Entry and Exit 2
PhD Industrial Organization

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Motivation

- Before, we studied three papers about entry.

- These papers were extremely creative, but all had to make strong assumptions to allow for point identification.

- **Central challenge:** each paper seeks to estimate parameters of the underlying variable profits, fixed costs etc only using only the observed equilibrium number of firms in each market.
  - Point identification requires 1:1 mapping between the equilibrium number of firms and each parameter.
  - Critical to this is that the model has a **unique** equilibrium.

- Today we will relax the assumption of a unique equilibrium and allow for potentially multiple equilibria

Plan

1. Partial identification: warm-up
2. Ciliberto and Tamer (2009)
3. Wollmann (2018)

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1. **Partial identification: warm-up**
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Partial identification: warm-up

- **Example**: missing data (Tamer, 2010)
- **Setup**:
- Let Y be a binary 0/1 random variable that is observed only when another binary 0/1 random variable Z is equal to 1.
- So, observe: $(Y|Z = 1)$
- **Question:** What is $P(Y = 1)$?
- **Issue:** data alone contain no information about $Y|Z = 0$.

Partial identification: warm-up

- What if we made <u>no assumptions</u> about $Y|Z = 0$?

- Then, there is a *set* of parameters that are consistent with the data.

- In this setting, the set is:

$$\Phi_I = \{p \in [0,1] : p = P(Y = 1|Z = 1)P(Z = 1) + qP(Z = 0), \text{ for some } q \in [0,1]\}$$

- Another way of writing this is in terms of the following bounds:

$$\Phi_I = [\underbrace{P(Y = 1|Z = 1)P(Z = 1)}_{\text{What if } P(Y=1|Z=0)=0?}, \underbrace{P(Y = 1|Z = 1)P(Z = 1) + P(Z = 0)}_{\text{What if } P(Y=1|Z=0)=1\ ?}]$$

Partial identification: warm-up

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- **Application:** biased coin flip (tails $= 0$, heads $= 1$).

- Know $P(Y=1|Z=1) = 0.7$ and $P(Z=1) = 0.9$. What is $P(Y=1)$?

Partial identification: what did we learn from the previous exercise?

- **Idea:** without any assumptions, we might still be able to say something useful about the parameters from the data.

- We say the model is **partially identified** when there is more than one parameter value that is consistent with the data and model.
  - Similar to point identification, partial identification is completely different to issues with statistical significance or not have a large enough sample size

  - Often the thought experiment with identification is: if we had unlimited data then what can we say about the parameters?

- Partially identified models might still be useful! E.g. the previous example could rule out out a value of $P(Y = 1) = 0.9$.

- We usually say that the bounds are **informative** if they are tight enough for us to still say something (economically) interesting about the problem.

Partial identification: what does all this have to do with entry models?

- We will see that allowing for multiple equilibria in entry models
  - $\rightarrow$ a <u>set</u> of parameters that are consistent with the data
  - $\rightarrow$ partial identification and bounds on the parameters

Plan

1. Partial identification: warm-up
2. **Ciliberto and Tamer (2009)**
3. Wollmann (2018)

Ciliberto and Tamer (2009)

- **Question:** How can we estimate the payoff functions of plays in complete information, static, discrete choice games **without** making assumptions about equilibrium selection?

- **Method:** Use 'moment inequalities' (I will explain this in more detail later)

- **Application:** Entry into airline markets

- **Policy counterfactual:** Repealing the Wright Amendment (policy which restricted air service out of Dallas Love airport)

- For this paper we will mainly focus on the method rather than the application.

Ciliberto and Tamer (2009): simple example

- Consider a simple version of a Bresnahan and Reiss (1990) 2x2 entry game:

$$y_{1m} = 1[\alpha_1' X_{1m} + \delta_2 y_{2m} + \epsilon_{1m} \geq 0]$$
$$y_{2m} = 1[\alpha_2' X_{2m} + \delta_1 y_{1m} + \epsilon_{2m} \geq 0]$$

- Here:

- (X_{1m}, X_{2m}) is a vector of observed exogenous regressors that contain market m specific variables

- (y_{1m}, y_{2m}): whether firm 1 and firm 2 enter

- Error terms $(\epsilon_{1m}, \epsilon_{2m})$ are observed by firms but not by econometrician

- Choices are interdependent

- **Note:** consider only pure strategy equilibria, also assume perfect information

