Entry and Exit: *

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1 Review

1.1 Bresnahan and Reiss (1991): "Entry and Competition in Concentrated Mar- kets"

Main question: What are the competitive effects of entry? How does the level of competition change when more firms enter? Theory has different predictions–for example *potential* entry may be all that is necessary.

Looks at several industries (e.g. dentists) in a cross-section of isolated towns in the US. Empirically determines if the amount of competition changes when more firms are operating in a market.

Simple model

- Firms face a 2-stage game: (1) decide whether to enter, (2) if enter, then compete (e.g. a la Cournot).
- Firms face a downward sloping demand curve, and firm profits are decreasing in the number of firms.
- Entry decisions:

*These notes draw upon Tom Holmes, Pat Bajari, and Matt Shum's lecture notes

1. All entrants make non-negative profits: $\Pi_{N_m^*} > 0$,
2. Any potential entrant would make negative profits: $\Pi_{N_m^*+1} < 0$.

- Looking at entry thresholds – or the # of people necessary to support firms. If this number rises as more firms enter, then infer that competition is increasing because firms are earning smaller mark-ups per sale. Thus firms need more sales to cover fixed costs.

Data

- Ideally want data on a single industry where market demand has fluctuated enough such that there is enough entry and exit.
- B/R look at a cross-section of markets of varying sizes.
- Look at dentists, doctors, druggists, plumbers, and tire dealers in towns across the western US. Want a narrowly defined product/service (unlike a grocery store).
- Focus on small isolated towns so that the town's population is a good predictor of market size. Use Census information on town demographics.
- Because assume firms are homogenous, only the number of firms matters. Information gathered from yellow pages and trade magazines.

Empirical implementation

- Specifies a reduced-form profit function (since prices and costs are not observed):

$$\Pi_{N,m} = S(Y_m, \lambda) \cdot V_N(Z_m, W_m, \alpha, \beta) - F_N(W_m, \gamma) + \epsilon_m \tag{1}$$
$$= \bar{\Pi}_{n,m} + \epsilon_m \tag{2}$$

  where ϵ_m is a shock common to all firms in market m. Firms observe the shock, but the econometrician does not.

- Firms are different in observable profits, in a limited fashion. Unobserved profits are the same across all firms.

- Data: observe N_m.

$$\text{Prob}(N_m) = \text{Prob}\big(\Pi_{N_m,m} > 0, \Pi_{N_m+1,m} < 0\big) \tag{3}$$
$$= \text{Prob}\big(\bar{\Pi}_{N_m+1,m} < \epsilon < \bar{\Pi}_{N_m,m}\big) \tag{4}$$

- B/R assume $\epsilon \sim N(0, \sigma^2)$ i.i.d. across markets m, so the likelihood is

$$\text{Prob}(N_m) = \begin{cases} \Phi(\bar{\Pi}_{N_m,m}) - \Phi(\bar{\Pi}_{N_m+1,m}), & \text{if } N_m > 0, \\ 1 - \Phi(\bar{\Pi}_{1,m}) & \text{if } N_m = 0. \end{cases} \tag{5}$$

  This is an ordered probit model.

1.2 Berry (1992): "Estimation of a Model of Entry in the Airline Industry"

Empirical question: How important is airport presence in determining city-pair flight profitability?
Methodological question: How can we estimate entry/exit models with heterogenous firms, where the heterogeniety is derived from observed and unobserved variations in costs and demands?

Model

- 2-stage game, where (1) do you enter and (2) if enter, then compete
- For each market m there are K_m potential entrants.
- Firms differ in their fixed costs and unobserved shock.
- There is an assumed order of entry based on profitability.

Data

- Data are from *Origin and Destination Survey of Air Passenger Traffic*.
- These data are a 10% random sample of all airline passenger tickets issued by US airlines.

- Data organized around a the idea of an origin/destination basis (e.g. BWI–JAX).
- Berry only mentions # of passengers by airline for a route, but I think there is price information as well.

Empirical implementation

- Allow for firm (indexed by k) heterogeneity in fixed costs: (m is the market and N is the total number of firms)

$$\Pi_{m,k,N} = v_m(N) - \phi_{m,k} \tag{6}$$

where the first term is the common component and the second term is the firm k component.

$$\Pi_{m,k,N} = X_m\beta - \delta\log(N) + \rho u_m 0 + Z_k\alpha + \sqrt{1-\rho^2}u_{m,k} \tag{7}$$

X are market characteristics observed by the econometrician, and u_{m0} are market characteristics unobserved by the econometrician. Similarly,Z are observed firm characteristics and u_{mk} are firm characteristics unobserved by the econometrician.

