Graduate Industrial Organization

Lecture: Moment Inequalities Part 2, Applications

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“What do Exporters Know?”

Dickstein and Morales (*QJE*, 2018)

Motivation / Broad Agenda

- Focus on decision-making under uncertainty:
  - Firm/agent forms expectations of variables needed for decisions (future revenues, exchange rates, productivity, etc.)
  - Econometrician does not observe these expectations
- Goal:
  - Infer the preferences of the decision-maker from observed choices
  - Test the content of agents' information sets
  - Conduct policy counterfactuals
- Problem to tackle:
  - Without direct measurement of firms'/agents' expectations (say by elicitation), need to approximate these expectations to make progress

Motivation: Unobserved expectations are common

For firms

- Developing a new product (Bernard et al., 2010).
  - Expectations about future demand?
- Investing in R&D (Aw et al., 2011).
  - Expectations about success of research activity?

For consumers/agents

- Enrolling in college (Manski, 1993)
  - Expectations about returns to schooling?
- Choosing a prescription drug treatment (Dickstein et al., 2020)
  - Expectations about out-of-pocket costs?

Motivation: Export Participation

- The decision to export involves considerable uncertainty
  - Firms enter a foreign market if the expected value of exporting is positive
  - Firms' entry depends on expectations about the future evolution of their own productivity, exchange rates, trade policy, political stability in foreign countries, etc.
- Export promotion or currency stabilization programs affect exports via firms' expectations

What we do:

- Focus on exporters' entry decisions into foreign markets
- Estimate fixed costs of exporting to each destination
- Use standard partial equilibrium model of export participation
  - CES demand, constant marginal cost, and monopolistic competition
  - Benchmark: two period model
  - Extensions (in paper): (a) fully dynamic model (Das et al., 2007); (b) sample selection model (Heckman, 1979).
- Crucially: Do not require that the researcher has perfect knowledge of the content of firms' information sets

Preview of Results

- **First**, we show that assumptions on the agents' information sets matter. In the Chilean export market:

Estimates of fixed costs of exporting (in thousands of year 2000 US$):

Exporters' Information	Argentina	U.S.	Japan
Perfect Foresight	868	1,645	2,621
Dist. + Lag. Sales + Lag. Exports	349	668	1,069

Preview of results

- **Second**, we use two types of moment inequalities,
  - (1) odds-based and (2) revealed-preference,

  that allow for **partial knowledge** of exporters' information sets.
- Estimates of fixed costs of exporting:

Exporters' Information	Argentina	U.S.	Japan
At least Dist. + Lag. Sales + Lag. Exports	(79, 103)	(181, 240)	(309, 414)

- Estimates are 40-60% smaller

Preview of results

- **Third**, we use our inequalities to learn about exporters' true information sets.
- Test whether a set of variables the researcher observes is a subset of exporters' information:

$$H_0 : \left\{ \begin{array}{c} \text{exporters at least know dist.} \\ + \text{ lag. sales} + \text{lag. exports} \end{array} \right\} \qquad \text{p-value:} = 0.11/0.98$$

$$H_0 : \left\{ \text{ perfect foresight } \right\} \qquad \text{p-value:} = 0.02/ < .001$$

- More tests:
  - Do large firms have more information than small firms?
  - Do previous exporters have more information?
  - Do firms know more about popular export destinations?

Preview of results

- **Fourth**, we quantify the value of information.
- Given our bounds on fixed costs, we compute counterfactual entry decisions under different information sets
- With more information, we find:
    - Firms export to fewer markets (3.5-5.7% fewer destination pairs)
    - Overall export revenue in the sector increases 6.4-9.5%
    - Firm profits increase 18-21%

Model: Overview

- Single-agent, partial equilibrium, two period model.
- First period:
  - firms decide whether to export to each country;
  - if they export, they pay fixed export costs;
  - decision depends on expectations about potential export profits;
  - expectations are rational;
  - **exporters' information set is left unspecified**.
- Second period:
  - firms observe realized demand, determine optimal price, obtain export profits.