Ciliberto and Tamer (2009): simple example

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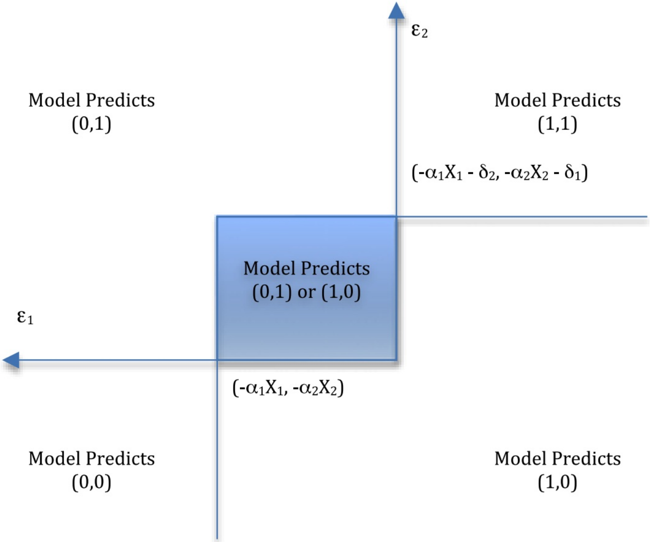
- We will now see that with large enough support for the ϵ's, we will now see that if $\delta_1, \delta_2 < 0$ (i.e. duopoly profits are smaller than monopoly profits) there are multiple equilibria.

- (Note: there are multiple equilibria if $\delta_1, \delta_2 > 0$)

Ciliberto and Tamer (2009): simple example



Ciliberto and Tamer (2009): simple example

- Based on the previous figure we can construct the following choice probabilities:

$$Pr(1,1|X) = Pr(\epsilon_1 \geq -\alpha_1' X_1 - \delta_2; \epsilon_2 \geq -\alpha_2' X_2 - \delta_1)$$
$$Pr(0,0|X) = Pr(\epsilon_1 \leq -\alpha_1' X_1; \epsilon_2 \leq -\alpha_2' X_2)$$
$$Pr(1,0|X) = Pr((\epsilon_1, \epsilon_2) \in R_1(X, \theta)) + \int Pr((1,0)|\epsilon_1, \epsilon_2, X) 1[(\epsilon_1, \epsilon_2) \in R_2(\theta, X)] dF_{\epsilon_1, \epsilon_2}$$

- Here:
  - $R_1(\theta, X)$: (1,0) is the unique equilibrium of the game
  - $R_2(\theta, X)$: (1,0) *potentially observable outcome of the game* + was "selected"

Ciliberto and Tamer (2009): simple example

- The "selection mechanism" is the function $Pr((1,0)|\epsilon_1, \epsilon_2, X)$.
- This is unknown to the econometrician and can differ across markets
- Noticing that the selection mechanism is a probability and so lies in $[0,1]$, an implication of the above model is:

$$Pr((\epsilon_1, \epsilon_2) \in R_1) \leq Pr((1,0)) \leq Pr((\epsilon_1, \epsilon_2) \in R_1) + Pr((\epsilon_1, \epsilon_2) \in R_2)$$

- (Notice the bounds and recall similarities to the 'missing data' partial identification example before)

Ciliberto and Tamer (2009)

- Profit for firm i in market m:

$$\pi_{im} = S_m'\alpha_i + Z_{im}'\beta_i + W_{im}'\gamma_i + \sum_{j\neq i}\delta_j^i y_{jm} + \sum_{j\neq i} Z_{jm}'\phi_j^i y_{jm} + \epsilon_{im}$$

- Where:
  - S_m: vector of market characteristics which are common among the firms in market m
  - Z_m: matrix of firm characteristics which enter into all firms (e.g. some product attributes that consumers value)
  - K: total number of potential entrants in market m
  - $W_m = (W_{1m}, ..., W_{Km})$: vector of firm characteristics where W_{im} enters only into firm i's profit in market m (e.g. cost variables)
  - y_{jm}: indicator if firm j enters into market m
  - ϵ_{im}: part of profits that is unobserved to the econometrician (but observable to the participants $\rightarrow$ this is a game of complete information).

