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

Online Appendix

Online Appendix B Proofs for the baseline model

B.1 Proof for Proposition 2

We want to show that the aggregate gains from trade are higher when $\kappa_{ig} = \kappa < \infty$ than when $\kappa_{ig} \to \infty$ for all $g \in G_i$. Given the definition of the gains from trade, and using Equation (14), we must show that $\sum_{g \in G_i} (Y_{ig}/Y_i) \prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa} < 1$, or using $y_{ig} \equiv Y_{ig}/Y$ and Equation (10),

$$\sum_g y_{ig} \prod_s \left(\hat{w}_{is} \left(\sum_k \pi_{igk} \hat{w}_k^{\kappa} \right)^{-1/\kappa} \right)^{-\beta_{is}} < 1.$$

Rewriting this equation as $\sum_{g \in G_i} y_{ig} \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} < \prod_s \hat{w}_{is}^{\beta_{is}}$, we can write what we want to show as

$$\sum_{g \in G_i} y_{ig} x_{ig} < \prod_s \hat{w}_{is}^{\beta_{is}},$$

where $x_{ig} \equiv \left(\sum_s \pi_{igs} \hat{w}_{is}^{\kappa} \right)^{1/\kappa}$, and where, from Equation (15), $\hat{w}_{is}$ is given by the solution of

$$\beta_{is} \sum_{g \in G_i} x_{ig} y_{ig} = \sum_{g \in G_i} \hat{w}_{is}^{\kappa} x_{ig}^{1-\kappa} \pi_{igs} y_{ig} \text{ for } s = 1, ..., S. \tag{36}$$

Solving for $\hat{w}_{is}$ from this equation and plugging into the inequality above we see that we need to prove that

$$\left(\sum_g y_{ig} x_{ig} \right)^{\kappa} < \prod_s \left(\beta_{is} \frac{\sum_g y_{ig} x_{ig}}{\sum_g x_{ig}^{1-\kappa} \pi_{igs} y_{ig}} \right)^{\beta_{is}}.$$

This can be rewritten as

$$\prod_s \left(\sum_g \left(\frac{x_{ig}}{\sum_m y_{im} x_{im}} \right)^{1-\kappa} \pi_{igs} y_{ig} \right)^{\beta_{is}} < \prod_s \beta_{is}^{\beta_{is}},$$

where $y_{ig}, \beta_{is}, \pi_{igs}$ are all between zero and one, and

$$\sum_s \beta_{is} = \sum_s \pi_{igs} = \sum_g y_{ig} = 1.$$

To proceed, let $z_{is} \equiv \sum_g \left(\frac{x_{ig}}{\sum_m y_{im} x_{im}} \right)^{1-\kappa} \pi_{igs} y_{ig}$ and note that

$$\sum_s z_{is} = \sum_g \left(\frac{x_{ig}}{\sum_m y_{im} x_{im}} \right)^{1-\kappa} y_{ig} \leq 1,$$

where the inequality comes from the fact that κ is positive combined with the power mean inequality, which implies that

$$\left(\sum_g y_{ig} x_{ig}^{1-\kappa} \right)^{1/(1-\kappa)} \leq \sum_g y_{ig} x_{ig}.$$

To finish the proof, note that if $\sum_s z_{is} \leq 1$ and $z_{is} > 0$ for all s then we must have

$$\prod_s z_{is}^{\beta_{is}} \leq \prod_s \beta_{is}^{\beta_{is}},$$

with equality only if $z_{is} = \beta_{is}$ for all s. We now show that if $r_{is} \neq \beta_{is}$ for some s then we must have $z_{is} \neq \beta_{is}$ for some s. We do so by contradiction: imagine that $r_{is} \equiv \sum_g \pi_{igs} y_{ig} \neq \beta_{is}$ for some s and that $z_{is} = \beta_{is}$ for all s. Plugging from the definition of x_{ig} into Equation 36 and rearranging we see that $\hat{w}_{is}$ for $s = 1, ..., S$ is determined from the system of equations given by

$$\beta_{is} \sum_g \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} y_{ig} = \sum_g \frac{\hat{w}_{is}^{\kappa}}{\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}} \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} \pi_{igs} y_{ig}$$

for $s = 1, ..., S$. For future purposes, note that $\hat{w}_{is} = 1$ for all s is not a solution given that, by assumption, $\sum_g \pi_{igs} y_{ig} \neq \beta_{is}$ for some s. Solving for β_s from this equation, we see that $z_s = \beta_s$ is equivalent to

$$\sum_g \left(\frac{\left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa}}{\sum_h \left(\sum_k \pi_{ihk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa} y_{ih}} \right)^{1-\kappa} \pi_{igs} y_{ig} = \sum_g \frac{\hat{w}_{is}^{\kappa}}{\sum_k \pi_{igk} \hat{w}_k^{\kappa}} \frac{\left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa}}{\sum_h \left(\sum_k \pi_{ihk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa} y_{ih}} \pi_{igs} y_{ig}.$$

Simplifying, this is equivalent to

$$\sum_g \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} y_{ig} = \hat{w}_{is}.$$

The only solution to this system is $\hat{w}_{is} = 1$ for all s, but we know that this is not possible. This establishes a contradiction and shows that if $\sum_g \pi_{igs} y_{ig} \neq \beta_{is}$ for some s then $z_{is} \neq \beta_{is}$ for some s. This finishes the proof.

B.2 Proof for Bartik approximation

To prove the statement in footnote 12, we aim to show that

$$\sum_s \pi_{igs} \frac{r'_{is}}{r_{is}} = \frac{\sum_s \pi_{igs} \beta_{is} / r_{is}}{\sum_s \pi'_{igs} \beta_{is} / r'_{is}}$$

using

$$\begin{aligned} \pi_{igs} &= L_{igs} w_{is} / Y_{ig}, \\ r_{is} &= \sum_g L_{igs} w_{is} / Y_i. \end{aligned}$$

Since

$$I_{ig} \equiv \sum_s \pi_{igs} \beta_{is} / r_{is}$$

and using hat notation, this can also be written as

$$\sum_s \pi_{igs} \hat{r}_{is} = 1 / \hat{I}_{ig}.$$

Proof: Using the above equations for π_{igs} and r_{is} we see that

$$\sum_s \pi_{igs} \frac{r'_{is}}{r_{is}} = \frac{\sum_s \pi_{igs} \beta_{is} / r_{is}}{\sum_s \pi'_{igs} \beta_{is} / r'_{is}}$$

is equivalent to

$$\sum_s \left(L_{igs}w_{is}/Y_{ig}\right)\frac{\sum_g L_{igs}w'_{is}/Y'_i}{\sum_g L_{igs}w_{is}/Y_i} = \frac{\sum_s \left(L_{igs}w_{is}/Y_{ig}\right)\beta_{is}/\left(\sum_g L_{igs}w_{is}/Y_i\right)}{\sum_s \left(L_{igs}w'_{is}/Y'_{ig}\right)\beta_{is}/\left(\sum_g L_{igs}w'_{is}/Y'_i\right)}$$

