)]$$

$$\Psi_n = E [\Delta_n (X)' \ell (Z, \theta_0) \ell (Z, \theta_0)' \Delta_n (X)]$$

where

$$\Delta_n (X) \equiv [\Delta_{\beta_0} (X), \Delta_{h_{0,n}} (X)]$$

$$\Delta_{\beta_0} (X) \equiv \sum_{k=1}^{N_K} \frac{\partial}{\partial \beta'} P^{(k)} (X, O; \beta_0) h_{0,k} (X)$$

$$\Delta_{h_{0,n}} (X) \equiv \left[ P^{(1)} (X, O; \beta_0) \otimes p^{K'_n} (X), \dots, P^{(N_K)} (X, O; \beta_0) \otimes p^{K'_n} (X) \right]$$

- ▶ Assume  $D_n$  and  $E [\ell (Z, \theta_0) \ell (Z, \theta_0)' | X]$  are positive definite



# Asymptotic Properties of the Estimator

- ▶ (Additional) Assumptions for Asymptotic Normality
1. Equilibrium probability  $\{P^{(k)}(s_i = \alpha_i | \mathcal{J}_{o_k(i)}; \beta)\}_{k=1}^{N_k}$  is twice continuously differentiable on  $\mathcal{X}$  and  $\mathcal{B}$
  2.  $J_n^{-\gamma/d_x} = o(n^{-1/4})$ ,  $K_n^{-\gamma/d_x} = o(n^{-1/4})$ , and  $J_n K_n \log n = o(n^{1/2})$

# Asymptotic Properties of the Estimator

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► **Asymptotic Normality:**

$$\sqrt{n} \|v_n^*\|_{sd, \beta}^{-1} (\hat{\beta}_n - \beta_0) \xrightarrow{d} N(0, I_{d_\beta})$$

where

$$\begin{aligned} \|v_n^*\|_{sd, \beta}^2 &= G_\beta' D_n^{-1} \Psi_n D_n^{-1} G_\beta \\ G_\beta &\equiv [I_{d_\beta}, \mathbb{O}_{d_\beta \times (N_k - 1) K_n}]' \end{aligned}$$

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► **Asymptotic Normality:**

$$\sqrt{n} \|\nu_n^*\|_{sd,h}^{-1} \left( \hat{h}_{k,n}(x) - h_{0,k}(x) \right) \xrightarrow{d} N(0, 1)$$

where

$$\begin{aligned} \|\nu_n^*\|_{sd,h}^2 &= G'_{h_k} D_n^{-1} \Psi_n D_n^{-1} G_{h_k} \\ G_{h_k} &= \left[ \mathbb{O}_{1 \times (d_\beta + (k-1)K_n)}, p^{K'_n}(x), \mathbb{O}_{1 \times (N_k - k)K_n} \right]' \end{aligned}$$

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# Simulation Setup I

$$u_1 = \begin{cases} X_1\beta_1 + \Delta_1 S_2 - \epsilon_1 & \text{if } S_1 = 1 \\ 0 & \text{if } S_1 = 0 \end{cases}$$
$$u_2 = \begin{cases} X_2\beta_2 + \Delta_2 S_1 - \epsilon_2 & \text{if } S_2 = 1 \\ 0 & \text{if } S_2 = 0, \end{cases}$$

- ▶ Parameters:  $(\beta_1, \beta_2) = (3, 2)$ ,  $(\Delta_1, \Delta_2) = (-6, -4)$
- ▶  $\epsilon_1, \epsilon_2$ : i.i.d. Type-I Extreme Distributions
- ▶ # of Games: 500, 1000, 5000
- ▶ *Experiment 1*:  $X_i \in \{0.5, 1.0, 1.5, 2.0\}$  uniformly distributed, sequential actions only

$$P(O = (1, 2)' | X) = \frac{X_1 + X_2}{10}$$

# Simulation Results: Experiment I

	$n = 500$	$n = 1000$	$n = 5000$
$\beta_1$	3.0224 (1.0244)	2.9317 (0.6819)	2.9851 (0.2848)
$\beta_2$	3.2107 (1.6446)	2.5848 (0.9277)	2.1032 (0.2727)
$\Delta_1$	-6.0939 (1.9919)	-5.8906 (1.3065)	-5.9763 (0.5412)
$\Delta_2$	-6.4342 (3.3420)	-5.1746 (1.8622)	-4.2078 (0.5303)
$P(O = (1, 2)'   X = (1, 1))$	0.2477 (0.1061)	0.2351 (0.0810)	0.2066 (0.0422)
$P(O = (1, 2)'   X = (2, 2))$	0.4482 (0.1593)	0.4314 (0.1241)	0.4075 (0.0567)
$P(O = (2, 1)'   X = (1, 2))$	0.3680 (0.1992)	0.3350 (0.1384)	0.3084 (0.0507)

