14.582: International Trade II — Lecture 13: Trade and Markups (Empirics)

Plan for Today's Lecture

1. A primer on estimating markups
   1. Demand-based methods
   2. Supply-based methods
2. How are markups affected by trade liberalization?
3. Consequences for aggregate efficiency?
4. Conclusion

Plan for Today's Lecture

1. **A primer on estimating markups**
    1. **Demand-based methods**
    2. **Supply-based methods**
2. How are markups affected by trade liberalization?
3. Consequences for aggregate efficiency?
4. Conclusion

Estimating Markups

- How do we estimate markups?
  1. Demand-based methods: estimate residual demand curve
  2. Production-based methods: estimate production function
- We will spend more time on #2 as it has been more commonly employed on Trade applications
- They involve quite different sets of assumptions so would be nice to compare the two approaches in one setting.
  - See de Loecker and Scott (wp 2016) for an exercise like that for the US beer industry.

Method #1: Demand-based methods

- This is by far the most common approach in the field of IO.
  - See, e.g., Ackerberg et al (2007 Handbook chapter)
- Basic idea is to imagine that within some industry grouping (with J products) we can estimate the demand system:

$$Q_i = d_i(\mathbf{P}), \forall i$$

- Then assume some sort of "conduct", or market structure
  - Formally, this is the game the producers of these products are playing in the model
  - Can think of it as a constraint that firm i faces: e.g. $h_j(P_i, \mathbf{P}_{-i}) = 0$, $\forall j \neq i$

Method #1: Demand-based methods

- Challenges to implementing this:
  1. Demand estimation is just hard
     - High-dimensional function
     - Hard to find instruments
  2. Which conduct to assume?
     - Though with wide range of supply- and demand-side instruments, conduct is identified in parametric (Bresnahan, 1989) and nonparametric (Berry and Haile, 2015) models
- Why little application in Trade? Probably just because demand estimation much harder (usual dimension-reduction tricks of projecting onto characteristics space require industry-specific data, typically lacking in Trade).

Method #1: Demand-based methods

- Then firm's FOC can be written as:

$$\frac{P_i}{MC_i} \equiv \mu_i = \frac{\varepsilon_i}{1 - \varepsilon_i}$$

with ε_i best thought of as the firm's "perceived elasticity" (official name: residual elasticity) given by:

$$\varepsilon_i \equiv -\frac{dQ_i}{dP_i} = -\left(\frac{\partial Q_i}{\partial P_i} + \sum_{j \neq i} \frac{\partial Q_i}{\partial P_j} \frac{dP_j}{dP_i}\right)$$

- Special cases (e.g. perfect/monopolistic competition, Bertrand, Cournot, Collusion, common ownership) restrict $\frac{dP_j}{dP_i}$

Method #2: Production-based methods

- Here, the basic idea is to use firm production data (outputs and inputs) to effectively measure something like MC (and then just take $\mu \equiv P/MC$). But measuring MC is hard! (Do firms even know it?)
- One idea (reference?): estimate firm's prod. function, derive the (SR or LR, as you assume) cost function $C_i(Q_i; \mathbf{w}_i, K_i)$, get data on variable input prices $\mathbf{w}_i$, and compute $\partial C_i / \partial Q_i$
- Hall (JPE, 1988): weaker data requirements, but requires instruments
- de Loecker and Warzynski (AER, 2012): combine insights from both of these approaches

Hall (1988)

- Basic insight:
  - In a perfectly competitive, non-IRTS economy, measured ("Solow residual") productivity shouldn't change in response to changes in demand conditions or input costs

- Basic idea was to estimate the regression

$$\ln \Delta Q_{it} = \beta(\alpha_{it}^{L} \ln \Delta L_{it}) + \theta_{it}$$

where Δ is the time-difference operator, α_{it}^{L} is the labor share ($\equiv \frac{w_{it} L_{it}}{p_{it} q_{it}}$) and θ_{it} is the unobserved productivity change

Hall (1988)