- The composite error term for firm k is $\epsilon_{m,k} = \rho u_{m0} + \sqrt{1-\rho^2}u_{m,k}$ where ρ essentially measures the correlation between the errors terms of the firms in a given market.
- Probability of N firms entering is:

$$\begin{aligned}\text{Prob}(n_m = N|Z_m) &= \text{Prob}\big(\epsilon_{m,1},\ldots,\epsilon_{m,K_m}|\sum_{k=1}^{K_m}\mathbf{1}(v_m(N;Z_m,X_m) > \phi_{m,k}) = N\big)\\ &= \int\ldots\int\mathbf{1}\big(\sum_{k=1}^{K_m}\mathbf{1}(v_m(N;Z_m,X_m) > \phi_{m,k}) = N\big)dF(\epsilon_{m,0},\ldots,\epsilon_{m,K_m};\theta)\end{aligned}$$

where θ is a parameter vector and v and ϕ in the equations above depend upon the ϵ's.

Identification

- For the model to be identified, for every θ there needs to be a unique number of firms entering
- If concerned about the identification of firms (not just the number), then there needs to be a unique vector of entering firms.
- Troublesome for entry/exit games since there are often multiple equilibria.
- Berry spends considerable time discussing this, b/c it permeates everything. For example,
  1. How firms are heterogenous. Note that only N effects a firm's profits–identity of entering firms does not effect a firm's profits.
  2. Sequence of entry. Estimates the model two different ways. (1) Firms enter based on a ranking of profitability. (2) "Incumbents" first enter based on profitability and second new entrants enter based on profitability. Note – the sequence of entry also simplifies the computational problem (i.e. suppose 26 possible entrants, and observe 11 actual entrants – there are over 7 million combinations of having 26 "choose" 11).
- Main point – need to think carefully about the underlying model and the possible constraints that result in a unique equilibrium (and so let the model be identified).

Simulation Estimation

- In order to simulate $E[n_m|Z_m, X_m; \theta)$ we follow these three steps:
  1. For $s = 1, \ldots, S$, draw ϵ^s according to the multivariate normal distribution.
  2. For each draw ϵ^s, calculate $n^{*,s}(\epsilon^s)$. Note – this is NOT easy! Relies heavily on order of entry assumption.
  3. Approximate $E[n_m|Z_m, X_m; \theta)$ by the average $\frac{1}{S}\sum_{s=1}^{S} n^{*,s}(\epsilon^s)$.
- In Appendix, Berry mentions that he also uses the identities on some firms as moments as well. For example, did the first (and second, and third, and fourth) firm with the largest city output share (I think: total number of flights out of city) enter this particular route?

Result

- Methodological result:

  1. Big thing: using simulation to estimate entry/exit models.
  2. Highlights ways (and pitfalls) to incorporate firm heterogeneity into these models

- Empirical result.

  1. Airport presence is a large factor in a city-pair's profitability (e.g. spreading fixed costs).
  2. Despite this factor, profits fall rapidly in the number of entrants.

- My big criticism: operations research folks (who actually help airlines make business decisions) harp on networks when focusing on airlines. Most economics papers (perhaps because of the data), don't focus much on networks, or try to explain entry or pricing, holding networks "fixed". Why ignore the elephant in the room? Although it is a very difficult problem.

2 Mazzeo (2002): Product choice and oligopoly market structure

Main question: What drives the product-type decisions of firms in oligopoly markets? By differentiating, decrease competition. But if demand is particular strong, then a firm may decide not to differentiate. Paper explores this trade-off empirically, within the US motel market (low/high quality motel choice) near highways.