## Simulation Setup II

$$u_1 = \begin{cases} X_1\beta_1 + \Delta_1 S_2 - \epsilon_1 & \text{if } S_1 = 1 \\ 0 & \text{if } S_1 = 0 \end{cases}$$
$$u_2 = \begin{cases} X_2\beta_2 + \Delta_2 S_1 - \epsilon_2 & \text{if } S_2 = 1 \\ 0 & \text{if } S_2 = 0, \end{cases}$$

- ▶ Parameters:  $(\beta_1, \beta_2) = (3, 2)$ ,  $(\Delta_1, \Delta_2) = (-6, -4)$
- ▶  $\epsilon_1, \epsilon_2$ : i.i.d. Type-I Extreme Distributions
- ▶ # of Games: 500, 1000, 5000
- ▶ *Experiment 2*:  $X_i \in \{1, 2, 3, 4\}$  uniformly distributed, simultaneous + sequential actions

$$P(O = (1, 2)' | X) = X_1/10$$

$$P(O = (2, 1)' | X) = X_2/10$$

## Simulation Results: Experiment II

	$n = 500$	$n = 1000$	$n = 5000$
$\beta_1$	4.0194 (1.7968)	3.4223 (1.1530)	3.2314 (0.5008)
$\beta_2$	2.8799 (1.6547)	2.3853 (1.0219)	2.1518 (0.3570)
$\Delta_1$	-8.0242 (3.8142)	-6.8062 (2.4815)	-6.4407 (1.0980)
$\Delta_2$	-5.8660 (3.5192)	-4.7713 (2.2413)	-4.3089 (0.7824)
$P(O = (1, 2)'   X = (1, 2))$	0.1423 (0.1742)	0.1206 (0.1187)	0.0995 (0.0293)
$P(O = (2, 1)'   X = (2, 1))$	0.1639 (0.2082)	0.1310 (0.1344)	0.1050 (0.0413)
$P(O = (2, 1)'   X = (2, 2))$	0.2196 (0.1604)	0.2164 (0.1394)	0.1998 (0.0487)



## Estimation Under the Misspecified Order of Actions

Simultaneous (Correct)	$n = 500$	$n = 1000$	$n = 5000$
$\beta_1$	3.6114 (2.6312)	3.4164 (2.2967)	3.1269 (0.9769)
$\beta_2$	2.4729 (1.6111)	2.3835 (1.4545)	2.1512 (0.6344)
$\Delta_1$	-5.9525 (4.4415)	-5.4472 (3.7776)	-5.9944 (1.7528)
$\Delta_2$	-4.3551 (3.3789)	-3.5876 (2.5196)	-3.9883 (1.1988)

- ▶ DGP: **Simultaneous** Actions
- ▶ Estimation: **Simultaneous** Actions
- ▶ Parameters:  $(\beta_1, \beta_2) = (3, 2)$ ,  $(\Delta_1, \Delta_2) = (-6, -4)$

## Estimation Under the Misspecified Order of Actions

Simultaneous (Misspecified)	$n = 500$	$n = 1000$	$n = 5000$
$\beta_1$	1.9210 (0.8322)	1.9710 (0.4596)	2.0053 (0.1838)
$\beta_2$	1.1123 (0.6155)	0.9349 (0.4636)	0.8546 (0.3436)
$\Delta_1$	-2.8356 (1.4094)	-2.9900 (0.8617)	-3.0692 (0.1795)
$\Delta_2$	-1.5654 (1.4947)	-1.1462 (1.1220)	-0.9185 (0.4424)

- ▶ DGP: **Simultaneous** Actions
- ▶ Estimation: **Sequential** Actions
- ▶ Parameters:  $(\beta_1, \beta_2) = (3, 2)$ ,  $(\Delta_1, \Delta_2) = (-6, -4)$

## Introduction

Introduction & Motivation

Previous Literature

## Model

Model Description

Perfect Bayesian Nash Equilibrium

## Main Results

Identification of Structural Parameters

Estimation of Structural Parameters

Inference on Functional of Structural Parameters

## Simulation & Empirical Application

Monte Carlo Simulation

Empirical Application: Entry Game of Walmart and Kmart

## Conclusion

# Entry Game of Walmart vs Kmart

$$u_i = \begin{cases} X_i' \beta_i + S_{-i} \Delta_i - \epsilon_i & \text{if } S_i = 1 \\ 0 & \text{if } S_i = 0 \end{cases}$$