But this is equivalent to

$$\sum_s \frac{L_{igs}w_{is}}{Y_{ig}}\frac{w'_{is}\sum_g L_{igs}}{w_{is}\sum_g L_{igs}} = \frac{Y'_{ig}}{Y_{ig}}\frac{\sum_s L_{igs}w_{is}\beta_{is}/w_{is}\sum_g L_{igs}}{\sum_s L_{igs}w'_{is}\beta_{is}/w'_{is}\sum_g L_{igs}}$$

or

$$\sum_s \frac{w'_{is}L_{igs}}{Y_{ig}} = \frac{Y'_{ig}}{Y_{ig}}\frac{\sum_s L_{igs}\beta_{is}/\sum_g L_{igs}}{\sum_s L_{igs}\beta_{is}/\sum_g L_{igs}}$$

or

$$\sum_s \frac{w'_{is}L_{igs}}{Y_{ig}} = \frac{Y'_{ig}}{Y_{ig}}$$

or

$$\sum_s w'_{is}L_{igs} = Y'_{ig}$$

which is true by definition.

Online Appendix C Data description

As in ADH, our group-level labor market data is obtained from the 1990 and 2000 Census and the American Community Survey (ACS).[60] Both datasets are downloaded from IPUMS using standardized variables. Our labor market data for the years 1990 and 2000 is derived from a 5% sample of the respective censuses. For the year 2007, labor market figures are based on ACS data. Group income is defined as the log of average wages at the commuting zone level. Following ADH, we restrict our sample to individuals who were between 16 and 64 years old and who were working in the year preceding the survey. Residents of institutional group quarters are dropped. Labor supply is measured by the product of weeks worked times usual number of hours per week. We also follow ADH and for workers with missing values, we impute the mean of workers in the same education-occupation cell, or, if the education-occupation cell is empty, the mean of

[60] The ACS is designed to be comparable to the Census.

workers in the same education cell and all calculations are weighted by the Census sampling weight multiplied with the labor supply weight. We exclude self-employed workers and individuals with missing wages, weeks or hours. Finally, as in ADH, wages are inflated to the year 2007 using the Personal Consumption Expenditure Index.

Detailed group-sector employment shares at the 3-digit SIC level (required for the China shock instruments) are obtained from the County Business Pattern database.[61]

For robustness tests, we also employ data the NBER-CES Manufacturing Industry Database and EU/KLEMS, etc. for the years 1990, 2000, and 2007 to construct the industry Bartik using payroll, The EU/KLEMS data is used to construct the change in non-manufacturing payroll. For the extension with heterogeneous workers (Section 7.4), we compute all employment and income variables using ACS data. This is necessary because the CBP data does not include worker demographic characteristics necessary to split workers by education, age, gender, etc. We employ ACS data to contruct group-level income and employment variables, with groups now defined by Commuting Zones, age (below and above 50 years), and eductation (no college vs. at least some college, following ADH's definition). The drawback of using ACS data is that the level of industry aggregation employed in our shift-share instruments will be higher (due to data limitations). Instead of having group employment shares in each of th 395 manufacturing industries, we are restricted to group-employment shares in each of our 13 manufacturing subsectors. Thus, in this section our shift-share insruments are given by $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age and education groups. We also employ contemporaneous shares (π_{gst}) instead of lagged shares due to data availability considerations. For the Section 8 extension with employment effects, we again rely on ACS data to obtain group level employment and home production shares. We define home production to include workers not in the labor force (NiLF). The employment share is given by the ratio of the number of employed workers and the number of individuals in the labor force.

[61]The Census and ACS Public Use Microdata Areas (PUMAs) are mapped into commuting zones using a crosswalk provided by David Dorn.

Online Appendix D Supplementary Estimation Results

Table D.1: Within-group Inequality and the China shock

	China Shock measure		
Dependent variable:	Other (lagged)	Other (no lag)	US (no lag)
$\ln \hat{\sigma}_{y_g}$	-0.560	-1.225*	-0.863**
	(0.482)	(0.691)	(0.417)
$\Delta SD(\ln y_g)$	0.293**	0.178	0.0881
	(0.0900)	(0.144)	(0.0948)
$\ln \frac{\hat{p90}}{\hat{p10}}$	0.886**	0.505	0.322
	(0.278)	(0.389)	(0.252)
$\ln \frac{\hat{p75}}{\hat{p25}}$	0.230	0.0262	0.0492
	(0.147)	(0.190)	(0.111)
$\ln \frac{\hat{y}_{gM}}{\hat{y}_{gNM}}$	0.422	0.406	0.324
	(0.297)	(0.416)	(0.272)
Observations	1444	1444	1444

Reduced form analysis of the impact on the China shock on measures of within-group inequality. Each row represents a different measure of within group inequality: log change in group-level standard deviation of weekly earnings, change in the standard deviation of log weekly earnings, log change in the 90/10 ratio in earnings, log change in the 75/25 ratio in earnings, and log change in the ratio of average manufacturing vs. non-manufacturing income (all measures are given in 10-year equivalents). Each column represents three different measures of the China shock. Column 1 reports the OLS point estimate in which lagged imports to other HI countries is used as as instrument, column (2) reports analogous estimates in which the China shock measure is not lagged, column (3) reports coefficients in the case in which US imports is used as an instrument (without any lag). Standard errors (in parentheses) are clustered at the state level, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. All specifications include the same set of controls employed in our baseline κ estimation (Table 1).

Table D.2: Rotemberg Weights (China to Other): Top 5 Industries

Industry	$-\widehat{(1/\kappa)}$	Weights	F-First Stage	Industry Code	Period
Electronic Computers	-1.707	0.246	3.92	3571	2000
Furnitures and Fixtures	-0.319	0.099	24.42	2599	2000
Semiconductors	-1.440	0.085	7.35	3674	2000
Blast Furnaces	0.120	0.049	10.56	3312	2000
Telephones	-0.927	0.0468	3.37	3661	2000

Rotemberg weights calculated for the shiftshare estimation where the "shares" are for the years 1990 and 2000, and the "shifts" are based on Chinese imports by Other countries, using the methodology from Goldsmith-Pinkham et al. (2018). The parameter β captures the second stage coefficient when the industry share is used as an instrument for $\ln \hat{\pi}_{NM}$, while the parameter α corresponds to the Rotemberg weight.