Model

- 2-stage game where entry varies in the quality dimension

  1. Choice whether to enter and whether to be a low (L) or high (H) quality motel

2. Compete (e.g. a la Cournot)

- $N = (n_l, n_H)$ is a vector of entry of two types. Reduced form profits for each type are:

$$\pi_L = \alpha_L + f(\theta_L, N) + \epsilon_L$$
$$\pi_H = \alpha_H + f(\theta_H, N) + \epsilon_H.$$

- Note – conditional on type, firms are homogenous in profits. f allows entry of low quality firm to effect other low-quality firms differently than high-quality firms.
- In entry stage Mazzeo considers two possibilities regarding entry:

  1. Stackelberg. Firms move sequentially. First firm makes entry/quality decisions, then second, then third, etc.
  2. Two sub-stage game: (a) n firms commit to enter, (b) then make quality choices

- Consider possible entrant (taking as given that L low firms enter and H high firms enter)

  Stackelberg

  – Usual Nash-solution equilibrium conditions

$$\pi_L(L-1, H) > 0$$
$$\pi_L(L, H) < 0$$
$$\pi_L(L-1, H) > \pi_H(L-1, H)$$
$$\pi_H(L, H-1) > 0$$
$$\pi_H(L, H) < 0$$
$$\pi_H(L, H-1) > \pi_H(L-1, H)$$

  – Assume that π_J decreases in L and H for $j = \{L, H\}$ and

$$\pi_L(L, H) - \pi_L(L+1, H) > \pi_L(L, H) - \pi_L(L, H+1)$$
$$\pi_H(L, H) - \pi_H(L, H+1) > \pi_H(L, H) - \pi_H(L+1, H)$$

or, that entry of similar type decreases profits faster than entry of a dissimilar type.

  – Then an equilibrium exists.

- In the two-stage case, under the same conditions an equilibrium exists and is unique.
- In some cases the two-stage and Stackelberg games will have different predictions on who enters (part of Sutton's critique). Think of it in terms of committment. IN Stackelberg, need to choose entry and quality, while with two-stage game the quality decision is made after the number of firms operating is known.

Data

- Information from all the motel establishments operating in 492 oligopoly markets located along interstate highways throughout the United States.
- AAA has ratings for different types of motels
- Focus on geographically isolated clusters of motels off of interstate highways (small rural exits).
- Uses AAA listing, trade industry directory and yellow pages to get data.
- Census data on nearest town population
- Federal Highway Administration data on average annual traffic on interstate exits.
- See tables 2 and 4 in paper

Empirical implementation

- Maximum likelihood selects the profit function parameters that maximize the probability of the observed market configurations across the dataset. The likelihood function is

$$L = \prod_{m=1}^{492} \text{Prob}\big[(L, H)_m^O\big],$$

where $(L, H)_m^O$ is the observed configuration of firms in market m–its probability is a function of the solution concept, the parameters, and the data for market m. For example, if $(L, H)_m^O = (1, 1)$, the contribution to the likelihood function for market m is Prob$[(1, 1)]$.

- Demand factors are: town's population, spacing of exits, average annual traffic, and a "west" dummy variable
- Lots of dummies to capture entry's effects on profits in a flexible fashion
  - first low competitor
  - second low competitor
  - first high competitor (without low competitor)
  - second high competitor (without low competitor)
  - etc
  - Done from a low-type's perspective and then high-type's perspective.
- Could estimate this model via simulation (he does this for a 3 quality type case).
- But with the assumption that ϵ_L and ϵ_H are iid normal, can compute probabilities w/o simulation (?).

Results

- Differentiation is big – entry of a same-type competitor is much more damaging than entry of differing-type competitor.
- Adding a second similar firm lowers profits much more than adding a third similar firm (echoing B/R).
- But if demand is strong enough (e.g. population is double its mean), prefer to come in as second high type than as a new low type.
- see table 6

- see figure 2 – model's predictions about market structure.
- Stackelberg and 2-stage solution concepts provide very similar predictions and estimates. While these solution concepts are often stressed in theoretical settings, they are not important in this particular case (and perhaps others).

3 Static games with private infomation

- Unlike papers considered so far, now consider games where firms will have private information – specifically an iid shock to profits. Firms don't see other firm's profit shocks, nor does the econometrician.
- Start by considering a simple example, and then look at a more general example.
- See "Estimating Static Models of Strategic Interactions" by Bajari/Hong/Krainer/Nekipelov . Pat Bajari (Univ of Minnesota) is leader in this area.