Model: Demand and Supply

- Firms face isoelastic demand in every country,
- Market structure: monopolistic competition in every destination country.
- Constant marginal production cost: c_{it}.
- If a firm exports a positive amount to j, it must pay two additional costs:
  - iceberg trade costs τ_{ijt}
  - fixed costs f_{ijt}

Model: Information Set

- When deciding whether to export to market j in period t, firm i knows:
  - fixed costs of exporting, f_{ijt};
  - information set, $\mathcal{J}_{ijt}$, relevant for i to predict export revenues.
- $\mathcal{J}_{ijt}$ includes variables i uses to predict:
  - demand conditions in market j, (Y_{jt}, P_{jt})
  - demand shifters, ζ_{ijt}
  - marginal cost of selling to j, $\tau_{ijt} c_{it}$
- Ex: $\mathcal{J}_{ijt}$ might include last period's market size, demand shifters

Model: Profits from Exporting

- If firm i enters destination market j, obtains revenue:

$$r_{ijt} = \left[\frac{\eta}{\eta - 1} \frac{\tau_{ijt} c_{it}}{\zeta_{ijt} P_{jt}} \right]^{1-\eta} Y_{jt}$$

  which we can rewrite

$$r_{ijt} = \alpha_{ijt} r_{iht}, \qquad \text{with} \qquad \alpha_{ijt} = \left(\frac{\zeta_{iht}}{\zeta_{ijt}} \frac{\tau_{ijt}}{\tau_{iht}} \frac{P_{ht}}{P_{jt}} \right)^{1-\eta} \frac{Y_{jt}}{Y_{ht}}.$$

- The export profits that i would obtain in j if it were to export to t are

$$\pi_{ijt} = \eta^{-1} r_{ijt} - f_{ijt},$$

Model: Profits from Exporting

- We model fixed export costs as

$$f_{ijt} = \beta_0 + \beta_1 dist_j + \nu_{ijt},$$

with

$$\nu_{ijt} | (\mathcal{J}_{ijt}, dist_j) \sim \mathbb{N}(0, \sigma^2).$$

Model: Decision to Export

- Firm i's expectations are rational.
- Firm i will export to j if and only if

$$\mathbb{E}[\pi_{ijt}|\mathcal{J}_{ijt}, f_{ijt}] \geq 0.$$

- Therefore,

$$\mathcal{P}(d_{ijt} = 1|\mathcal{J}_{ijt}, dist_j) = \Phi\big(\sigma^{-1}\big(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j\big)\big).$$

- Parameters to estimate $\theta^* \equiv (\beta_0, \beta_1, \sigma)$; fix $\eta = 5$
- But, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]$?

DATA

Export Data

- Data sources and variables used in the analysis:
  - Chilean customs database:
    - dummy for positive exports: d_{ijt},
    - firm-destination specific exports: r_{ijt},
  - Chilean industrial survey:
    - domestic sales: $r_{iht} = r_{it} - \sum_j r_{ijt}$
  - CEPII:
    - distance to Chile: $dist_j$ (in thousands of kilometers)
- Unbalanced panel of firms for the sample period: 1995-2005.
- Sectors:
  - manufacturing of chemicals and chemical products ($\checkmark$)
  - food products (**X**)

Export Data

Year	Share of domestic firms exporting	Mean exports per exporting firm ($M)	Median exports per exporting firm ($M)	Mean domestic revenue per firm ($M)	Mean domestic revenue per exporting firm ($M)	Mean no. of markets exporting firm enters
Sector 24: chemical products						
1996	35.7%	2.18	0.15	13.23	23.10	4.24
1997	36.1%	2.40	0.19	13.29	22.99	4.54
1998	42.5%	2.41	0.17	14.31	22.25	4.35
1999	38.7%	2.60	0.19	14.43	23.95	4.53
2000	37.6%	2.55	0.21	14.41	25.93	4.94
2001	39.8%	2.35	0.12	12.89	21.92	4.68
2002	38.7%	2.37	0.15	13.25	23.73	4.95
2003	38.0%	3.08	0.17	10.41	19.54	5.11
2004	37.6%	3.27	0.15	10.05	18.70	5.17
2005	38.0%	3.58	0.11	12.50	21.65	5.19

- 266 unique firms
- Restrict to 22 destinations where at least 5 firms export in every year.

