Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade

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Motivation

- Gravity models → quantify *aggregate* welfare effects of trade
- Empirical research → large *distributional* effects of trade
- This paper: bridge the two literatures and quantify the aggregate and distributional effects of the “China Shock” for the US.
Gravity and Welfare

- Armington, Krugman, EK, Melitz-Pareto are all gravity models
  - Trade data + trade elasticity $\rightarrow$ counterfactual analysis

- Here use multi-sector gravity model with CD preferences

- Sector-level gravity equation to get trade elasticity $\theta_s$
  - Here, $\theta_s = 5$ for all $s$

- US aggregate gains from China shock approx. 0.3%
The China Syndrome

- Autor, Dorn and Hanson AER 2013

- Focus on local labor markets (commuting zones)

- Major finding: relative decline in wages and employment for CZs most exposed to competition from ↑ US imports from China

- Other findings: ↑ federal transfers, ↓ marriage, ↑ suicide and drug overdose, electoral polarization... and maybe even Trump
What about welfare?

- Empirical methodology can only identify relative effects

- But ↑ imports also imply gains via lower prices

- What are the absolute effects? Are groups better or worse off?

- Specific factors intuition: ↓ in relative wage for workers in import competing industries
  - But such workers may still gain due to lower consumption prices

- Need general equilibrium model... back to gravity
Gravity + Roy-Frechet

- Standard multi-sector gravity: workers are perfectly mobile
- Other extreme: workers are stuck in their sector (specific factors)
- Roy-Frechet: parameter $\kappa \in [1, \infty]$ determines where we are
- Low $\kappa \rightarrow$ larger distributive effects
Model
Basics

- $N$ countries, index $i$
- $S$ sectors, index $s$
- $G_i$ groups in country $i$, index $ig$
Comparative Statics: Welfare

\[ \hat{W}_{ig} = \prod_{s} \tilde{\lambda}_{iis}^{-\beta_{is}/\theta} \cdot \prod_{s} \tilde{\pi}_{igs}^{-\beta_{is}/\kappa} \]

- Country-level ACR gains
- New group-level “Roy” term
Empirical Analysis
Data

- For $i = \text{US, sector } s$

- US Labor Market:
  - Census and ACS data
  - Group employment shares at the Commuting Zone (CZ)-Skill level
  - $G = 1,444$ (722 CZs $\times$ 2 skill groups)
  - $S = 14$, with 13 manufacturing sectors and 1 non-manufacturing sector
  - Time period: 2000 - 2011

- Trade data from WIOD
Estimation

- Two key elasticities: $\theta$ and $\kappa$
  - Estimation of $\theta$ is standard in the literature - gravity equation
  - Key challenge here is estimation of $\kappa$

- Combine empirical and theoretical elements to estimate $\kappa$
  - Empirical: higher exposure to China shock $\rightarrow \downarrow$ manuf. employment
  - Theoretical: $\downarrow$ manuf. employment $\rightarrow \downarrow$ relative income depending on $\kappa$

- Formally, focusing on $i = US$ and supressing that subindex, model implies
  \[
  \ln \hat{y}_g = \ln \hat{w}_{NM} - \frac{1}{\kappa} \ln \hat{\pi}_{gNM} + \varepsilon_{gNM},
  \]
  where $\varepsilon_{gNM} = (1/\kappa) \ln \hat{A}_g NM$.