Table D.3: Estimation of κ - Excluding industries (China to Other instrument)

		Industry Excluded				
	Baseline	Electronic Computers	Furnitures and Fixtures	Semiconductors	Blast Furnaces	Telephones
$\ln \hat{\pi}_{NM}$	-0.639**	-0.316	-0.682**	-0.584*	-0.676**	-0.631**
	(0.303)	(0.290)	(0.328)	(0.303)	(0.312)	(0.296)
Implied κ	1.564	3.161	1.467	1.711	1.479	1.584
First Stage Coeff.	0.489	0.680	0.446	0.478	0.475	0.489
First Stage F	24.02	25.70	17.68	22.43	24.59	24.56
Observations	1444	1444	1444	1444	1444	1444
First Stage R^2	0.667	0.684	0.664	0.671	0.665	0.668
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Instrument	IP to Other	IP to Other	IP to Other	IP to Other	IP to Other	IP to Other

IV-estimation results for specification (23), corresponding to results of column 2, Table 1. Standard errors in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Columns (2) through (6) exclude each of the top five industries from the construction of the shiftshare instrument, where the "shifts" are based on Chinese imports by Other countries.

Table D.4: Rotemberg Weights (China to US): Top 5 Industries

Industry	$-\widehat{(1/\kappa)}$	Weights	F-First Stage	Industry Code	Period
Electronic Computers	-1.707	0.297	0.874	3571	2000
Furnitures and Fixtures	-0.319	0.220	14.756	2599	2000
Motor Vehicle Parts	-1.330	0.059	5.001	3714	2000
House Furnishings	-1.052	0.059	4.107	2392	2000
Electronic Components	-0.762	0.049	1.637	3679	2000

Rotemberg weights calculated for the shiftshare estimation where the "shares" are for the years 1990 and 2000, and the "shifts" are based on US imports from China, using the methodology from Goldsmith-Pinkham et al. (2018) . The parameter β captures the second stage coefficient when the industry share is used as an instrument for $\ln \hat{\pi}_{NM}$, while the parameter α corresponds to the Rotemberg weight.

Table D.5: Estimation of κ - Excluding industries (China to US instrument)

		Industry Excluded				
	Baseline	Electronic Computers	Furnitures and Fixtures	Motor Vehicle Parts	House Furnishing	Electronic Components
$\ln \hat{\pi}_{NM}$	-0.704**	-0.352	-0.852**	-0.672**	-0.692**	-0.773**
	(0.295)	(0.344)	(0.360)	(0.312)	(0.311)	(0.313)
Implied κ	1.420	2.844	1.174	1.488	1.445	1.294
First Stage Coeff.	0.287	0.337	0.237	0.270	0.275	0.285
First Stage F	29.52	16.44	17.72	26.97	26.42	27.47
Observations	1444	1444	1444	1444	1444	1444
First Stage R^2	0.662	0.683	0.648	0.665	0.663	0.656
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Instrument	IP to US	IP to US	IP to US	IP to US	IP to US	IP to US

IV-estimation results for specification (23), corresponding to results of column 3, Table 1. Standard errors in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Columns (2) through (6) exclude each of the top five industries from the construction of the shiftshare instrument, where the "shifts" are based on US imports from China.

Table D.6: [BHJ] Industry-level Estimation of κ

	(1)	(2)	(3)	(4)
Panel A: Other (lag)				
$\ln \hat{\pi}_{NM}$	-0.358*	-0.270	0.575	0.750
	(0.209)	(0.295)	(0.803)	(0.979)
	[0.302]	[0.395]	[0.935]	[1.187]
Implied κ	2.791	3.699	-1.739	-1.334
First-stage F-stat.	30.447	26.552	9.158	4.450
Panel B: Other (no lag)				
$\ln \hat{\pi}_{NM}$	-0.639**	-0.639**	-0.366	-0.252
	(0.261)	(0.302)	(0.549)	(0.623)
Implied κ	1.564	1.564	2.732	3.968
First-stage F-stat.	11.913	12.997	11.470	7.144
Panel C: US (no lag)				
$\ln \hat{\pi}_{NM}$	-0.704**	-0.704**	-0.412	0.009
	(0.254)	(0.305)	(0.642)	(0.861)
Implied κ	1.420	1.420	2.430	-108.0
First-stage F-stat.	8.708	9.493	6.058	2.361
Panel D: US Bartik (in level)				
$\ln \hat{\pi}_{NM}$	-0.559*	-0.354	-0.306	-0.748**
	(0.317)	(0.273)	(0.285)	(0.367)
Implied κ	1.788	2.829	3.264	1.337
First-stage F-stat.	41.68	52.17	51.59	19.81
CZ Controls				
ADH	X	X	X	X
Beginning-of-period mfg. share	X			
IV mfg. share		X	X	X
IV mfg. share $\times t$			X	X
Sectoral IV mfg. shares $\times t$				X
Industry Controls				
Period Indicators			X	X
Sector-by-period Indicators				X
Observations	796	794	794	794

*** p<0.01, ** p<0.05, * p<0.1. This table performs industry-level estimation and various specification tests proposed by BHJ (Borusyak et al. 2018) -Table 1. The results in this table correspond to the shift-share IV coefficients from our main estimation model (equation (23), Table 1). Column (1) replicates our main estimation approach (including all the original ADH regressors and beginning-of-period manufacturing shares controls). Column (2) replaces the beginning-of-period manufacturing shares control with manufacturing shares for the time-period that underlies the instrument (we refer to these as "IV mfg. shares"). Column 3 interacts the aforementioned shares with period indicators. Column (4) adds regional shares of 10 manufacturing sub-sectors (based on Acemoglu et al. (2016) definitions), all interacted with period indicators. The last row reflects the number of observations in the equivalent industry-level regressions, with the non-manufacturing industry aggregate included in column 1 (with a shock of zero), but not in columns (2)-(4). Significance stars reflect the standard errors in parentheses, which are clustered at the level of 3-digit SIC codes following the procedure in BHJ. Standard errors in square brackets are obtained from *location-level* regressions and clustered at the industry level using 3-digit SIC codes, following AKM (Adão et al. 2019). We do not obtain AKM standard errors for the China shocks with no lag since our industry-employment share matrix for the year 2000 is not full rank. For "Other (lag)", these shares are lagged by 10 years, whereas for "Other (no lag)" and "US (no lag)", these shares are from the beginning of the period.

