14.581: International Trade I
— Lecture 16: 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
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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.

- Basic idea is to imagine that within some industry grouping (with \( J \) products) we can estimate the demand system:

\[
Q_i = d_i(P), \forall i
\]

- 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. \( h_j(P_i, P_{-i}) = 0, \forall j \neq i \)
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 \( \varepsilon_i \) 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 $C_i(Q_i; w_i, K_i)$, get data on variable input prices $w_i$, 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.
  - So write down model in which only cause of such effects is markups, and use correlation between demand shocks and Solow residual to estimate markups.

- Basic idea was to estimate the regression

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

where \(\Delta\) is the time-difference operator, \(\alpha_{it}^L\) is the labor share \((\equiv \frac{w_{it}L_{it}}{p_{it}q_{it}})\) and \(\theta_{it}\) is the unobserved productivity change.

- Under assumption of CRTS then \(\beta = \mu\).
Hall (1988)

- With a suitable demand (or input cost) IV for $\ln \Delta L_{it}$, can estimate $\beta$.

- 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.)
DLW formalize and extend the Hall (1988) logic. Suppose firm has production function 
\[ Q_{it} = F_{it}(X^1_{it}, \ldots, X^V_{it}, K_{it}, \theta_{it}) \], where \( X \) is a variable input. Then if takes variable input price \( (P^X_{it}) \) as given, FOC for cost-minimization (for any virtually demand curve and conduct) will be

\[ P^X_{it} = \lambda_{it} \frac{\partial F_{it}(.)}{\partial X^v_{it}} \]

Here, \( \lambda_{it} \) is the LM on the constraint that \( Q_{it} = F_{it}(\cdot) \). So \( \lambda_{it} \) is the firm’s MC at \( Q_{it} \).
Or alternatively:

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

So this is similar to Hall’s insight: whenever a variable input’s output elasticity (LHS) is greater than that input’s revenue share (i.e. \(\frac{P_{it}^X X_{it}^v}{P_{it} Q_{it}}\)), 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. \(\frac{\partial F_{it}(\cdot) X_{it}^v}{\partial X_{it}^v} \frac{X_{it}^v}{Q_{it}}\))
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 than 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).
directly obtain an estimate for the markup. In specification VIII we estimate in first differences, which allows us to directly compare our estimate of the markup to the traditional Hall approach and verify the importance of controlling for unobserved productivity shocks using our proxy approach.

Estimated Markups.

Table 2 presents the median markup of the various specifications. We will exploit the heterogeneity in markups in the next section by relating markups to firm-level characteristics.

Our estimates of the markup are consistently higher compared to the Hall and Klette approach. The markup estimate under Hall is obtained by regressing output growth on an index of input growth where each input is weighted by their expenditure share, and we find a markup of 1.03. In the second row, we estimated a higher markup of 1.12 using Klette's algorithm. Both these models are estimated in first differences, and it is well known to lead to a downward bias of the estimates, here the markup, by exacerbating measurement error.

We obtain markups in the range of 1.17–1.28 and our various specifications give very similar results. Note that the markups obtained using specifications I–VI are medians over the underlying distribution, and in all cases the standard deviations are substantial as expected (around 0.5), and indicates a substantial variation in markups across all firms of the manufacturing sector, as expected.

Table 2—Estimated Markups

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hall(^a)</td>
<td>1.03 (0.004)</td>
</tr>
<tr>
<td>Klette(^a)</td>
<td>1.12 (0.020)</td>
</tr>
</tbody>
</table>

Specification

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>I (Cobb-Douglas)</td>
<td>1.17</td>
</tr>
<tr>
<td>II (I w/ endog. productivity)</td>
<td>1.10</td>
</tr>
<tr>
<td>III (I w/ additional moments)</td>
<td>1.23</td>
</tr>
<tr>
<td>IV (Translog)</td>
<td>1.28</td>
</tr>
<tr>
<td>V (II w/ export input)</td>
<td>1.23</td>
</tr>
<tr>
<td>VI (Gross Output: labor)</td>
<td>1.26</td>
</tr>
<tr>
<td>VI (Gross Output: materials)</td>
<td>1.22</td>
</tr>
<tr>
<td>VII(^a) (I w/ single markup)</td>
<td>1.16 (0.006)</td>
</tr>
<tr>
<td>VIII(^a) (First difference)</td>
<td>1.11 (0.007)</td>
</tr>
</tbody>
</table>

\(^a\)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.