ESTIMATION WITH FULL KNOWLEDGE OF EXPORTERS' INFORMATION SETS

Assuming an Information Set

- The model above does not specify the information set $\mathcal{J}_{ijt}$.
- These information sets are generally not observed in trade datasets.
- Under the assumption that

$$\mathcal{J}^a_{ijt} = \mathcal{J}_{ijt},$$

the researcher's assumed export probability conditional on $(\mathcal{J}^a_{ijt}, dist_j)$ is

$$\mathcal{P}(d_{ijt} = 1 | \mathcal{J}^a_{ijt}, dist_j) = \Phi\big(\sigma^{-1}\big(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}] - \beta_0 - \beta_1 dist_j\big)\big),$$

and the researcher can estimate $\mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}]$ non-parametrically.

Assuming an Information Set: Options

Export probability:

$$\mathcal{P}(d_{ijt} = 1 | \mathcal{J}^a_{ijt}, dist_j) = \Phi\big(\sigma^{-1}\big(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}] - \beta_0 - \beta_1 dist_j\big)\big),$$

(1) Perfect foresight

- $\mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}] = r_{ijt}$

(2) Two-step approach, "minimal information set"

- Estimate $\mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}]$ nonparametrically in a first stage
- $\mathcal{J}^a_{ijt} \equiv (r_{iht-1}, R_{jt-1}, dist_j)$

Assuming an Information Set: Bias?

- If the assumption that $\mathcal{J}^a_{ijt} = \mathcal{J}_{ijt}$ is incorrect, the right export probability is

$$\mathcal{P}(d_{ijt} = 1 | \mathcal{J}^a_{ijt}, dist_j) =$$
$$\int_\xi \Phi\big(\sigma^{-1}\big(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}] - \beta_0 - \beta_1 dist_j - \eta^{-1}\xi\big)\big) f(\xi|\mathcal{J}^a_{ijt}, dist_j),$$

  where

$$\xi_{ijt} \equiv \mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}] - \mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}].$$

- The bias in the estimates of $(\beta_0, \beta_1, \sigma)$ depends on

$$f(\xi_{ijt}|\mathcal{J}^a_{ijt}, dist_j).$$

Example: Bias when $\mathcal{J}_{ijt} \subset \mathcal{J}_{ijt}^{a}$

- Perfect foresight case: $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}^{a}] = r_{ijt}$.
- Under perfect foresight:
  - True expectational error: $\varepsilon_{ijt} = r_{ijt} - \mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]$
  - Diff with researcher's proxy: $\xi_{ijt} = \mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}^{a}] - \mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]$
- Assuming rational expectations implies $cov(\varepsilon_{ijt}, r_{ijt}) > 0$.
- Therefore, wrongly assuming perfect foresight is equivalent to introducing classical measurement error in firms' expectations

$$cov(\xi_{ijt}, \mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}^{a}]) > 0.$$

- Given normalization by η, upward bias in estimates of $(\beta_0, \beta_1, \sigma)$.

More detail on bias

Average Fixed Export Costs - Chemicals

- Under perfect foresight ($000s (year 2000)):

Argentina	U.S.	Japan
868	1,645	2,621
(767, 969)	(1,454, 1,836)	(2,309, 2,934)

- Under minimal information set ($000s (year 2000)):

Argentina	U.S.	Japan
349	668	1,069
(323, 374)	(621, 716)	(989, 1,150)

- Perfect foresight estimates 2.5 times larger

ESTIMATION WITH PARTIAL KNOWLEDGE OF EXPORTERS' INFORMATION SETS

Exporters' Information Sets are Partially Observed

- We assume firms are likely to know **at least**:
  - lagged own domestic sales: r_{iht-1},
  - lagged aggregate exports from Chile to each destination: R_{jt-1},
  - distance from Chile: $dist_j$.
- Under the assumption that firms' information sets are only partially observed, the model parameters are only partially identified.
- We define two types of moment inequalities,
  - odds-based
  - revealed-preference

Odds-Based Moment Inequalities

- If $Z_{ijt} \subseteq \mathcal{J}_{ijt}$, then

$$\mathcal{M}^{ob}(Z_{ijt};\theta^*) = \mathbb{E}\left[\begin{array}{c} m_l^{ob}(d_{ijt}, r_{ijt}, dist_j;\theta^*) \\ m_u^{ob}(d_{ijt}, r_{ijt}, dist_j;\theta^*) \end{array} \middle| Z_{ijt}\right] \geq 0,$$

with

$$m_l^{ob}(\cdot) = d_{ijt}\frac{1-\Phi\big(\sigma^{-1}\big(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j\big)\big)}{\Phi\big(\sigma^{-1}\big(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j\big)\big)} - (1-d_{ijt}),$$

$$m_u^{ob}(\cdot) = (1-d_{ijt})\frac{\Phi\big(\sigma^{-1}\big(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j\big)\big)}{1-\Phi\big(\sigma^{-1}\big(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j\big)\big)} - d_{ijt}.$$

- We denote $\mathcal{M}^{ob}(\cdot)$ as the conditional **odds-based moment inequalities**.