Table D.7: [BHJ] Overidentification Tests for κ

	(1)	(2)	(3)
$\ln \hat{\pi}_{NM}$	-0.294	-0.294	-0.266*
	(0.180)	(0.209)	(0.152)
Estimator	2SLS	LIML	GMM
Implied κ	3.397	3.403	3.760
First-stage F-stat.	12.68	12.68	12.68
Hansen J Stat.	6.303	6.296	6.303
Hansen J d.f.	7	7	7
Hansen J p-value	0.505	0.506	0.505
Observations	796	796	796

This table presents overidentified estimates analogous to BHJ (Borusyak et al. 2018) (Table 4), applied to our baseline estimation model (equation (23)). Column 1 reports an overidentified estimate of the coefficient corresponding to column 1 of Table 1 (using the "Other (no lag)" version of our instrument), obtained via a two-stage least squares regression of industry-level average earnings growth residuals on industry-level average manufacturing employment growth residuals, instrumenting by growth of imports (per U.S. worker) in eight non-U.S. countries separately (Australia, Switzerland, Germand, Denmark, Spain, Finland, Japan, New Zealand), controlling for period fixed effects, and weighting by average industry exposure. Column 2 reports the corresponding limited information maximum likelihood estimate, while column 3 reports a two-step optimal GMM estimate. Standard errors, the optimal GMM weight matrix, first-stage F-statistics, and the Hansen χ^2 test of overidentifying restrictions all allow for clustering of shocks at the SIC3 industry group level.

Table D.8: The rise of China and the Bartik measure for import competition

	(1)	(2)	(3)
	$\ln \hat{y}_g$	$\ln \hat{y}_g$	$\ln \hat{y}_g$
$\ln \sum_s \pi_{gs} \hat{r}_s$	1.230*	1.735**	1.845**
	(0.727)	(0.824)	(0.787)
Implied κ	0.810	0.576	0.542
F First Stage	42.66	18.80	16.35
Observations	1444	1444	1444
R^2	0.677	0.664	0.660
Instrument	IP to other (lagged)	IP to other (no lag)	IP to the US

Estimation results when regressing changes in CZs' average income per worker on $\ln \sum_s \pi_{gs} \hat{r}_s$, instrumented by the ADH shock. Labor shares π_{gs} are measured as the share of workers using the CBP data in 1990 and 2000. We aggregate the shares at the 2 digit-ISIC industry level. Column (1) reports the second stage coefficient in which imports to other high income countries and lagged employment shares are used when constructing the instrument, column (2) is analogous to column (1) but does not employ lagged shares. Column (3) reports the second stage coefficient in the case in which US imports is used as an instrument (without lagged employment shares). Standard errors (in parentheses) are clustered at the state level, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. All specifications include the same set of controls employed in our baseline κ estimation (Table 1).

Online Appendix E Supplementary counterfactual results for the baseline model

Table E.1: Welfare effects for separately calibrated China shocks

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.25	0.33	1.43	-2.20	2.46	0.15
1.5	0.22	0.27	1.16	-1.42	1.64	0.15
	(0.02)	*(0.03)*	*(0.25)*	*(0.35)*	*(0.58)*	*(0.01)*
3.0	0.18	0.21	0.74	-0.63	0.84	0.15
$\to \infty$	0.14	0.14	0	0.14	0.14	0.14

Compared to Table 2, here the values for $\hat{T}_{China,s}$ are separately calibrated for each value of κ. The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $(100(\widehat{W}_{US}-1)$, and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g}-1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$\equiv$ $\min_g 100(\widehat{W}_{US,g}-1)$ and Max.$\equiv$ $\max_g 100(\widehat{W}_{US,g}-1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}-1\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta}=1/\hat{\kappa}$, for each statistic when $\kappa=1.5$.

Table E.2: Welfare effects of the China shock for alternative θ_s values

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.18	0.25	1.84	-2.05	1.58	0.07
1.5	0.17	0.24	1.62	-1.81	1.35	0.08
	(0.01)	*(0.02)*	*(0.24)*	*(0.29)*	*(0.25)*	*(0.01)*
3.0	0.15	0.21	1.25	-1.34	1.00	0.10
$\to \infty$	0.17	0.17	0	0.16	0.16	0.16

Compared to Table 2, here the values for the trade elasticities take on the median value of prominent estimates of θ_s in the literature (see Table B.3, column 5 of Bartelme et al. (2019)). The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $(100(\widehat{W}_{US} - 1)$, and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$\equiv$ $\min_g 100(\widehat{W}_{US,g} - 1)$ and Max.$\equiv$ $\max_g 100(\widehat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s} - 1\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, for each statistic when $\kappa = 1.5$.

Table E.3: Gains from trade for alternative θ_s values

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	1.36	1.40	0.97	-7.26	3.47	1.20
1.5	1.31	1.33	0.69	-4.46	2.72	1.20
	(0.05)	*(0.06)*	*(0.27)*	*(2.55)*	*(0.68)*	*(0)*
3.0	1.25	1.27	0.37	-1.64	1.97	1.20
$\to \infty$	1.20	1.20	0.01	1.16	1.21	1.20

Compared to Table 3, here the values for the trade elasticities take on the median value of prominent estimates of θ_s in the literature (see Table B.3, column 5 of Bartelme et al. (2019)). The first column displays the aggregate gains from trade for the US, in percentage terms $(100(1 - \widehat{W}_{US}))$ and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g 1 - \widehat{W}_{US,g})$. Here, $\widehat{W}_{US}$ and $\widehat{W}_{US,g}$ are the aggregate and group-level welfare change from a return to autarky for the US. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$=$ $\min_g 100(1 - \widehat{W}_{US,g})$ and Max.$=\max_g 100(1 - \widehat{W}_{US,g})$, respectively. The final column displays the multi-sector ACR term $100\left(1 - \prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, for each statistic when $\kappa = 1.5$.

Online Appendix F Extension with intermediate goods

F.1 Theory for the extension with intermediates

Here we provide the theoretical background for the extended model in Section 7, and prove Proposition 3.

Recall that the labor supply in this model is exactly as in the baseline model (see equations (3) and (4)), and trade shares and the price indices are given as in equations (1) and (2), except that instead of w_{is} we now have c_{is}, where c_{is} is given by

$$c_{is} = w_{is}^{1-\gamma_{is}} \prod_k P_{ik}^{\gamma_{iks}}, \tag{37}$$

with

$$P_{js} = \zeta_s^{-1} \left(\sum_i T_{is} \left(\tau_{ijs} c_{is}\right)^{-\theta_s} \right)^{-1/\theta_s}. \tag{38}$$

The terms γ_{iks} are Cobb-Douglas input shares: a share γ_{iks} of the output of industry s in country i is used buying inputs from industry k, and $1-\gamma_{is}$ is the share spent on labor, with $\gamma_{is} = \sum_k \gamma_{iks}$.