We run the regression for the various estimates of the markups as described above. The parameter $\delta_1$ is estimated very precisely in all specifications (I–V) and is around 0.078.48 As expected, all the results relying on a CD technology are very similar because the variation in markups is almost identical across the various specifications.49 Only the level of the markup differs due to different $\beta_l$ estimates, which is captured by the constant term. The results using a translog production function, IV, rely on firm-specific output elasticities and we get a somewhat lower estimated $\mu_E$ of 0.1304. One important message that comes from this table is that no significant markup differences are detected when relying on the Hall or the Klette approach. In order to check whether restricting the markup to be constant across firms is important for this result, we consider a restricted version of our approach (VIII). The markup premium is estimated to be 0.1263, which is similar to the results under the more general framework. These results highlight the importance of controlling for unobserved productivity shocks when estimating markups directly.

An important advantage of considering log markups is that our results are unchanged even if all the variable inputs we considered to compute markups are subject to adjustment costs. As long as exporting firms are not more (or less) subject to these adjustment costs, our results are not affected.50

These results are consistent with recent models of international trade such as the model of Bernard et al. (2003), where exporters charge, on average, higher markups simply because they are more productive and can therefore undercut their rivals. This prediction is supported by comparing the average markup of exporters to non-exporters in the cross-section. In their model, however, firms of the same productivity will charge the same markup, making productivity differences the only source

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**Table 3—Markups and Export Status I: Cross-Section**

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Export Premium</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hall</td>
<td>0.0155 (0.010)</td>
</tr>
<tr>
<td>Klette</td>
<td>0.0500 (0.090)</td>
</tr>
</tbody>
</table>

**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

When relying on the same regression framework and allowing the markup effect to depend on export intensity, by interacting the export dummies with the share of export sales in total sales, the coefficient on the export entry effect is larger, 0.097, and allows us to compute the export entry markup trajectory as obtained by tracing the share of export sales in total sales over time.

It is important to note that we do not find the markup-export relationships when relying on standard methods. When we rely on our approach, we find significantly higher markups for exporters in the cross-section, and find that markups increase with export entry.

Interpreting Our Results

—In sum, we report two major findings: (i) in the cross-section we find that exporters have higher markups than their domestic counterparts in the same industry, and (ii) in the time series we find that markups increase when firms enter export markets, while controlling for aggregate demand and supply effects through year dummies. How can we explain our results?

A few recent models (Bernard et al. 2003; Melitz and Ottaviano 2008) provide a theoretical analysis of the relationship between firm export status and market-specific markups. Under various hypotheses regarding the nature of competition, more efficient producers are more likely to have more efficient rivals, to charge lower prices, to sell more on the domestic market, and to beat rivals on export markets. They benefit from a cost advantage over their competitors, set higher markups (under certain conditions regarding the relative efficiency between firms on the domestic and the export market, in the case of the Melitz and Ottaviano model), and have higher levels of measured productivity. An alternative explanation could be that the elasticity of demand is different on the export market, or that consumers have different valuation for the good. The exact mechanism underlying these results is not testable given the data at hand. For instance, we do not have firm-specific

<table>
<thead>
<tr>
<th>Table 4—Markups and Export Status II: Export Entry Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method output elasticity</td>
</tr>
<tr>
<td>Percentage ($\gamma_1$)</td>
</tr>
<tr>
<td>--------------------------------</td>
</tr>
<tr>
<td>I (Cobb-Douglas)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>II (I w/ endog. productivity)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>IV (Translog)</td>
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<tr>
<td></td>
</tr>
<tr>
<td>V (II w/ export input)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>VIII (First difference)</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

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.
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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)
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 $Q_{ijt} = F_{ijt}(X_{ijt}^\nu, K_{ijt})\theta_{it}$) 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.
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 $\theta_{it}$.

