Conduct

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Grad IO

Conduct Overview

- A second set of important questions in IO is being able to use data to decide whether firms are competing or colluding.
- Absent additional restrictions, we cannot generally look at data on (P, Q) and decide whether or not collusion is taking place.
  - You say we started colluding at date t, I say we received a correlated shock to mc.
- We can make progress in two ways: (1) parametric restrictions on marginal costs; (2) exclusion restrictions on supply.
  - Most of the literature focuses on (1) by assuming something like: $\ln mc_{jt} = x_{jt}\gamma_1 + w_{jt}\gamma_2 + \omega_{jt}$.
  - In principle (2) is possible if we have instruments that shift demand for products but not supply. (These are much easier to come up with than "supply shifters").

A famous plot (Bresnahan 87)

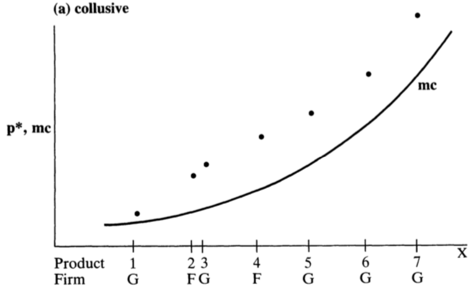

Figure 2(a)

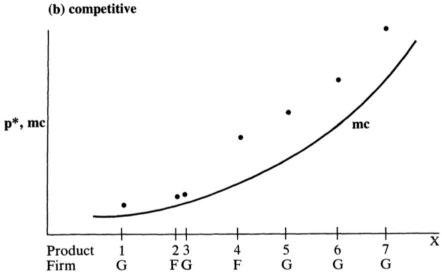

Figure 2(b)

Bresnahan (1980/1982) recognized this problem: we need "rotations of demand".

Testing For Collusion: Challenges

We generalize the $\mathcal{H}(\kappa)$ and derive multi-product Bertrand FOCs:

$$\arg\max_{p \in \mathcal{J}_f} \pi_f(\mathbf{p}) = \sum_{j \in \mathcal{J}_f} (p_j - c_j) \cdot q_j(\mathbf{p}) + \kappa_{fg} \sum_{j \in \mathcal{J}_g} (p_j - c_j) \cdot q_j(\mathbf{p})$$

$$\rightarrow 0 = q_j(\mathbf{p}) + \sum_{k \in (\mathcal{J}_f, \mathcal{J}_g)} \kappa_{fg} \cdot (p_k - c_k) \frac{\partial q_k}{\partial p_j}(\mathbf{p})$$

- Instead of 0's and 1's we now have $\kappa_{fg} \in [0,1]$ representing how much firm f cares about the profits of g.
    - If f and g merge (or fully colluded) then $\kappa_{fg} = 1$
    - Often in the real world firms cannot reach fully collusive profits and $\kappa_{fg} \in (0,1)$.
    - Evidence that $\kappa_{fg} > 0$ is not necessarily evidence of malfeasance, just a deviation from static Bertrand pricing

Testing For Conduct: Challenges

- Recall the Δ matrix which we can write as $\Delta = \tilde{\Delta} \odot \mathcal{H}(\kappa)$, where $\odot$ is the element-wise or Hadamard product of two matrices.
  - $\tilde{\Delta}$ is the matrix of demand derivatives with $\Delta(j,k) = \frac{\partial q_j}{\partial p_k}$ for all elements.
  - $\mathcal{H}(\kappa) = \kappa_{fg}$ for products owned by (f,g) where $\kappa_{ff} = 1$ always.
- Mergers are about changing 0's to 1's in the $\mathcal{H}(\kappa)$ matrix.
- Matrix form of FOC: $q(\mathbf{p}) = \Delta(\mathbf{p},\kappa) \cdot (\mathbf{p} - \mathbf{mc})$
- $\mathbf{mc} = \mathbf{p} - \underbrace{\Delta(\mathbf{p},\theta_2,\kappa)^{-1} s(\mathbf{p})}_{\eta(\mathbf{p},\mathbf{s},\theta_2,\kappa)}$ where η_{jt} is the markup.

Reasons for Deviations from Static Bertrand

Biased estimates of own and cross price derivatives: For anything to work, you have correct estimates of $\tilde{\Delta}$. My prior is most papers underestimate diversion ratios for close substitutes.

Vertical Relationships: Who sets supermarket prices? Just the retailer? Just the manufacturer? Some combination of both? Retailers tend to soften downstream price competition.

Faulty Timing Assumptions: Bertrand is a simultaneous move pricing game. Lots of alternatives (Stackelberg leader-follower, Edgeworth cycles, etc.).

Dynamics and Dynamic Pricing: Forward looking firms or consumers might not set static Nash prices. [e.g. Temporary Sales, Switching Costs, Network Effects, etc.]