Odds-Based Moment Inequalities: Derivation

- Log-likelihood conditional on $\mathcal{J}$, *dist*

$$L(d|\mathcal{J}, dist; \theta) = \mathbb{E}\Big[d \log(1 - \Phi(-\theta X^*)) + (1-d)\log(\Phi(-\theta X^*))|\mathcal{J}, dist_j].$$

where

$$\theta X^* = \sigma_\nu^{-1}(\eta^{-1}\mathbb{E}[r|\mathcal{J}] - \beta_0 - \beta_1 dist),$$

- The score function:

$$\frac{\partial L(d|\mathcal{J}, Z; \theta)}{\partial \theta} = \mathbb{E}\left[d\frac{\Phi(-\theta X^*)}{1 - \Phi(-\theta X^*)} - (1-d)\middle|\mathcal{J}\right] = 0.$$

- BUT, we do not observe $\mathbb{E}[r|\mathcal{J}]$, only $r = \mathbb{E}[r|\mathcal{J}] + \varepsilon$

Odds-Based Moment Inequalities: Derivation

- We rely on two assumptions:
  - Rational expectations — $\mathbb{E}[\varepsilon|\mathcal{J}] = 0$
  - $F(.)$ chosen such that $\frac{F(y)}{1-F(y)}$ is convex for any value of y
- Then, by Jensen's inequality:

$$\mathbb{E}\left[\frac{\Phi(-\theta X)}{1-\Phi(-\theta X)}\bigg|\mathcal{J}\right] \geq \mathbb{E}\left[\frac{\Phi(-\theta X^*)}{1-\Phi(-\theta X^*)}\bigg|\mathcal{J}\right].$$

- Therefore, we can conclude that

$$\mathbb{E}\left[d\frac{\Phi(-\theta X)}{1-\Phi(-\theta X)} - (1-d)\bigg|\mathcal{J}\right] \geq 0.$$

Proof sketch in detail

Revealed-Preference Moment Inequalities

- If $Z_{ijt} \subseteq \mathcal{J}_{ijt}$, then

$$\mathcal{M}^r(Z_{ijt};\theta^*) = \mathbb{E}\left[\begin{array}{c} m_l^r(d_{ijt}, r_{ijt}, dist_j;\theta^*) \\ m_u^r(d_{ijt}, r_{ijt}, dist_j;\theta^*) \end{array} \middle| Z_{ijt}\right] \geq 0,$$

with

$$m_l^r(\cdot) = -(1-d_{ijt})\left(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j\right) + d_{ijt}\sigma\frac{\phi\left(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\right)}{\Phi\left(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\right)}$$

$$m_u^r(\cdot) = d_{ijt}\left(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j\right) + (1-d_{ijt})\sigma\frac{\phi\left(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\right)}{1-\Phi\left(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\right)}.$$

- We denote $\mathcal{M}^r(\cdot)$ as the conditional **revealed-preference moment inequalities**.

Proof sketch in detail

Inference Procedure

- Use odds-based and revealed-preference inequalities
- Compute the confidence set for θ^* via Andrews and Soares (2010):
  - Test statistic: use 'modified method of moments'
  - Critical value: use 'generalized moment selection' and the Bayesian Information Criterion constant
- We base inference on a finite set of unconditional moment inequalities.