- With a suitable demand (or input cost) IV for $\ln \Delta L_{it}$, can estimate β. Under assumption of CRTS then $\beta = \mu$.
- Hall's application was to US time-series data (on aggregate, or run separately by industry). IVs (via Ramey) came from military spending, oil prices, and the political party of the President.
- It has proven difficult in the firm-level literature to find broadly applicable and powerful IVs that drive similar variation at the firm level.
    - But it must be possible nowadays to isolate firm-level demand and supply shocks. (E.g. Amiti, Konings and Itskhoki, 2017 use firm-level exchange rate variation on input side.)

de Loecker and Warzynski (2012)

- DLW formalize and extend the Hall (1988) logic. Suppose firm has production function $Q_{it} = F_{it}(X_{it}^{1}, ..., X_{it}^{V}, K_{it}, \theta_{it})$, where X is a variable input. Then if takes variable input price ($P_{it}^{X^{v}}$) as given, FOC for cost-minimization (for any virtually demand curve and conduct) will be
$$P_{it}^{X^{v}} = \lambda_{it} \frac{\partial F_{it}(\cdot)}{\partial X_{it}^{v}}$$
- Here, λ_{it} is the LM on the constraint that $Q_{it} = F_{it}(\cdot)$. So it is effectively the firm's MC at Q_{it}.

de Loecker and Warzynski (2012)

- Or alternatively:

$$\frac{\partial F_{it}(\cdot)}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}} = \mu_{it} \frac{P_{it}^{X^v} X_{it}^{v}}{P_{it} Q_{it}}$$

- So this is similar to Hall's insight: whenever a variable input's output elasticity (LHS) is greater then that input's revenue share (i.e. $\frac{P_{it}^{X^v} X_{it}^{v}}{P_{it} Q_{it}}$), the difference is the markup ($\mu_{it} > 1$).
- Implementation:
  - Can measure input share for variable input easily and robustly
  - Hard part is knowing that input's output elasticity (i.e. $\frac{\partial F_{it}(\cdot)}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}}$)

How to Estimate the Output Elasticity

- DLW estimate the production function $F_{it}(\cdot)$ using standard tools for that purpose (OP/LP/ACF)
- Note that since the goal is the variable input's output elasticity, rather than, say, productivity, DLW are perhaps less exposed then usual to the problem that we see firm revenue $(P_{it}Q_{it})$ not output (Q_{it}).
- Once $F_{it}(\cdot)$ estimated, can pick an input to be (assumed to be) the variable one (DLW choose labor) and calculate $\frac{\partial F_{it}(\cdot)}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}}$ for each firm (of course for Cobb-Douglas production function this would be the same for all firms, but DLW use translog)

(Median) Markup Estimates

TABLE 2—ESTIMATED MARKUPS

Methodology	Markup
Hall[a]	1.03 (0.004)
Klette[a]	1.12 (0.020)
Specification	
I (Cobb-Douglas)	1.17
II (I w/ endog. productivity)	1.10
III (I w/ additional moments)	1.23
IV (Translog)	1.28
V (II w/ export input)	1.23
VI (Gross Output: labor)	1.26
VI (Gross Output: materials)	1.22
VII[a] (**I** w/ single markup)	1.16 (0.006)
VIII[a] (First difference)	1.11 (0.007)

[a]Markups are estimated jointly with the production function (as discussed in Section III), and we report the standard errors in parentheses. The standard deviation around the markups in specifications **I–VI** is about 0.5.

How Markups Correlate with Export Status

NB: Controlling for productivity makes these fall by 70%. Coefficient on productivity is 0.3.

TABLE 3—MARKUPS AND EXPORT STATUS I: CROSS-SECTION

	Methodology	Export Premium
	Hall	0.0155 (0.010)
	Klette	0.0500 (0.090)
Specification		
	I (Cobb-Douglas)	0.1633 (0.017)
	II (I w/ endog. productivity)	0.1608 (0.017)
	IV (Translog)	0.1304 (0.014)
	V (II w/ export input)	0.1829 (0.017)
	VIII (First difference)	0.1263 (0.013)

Notes: Estimates are obtained after running equation (21) where the different specifications refer to the different markup estimates, and we convert the percentage markup difference into levels as discussed above. The standard errors under specifications **I**–**V** are obtained from a nonlinear combination of the relevant parameter estimates. All regressions include labor, capital, and full year and industry dummies as controls. Standard errors are in parentheses.