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.
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)
Topalova and Khandelwal (2011) have emphasized the importance of declines in input tariffs in shaping firm performance. We separate the effects of output tariffs and input tariffs on prices. Output tariff liberalization reflects primarily an increase in competition, while the input tariff liberalization should provide access to lower cost (and more variety of) inputs. We run the analog of the regression in (37), but separately include input and output tariffs:

\[ p_{fjt} = \lambda_{fj} + \lambda_{st} + \lambda_{1} \tau_{output_{it}} + \lambda_{2} \tau_{input_{it}} + \eta_{fjt/periodori} \] (38)

The results are shown in Column 1 of Table IX. There are two interesting findings that are important for understanding how trade affects prices in this liberalization episode. First, there is a positive and statistically significant coefficient on output tariffs. This result is consistent with the common intuition that increases in competitive pressures through lower output tariffs will lead to price declines. The effect is traditionally attributed to reductions in markups.

### Table IX

<table>
<thead>
<tr>
<th></th>
<th>( \ln P_{fjt} ) (1)</th>
<th>( \ln mc_{fjt} ) (2)</th>
<th>( \ln \mu_{fjt} ) (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \tau_{output_{it}} )</td>
<td>0.156***</td>
<td>0.047</td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>0.059</td>
<td>0.084</td>
<td>0.076</td>
</tr>
<tr>
<td>( \tau_{input_{it}} )</td>
<td>0.352</td>
<td>1.160**</td>
<td>(-0.807)‡</td>
</tr>
<tr>
<td></td>
<td>0.302</td>
<td>0.557</td>
<td>0.510</td>
</tr>
<tr>
<td>Within ( R )-squared</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Observations</td>
<td>21,246</td>
<td>21,246</td>
<td>21,246</td>
</tr>
<tr>
<td>Firm–product FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Sector–year FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Overall impact of trade liberalization</td>
<td>(-18.1)**</td>
<td>(-30.7)**</td>
<td>12.6</td>
</tr>
<tr>
<td></td>
<td>7.4</td>
<td>13.4</td>
<td>11.9</td>
</tr>
</tbody>
</table>

\( a \)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 \(-0.62 \times 100 \times \{\text{coefficient on output tariff}\} \pm 0.24 \times 100 \times \{\text{coefficient on input tariff}\} \). 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.

The regressions exclude outliers in the top and bottom third percent of the markup distribution. We trim to ensure that the results are not driven by outliers. Nevertheless, the results are robust (e.g., magnitudes change slightly but statistical significance is unaffected) to alternative trims (e.g., the top and bottom first) and to not trimming at all (results are available upon request).
How Markups Affected by Tariff Reforms (Controlling for MC)

To isolate the pro-competitive effects, we need to control for simultaneous shocks to marginal costs. We do this by re-running the markup regression while controlling flexibly for marginal costs. Conditioning on marginal costs, the output tariff coefficient isolates the direct pro-competitive effect of the trade liberalization on markups. We report the results in Table X. The coefficient on output tariffs in Column 1 is positive and significant; this provides direct evidence that output tariff liberalization exerted pro-competitive pressure on markups. The way to interpret the results in Column 1 is to consider the markups of two products in different industries. Conditional on any (potentially differential) impact of the trade reforms on their respective costs,