Average Fixed Export Costs

Table: Average Fixed Export Costs (95% confidence set)

Sector	Argentina	U.S.	Japan
Chemicals	(80, 103)	(181, 244)	(309, 421)

Table: Fixed Export Costs Relative to Perfect Foresight Estimates

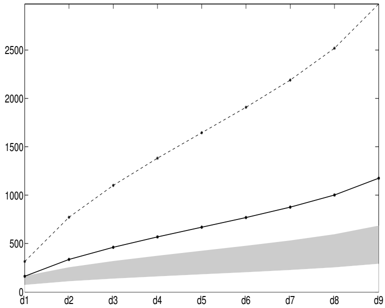
		Chemicals	
Estimator	Argentina	Japan	United States
Minimal Info.	40.2%	40.8%	62.0%
Moment Ineq.	[9.1%, 11.9%]	[11.8%, 15.8%]	[11.1%, 14.6%]

- This table reports the ratio of (a) the minimal information ML point estimates and (b) extremes of the moment inequality confidence set, compared to the perfect foresight ML point estimate. All numbers reported in this table are independent of the value of η.

country-specific estimates

Distribution of Fixed Export Costs

Figure: Fixed costs ($000s) to export to the United States, Chemicals



- Perfect foresight (dashed), two step (solid), inequalities (gray) nearly coincide at the lowest quantiles.

TESTING FIRMS' INFORMATION SETS

Testing Firms' Information Sets

- Given a set of moment inequalities, we test the null hypothesis that there exists at least one value of the parameters consistent with all inequalities.
- Intuitively, our test is a test of validity of moments.
- Conditional on the model, this is a test of the null hypothesis that

$$Z_{ijt} \subseteq \mathcal{J}_{ijt}.$$

- We perform multiple model tests in which we vary the vector Z_{ijt}.

more detail

Table: Testing Content of Information Sets, Chemicals Sector

Set of Firms	Set of Export Destinations	Individual p-value	Adjusted p-value	Reject at 5%
Panel A: Minimal Information				
All	All	0.111	0.111	No
Panel B: Perfect Foresight				
All	All	0.023	0.023	Yes
Panel C: Minimal Information & Country Shifter				
Large	Popular	0.144	0.418	No
Small	Popular	< 0.001	< 0.001	Yes
Large Exporter	All	0.104	0.418	No
Large Non-exporter	All	0.140	0.418	No
Small Exporter	All	< 0.001	< 0.001	Yes
Small Non-exporter	All	< 0.001	< 0.001	Yes
Panel D: Minimal Information & Number of Exporters				
Large Exporter	All	0.018	0.080	No
Large Non-exporter	All	0.016	0.080	No
Small Exporter	All	< 0.001	< 0.001	Yes
Small Non-exporter	All	< 0.001	< 0.001	Yes

Note: minimal info $= (dist_j, r_{iht-1}, R_{jt-1})$. P-values from Bugni et al. (2015).

What do Exporters Know?

- We reject that firms have perfect foresight.
- We fail to reject that potential exporters know *at least* the baseline information set
- Large vs. small: Large firms possess relevant information about potential export revenues that small firms do not possess.
- *Gathering information from others?* —no evidence using popularity of markets
- *Gathering information from experience?* — no evidence using past export experience

Counterfactuals: Information Intervention

Provide minimally informed firms with more information

1. Share every destination's lagged aggregate revenue shock $\alpha_{j,t-1}$ (country shifter)
2. Share all information needed to perfectly predict observed component of export revenues ("perfect foresight")

How does this help?

- In model, firms obtain all relevant information upon entering a market
- Intervention changes the set of firms that select into each market

Table: Effect of Improving Information: Chemical Sector

		Percentage Change in:		
Firms	Markets	Number of Exporters	Mean Export Profits	Aggregate Exports
Panel A: Add Information on Aggregate Revenue Shocks				
All	All	[-5.7, -3.5]	[17.5, 20.6]	[6.4, 9.5]
Large	All	[-9.0, -7.1]	[22.0, 24.9]	[0.6, 2.5]
Small	All	[0.0, 0.0]	[0.0, 0.1]	[2.0, 2.7]
Panel B: Switch from Minimal Information to Perfect Foresight				
All	All	[-10.2, -6.1]	[46.0, 52.9]	[25.1, 33.5]
Large	All	[-17.3, -12.7]	[59.2, 67.4]	[13.5, 20.3]
Small	All	[0.3, 0.5]	[0.1, 0.4]	[21.1, 30.8]

“Hospital Choices, Hospital Prices, and Financial Incentives to Physicians”

Ho and Pakes (*AER*, 2014)

Ho and Pakes (2014)

Research Goals:

- Health: Investigate the effect of physician incentives on costs/quality of hospital care.
  - Specifically, for privately insured patients giving birth, do capitated physicians refer patients to lower-cost hospitals? Lower-quality hospitals?
- Methodology: Illustrate the value of moment inequality methods to allow (a) many fixed effects and (b) measurement/expectational error in covariates

Approach:

- Estimate a hospital referral model
- Compare physicians with "shared risk arrangements" vs. those without

Hospital Referral Model

- Choices in model depend on: (a) hospital prices, (b) distance from patient to hospital, and (c) severity-specific measure of "hospital quality"
- Why is this difficult to estimate?
  - Authors do not observe physician choices directly. Use share of an insurer's patients under capitation
  - Poor measure of hospital prices (list prices + average discount)
  - Poor measure of price expectations (true expectations may differ from both the econometrician's measure of price and true price)
  - Price is endogenous; likely correlated with unobserved hospital quality. Difficult to include severity x hospital FE (incidental parameters)
- How to solve? Define moment inequalities

Step 1: Illustrate the limitations of a traditional logit

TABLE 5—LOGIT ANALYSIS RESULTS

	All birth patients	Least sick patients			Sickest patients		
Price	0.010** (0.002)	−0.017* (0.009)		0.069** (0.014)	0.012** (0.002)		0.028** (0.006)
Price interactions:							
Percent capitated				−0.127** (0.016)			−0.025** (0.008)
Pacificare			−0.077** (0.012)			−0.006 (0.006)	
Aetna			−0.011 (0.016)			0.021** (0.008)	
Health Net			−0.038** (0.011)			0.007 (0.005)	
Cigna			−0.021 (0.014)			0.004 (0.007)	
Blue Shield			0.018 (0.011)			0.024** (0.004)	
Blue Cross			0.008 (0.011)			0.014** (0.003)	
Distance	−0.215** (0.001)	−0.215** (0.002)	−0.215** (0.002)	−0.215** (0.002)	−0.217** (0.002)	−0.216** (0.002)	−0.216** (0.002)
Distance squared	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
$z_h x_i$ controls (15 coeffts)	Y	Y	Y	Y	Y	Y	Y
Hospital FEs (194 coeffts)	Y	Y	Y	Y	Y	Y	Y
Observations	88,157	43,742	43,742	43,742	44,059	44,059	44,059

- Errors in price variable, limited fixed effects to capture severity x hospital quality leads to upward bias in price coefficient
- Narrowing the sample to homogenous diagnosis groups leads to negative price coefficient

Step 2: Introduce Moment Inequalities

- Choice function is additively separable in the insurer's price, insurer- and severity-specific hospital quality, and distance to the hospital

$$W_{i,\pi,h} = \theta_{p,\pi} p(c_i, h, \pi) + g_\pi(q_h(s), s_i) + f_\pi(d(l_i, l_h))$$

- Identify pairs of patients with the same severity and the same insurer, but who choose different hospitals.
- Sum the two patients' revealed preference inequalities, thus differencing out the severity-specific hospital quality terms

$$\Delta W(i, h, h') + \Delta W(i', h', h) =$$
$$\theta_{p,\pi}[\Delta p(c_i, h, h') + \Delta p(c_i', h', h)]) + [\Delta f_\pi(l_i, l_h, l_{h'}) + \Delta f_\pi(l_{i'}, l_{h'}, l_h)]$$

- Average inequalities over patients and hospitals to eliminate the effects of the errors in the price measurement.

Step 2: Introduce Moment Inequalities

$$\Delta W(i, h, h') + \Delta W(i', h', h) =$$
$$\theta_{p,\pi}[\Delta p(c_i, h, h') + \Delta p(c_i', h', h)]) + [\Delta f_\pi(l_i, l_h, l_{h'}) + \Delta f_\pi(l_{i'}, l_{h'}, l_h)]$$

Comments:

- Differences out quality/severity terms; can define many interactions
- To find price coefficient, need differences in prices across consumers at the same hospitals (for the same insurer). How?
  - different service use for same severity
  - different services leading to different prices can affect hospital choice only through price
- No (i, h) specific structural error (known to the agent)

Comparison of Logit and Inequality Results

TABLE 10—MAGNITUDES OF LOGIT AND INEQUALITY RESULTS

	Percent capitated	Logits (less-sick patients) average η_i	Inequalities (all patients) average η_i
Pacificare	0.97	0.33	11.08
Aetna	0.91	0.10	11.47
Health Net	0.80	0.15	6.52
Cigna	0.75	0.10	2.49
Blue Shield	0.57	−0.08	0.51
Blue Cross	0.38	−0.03	3.24

Notes: Estimated cross-patient average value of $\eta_i = \frac{\partial d_i}{\partial p_i} \frac{p_i}{d_i}$ for each insurer implied by logit and inequality analyses. logit model uses less-sick population as defined in notes to Table 5. Inequality model uses price defined using discount δ_h (column 1 of Table 7).