Combining equations (37) and (38) yields

$$P_{js} = \zeta_s^{-1} \left(\sum_i T_{is} \left(\tau_{ijs} w_{is}^{(1-\gamma_{is})} \prod_k P_{ik}^{\gamma_{iks}} \right)^{-\theta_s} \right)^{-1/\theta_s}.$$

Given wages, this equation represents a system of $N \times S$ equations in P_{js} for all j and s, which can be used to solve for P_{js} and hence c_{is} and λ_{ijs} given wages. This implies that trade shares are an implicit function of wages. Letting X_{js} and R_{js} be total expenditure and total revenues for country j on sector s, then $R_{is} = \sum_{j=1}^{n} \lambda_{ijs} X_{js}$, while Cobb-Douglas preferences and technologies imply that $X_{js} = \beta_{js}(Y_j + D_j) + \sum_{k=1}^{S} \gamma_{jsk} R_{jk}$, where D_j are trade imbalances satisfying $\sum_j D_j = 0$. These equations constitute a system of linear equations that we can use to solve for revenues given income levels and trade shares,

$$R_{is} = \sum_j \lambda_{ijs} \left(\beta_{js} Y_j (1 + d_j) + \sum_{k=1}^{S} \alpha_{jsk} R_{jk} \right),$$

where $d_j \equiv D_j/Y_j$. Since trade shares and income levels themselves are a function of wages, this implies that revenues are a function of wages. The excess demand for efficiency units in sector s of country i is now

$$ELD_{is} \equiv \frac{(1-\gamma_{is})}{w_{is}} R_{is} - \sum_{g \in G_i} E_{igs}.$$

As in the baseline model, the system $ELD_{is} = 0$ for all i and s is a system of equations that we can use to solve for wages. In turn, given wages we can solve for all the other variables of the model.

The next step is to write the hat algebra system. From $ELD'_{is} = 0$ we get

$$\sum_{g \in G_i} \hat{\pi}_{igs} \hat{\Phi}_{ig} \pi_{igs} Y_{ig} = (1-\gamma_{is}) \sum_{j=1}^{n} \lambda_{ijs} \hat{\lambda}_{ijs} \left(\beta_{js} \left(\sum_{g \in G_j} \hat{\Phi}_{jg} Y_{jg} (1 + \hat{d}_j d_j) \right) + \sum_{k=1}^{S} \gamma_{jsk} \hat{R}_{jk} R_{jk} \right),$$

where $\hat{\Phi}_{ig}$ is as in (8) and

$$\hat{\lambda}_{ijs} = \frac{\hat{T}_{is} \left(\hat{\tau}_{ijs} \hat{w}_{is}^{1-\gamma_{is}} \prod_k \hat{P}_{ik}^{\gamma_{iks}} \right)^{-\theta_s}}{\hat{P}_{js}^{-\theta_s}},$$

$$\hat{P}_{js}^{-\theta_s} = \sum_i \lambda_{ijs} \hat{T}_{is} \left(\hat{\tau}_{ijs} \hat{w}_{is}^{(1-\gamma_{is})} \prod_k \hat{P}_{ik}^{\gamma_{iks}} \right)^{-\theta_s},$$

and

$$\hat{R}_{is} R_{is} = \sum_j \lambda_{ijs} \hat{\lambda}_{ijs} \left(\beta_{js} \left(\sum_{g \in G_j} \hat{\Phi}_{jg} Y_{jg} (1 + \hat{d}_j d_j) \right) + \sum_{k=1}^{S} \gamma_{jsk} \hat{R}_{jk} R_{jk} \right).$$

For welfare analysis, it is useful to fully solve for $\{P_{js}\}$ in terms of trade shares. We start with $\lambda_{jjs} = T_{js} c_{js}^{-\theta_s} / (\zeta_s P_{js})^{-\theta_s}$, which implies that

$$\ln P_{is} = \ln \left(\zeta_s^{-1} \left(T_{is}/\lambda_{iis} \right)^{-1/\theta_s} w_{is}^{1-\gamma_{i,s}} \right) + \sum_k \gamma_{iks} \ln P_{ik}.$$

Letting $\Upsilon_i \equiv \{\gamma_{iks}\}_{k,s=1,\ldots,S}$ (an $S \times S$ matrix), $B_i \equiv \left\{ \ln \left(\zeta_s^{-1} \left(T_{is}/\lambda_{iis} \right)^{-1/\theta_s} w_{is}^{1-\gamma_{is}} \right) \right\}_{s=1,\ldots,S}$

(an $S \times 1$ matrix) and $X_i \equiv \{\ln P_{is}\}_{s=1,\ldots,S}$ (an $S \times 1$ matrix), then we have

$$X_i = \left(I - \Upsilon_i^T\right)^{-1} B_i,$$

where I is the $S \times S$ identity matrix. Letting $\widetilde{a}_{isk}$ be the typical element of $\left(I - \Upsilon_i^T\right)^{-1}$, then we see that

$$P_{is} = \prod_k \left(\zeta_s^{-1} \left(T_{ik}/\lambda_{iik}\right)^{-1/\theta_s} w_{ik}^{1-\gamma_{ik}}\right)^{\widetilde{a}_{isk}}.$$

This implies that welfare changes for group ig are given by

$$\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{\hat{\Phi}_{ig}^{1/\kappa_{ig}}}{\prod_{s,k}\left(\hat{\lambda}_{iik}^{1/\theta_s} \hat{w}_{ik}^{1-\gamma_{ik}}\right)^{\beta_{is}\widetilde{a}_{isk}}}.$$

In general, we can check that $\sum_k \left(1 - \gamma_{i,k}\right) \widetilde{a}_{i,sk} = 1$, and hence $\sum_{s,k} \left(1 - \gamma_{i,k}\right) \beta_{is}\widetilde{a}_{i,sk} = 1$, so we can rewrite the above result as

$$\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{1}{\prod_{s,k}\left(\hat{\lambda}_{iik}^{1/\theta_s} \hat{\Phi}_{ig}^{-(1-\gamma_{ik})/\kappa_{ig}} \hat{w}_{ik}^{1-\gamma_{ik}}\right)^{\beta_{is}\widetilde{a}_{isk}}}$$