How Markups Change when Export Status Changes

TABLE 4—MARKUPS AND EXPORT STATUS II: EXPORT ENTRY EFFECT

Method output elasticity	Export entry effect	
	Percentage (γ_1)	Level (μ_{st})
I (Cobb-Douglas)	0.0467	0.0939
	(0.0127)	(0.0260)
II (I w/ endog. productivity)	0.0467	0.0925
	(0.0127)	(0.0250)
IV (Translog)	0.0481	0.0797
	(0.0128)	(0.021)
V (II w/ export input)	0.0497	0.0994
	(0.0127)	(0.0260)
VIII (First difference)	NA	0.0700
		(0.022)

Notes: The standard errors under **I**–**V** are obtained from a nonlinear combination of the relevant parameter estimates. We drop the estimates from specifications **III** and **VI** since they are identical to the ones reported in this table. The latter is as expected since the estimate of the capital coefficient does not impact the markup estimates for instance. Specification **VIII** delivers an immediate estimate of the level impact on markups. All regressions include labor, capital, and full year and industry fixed effects as controls.

Plan for Today's Lecture

1. A primer on estimating markups
    1. Demand-based methods
    2. Supply-based methods
2. **How are markups affected by trade liberalization?**
3. Consequences for aggregate efficiency?
4. Conclusion

How Are Markups Affected by Trade Liberalization?

- de Loecker, Goldberg, Khandelwal and Pavcnik (ECMA, 2015) look at India's tariff reforms post-1991
- Draw on unique Indian plant-level panel data with rich data on quantities and prices of output...
- But with such data comes the tough reality of multi-product firms (see output by product, but not inputs by product)

Production Function Estimation for Multi-Product Firms

- deLGKP propose a procedure for this under the following assumptions:
  1. Production is product-specific (which rules out production synergies across products within the firm), and productivity shocks are Hicks-neutral and firm-specific (so think of $Q_{ijt} = F_{ijt}(\mathbf{X}^{v}_{ijt}, K_{ijt})\theta_{it}$) for firm i and product j
  2. Expenditures on all inputs are attributable to individual products (rules out shared inputs, and together with #1 this curtails scope for economies of scope; see paper for details). But note that the data only documents total firm-wide inputs.
- Once $F_{ijt}(\cdot)$ is estimated, can compute product-firm-specific markups in same way as DLW did

Production Function Estimation for MP Firms

- Given the above assumptions, can proceed via two steps:
  1. Estimate $F_{ijt}(\cdot)$ on sample of single-product firm-year observations. But have to do sample selection (analogous to Olley and Pakes (1996) correction for exit/entry) as selection into being single-product may depend on θ_{it}.
  2. Then, for multi-product firms, solve for the (unique?) assignment of total firm-wide input use across products given the single-product production functions $F_{ijt}(\cdot)$—a nonlinear system of equations or each firm-year.

Additional Note on Production Function Estimation

- deLGKP also develop a procedure to control for unobserved input quality bias since input prices not observed.
  - Uses a control function argument based on a theory in which firms that produce high quality/price output also use high-quality inputs
  - Interestingly, de Loecker and Goldberg (ARE, 2014) discuss reasons for why it is important to either correct for both this and the output price bias, or to correct for neither (with Cobb-Douglas tech and CES prefs the two biases exactly cancel)

How Firm Outcomes Affected by Tariff Reforms

TABLE IX

PRICES, COSTS, AND MARKUPS AND TARIFFS[a]

	$\ln P_{fjt}$ (1)	$\ln mc_{fjt}$ (2)	$\ln \mu_{fjt}$ (3)
$\tau_{it}^{\text{output}}$	0.156***	0.047	0.109
	0.059	0.084	0.076
τ_{it}^{input}	0.352	1.160**	−0.807‡
	0.302	0.557	0.510
Within R-squared	0.02	0.01	0.01
Observations	21,246	21,246	21,246
Firm–product FEs	yes	yes	yes
Sector–year FEs	yes	yes	yes
Overall impact of trade liberalization	−18.1**	−30.7**	12.6
	7.4	13.4	11.9