Simple Example

- Suppose have data on a cross-section of markets
- Entry by Walmart and/or Target
- Markets $t = 1, \ldots, T$ and firms $i = 1, 2$.
- Let $a_{i,t} = 1$ denote entry and $a_{i,t} = 0$ denote no entry
- Economic theory suggests that profits depends on demand, costs, and number of competitors
  - POP_t is population of market t (demand)
  - $DIST_{it}$ is distance from headquarters (costs)
  - a_{-i} indicates entry by competitors
- profit of firm i is

$$
\begin{aligned}
&u_{it} = \alpha POP_t + \beta DIST_{it} + \delta a_{-i,t} + \epsilon_{it} \quad \text{if } a_{i,t} = 1 \\
&u_{it} = 0 \quad \text{if } a_{i,t} = 0
\end{aligned}
$$

- ϵ_{it} is private information

- $\sigma(a_{it} = 1)$ is the probability that i enters market t
- In a Bayes-Nash equilibrium, agent i makes best response to $\sigma_{-i}(a_{-i,t} = 1)$.
- Therefore i's decision rule is

$$\sigma_i = 1 \longleftrightarrow \alpha POP_t + \beta DIST_{it} + \delta\sigma_{-i,t}(a_{-i,t} = 1) + \epsilon_{it} > 0$$

- So what's the distribution of ϵ? Assume extreme value, then get

$$\sigma_i(a_i = 1) = \frac{\exp(\alpha POP_t + \beta DIST_{it} + \delta\sigma_{-i,t}(a_{-i,t} = 1))}{1 + \exp(\alpha POP_t + \beta DIST_{it} + \delta\sigma_{-i,t}(a_{-i,t} = 1))} \tag{8}$$

- Equilibrium – two equations and two unknowns ($\sigma_1(a_1 = 1)$ and $\sigma_2(a_2 = 1)$).

$$\sigma_1(a_1 = 1) = \frac{\exp(\alpha POP_t + \beta DIST_{1t} + \delta\sigma_{2,t}(a_{2,t} = 1))}{1 + \exp(\alpha POP_t + \beta DIST_{1t} + \delta\sigma_{2,t}(a_{2,t} = 1))} \tag{9}$$

$$\sigma_2(a_2 = 1) = \frac{\exp(\alpha POP_t + \beta DIST_{2t} + \delta\sigma_{1,t}(a_{1,t} = 1))}{1 + \exp(\alpha POP_t + \beta DIST_{2t} + \delta\sigma_{1,t}(a_{1,t} = 1))} \tag{10}$$

Two-Step Estimator

- First, estimate $\hat{\sigma}_i(a_i = 1|POP_j, DIST_{1j}, DIST_{2j})$ using a flexible method
- This is the frequency that entry is observed empirically – a fairly standard problem
- We are recovering an agent's equilibrium beliefs by using the sample analogue.
- Given this first stage estimate, agent i's decision rule is estimated as

$$\sigma_i = 1 \longleftrightarrow \alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1) + \epsilon_{it} > 0$$

- The probability that i chooses to enter is

$$\sigma_i(a_i = 1) = \frac{\exp(\alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1))}{1 + \exp(\alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1))} \tag{11}$$

- This is the familiar conditional logit model!
- In the second step, let $L(\alpha, \beta, \delta)$ denote the pseudo likelihood function defined as

$$L(\alpha, \beta, \delta) = \Pi_{t=1}^{T}\Pi_{i=1}^{2}\left(\frac{\exp(\alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1))}{1 + \exp(\alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1))}\right)^{1\{a_{it}=1\}}$$
$$\left(1 - \frac{\exp(\alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1))}{1 + \exp(\alpha POP_t + \beta DIST_{it} + \delta\hat{\sigma}_{-i,t}(a_{-i,t} = 1))}\right)^{1\{a_{it}=0\}} \tag{12}$$

- Maximize psuedo-likelihood to estimate (α, β, δ).

- Bottom line: this is the logit model with $\hat{\sigma}_i(a_i = 1|POP_j, DIST_{1j}, DIST_{2j})$ as an additional independent variable.
- Simple generalization of a widely used model
- Computationally simple and accurate
- Can generalize to richer models, including dynamic models (see Pat Bajari's website).

General Model

Setup:

- Players $i = 1, \ldots, n$
- Actions $a_i \in \{0, 1, \ldots, K\}$
- Action profiles $a = (a_1, \ldots, a_n)$ and $a \in A = \{0, 1, \ldots, K\}^n$.
- State variables
  - $s_i \in S_i$ state for player i. Let $s = (s_1, \ldots, s_n)$. All players observe s and the econometrician observes s.
  - For each agent $K+1$ state variables associated with each possible action $\epsilon_i = (\epsilon_i(0), \ldots, \epsilon_i(K))$. Only player i knows ϵ_i. Other firms and econometrician do not observe ϵ_i. Firms and the econometrician observe the density $f(\epsilon_i)$, which is iid across players i.