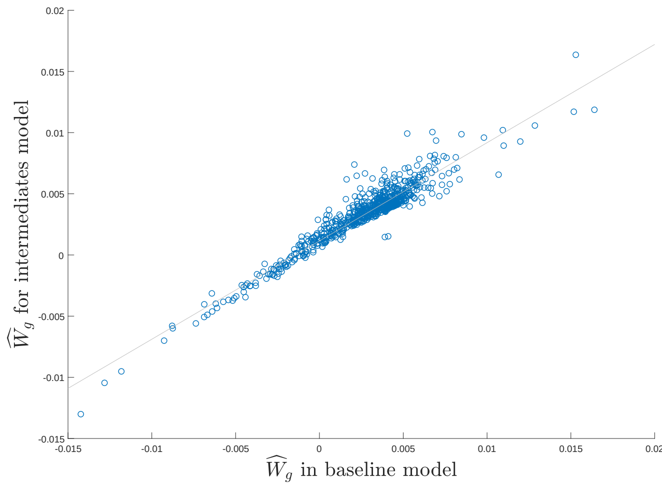
But then, using $\hat{w}_{is}\hat{\Phi}_{ig}^{-1/\kappa_{ig}} = \hat{\pi}_{igs}^{1/\kappa_{ig}}$, we get

$$\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{1}{\prod_{s,k}\left(\hat{\lambda}_{iik}^{1/\theta_s} \hat{\pi}_{igk}^{(1-\gamma_{ik})/\kappa_{ig}}\right)^{\beta_{is}\widetilde{a}_{isk}}}.$$

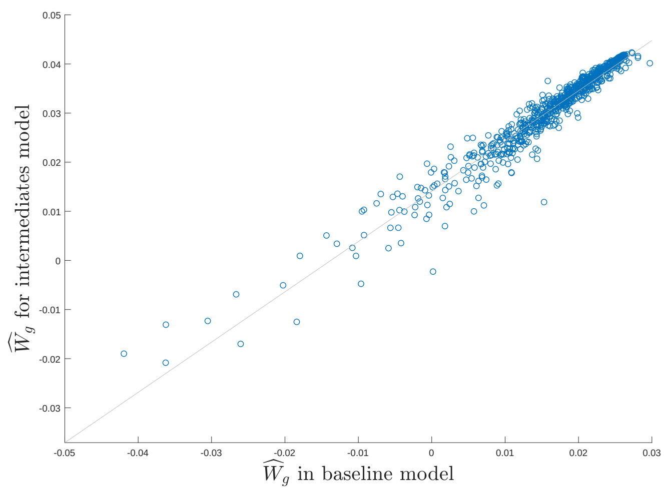
This establishes the result in Proposition 3.

F.2 Counterfactual results for the extension with intermediates

Figure F.1: Comparison of the baseline model and the model with intermediate goods



(a) The rise of China



(b) Gains from trade

This figure compares the welfare changes for the two models, showing $\widehat{W}_g - 1$ for the rise of China, and $1 - \widehat{W}_g$ for the return to autarky, each time for $\kappa = 1.5$.

Table F.1: Counterfactual analysis for the model with intermediates

(a) The rise of China

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.39	0.47	0.71	-1.43	1.73	0.28
1.5	0.37	0.43	0.58	-1.07	1.27	0.29
	(0.02)	*(0.03)*	*(0.14)*	*(0.39)*	*(0.41)*	*(0.01)*
3.0	0.35	0.39	0.37	-0.53	0.83	0.31
$\to \infty$	0.34	0.34	0	0.34	0.34	0.34

(b) Gains from trade

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	2.91	3.06	0.37	-3.36	4.71	2.74
1.5	2.86	2.95	0.26	-1.34	4.06	2.74
	(0.05)	*(0.09)*	*(0.11)*	*(1.84)*	*(0.59)*	*(0)*
3.0	2.80	2.85	0.14	0.69	3.40	2.74
$\to \infty$	2.74	2.74	0	2.74	2.74	2.74

The tables show summary statistics for welfare effects of US groups for the model with an input-output structure. Panel (a) shows results for the counterfactual rise of China, where the values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$, under the model with intermediates. Panel (b) shows results for group-level gains from trade. The first column displays the aggregate welfare effect for the US, in percentage terms $100(\widehat{W}_{US} - 1)$ and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$=$ $\min_g 100(\widehat{W}_{US,g} - 1)$ and Max.=$\max_g 100(\widehat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_{s,k} \hat{\lambda}_{US,US,k}^{-\beta_{US,s}\widetilde{a}_{US,sk}/\theta_s} - 1\right)$. For the gains from trade we simulate the return to autarky and report the negative of the above statistics for the obtained counterfactual results. The third row has standard errors, computed using the delta method, in parentheses.

Online Appendix G Costly trade within the United States

Here we allow for trade costs between U.S. states (in addition to trade costs across countries), while retaining the assumption of frictionless trade across groups within states. Conceptually, the model is identical to the baseline from Section 2, except that U.S. states now play a role identical to the role of countries in the baseline model. In particular, if group ig belongs to state n then

$$\hat{W}_{ig} = \prod_s \hat{\lambda}_{nns}^{-\beta_{ns}/\theta_s} \cdot \prod_s \hat{\pi}_{igs}^{-\beta_{ns}/\kappa_{ig}}. \tag{39}$$

We use this framework to analyze how the quantitative results change when we allow for within-US trade costs. We borrow the necessary data from Rodríguez-Clare et al. (2019), who construct a dataset using data from the Import and Export Merchandise Trade Statistics (from the U.S. Census Bureau), the Commodity Flow Survey and the Regional Economic Accounts of BEA Commodity Flow Service.

Incorporating trade costs across states requires a slight modification in our approach to estimating κ. Treating each U.S. state as a separate country requires Equation 23 to incorporate state-specific intercepts. In practice, this can be achieved by estimating equation 23 and adding state-fixed effects to the list of regressors. We present the resulting κ estimates in Table G.1 below.[62] The updated results are broadly consistent with those in the baseline (Table 1).

The welfare effects of overall trade and the rise of China in this updated model differ only modestly from those in the baseline. The average welfare gains in the updated model are somewhat smaller (see Table G.2).[63] Focussing on the case with $\kappa = 1.5$, the rise of China leads to a mean welfare change of 0.2% in the updated model, slightly lower than the 0.27% in the baseline model. Turning to the distributional implications, and again focusing on $\kappa = 1.5$, the range and CV of the welfare effects is [-1.33,1.90]

[62] Specifically, each regression includes states fixed effects in lieu of Census division fixed effects, which were part of the original set of ADH regressors. Note also that our revised specification includes state and time fixed effects separately. This allows non-manufacturing wages to vary across states and time periods, but restricts wage differences across states to remain constant over time. If instead we use joint state by time fixed effects, the estimation becomes less precise, or has a weak first stage. However, its coefficient estimates are typically not significantly different from our preferred specification.