- Measures, on average, how much further the consumer would have to drive (in percentage terms) to offset a one percent price increase.
- Compares the elasticity from the logit estimates for the least sick patients vs. elasticities computed from inequalities

Bias: Yatchew and Griliches (1985)

- In the specific case in which perfect foresight is assumed

$$\mathbb{E}[r_{ijt}|\mathcal{J}^{a}_{ijt}] = r_{ijt},$$

agent's true expectations are normally distributed

$$\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] \sim \mathbb{N}(0, \sigma^2_e),$$

and the expectational error is normal conditional on agents' information sets

$$\varepsilon_{ijt}|(\mathcal{J}_{ijt}, \nu_{ijt}) \sim \mathbb{N}(0, \sigma^2_\varepsilon),$$

there is an upward bias in the estimates of β_0 and β_1.

- Bias increases in $\sigma^2_\varepsilon/\sigma^2_e$.

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Bias Due to Misspecified Information Sets

Table: Bias under Perfect Foresight

Model	Distribution of $\mathbb{E}[r_{ijt}\|\mathcal{J}_{ijt}]$	Distribution of ε_{ijt}	Upward Bias in β_0
1	$\mathbb{N}(0,1)$	$\mathbb{N}(0,0.25)$	31%
2	$\mathbb{N}(0,1)$	$\mathbb{N}(0,0.5)$	49%
3	$\mathbb{N}(0,1)$	$\mathbb{N}(0,1)$	124%
4	t_2	t_2	241%
5	t_5	t_5	131%
6	t_{20}	t_{20}	125%
7	t_{50}	t_{50}	124%
8	$log\text{-}normal(0,1)$	$log\text{-}normal(0,1)$	274%
9	$-log\text{-}normal(0,1)$	$-log\text{-}normal(0,1)$	197%

- $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]$ = firms' true expectations (unobserved to the researcher)
- ε_{ijt} = firms' expectational error (unobserved to the researcher)

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Bias when $\mathcal{J}^a_{ijt} \subset \mathcal{J}_{ijt}$

- The assumed information set $\mathcal{J}^a_{ijt}$ is too small.
- In this case, the difference between the true agents' expectation and the researchers' proxy for it is mean independent of this researchers' proxy:

$$cov(\xi_{ijt}, \mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}]) = 0.$$

- The estimates of the variance of fixed export costs are always upward biased.
- Only in the specific case in which the distribution of ν_{ijt} and $\nu_{ijt} + \eta^{-1}\xi_{ijt}$ differ only in their variance, the ML estimates of β_0 and β_1 will be consistent.
- Bias always smaller than when we assume an information set that is too large.

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Test of Instrument Relevance

Table: Instrument Relevance for $r_{ijt} = \hat{\alpha}_{jt} r_{iht}$

	Chemicals		Food	
Covariates	(1)	(2)	(3)	(4)
R_{jt-1}	0.010^a	0.007^a	0.005^a	0.003^a
	(20.7)	(11.1)	(28.2)	(15.7)
r_{iht-1}	0.012^a	0.012^a	0.028^a	0.028^a
	(16.0)	(16.1)	(33.2)	(33.3)
$dist_j$	0.201^a	0.159^a	0.055^a	0.035^a
	(23.9)	(12.8)	(10.5)	(5.40)
α_{jt-1}		2.817^a		2.947^a
		(5.14)		(8.86)
Firms	All	All	All	All
Countries	All	All	All	All
Num. Obs.	44,037	44,037	84,975	84,975
R^2	0.293	0.295	0.315	0.322

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Odds-Based Moment Inequalities - Proof for $m_l^{ob}(\cdot)$

- From model,

$$\mathbb{E}[\mathbb{1}\{\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j - \nu_{ijt} \geq 0\} - d_{ijt}|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