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td>( \tau_{it} )</td>
<td>0.143***</td>
<td>0.150**</td>
<td>0.129**</td>
<td>0.149**</td>
</tr>
<tr>
<td></td>
<td>0.050</td>
<td>0.062</td>
<td>0.052</td>
<td>0.062</td>
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<tr>
<td>( \tau_{it} \times \text{Top}_{fp} )</td>
<td>0.314**</td>
<td>0.028</td>
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<tr>
<td></td>
<td>0.134</td>
<td>0.150</td>
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<tr>
<td>Within R-squared</td>
<td>0.59</td>
<td>0.65</td>
<td>0.59</td>
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<tr>
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<td>16,012</td>
<td>21,246</td>
<td>16,012</td>
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<tr>
<td>Second-order polynomial of marginal cost</td>
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<td>yes</td>
<td>yes</td>
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<tr>
<td>Firm–product FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
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<tr>
<td>Sector–year FEs</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Instruments</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>First-stage F-test</td>
<td>–</td>
<td>8.6</td>
<td>–</td>
<td>8.6</td>
</tr>
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</table>

\( a \)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.

To control for marginal costs as flexibly as possible, we use a second-order polynomial for marginal costs and suppress these coefficients in Table X. We find very similar results if we simply include marginal costs as the only control (results are available upon request).
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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.)
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)
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
### Panel A. Benchmark model

<table>
<thead>
<tr>
<th>Change in import share</th>
<th>0 to 10</th>
<th>10 to 20</th>
<th>20 to 30</th>
<th>30 to Taiwan</th>
<th>0 to Taiwan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change TFP, percent</td>
<td>3.4</td>
<td>2.7</td>
<td>3.3</td>
<td>3.0</td>
<td>12.4</td>
</tr>
<tr>
<td>Change first-best TFP, percent</td>
<td>1.8</td>
<td>2.5</td>
<td>3.2</td>
<td>3.0</td>
<td>10.4</td>
</tr>
<tr>
<td>Procompetitive gains, percent</td>
<td>1.7</td>
<td>0.3</td>
<td>0.1</td>
<td>0.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Misallocation relative to autarky</td>
<td>0.81</td>
<td>0.79</td>
<td>0.78</td>
<td>0.78</td>
<td>0.78</td>
</tr>
<tr>
<td>Change aggregate markup, percent</td>
<td>−1.9</td>
<td>−0.6</td>
<td>−0.4</td>
<td>−0.1</td>
<td>−2.9</td>
</tr>
<tr>
<td>Domestic</td>
<td>−1.6</td>
<td>−0.6</td>
<td>−0.4</td>
<td>−0.3</td>
<td>−2.9</td>
</tr>
<tr>
<td>Import</td>
<td>16.6</td>
<td>−0.1</td>
<td>0.4</td>
<td>0.2</td>
<td>17.1</td>
</tr>
<tr>
<td>Change markup dispersion, percent</td>
<td>−1.7</td>
<td>−0.2</td>
<td>1.1</td>
<td>−0.1</td>
<td>−0.9</td>
</tr>
<tr>
<td>Domestic</td>
<td>−1.9</td>
<td>−0.4</td>
<td>1.0</td>
<td>−0.4</td>
<td>−1.7</td>
</tr>
<tr>
<td>Import</td>
<td>10.3</td>
<td>−0.1</td>
<td>0.0</td>
<td>0.1</td>
<td>10.3</td>
</tr>
<tr>
<td>Trade elasticity (ex post)</td>
<td>4.2</td>
<td>4.1</td>
<td>4.0</td>
<td>4.0</td>
<td>4.0</td>
</tr>
<tr>
<td>ACR gains, percent</td>
<td>2.5</td>
<td>2.9</td>
<td>3.3</td>
<td>2.8</td>
<td>11.7</td>
</tr>
</tbody>
</table>
Basic features:
- 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, which we will start to discuss next week)
- 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...
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, $\theta$ is the trade elasticity, $\ln \lambda_{jj}$ is the home trade share, and $\eta$ 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 $\rho$ 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.
### TABLE VII
**PASS-THROUGH OF COSTS TO PRICES**

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

*aThe 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."
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 $\eta$) 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
   - Demand-based methods
   - 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)