Ciliberto and Tamer (2009)

- Nash equilibrium in each market:

$$y_{im}\pi_{im} = y_{im}(S'_m\alpha_i + Z'_{im}\beta_i + W'_{im}\gamma_i + \sum_{j\neq i}\delta^i_j y_{jm} + \sum_{j\neq i} Z'_{jm}\phi^i_j y_{jm} + \epsilon_{im}) \geq 0$$

- By similar arguments to the 2x2 example before, the predicted choice probabilities are:

$$\begin{aligned} Pr(y'|X) &= \int Pr(y'|\epsilon, X)dF \\ &= \underbrace{\int_{R_1(\theta,X)} dF}_{\text{unique outcome region}} + \underbrace{\int_{R_2(\theta,X)} Pr(y'|\epsilon, X)dF}_{\text{multiple outcome region}} \end{aligned}$$

- Note: $y' = (y'_1, ..., y'_K)$ is some outcome which is a sequence of 0's or 1's corresponding to different airlines serving the market.

Ciliberto and Tamer (2009)

- Using that the selection function is bounded between 0 and 1:

$$\int_{R_1(\theta,X)} dF \leq Pr(y'|X) \leq \int_{R_1(\theta,X)} dF + \int_{R_2(\theta,X)} dF$$

- The above conditions yields many **moment inequalities** (denote - for later - $H_1(\theta, X)$ as the LHS and $H_2(\theta, X)$ as the RHS)

- These define an identified set:

$$\Phi_I = \{\theta : \text{ inequalities above are satisfied for all X}\}$$

Ciliberto and Tamer (2009)

- To estimate, use the following objective function

$$Q(\theta) = \int [||(P(y'|X) - H_1(\theta, X_m))_-|| + ||(P(y'|X) - H_2(\theta, X_m))_+||dF_X]$$

- Work with the sample analogue:

$$Q_n(\theta) = \frac{1}{n}\sum_{m=1}^{n} [||(\hat{P}(y'|X_m) - H_1(\theta, X_m))_-|| + ||(\hat{P}(y'|X_m) - H_2(\theta, X_m))_+||]$$

- Will need to estimate P (estimate denoted $\hat{P}$). Do this flexibly/non-parametrically.

- (Paper has a lot more detail about how they discretize the covariates etc)

Ciliberto and Tamer (2009)

- The procedure on the previous slide allows for the estimation of the parameters.
- However, inference is a lot trickier. There are quite a few alternative procedures to do inference in the literature (and many have been created since this paper was written).
- See IO Handbook Vol 4 Chapter "Moment Inequalities and Partial Identification in Industrial Organization" for an up-to-date overview of current best-practices

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3. **Wollmann (2018)**

Wollmann (2018)

- **Question:** What would have happened if the auto industry had not been bailed out in 2009?
  - (Mitt Romney: "Let Detroit Go Bankrupt")
- **Application:** Market for trucks in the US
  - (Note: 'chicken tax' implies all trucks domestically produced)
- **Method:** Allows for BLP-style demand while also endogenizing entry of different products with different characteristics
- **Main takeaway:** Product entry/exit moderates the markup increases and output decreases from a liquidation of GM and Chrysler by up to three-quarters.

Wollmann (2018): Main Sources of Data

- 1. All commercial vehicles sold in USA 1986-2012 from 'The Truck Blue Book'
  - Each observation includes brand, model, year, suggested retail price, other characteristics (like the load capacity, cab, chassis, etc)
- 2. Unit sales data from R.L. Polk Database
- 3. Microdata on commercial vehicle purchases available through the US Census
  - Up to 2002 the Census mailed 130000 owners of trucks and vans and asked about how they used their vehicle, and industry/state buyer operates in.

Wollmann (2018): Model - Stage 2, Demand

- Each buyer r chooses whether to purchase vehicle j:

$$U_{r,j} = x_j(\beta_x + \beta_x^o z_r^o + \beta_x^u z_r^u) + p_j\beta_p + \xi_j + \epsilon_{r,j}$$

- Where:
  - x_j: vehicle characteristics (e.g. Gross Weight Rating (GWR), if it has a 'cabover')
  - z_r^o: observed buyer attributes
  - z_r^u: unobserved buyer attributes
  - Other notation similar to what we have seen before.

Wollmann (2018): Model - Stage 2, Prices

- Firms f offer a set of products $J_{f,t}$ and choose prices to maximize profits:

$$\Pi_{f,t} = \sum_{j \in J_{f,t}} [p_{j,t} - mc_{j,t}] s(x_{j,t}, x_{-j,t}, p_t, z_t; \beta, \xi_t) M_t$$

- Where:
  - $mc_{j,t}$: denotes the marginal costs of producing j at t
  - $x_{-j,t}$: matrix of characteristics for products other than j at t
  - M_t: market size (note: disappears after taking first-order condition)
- Parametrize marginal cost:
  - $\log(mc_{j,t})$ is linear in observable product characteristics and some other cost components, as well as an unobserved factor specific to the product and time $\omega_{j,t}$.
  - $\rightarrow$ additional parameter γ which is the vector of coefficients needs to be estimated.