Unmodeled Supergame: Maybe firms are legally tacitly colluding, higher prices might be about what firms believe will happen in a price war.

Simultaneous Problem

Assume additivity, and write in terms of structural errors:

$$\delta_{jt}(\mathcal{S}_t, \widetilde{\theta}_2) + \alpha p_{jt} = h_d(x_{jt}, v_{jt}, \theta_1) + \xi_{jt}$$
$$f\left(p_{jt} - \eta_{jt}(\mathbf{p}, \mathbf{s}, \theta_2, \kappa)\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$

- To simplify slides we let $f(x) = x$ (often $f(x) = \log(x)$).
- $h(\cdot)$ are often just linear relationships $\theta_1[x_{jt}, v_{jt}]$.
- (θ_2, κ) parameters are what determine markups
- so does (ξ, ω) through

Approach #1: Demand Side

1. Estimate θ_2 from demand alone.

$$\delta_{jt}(\mathcal{S}_t, \widetilde{\theta}_2) + \alpha p_{jt} = h_d(x_{jt}, v_{jt}, \theta_1) + \xi_{jt}$$
$$E[\xi_{jt} | x_t, v_t, w_t] = 0$$

2. Recover marginal costs $\widehat{\mathbf{mc}} = \mathbf{p} + (\mathcal{H}(\kappa) .* \tilde{\Delta}(\mathbf{p}, \theta_2)^{-1} q(\mathbf{p}))$.

Challenges:

- Given $[\mathbf{q}, \mathbf{p}, \tilde{\Delta}, \mathcal{H}(\kappa)]$ I can always produce a vector of marginal costs $\mathbf{mc}$ that rationalizes what we observe. [ie: J equations J unknowns].
- Nonparametrically we cannot identify κ without more restrictions (!).

What do people do?

Maybe some vectors of $\mathbf{mc}$ look less "reasonable" than others.

- Marginal costs ≤ 0 seem problematic. [Might just be that your estimates for demand are too inelastic...]
- or I have a parametric model of MC in mind.

$$f\left(p_{jt} - \eta_{jt}(\mathbf{p}, \mathbf{s}, \theta_2, \kappa)\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$
$$E[\omega_{jt} | x_t, w_t, v_t] = 0$$

- Can test that model with GMM objective of mc_{jt} on regressors.
- Maybe marginal costs cannot deviate too much within product from period to period. (We can write these as moment restrictions too).

Approach #2: Simultaneous Supply and Demand

Estimate θ_2 using both supply and demand. The fit of my supply side will also inform my demand parameters, particularly α the price coefficient. [BLP 95 used this for additional power with lots of random coefficients and potentially weak instruments].

$$\delta_{jt}(\mathcal{S}_t, \widetilde{\theta}_2) + \alpha p_{jt} = h_d(x_{jt}, v_{jt}, \theta_1) + \xi_{jt}$$
$$f\left(p_{jt} - \eta_{jt}(\mathbf{p}, \mathbf{s}, \theta_2, \kappa)\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$

Challenges:

- Should I try to estimate κ? or just compare objective values at $\kappa_{fg} \in \{0, 1\}$?
- Am I testing conduct? Or am I testing the functional form for my supply model?
- Will a missing IV/restriction change whether or not I believe firms are colluding?

What is Excluded?

Berry and Haile (2014) discuss non-parametric identification of conduct via exclusion restrictions:

- We used exlcuded cost shifters w_{jt} as IV for demand. We can use excluded demand shifters v_{jt} as IV for supply.
  - Probably easier to find these. Rich people are less price sensitive but not more costly to sell to (demographics, seasonality, etc.).
  - Well-documented geographic persistence in preferences unrelated to costs.

If we take the structural interpretation seriously any v_{jt} should show up in the utility equation to be relevant (!).

What else is Excluded?

BLP style instruments (characteristics of other goods)

- $f(x_{-j})$: BLP or GH style instruments (how many similar cars to me?).
- w_{-j} Cost shifters for other products (Price of Rice for Corn Flakes, Price of Corn for Rice Krispies).
- v_{-j} Demand shocks for similar products (Advertising? Product Recalls?)
- κ parameters or κ weighted diversion ?

An ideal restriction should not shift marginal costs under the true model of conduct κ but could potentially shift marginal costs under the alternative κ (this is relevance).

Things that don't work

- ξ_{jt} only makes sense if you believe $Cov(\xi_{jt}, \omega_{jt}) = 0$.
    - MacKay Miller exploit this to estimate demand without IV? Is this a good idea(?)
- $p_{j,t,-s}$ (Hausman instruments) same good in other markets: pick up cost shocks (but could pick up changes in conduct!).
- If it isn't in one of our equations: does it have anything to do with demand or supply?