Specification

- Period utility for player i with action prole a (additive in error):

$$u_i(a, s, \epsilon_i; \theta) = \Pi_i(a_i, a_{-1}, s; \theta) + \epsilon_i(a_i) \tag{13}$$

- Strategic interdependence: utility for player i from action a_i depends on actions of other players a_{-i}.
- Player i's decision rule: $a_i = \delta_i(s, \epsilon_i)$. Note that ϵ_{-i} does not enter, because i does not know ϵ_{-i} when making action choice.

Estimation

- Conditional choice probability $\sigma_i(a_i|s)$ for player i:

$$\sigma_i(a_i = k|s) = \int 1(\delta_i(s, \epsilon_i) = k) f(\epsilon_i) d\epsilon_i \tag{14}$$

  These conditional choice probabilities can be estimated from the data (recall the first logit from the simple example). Now derive expression for CCP in model.

- Define choice-specific expected payoff for player i:

$$\Pi_i(a_i, a; \theta) = \sum_{a_{-i}} \Pi_i(a_i, a_{-i}, s; \theta)\sigma_{-i}(a_{-i}|s) \tag{15}$$

Then optimal action for player i satises:

$$\sigma_i(a_i|s) = \text{Prob}\left\{\epsilon_i|\Pi_i(a_i, s; \theta) + \epsilon_i(a_i) > \Pi_i(a_j, s; \theta) + \epsilon_i(a_j), \text{for } i \neq j\right\} \tag{16}$$

- Next make some simplications:

  1. Two actions: $a_i = \{0, 1\}$.
  2. Linearity and additivity of profits:

$$\Pi_i(a, s) = \begin{cases} s \cdot \beta + \delta \sum_{j\neq i} 1(a_j = 1) & \text{if } a_i = 1 \\ 0 & \text{if } a_i = 0 \end{cases} \tag{17}$$

  (Only total number of other entrants matter, not identities of other entrants.)

  3. Assume ϵ's are iid Type I extreme Value, across players i and actions a.

- Then $\tilde{\Pi}_i(a_i = 1|s) \equiv E_{a_{-i}}\Pi_i(a, s) = s \cdot \beta + \delta \sum_{j\neq i} \sigma_j(a_j = 1)$

- CCP's are:

$$\sigma_i(a_i|s) = \frac{\exp(s \cdot \beta + \delta \sum_{j\neq i} \sigma_j(a_j = 1))}{1 + \exp(s \cdot \beta + \delta \sum_{j\neq i} \sigma_j(a_j = 1))} \tag{18}$$

- Parameters $\theta = \{\beta, \delta\}$

- Likelihood function:

$$L(\theta) = \Pi_t \Pi_i \left[\sigma_i(a_i = 1|s; \theta)\right]^{1(a_{it}=1)} \left[1 - \sigma_i(a_i = 1|s; \theta)\right]^{1(a_{it}=0)} \tag{19}$$

where, for each value of s, the n (one for each player) "predicted" choice probabilities $\sigma_i(s, \theta) \equiv \sigma_i(a_i = 1|s; \theta)$ can be solved from the n-system of nonlinear equations

$$\sigma_i(s, \theta) = \frac{\exp(s \cdot \beta + \delta \sum_{j\neq i} \sigma_j(a_j = 1))}{1 + \exp(s \cdot \beta + \delta \sum_{j\neq i} \sigma_j(a_j = 1))} \tag{20}$$

Clearly, this is computationally quite burdensome.

- BHKNs alternative two-step approach

  1. Estimate CCPs directly from data: for all i and s: $\sigma_i(a_i = 1|s)$ (e.g. using a flexible method, logit, etc)

  2. Plug these estimated CCPs into RHS of choice probabilities to form pseudo-likelihood function:

  $$\tilde{L}(\theta) = \Pi_t \Pi_i \left[\frac{\exp(s \cdot \beta + \delta \sum_{j \neq i} \sigma_j(a_j = 1))}{1 + \exp(s \cdot \beta + \delta \sum_{j \neq i} \sigma_j(a_j = 1))} \right]^{1(a_{it}=1)} \left[1 - \frac{\exp(s \cdot \beta + \delta \sum_{j \neq i} \sigma_j(a_j = 1))}{1 + \exp(s \cdot \beta + \delta \sum_{j \neq i} \sigma_j j(a_j = 1))} \right]^{1(a_{it}=0)} \quad (21)$$

  Look at BHKN for identification arguments