[a]The dependent variable is noted in the columns. The sum of the coefficients from the markup and marginal costs regression equals their respective coefficient in the price regression. The regressions exclude outliers in the top and bottom 3rd percent of the markup distribution, and include firm–product fixed effects and sector–year fixed effects. The final row uses the average 62% and 24% declines in output and input tariffs from 1989–1997, respectively, to compute the mean and standard error of the impact of trade liberalization on each performance measure. That is, for each column the mean impact is equal to the $-0.62 \times 100 \times$ {coefficient on output tariff} $\pm\, 0.24 \times 100 \times$ {coefficient on input tariff}. The regressions use data from 1989–1997. The table reports the bootstrapped standard errors that are clustered at the industry level. Significance: ‡11.3 percent, *10 percent, **5 percent, ***1 percent.

How Markups Affected by Tariff Reforms (Controlling for MC)

TABLE X

PRO-COMPETITIVE EFFECTS OF OUTPUT TARIFFS[a]

	$\ln \mu_{fjt}$			
	(1)	(2)	(3)	(4)
$\tau_{it}^{\text{output}}$	0.143***	0.150**	0.129**	0.149**
	0.050	0.062	0.052	0.062
$\tau_{it}^{\text{output}} \times \text{Top}_{fp}$			0.314**	0.028
			0.134	0.150
Within R-squared	0.59	0.65	0.59	0.65
Observations	21,246	16,012	21,246	16,012
Second-order polynomial of marginal cost	yes	yes	yes	yes
Firm–product FEs	yes	yes	yes	yes
Sector–year FEs	yes	yes	yes	yes
Instruments	no	yes	no	yes
First-stage F-test	–	8.6	–	8.6

[a]The dependent variable is (log) markup. All regressions include firm–product fixed effects, sector–year fixed effects and a second-order polynomial of marginal costs (these coefficients are suppressed and available upon request). Columns 2 and 4 instrument the second-order polynomial of marginal costs with second-order polynomial of lag marginal costs and input tariffs. Columns 3 interacts output tariffs and the second-order marginal cost polynomial with an indicator if a firm–product observation was in the top 10 percent of its sector's markup distribution when it first appears in the sample. The regressions exclude outliers in the top and bottom 3rd percent of the markup distribution. The table reports the bootstrapped standard errors that are clustered at the industry level. Significance: *10 percent, **5 percent, ***1 percent.

Plan for Today's Lecture

1. A primer on estimating markups
    1. Demand-based methods
    2. Supply-based methods
2. How are markups affected by trade liberalization?
3. **Consequences for aggregate efficiency?**
4. Conclusion

Putting It All Together

- How could we go from the above estimates to an understanding of how markup responses (or lack thereof) to trade liberalization affect the welfare effects of such policy changes?
- Missing features:
  1. How to aggregate across firms? Need demand system. And obviously that would help us to recognize that much of any given markup is "good" as it allows the firm to pay for the fixed cost of developing its differentiated product.
  2. What about prices of foreign firms' goods? Their markups might have changed too.
  3. (Other "defensive" responses by firms in technological change, product differentiation, etc.)

Putting It All Together

- 3 recent papers make progress on this:
  1. Holmes, Hsu and Stevens (JIE, 2014)
  2. Edmond, Midrigan and Xu (AER, 2015)
  3. Arkolakis, Costinot, Donaldson and Rodriguez-Clare (RESTUD, 2018)

Edmond, Midrigan and Xu (2015)

- Develop and calibrate (to Taiwan firm data) a Cournot model (a la Atkeson and Burstein, AER 2008) with features:
  - Firm productivities drawn randomly, but with copula governing correlation between home and foreign distributions.
  - Nested CES demand system with lowest level ("sector") at a level where most sectors have high domestic sales Herfindahl in Taiwan (median is 0.25)
- Define "pro-competitive effect" as change in misallocation (market power is only distortion) when trade costs change

Edmond, Midrigan and Xu (2015)