[63] The gains from trade are computed as the negative of the percentage change in welfare from a counterfactual move to autarky by the whole United States but allowing US states to trade among themselves.

Table G.1: Estimation of κ - Costly trade across states

	(1)	(2)	(3)	(4)
$\ln \hat{\pi}_{NM}$	-0.457**	-0.747**	-1.010**	-0.598**
	(0.229)	(0.358)	(0.347)	(0.199)
Implied κ	2.190	1.338	0.990	1.673
F-First Stage	39.60	14.85	15.09	68.29
Coef.-First Stage	0.548	0.437	0.234	-0.584
Observations	1444	1444	1444	1444
Import Penetration	Other (lagged)	Other (no lag)	US (no lag)	ln US Bartik

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing, measured using the CBP data. The columns differ in the construction of the instrument: column (1) uses the exact instrument borrowed from ADH $Z_{gt} \equiv \sum_{s \in M} \pi_{gst-10} \Delta IP_{st}^{China \to Other}$, column (2) uses $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, column (3) uses $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to US}$, and column (4) uses our Bartik variable for the US: $Z_{gt} \equiv \ln \sum_s \pi_{gst} \hat{r}_{st}$. Due to data constraints on π_{gst-10}, we have not constructed $Z_{gt} \equiv \sum_{s \in M} \pi_{gst-10} \Delta IP_{st}^{China \to US}$. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fourth row displays the F-statistic from the first stage. All regressions include the same controls employed in ADH's preferred specification and in Table 1. The only difference is that we include fixed effects for U.S. states instead of Census division fixed effects.

and 1.57 in the updated model, reflecting slightly more positive effects for some groups than under the baseline model, where the respective results are [-1.42,1.64] and 1.4. Note also that since the US is now split into multiple countries, the CV of the welfare effects across all US groups no longer tends to 0 as $\kappa \to \infty$. Similarly, the distribution of the gains from trade has also widened in the model with states as countries. For $\kappa = 1.5$, the CV is now 0.85 and the range of group-level gains from trade is [-6.42, 9.53], compared to a CV of 0.58 and a range of [-4.19, 2.97] in the baseline model.

Table G.2: Counterfactual analysis when within-US trade is costly

(a) The rise of China

κ	Mean	CV	Min.	Max.
$\to 1$	0.22	1.80	-1.66	2.50
1.5	0.20	1.57	-1.33	1.90
	(0.02)	*(0.24)*	*(0.37)*	*(0.57)*
3.0	0.18	1.25	-0.80	1.23
$\to \infty$	0.16	0.89	-0.15	0.71

(b) Gains from trade

κ	Mean	CV	Min.	Max.
$\to 1$	1.52	0.98	-7.34	7.48
1.5	1.50	0.79	-5.22	7.32
1.5	*(0.02)*	*(0.17)*	*(2.15)*	*(0.23)*
3.0	1.48	0.61	-2.29	6.87
$\to \infty$	1.45	0.50	0.65	5.78

The tables show summary statistics for welfare effects of US groups for the model where US states are treated as individual countries. Panel (a) shows results for the counterfactual rise of China, where the values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$. Panel (b) shows results for group-level gains from trade. The first column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{ng} - 1)$ for all groups in the US. The second column shows the coefficient of variation (CV), and for the third and fourth column we have Min.$\equiv \min_g 100(\widehat{W}_{US,g} - 1)$ and Max.$\equiv \max_g 100(\widehat{W}_{US,g} - 1)$, respectively. For the gains from trade, we simulate the return to autarky and for that simulation report the negative of the above statistics. Standard errors for the benchmark results in the second row, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses. We are unable to calculate welfare changes across all states and groups in the US without knowledge of the initial value of P_n for each state.

Online Appendix H Additional results for the extension with imperfect substitutes

Table H.1: The rise of China for college and non-college workers as imperfect substitutes.

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	ACR	Roy gains	$\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$
				Non-College Workers				
$\rightarrow 1$	0.24	0.32	0.99	-1.06	1.48	0.14	0.10	0.00
1.5	0.23	0.30	0.75	-0.57	1.05	0.15	0.08	0.00
	(0.29)	*(2.04)*	*(24.47)*	*(29.95)*	*(36.05)*	*(0.83)*	*(1.93)*	*(0.85)*
3.0	0.24	0.28	0.44	-0.29	0.66	0.16	0.05	0.02
$\rightarrow \infty$	0.27	0.27	0.00	0.27	0.27	0.20	0.00	0.07
				College Workers				
$\rightarrow 1$	0.23	0.40	1.00	-1.63	2.35	0.14	0.09	0.00
1.5	0.19	0.33	0.85	-1.37	1.60	0.15	0.04	-0.01
	(0.04)	*(0.07)*	*(0.14)*	*(0.31)*	*(0.67)*	*(0.01)*	*(0.04)*	*(0.01)*
3.0	0.14	0.24	0.66	-0.90	0.87	0.16	0.01	-0.03
$\rightarrow \infty$	0.09	0.09	0.00	0.09	0.10	0.20	0.00	-0.10

Results for the rise of China for the model in Section 7.4, where college and non-college workers are imperfect substitutes. The first column displays the aggregate welfare effect of the China shock for the US for education type m, in percentage terms $100(\widehat{W}_{US,m} - 1)$, and the second column shows the mean welfare effect for that education type: $100(\frac{1}{G_{US,m}} \sum_g \widehat{W}_{US,mg} - 1)$. The third column shows the coefficient of variation, and for the fourth and fifth column we have Min.$\equiv$ $\min_g 100(\widehat{W}_{US,mg} - 1)$ and Max.$\equiv$ $\max_g 100(\widehat{W}_{US,mg} - 1)$, respectively. The sixth column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s} - 1\right)$, the seventh column the aggregate Roy term for education type m, $100(\sum_{g\in G_m}\left(\frac{Y_{img}}{Y_{im}}\right)\prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa} - 1)$, and the eight column $100(\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)} - 1$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$. Standard errors for the benchmark results in the second row, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses.

Table H.2: Gains from trade for college and non-college workers as imperfect substitutes.