- Use China shock $Z_g$ as instrument for $\ln \hat{\pi}_{gNM}$ building on ADH.
  Exclusion restriction: $E(Z_g \varepsilon_{gNM}) = 0$
Table: Estimation of $\kappa$

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable: $\ln \hat{y}_g$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Workers Hours</td>
<td></td>
</tr>
<tr>
<td>$\ln \hat{\pi}_{gNM}$</td>
<td>-0.466</td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
</tr>
<tr>
<td>Implied $\kappa$</td>
<td>2.147</td>
</tr>
<tr>
<td></td>
<td>(0.743)</td>
</tr>
<tr>
<td>First-stage F-Statistic</td>
<td>23.19</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
</tr>
</tbody>
</table>

IV-estimation results where $y_g$ is measured as average earnings per worker, and $\pi_{gNM}$ is the labor share employed in non-manufacturing. Labor shares $\pi_{gs}$ are measured as the share of workers, share of labor hours and share of earnings for columns 1, 2 and 3 respectively. Conley standard errors (in parentheses), with a cutoff for the spatial correlation at approximately 400km.
Counterfactual Analysis
China-shock calibration

• China shock = sector-level productivity shocks in the model, $\hat{T}_{China,s}$

• Calibration of $\hat{T}_{China,s}$
  ▶ Inspired by Caliendo, Dvorkin & Parro (2016)

• Run a variation on ADH’s first-stage regression for our data

$$\hat{\lambda}_{China,US,s} = \alpha + \beta \hat{\lambda}_{China,Other,s} + \epsilon_s$$

▶ Obtain $\hat{\lambda}_{China,US,s} \equiv \hat{\beta} \hat{\lambda}_{China,Other,s}$

▶ Calibrate $\hat{T}_{China,s}$ to fit the simulated $\hat{\lambda}_{China,US,s}$ to $\hat{\lambda}_{China,US,s}$
Simulated China shock and groups’ income changes

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>$\hat{W}_{US}$</th>
<th>Mean</th>
<th>CV</th>
<th>Min.</th>
<th>Max.</th>
<th>$\prod_{s} \hat{\lambda}<em>{s}^{-\beta</em>{s}/\theta_{s}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rightarrow 1$</td>
<td>0.29</td>
<td>0.38</td>
<td>0.87</td>
<td>-2.24</td>
<td>2.56</td>
<td>0.20</td>
</tr>
<tr>
<td>2</td>
<td>0.25</td>
<td>0.32</td>
<td>0.56</td>
<td>-1.64</td>
<td>1.34</td>
<td>0.20</td>
</tr>
<tr>
<td>4</td>
<td>0.23</td>
<td>0.28</td>
<td>0.36</td>
<td>-1.01</td>
<td>0.76</td>
<td>0.21</td>
</tr>
<tr>
<td>$\rightarrow \infty$</td>
<td>0.24</td>
<td>0.24</td>
<td>0.00</td>
<td>0.24</td>
<td>0.24</td>
<td>0.24</td>
</tr>
</tbody>
</table>

The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms ($100(\hat{W}_{US} - 1)$), and the second column shows the mean welfare effect: $100\left(\frac{1}{G} \sum_{g} \hat{W}_{US,g} - 1\right)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have $\text{Min.} \equiv \min_{g} 100(\hat{W}_{US,g} - 1)$ and $\text{Max.} \equiv \max_{g} 100(\hat{W}_{US,g} - 1)$, respectively. The final column displays $100 \left(\prod_{s} \hat{\lambda}_{US,s}^{-\beta_{US,s}/\theta_{s}} - 1\right)$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 2$. 
Figure: Geographical distribution of the welfare gains from the rise of China for low-educated workers

This figure plots the geographic distribution of $100(\hat{W}_g - 1)$, where $\hat{W}_g$ are the welfare effects for group $g$ in the US from the counterfactual rise of China, for our preferred value of $\kappa = 2$. 

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Figure: Geographical distribution of the welfare gains from the rise of China for high-educated workers

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Approximate sufficient statistic for income changes

- A Bartik-style measure of group-level income competition:

\[ I_g \equiv \sum_s \pi_{gs} \frac{\beta_s}{r_s} \]

with \( r_s \equiv \sum_g \pi_{gs} Y_g / Y \)

- For any trade shock:

\[ \ln \hat{Y}_g / \hat{Y} \approx \frac{1}{\kappa} \ln \sum_s \pi_{gs} \hat{r}_s = \frac{1}{\kappa} \ln \hat{I}_g \]

- This approximate sufficient statistic is exact for \( \kappa \to 1 \), and almost exact in our simulations.