TABLE 3—GAINS FROM TRADE

Change in import share	0 to 10	10 to 20	20 to 30	30 to Taiwan	0 to Taiwan
Panel A. Benchmark model					
Change TFP, percent	3.4	2.7	3.3	3.0	12.4
Change first-best TFP, percent	1.8	2.5	3.2	3.0	10.4
Procompetitive gains, percent	1.7	0.3	0.1	0.0	2.0
Misallocation relative to autarky	0.81	0.79	0.78	0.78	0.78
Change aggregate markup, percent	−1.9	−0.6	−0.4	−0.1	−2.9
Domestic	−1.6	−0.6	−0.4	−0.3	−2.9
Import	16.6	−0.1	0.4	0.2	17.1
Change markup dispersion, percent	−1.7	−0.2	1.1	−0.1	−0.9
Domestic	−1.9	−0.4	1.0	−0.4	−1.7
Import	10.3	−0.1	0.0	0.1	10.3
Trade elasticity (ex post)	4.2	4.1	4.0	4.0	4.0
ACR gains, percent	2.5	2.9	3.3	2.8	11.7

Arkolakis, Costinot, Donaldson and Rodriguez-Clare (2018)

- Arnaud will cover this in detail. But basic features are:
  - Monopolistic competition
  - Non-CES class of preferences nesting popular cases
  - Pareto-distributed productivities in each country
- Main payoffs:
  - Still get gravity equation for trade flows (as in ACR)
  - And counterfactual trade flow (and nominal factor price) changes for any change in environment are same as in gravity model (so same as ACR)
  - But welfare change from small change in import share is like ACR but augmented...

ACDR (2018): Augmented ACR Formula

Augmented form (for small change in welfare W_j) is now:

$$d \ln W_j = -(1 - \eta) \frac{d \ln \lambda_{jj}}{\theta}$$

where, as in ACR, θ is the trade elasticity, $\ln \lambda_{jj}$ is the home trade share, and η is the "augmented" bit (that comes from the non-CES prefs), given by:

$$\eta \equiv \left(\frac{1 - \beta}{1 - \beta + \theta} \right) \rho$$

where $\beta \geq 0$ is a demand parameter governing homotheticity ($\beta = 1$ if homothetic) and ρ is the sales-weighted average of one minus the pass-through rate. CES limit has $\rho \to 0$ and hence $\eta \to 0$, and hence recover ACR.

Pass-Through of MC (IV w tariffs) to Prices

TABLE VII

PASS-THROUGH OF COSTS TO PRICES[a]

	$\ln P_{fjt}$		
	(1)	(2)	(3)
$\ln mc_{fjt}$	0.337***	0.305***	0.406†
	0.041	0.084	0.247
Observations	21,246	16,012	12,334
Within R-squared	0.27	0.19	0.09
Firm–product FEs	yes	yes	yes
Instruments	–	yes	yes
First-stage F-test	–	98	5

[a]The dependent variable is (log) price. Column 1 is an OLS regression on log marginal costs. Column 2 instruments marginal costs with input tariffs and lag marginal costs. Column 3 instruments marginal costs with input tariffs and two-period lag marginal costs. The regressions exclude outliers in the top and bottom 3rd percent of the markup distribution. All regressions include firm–product fixed effects. The regressions use data from 1989–1997. The standard errors are bootstrapped and are clustered at the firm level. Significance: †10.1 percent, *10 percent, **5 percent, ***1 percent.

Arkolakis, Costinot, Donaldson and Rodriguez-Clare (2018)

- So if we take deLGKP's estimate of $\rho = 1 - 0.305$ and $\theta = 5$ (Head and Mayer, 2014 handbook chapter), then even with conservative case of $\beta = 0$ we will have $\eta = 0.11$
- This suggests that pro-competitive effects (as defined by the size of η) are pretty small (not unlike EMX).
- And note that they are actually "anti-competitive" ($\eta > 0$). Arnaud will explain why!

Plan for Today's Lecture

1. A primer on estimating markups
   1. Demand-based methods
   2. Supply-based methods
2. How are markups affected by trade liberalization?
3. Consequences for aggregate efficiency?
4. **Conclusion**

Ideas for Future Work

- Directly estimate how policy changes mark-ups charged by foreigners (building on Feenstra (AER, 1989), Chang and Winters (AER, 2002), and Irwin (2014 wp))
- More integration between micro approaches and aggregate welfare calculations so as to study misallocation directly.
- In a world of markups, incomplete pass-through, and trade costs, isn't there too much trade?
- Distributional implications of markups? (e.g. Autor et al, 2018 on rising US concentration ratios)