- ▶  $S_i$ : entry decision of player  $i \in \{W, K\}$
- ▶  $X_i$ : population, retail sales, urban population (%), # of small stores, # of nearby branches
- ▶  $\epsilon_i$ : private information with i.i.d. Type-I extreme distribution
- ▶  $\Delta_i$ : Interaction effects
- ▶ Jia (2008), Competition of Walmart and Kmart
  - ▶ Sample Size: 2065 counties
  - ▶ Entry of Walmart: 48% / Entry of Kmart: 19% (1997)
- ▶ Sequential Actions (Walmart  $\rightarrow$  Kmart or Kmart  $\rightarrow$  Walmart) + Simultaneous Actions
- ▶ Order distribution is a function of regional dummies

## Entry Game Estimation (Simultaneous Actions Only)

	Walmart	Kmart
Log Population	2.0205 (0.2051)	2.0422 (0.3739)
Log Retail Sales per Capita	0.9744 (0.1625)	2.1261 (0.3034)
Percentage of Urban Population	1.0858 (0.2701)	0.9940 (0.4312)
Small Stores	-0.0277 (0.0270)	-0.0362 (0.0245)
# of nearby branches	-3.4444 (1.1099)	-0.6699 (0.9996)
Constant	-13.5967 (1.5686)	-24.9788 (3.0105)
Interaction Effects ( $\Delta_W, \Delta_K$ )	<b>-0.9934</b> (0.5338)	<b>-0.6866</b> (1.3232)

## Entry Game Estimation (Sequential Actions Only)

	Walmart	Kmart
Log Population	2.6290 (0.2243)	2.1567 (0.2062)
Log Retail Sales per Capita	1.4394 (0.1856)	1.9640 (0.2599)
Percentage of Urban Population	1.2483 (0.3337)	1.0260 (0.3533)
Small Stores	-0.0724 (0.0325)	-0.0298 (0.0241)
# of nearby branches	-3.7524 (0.9668)	-1.4352 (0.9091)
Constant	-18.8790 (1.6805)	-23.2951 (2.4164)
Interaction Effects ( $\Delta_W, \Delta_K$ )	<b>-1.8410</b> (0.2543)	<b>-1.4281</b> (0.2245)

## Estimated Order of Actions (Sequential Actions Only)

	Midwest	South	Other Regions
Walmart → Kmart	0.0827 (0.1372)	0.9999 (0.0000)	0.0011 (0.0171)
Kmart → Walmart	0.9173 (0.1372)	0.0001 (0.0000)	0.9989 (0.0171)

## Entry Game Estimation (Simultaneous + Sequential)

	Walmart	Kmart
Log Population	2.5840 (0.2981)	2.5544 (0.3393)
Log Retail Sales per Capita	1.4665 (0.2187)	2.1796 (0.3094)
Percentage of Urban Population	1.2476 (0.3808)	1.1590 (0.3936)
Small Stores	-0.0757 (0.0352)	-0.0366 (0.0275)
# of nearby branches	-3.3114 (0.9876)	-1.6872 (1.0192)
Constant	-18.9547 (2.2993)	-25.6431 (3.1450)
Interaction Effects ( $\Delta_W, \Delta_K$ )	<b>-2.2053</b> (0.6367)	<b>-2.6667</b> (0.5309)



## Estimated Order of Actions (Simultaneous + Sequential)

	Midwest	South	Other Regions
Walmart → Kmart	0.0018 (0.0158)	0.2449 (0.2006)	0.0450 (0.0960)
Kmart → Walmart	0.4705 (0.1408)	0.0042 (0.0606)	0.6836 (0.1956)
Simultaneous	0.5278 (0.1390)	0.7509 (0.2051)	0.2714 (0.1956)

# Conclusion

- ▶ This paper studies the identification and estimation of incomplete information sequential games considering multiple PBNE and unknown order of actions
- ▶ There are some necessary and sufficient conditions to identify structural parameters, and an exclusion restriction is helpful to attain the necessary order condition for identification
- ▶ The SMD estimator based on conditional moments is consistent and asymptotically normal
- ▶ Monte Carlo simulation & empirical application to the Walmart vs. Kmart entry game highlight the importance of correct specification on the order of actions