Estimation vs. Menus

There are two ways to think about conduct:

1. Using moment conditions to estimate $\widehat{\kappa}$ or $\mathcal{H}(\kappa)$ directly.
   - Often with a small number of parameters (ie: $\kappa_{fg} = 0$ except for firms I know are in a cartel).
   - Can be challenging to tell similar values of κ_{fg} apart (under-powered).
2. "Menu Approach"
   - Nevo (Economics Letters 1998)
   - Bresnahan (1987)
   - Compare some goodness-of-fit critieria across assumed values of κ (Bertrand vs. Collusion)

Testing a single model of κ

Put the η_{jt} on the RHS and test whether $\lambda = 1$:

$$
\begin{aligned}
p_{jt} &= h_s(x_{jt}, w_{jt}, \theta_3) + \lambda \cdot \eta_{jt}\left(\mathbf{p}, \mathbf{s}, \theta_2, \kappa\right) + \omega_{jt} \\
E[\omega_{jt} | x_t, w_t, z_t] &= 0
\end{aligned}
$$

- We are basically running 2SLS with IV for the endogenous η_{jt}
- "Informal" test of Villas Boas (2007): $E[\omega_{jt} | x_{jt}, w_{jt}, \eta_{jt}] = 0$.
    - Considers different forms of $f(\cdot)$: linear, exponential, logarithmic.
    - Not sure the published paper includes these results (?) WP does?
- Pakes (2017) uses Wollman (2018) data and BLP IV $E[\omega_{jt} | x_{jt}, w_{jt}, f(x_{-j})] = 0$.
- $\lambda \neq 0$ is hard to interpret.

Pakes (2018)/Wollman (2017) Regressions: Heavy Trucks

Table 1: Wollman & Pricing Equilibrium.

Taken from Pakes, 2017, *Journal of Industrial Economics.*

	Price	(S.E.)	Price	(S.E.)
Gross Weight	.36	(0.01)	.36	(.003)
Cab-over	.13	(0.01)	.13	(0.01)
Compact front	-.19	(0.04)	0.21	(0.03)
long cab	-.01	(0.04)	0.03	(0.03)
Wage	.08	(.003)	0.08	(.003)
$\widehat{Markup}$	.92	(0.31)	1.12	(0.22)
Time dummies?	No	n.r.	Yes	n.r.
R^2	0.86	n.r.	0.94	n.r.

Note. There are 1,777 observations; 16 firms over the period 1992-2012. S.E.=Standard error.

These are somewhat reassuring:

- $\lambda \approx 1$ for multiproduct-oligopoly
- Fit is pretty good $R^2 > 0.8$ and $R^2 > 0.5$ for within vehicle regressions (not shown).
- As a behavioral model, multiproduct demand estimation seems successful.
- But, do we know that an alternative $\mathcal{H}(\kappa)$ would have a $\lambda \neq 1$ or a lower R^2, and if so how low before we can "reject" the model?

Goodness of Fit Tests

Another idea (Bonnet and Dubois, Rand 2010) runs the following regression:

$$\log\left(p_{jt} - \eta_{jt}(\mathbf{p}, \mathbf{s}, \widehat{\theta}_2, \kappa)\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$

- Run a regression for each κ and obtain $Q(\kappa) = \sum_{jt} \widehat{\omega}_{jt}^2$
- Employ the non nested test of Rivers and Vuong (2002). Why?
- Working out the distribution of $Q(\kappa_1) - Q(\kappa_2) = T(\kappa_1, \kappa_2)$ is the hard part.
- Also this is OLS (or NLLS) and there are no instruments or exclusion restrictions for the supply side. Presumably we could add some and do GMM?

Recap

So far three approaches to exploit $E[\omega_{jt}|x_t, w_t, z_t] = 0$

1. Put the markup on RHS and instrument for it to test $\lambda = 1$

$$p_{jt} = h_s(x_{jt}, w_{jt}, \theta_3) + \lambda \cdot \eta_{jt}\left(\mathbf{p}, \mathbf{s}, \widehat{\theta}_2, \kappa\right) + \omega_{jt}$$

2. Put the markup on LHS assuming $\lambda = 1$ and test goodness of fit of supply equation

$$p_{jt} - \eta_{jt}\left(\mathbf{p}, \mathbf{s}, \widehat{\theta}_2, \kappa\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$

3. Estimate supply and demand simultaneously $[\theta_1, \theta_2, \theta_3]$ and compare goodness of fit for different κ.