- In the data, we (i) test the validity of this import-competition measure and (ii) estimate \( \kappa \) indirectly.
We regress $\ln \hat{y}_g = \alpha + \beta \ln \sum_s \pi_{gs} \hat{r}_s + \varepsilon_g$ on simulated data and display the obtained $\beta$ for data generated for a given $\kappa$. 
### Table: Empirical analysis of the Bartik measure for import competition

<table>
<thead>
<tr>
<th>Dependent variable: ln $\hat{y}_g$</th>
<th>(1) Workers</th>
<th>(2) Hours</th>
<th>(3) Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln $\sum_s \pi_{gs} \hat{r}_s$</td>
<td>0.712</td>
<td>0.703</td>
<td>0.648</td>
</tr>
<tr>
<td></td>
<td>(0.228)</td>
<td>(0.221)</td>
<td>(0.212)</td>
</tr>
<tr>
<td>Implied $\kappa$</td>
<td>1.404</td>
<td>1.422</td>
<td>1.543</td>
</tr>
<tr>
<td></td>
<td>(0.450)</td>
<td>(0.446)</td>
<td>(0.504)</td>
</tr>
<tr>
<td>First-stage F-Statistic</td>
<td>12.52</td>
<td>12.71</td>
<td>8.924</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
</tbody>
</table>

IV-estimation results where $y_g$ is measured as average earnings per worker. Labor shares $\pi_{gs}$ are measured as the share of workers, share of labor hours and share of earnings for columns 1, 2 and 3 respectively. Standard errors (in parentheses) are calculated as in Conley (1999) and with a cutoff for the spatial correlation at approximately 400km. The first row shows the second-stage results, while the third row has the corresponding estimate for $\hat{\kappa} = \frac{1}{\hat{\beta}}$ and the fifth row displays the F-statistic from the first stage.
Theory: Inequality-Adjusted Welfare Effects

- Let $W_g \equiv Y_g / P$. Utility for agent behind the veil of ignorance

\[ U \equiv \left( \sum_g \frac{L_g}{L} W_g^{1-\rho} \right)^{1/(1-\rho)} \]

- The higher $\rho$, the more risk (or inequality) averse
  
  - For $\rho = 0$, $U = W$, with $W \equiv \sum_g \frac{L_g}{L} W_g$

- Inequality-adjusted welfare effects:

\[ \hat{U} = \left( \sum_g \omega_g \hat{W}_g^{1-\rho} \right)^{\frac{1}{1-\rho}} \quad \text{with} \quad \omega_g \equiv \frac{L_g (Y_g / L_g)^{1-\rho}}{\sum_h L_h (Y_h / L_h)^{1-\rho}} \]
Inequality-adjusted welfare effects

The figure plots the relationship between $\hat{U}$, the inequality-adjusted welfare effects of the rise of China, with $U \equiv \left( \sum_i l_i W_i^{-1-\rho} \right)^{1/(1-\rho)}$, and $\rho$ which is the coefficient of relative risk aversion for the agent behind the veil of ignorance.
Conclusion

- Framework to study aggregate and distributional effects of trade
- Welfare effects are summarized in a parsimonious equation that nests the multi-sector ACR result
- Key additional parameter $\kappa$ governs strength of distributional effects
- Estimate $\kappa$ combining ADH Bartik strategy with structural equation from model, $\kappa \approx 2$
- Counterfactual analysis reveals that China shock increases average welfare, but some groups experience losses as high as five times the average gain
- Adjusted for plausible measures of inequality aversion, gains in social welfare are positive, and only slightly lower than with the standard aggregation.
Conclusion

• Results do not change significantly when allowing for intermediate goods, trade costs across US states, non-tradable goods at the group level (in progress).

• One shortcoming: no employment effects.