Wollmann (2018): Model - Stage 1, Product Offerings

- In the second stage, expected profits (expectation taken over the distribution of the disturbances (F_{ξ}, F_{ω})) are:

$$\pi(J_{f,t}, J_{-f,t}, z_t, w_t) = \int_{\xi',\omega'} \Pi(J_{f,t}, J_{-f,t}, z_t, w_t; \beta, \gamma, \xi', \omega') dF_{\xi'} dF_{\omega'}$$

- The sunk cost/scrap value of a product is:

$$SC_{f,j,t,J_{f,t-1}} = x_j' \tilde{\theta}_{f,x_j,t} \times \left[\{ j \in J_{f,t}, j \notin J_{f,t-1} \} + \lambda \{ j \notin J_{f,t}, j \in J_{f,t-1} \} \right]$$

- In above equation, $\{.\}$ is the indicator function, λ indexes how much is returned in scrap value relative to the entry cost. The term $\tilde{\theta}_{f,x_j,t}$ is a sunk cost parameter (see paper for details on parametrization).

Wollmann (2018): Model - Stage 1, Product Offerings

- Decisions to introduce products (or to not introduce) produces the following moment inequalities (which I write using the sample analogues):

$$\frac{1}{XTF}\sum_{x_j}\sum_{t}\sum_{f} h^i_{f,x_j,t}\{j \in J_{f,t}\}$$
$$\times\left[\Delta\pi(J_{f,t}, J_{f,t}\backslash j, J_{-f,t}, z_t, w_t) + x_j'\theta_f(\{j \notin J_{f,t-1}\} - \lambda\{j \in J_{f,t-1}\})\right] \geq 0$$

- And:

$$\frac{1}{XTF}\sum_{x_j}\sum_{t}\sum_{f} h^i_{f,x_j,t}\{j \notin J_{f,t}\}$$
$$\times\left[\Delta\pi(J_{f,t}, J_{f,t}\cup j, J_{-f,t}, z_t, w_t) - x_j'\theta_f(\{j \notin J_{f,t-1}\} - \lambda\{j \in J_{f,t-1}\})\right] \geq 0$$

- Here, $h^i_{f,x_j,t}$ are moment inequality weights (see paper for how these are constructed)
- X, T, F: the number of unique x_j vectors, time periods, firms
- $\Delta\pi$: change in the profits

Wollmann (2018): Estimation

- Stage 2: ‘standard’ BLP estimation
- Stage 1: Use moment inequalities

Wollmann (2018): Results - sunk costs

Scrap value scale parameter $(-\lambda)$	[0.531, 0.613]
Observations	11,123
Moments	97

Figure: 95% confidence interval in brackets.

- Above is just one part of the sunk costs (see paper for all the other parameters)
- Note that it is set-identified
- Interpretation: "firms recover about 55-60% of the sunk cost when they retire vehicles"

Wollmann (2018): Counterfactuals

- What would have happened in the absence of the $85 billion rescue of GM and Chrysler?
- 1. Acquisition: GM and Chrysler products acquired by Ford
- 2. Acquisition: GM and Chrysler products acquired by PACCAR (this is a truck manufacturer)
- 3. Liquidation

Wollmann (2018): Counterfactuals

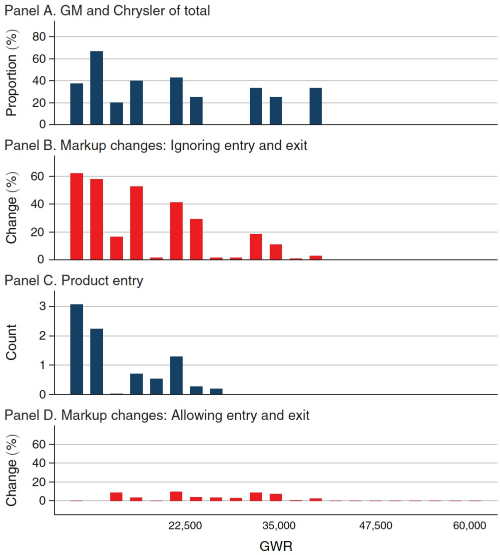

FIGURE 4. COUNTERFACTUAL OUTCOMES UNDER ACQUISITION BY FORD