- Given distributional assumption on ν_{ijt},

$$\mathbb{E}[\Phi(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j)) - d_{ijt}|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

- Doing simple algebra,

$$\mathbb{E}[d_{ijt}\frac{1 - \Phi(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j))}{\Phi(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j))} - (1 - d_{ijt})|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

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Odds-Based Moment Inequalities - Proof for $m_l^{ob}(\cdot)$

- Given rational expectations assumption and convexity of $\Phi(\cdot)/(1-\Phi(\cdot))$,

$$\mathbb{E}[d_{ijt}\frac{1-\Phi(\sigma^{-1}(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j))}{\Phi(\sigma^{-1}(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j))}-(1-d_{ijt})|\mathcal{J}_{ijt}, dist_j]\geq 0.$$

- Given assumption that $Z_{ijt}\subseteq\mathcal{J}_{ijt}$ and Law of Iterated Expectations

$$\mathbb{E}[d_{ijt}\frac{1-\Phi(\sigma^{-1}(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j))}{\Phi(\sigma^{-1}(\eta^{-1}r_{ijt}-\beta_0-\beta_1 dist_j))}-(1-d_{ijt})|Z_{ijt}]\geq 0.$$

- Identical process for $m_u^{ob}(\cdot)$ but starting from

$$\mathbb{E}[d_{ijt}-\mathbb{1}\{\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]-\beta_0-\beta_1 dist_j-\nu_{ijt}\geq 0\}|\mathcal{J}_{ijt}, dist_j]\geq 0.$$

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Revealed-Preference Moment Inequalities - Proof for $m_u^r(\cdot)$

- From model,

$$\mathbb{E}[d_{ijt}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j - \nu_{ijt})|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

- Given distributional assumption on ν_{ijt},

$$\mathbb{E}[d_{ijt}\big(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j\big) + (1 - d_{ijt})\sigma \frac{\phi\big(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j)\big)}{1 - \Phi\big(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j)\big)}|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

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Revealed-Preference Moment Inequalities - Proof for $m_u^r(\cdot)$

- Given rational expectations assumption and convexity of $\phi(\cdot)/(1-\Phi(\cdot))$,

$$\mathbb{E}[d_{ijt}\big(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j\big) + (1-d_{ijt})\sigma\frac{\phi\big(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\big)}{1-\Phi\big(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\big)}|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

- Given assumption that $Z_{ijt} \subseteq \mathcal{J}_{ijt}$ and Law of Iterated Expectations

$$\mathbb{E}[d_{ijt}\big(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j\big) + (1-d_{ijt})\sigma\frac{\phi\big(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\big)}{1-\Phi\big(\sigma^{-1}(\eta^{-1}r_{ijt} - \beta_0 - \beta_1 dist_j)\big)}|Z_{ijt}] \geq 0.$$

- Identical process for $m_l^r(\cdot)$ but starting from

$$\mathbb{E}[(1-d_{ijt})(-(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0 - \beta_1 dist_j - \nu_{ijt}))|\mathcal{J}_{ijt}, dist_j] \geq 0.$$

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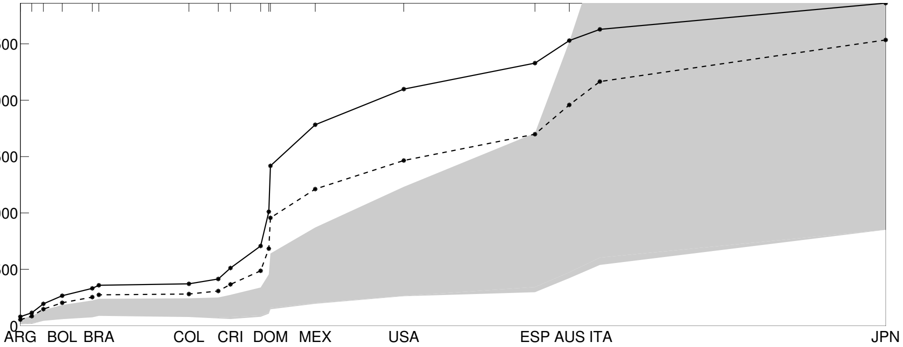
Country-specific Average Fixed Export Costs

Figure: Chemicals



- Perfect foresight (dashed), two step (solid), inequalities (gray)
- Estimate country fixed effects.

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