Simultaneous Problem: Menu Approach

Assume two models of conduct (correct: κ_0) (incorrect: κ_1)

$$f(p_{jt} - \eta_{jt}(\kappa_0)) = h(x_{jt}, w_{jt}; \theta_3^0) + \omega_{jt}^0,$$
$$f(p_{jt} - \eta_{jt}(\kappa_1)) = h(x_{jt}, w_{jt}; \theta_3^1) + \omega_{jt}^1.$$

Write things in terms of the markup difference:

$$p_{jt} - \eta_{jt}(\kappa_1) = h(x_{jt}, w_{jt}; \theta_3) + \overbrace{\lambda \cdot \Delta\eta_{jt}(\mathbf{p}, \mathbf{s}, \theta, \kappa_0, \kappa_1) + \omega_{jt}}^{\widetilde{\omega_{jt}}}$$

Tempting idea: run the above regression and test if $\lambda = 0$.

- True model $\lambda = 0$, alternate model $\lambda \neq 0$.
- True model will satisfy $E[\widetilde{\omega}_{jt} | x_t, w_t, v_t] = 0$
- η_{jt} is endogenous: it depends on everything including (ξ, ω).

A subtle solution

- Berry Haile 2014 tell us we need marginal revenue shifters to act as exclusion restrictions.
- Needs to be uncorrelated with $p_{jt} - \eta_{jt}(\kappa_0)$ but correlated with $p_{jt} - \eta_{jt}(\kappa_1)$
  - If my marginal cost is correlated with marginal costs of other products or "closeness of competitors", I've got the wrong conduct assumption!
- We need an instrument for $\Delta\eta_{jt}(\mathbf{p}, \mathbf{s}, \theta, \kappa_0, \kappa_1)$
  - Maybe not so hard since it is basically a function of everything.
  - Cannot have a direct effect on mc_{jt} (exclusion restriction).

Backus, Conlon, Sinkinson (2020)

What would a really good instrument look like?

- Chamberlain (1987) style optimal IV for κ_{fg} would be $E\left[\frac{\partial \eta_{jt}(\theta_2, \mathbf{s}, \mathbf{p}, \kappa)}{\partial \kappa_{fg}} | x_t, w_t, v_t\right]$
    - But infeasible without knowledge of (κ, ξ, ω)!
    - We could try to recover the infeasible estimate and project it onto (x_t, w_t, v_t) (note: lack of j subscripts!)
- Menu approach: could look at discrete analogue: $E\left[\Delta \eta_{jt}(\kappa_1, \kappa_0, \theta_2, \mathbf{s}, \mathbf{p}) | x_t, w_t, v_t\right]$
    - I would need to know κ_1, κ_0.
    - Still infeasible but could run a first-stage regression

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  - But infeasible without knowledge of (κ, ξ, ω) so we take expectation over exogenous variables.
  - We could try to recover the infeasible estimate and project it onto (x_t, w_t, v_t) (note: lack of j subscripts!)
- Menu approach: could look at discrete analogue: $E\left[\Delta \eta_{jt}(\kappa_1, \kappa_0, \theta_2, \mathbf{s}, \mathbf{p}) | x_t, w_t, v_t\right]$
  - I would need to know κ_1, κ_0.
  - Still infeasible but could run a first-stage regression

Backus, Conlon, Sinkinson (2020)

Our procedure ((1)+(2) can be done separately)

1. Run OLS to obtain $\widehat{\omega}_1, \widehat{\omega}_2$ for (κ_1, κ_2)

$$\log\left(p_{jt} - \eta_{jt}(\mathbf{p}, \mathbf{s}, \widehat{\theta}_2, \kappa)\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$

2. Recover $\Delta\widehat{\eta}_{jt}(\kappa_1, \kappa_2)$ via nonparametric regression/machine-learning

$$\Delta\widehat{\eta_{jt}}(\kappa_1, \kappa_2) = E\left[\Delta\eta_{jt}(\kappa_1, \kappa_2) | z_t, w_t, x_t\right]$$

3. Compute the violations of the moment condition $Q(\kappa^m) = \left(n^{-1}\sum_{j,t} \hat{\omega}_{jt}^m \cdot \widehat{\Delta}\eta_{jt}\right)^2$
4. Compute the test statistic: $T = \frac{\sqrt{n}\left(Q\left(\kappa^1\right) - Q\left(\kappa^2\right)\right)}{\hat{\sigma}}$ and bootstrap the standard error.

Techincally we should sample split and estimate the the regressions on independent samples.

Backus, Conlon, Sinkinson (2020) [Alternative]

$$p_{jt} - \eta_{jt}\left(\mathbf{p}, \mathbf{s}, \widehat{\theta_2}, \kappa\right) = h_s(x_{jt}, w_{jt}, \theta_3) + \omega_{jt}$$

- We can also directly test violations of $E[\omega_{jt}|x_t, v_t, w_t]$ by comparing resulting CUE or GEL (or GMM) objective values.
- Probably want to include approximate optimal IV $E\left[\frac{\partial \eta_{jt}(\theta_2, \mathbf{s}, \mathbf{p}, \kappa)}{\partial \kappa_{fg}} | x_t, w_t, v_t\right]$ in instrument set.