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	ACR	Roy gains	$\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$
				Non-College workers				
$\to 1$	1.41	1.52	0.81	-7.23	3.03	1.45	-0.03	0.00
1.5	1.39	1.46	0.57	-4.38	2.47	1.45	-0.02	-0.04
	(0.03)	*(0.06)*	*(0.23)*	*(2.59)*	*(0.51)*	*(0)*	*(0.01)*	*(0.04)*
3.0	1.36	1.39	0.30	-1.53	1.90	1.45	-0.01	-0.08
$\to \infty$	1.33	1.33	0.00	1.33	1.33	1.45	0.00	-0.12
				College workers				
$\to 1$	1.89	1.96	0.40	-4.18	2.96	1.45	0.45	0.00
1.5	1.80	1.85	0.29	-2.24	2.53	1.45	0.30	0.06
	(0.08)	*(0.1)*	*(0.11)*	*(1.77)*	*(0.4)*	*(0)*	*(0.13)*	*(0.05)*
3.0	1.72	1.74	0.15	-0.29	2.09	1.45	0.15	0.12
$\to \infty$	1.63	1.63	0.00	1.63	1.63	1.45	0.00	0.18

Results for the gains from trade for the model in Section 7.4, where college and non-college workers are imperfect substitutes. The first column displays the aggregate welfare effect of the China shock for the US for education type m, in percentage terms $100(1-\widehat{W}_{US,m})$, and the second column shows the mean welfare effect for that education type: $100(1-\frac{1}{G_{US,m}}\sum_g \widehat{W}_{US,mg})$. The third column shows the coefficient of variation, and for the fourth and fifth column we have Min.$\equiv \min_g 100(1-\widehat{W}_{US,mg})$ and Max.$\equiv \max_g 100(1-\widehat{W}_{US,mg})$, respectively. The sixth column displays the multi-sector ACR term $100\left(1-\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}\right)$, the seventh column the aggregate Roy term for education type m, $100(\sum_{g\in G_m}\left(1-\frac{Y_{img}}{Y_{im}}\right)\prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa})$, and the eight column $100(1-\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$. Standard errors for the benchmark results in the second row, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses.

Online Appendix I Heterogeneity within commuting zones

I.1 Heterogeneity by age and education

As mentioned in Section 7.4, we can easily extend the baseline model to allow for heterogeneous effects of trade shocks by age and education level. To this end, we simply split each commuting zone by worker type, where the four types are defined by workers' age (younger versus older than 50 years) and level of education (non-college versus college educated[64]), so that now we have 2888 groups. The model remains exactly as in the baseline, but each worker type m now has a potentially different value for κ_m.

The point estimates for κ_m are relatively similar across worker types and reasonably close to our baseline value of 1.5 (see Table I.3). They vary from 1.03 for young college educated workers, to 1.7 for old college educated workers, and among the non-college educated, the estimates are 1.29 and 1.5 for young and old workers respectively.

When we simulate the welfare impact of the China shock, we find only modest differences across worker groups (see Table I.4, Panel a).[65] Old college workers experience the highest average gains, while old non-college workers the lowest, at 0.25% and 0.18% respectively. These differences persist when we impose an identical κ for all types, so the variation in κ_m is not driving these differences. Notably, the type with the lowest gains – old non-college workers – have the highest average employment shares in the three sectors that contract the most, namely electrical and optical equipment, textiles and "manufacturing NEC & Recycling." In contrast, old college workers have higher employment shares in the sectors that expand the most, namely the chemicals industry and the coke, petroleum and nuclear fuel industry. For the overall gains from trade, Panel (b) shows that college workers (young or old) have higher gains than non-college workers, which is mainly driven by their higher average employment shares in the non-manufacturing sector (78% versus 72%). This non-manufacturing sector is one of the few net exporting sectors, which therefore expands when the economy opens up to trade.

A simple variance decomposition shows that 84.5 percent of the variance in wel-

[64] Following ADH, we include workers with at least one year of college in the college educated group.

[65] In this and all other simulations of the China shock, we recalibrate the shock following the same procedure as that in Section 5.1.

Table I.3: Estimates for κ_m by age and education level

	(1)	(2)	(3)	(4)
$\ln \hat{\pi}_{NM}$	-0.774***	-0.975**	-0.667**	-0.587
	(0.219)	(0.385)	(0.324)	(0.390)
Implied κ	1.292	1.026	1.499	1.703
First Stage Coeff.	2.657	1.732	1.988	1.622
First Stage F	98.46	79.93	63.49	32.88
College educated	No	Yes	No	Yes
Age 50 or older	No	No	Yes	Yes
Observations	1444	1444	1444	1444

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing for group g. Groups are now defined by commuting zones and worker type m (non-college vs. college, and below age 50 vs. age 50 and above). We estimate the model separately for each worker type τ: column (1) presents estimates for young non-college workers, column (2) for young college workers, while columns (3) and (4) present results for older non-college and college workers, respectively. The shift-share insruments are constructed using contemporaneous group-specific employment shares at the 13-sector level obtained from ACS data (this is the only available level of disaggregation available that contains worker demographic data). Our instruments are $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age and education groups. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fourth row displays the F-statistic from the first stage. All regressions include the same controls employed in ADH's preferred specification: lagged manufacturing shares, period fixed effects, Census division fixed effects, and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

fare changes across groups is explained by the commuting zone to which they belong, while their type explains only 1.4 percent of the overall variance.[66] This implies that the baseline model already captures most of the action regarding the distributional welfare effects of the China shock.

[66] We run the regression $\ln \hat{y}_g = \delta_m + \delta_{CZ} + \epsilon_g$, where δ_m and δ_{CZ} are fixed effects for worker type and CZ, respectively, and then use $\frac{cov(\ln \hat{y}_g, \delta_{CZ})}{var(\ln \hat{y}_g)}$ as the share of the variance explained by the commuting zone, and similarly for the share of the variance explained by the group's type.

Table I.4: Heterogeneity in Welfare Effects by Age and Education

	The rise of China			Gains from trade		
	$\widehat{W}_{US,m}$	Mean	CV	$\widehat{W}_{US,m}$	Mean	CV
All	0.22	0.34	0.87	1.58	1.56	0.66
	(0.002)	*(0.008)*	*(0.06)*	*(0.025)*	*(0.033)*	*(0.12)*
Young, Non-college	0.25	0.32	0.79	1.27	1.32	0.88
	(0.005)	*(0.008)*	*(0.056)*	*(0.059)*	*(0.048)*	*(0.218)*
Old, Non-college	0.20	0.29	1.05	0.99	1.24	1.05
	(0.013)	*(0.011)*	*(0.101)*	*(0.136)*	*(0.1)*	*(0.273)*
Young, College	0.20	0.35	0.79	1.85	1.88	0.32
	(0.005)	*(0.011)*	*(0.048)*	*(0.076)*	*(0.086)*	*(0.054)*
Old, College	0.24	0.38	0.83	1.64	1.80	0.39
	(0.015)	*(0.013)*	*(0.069)*	*(0.088)*	*(0.118)*	*(0.073)*

The first three columns display the welfare effects for the counterfactual rise of China, while the final three columns show the gains from trade. Columns 1 and 4 displays, for the relevant worker type, the aggregate welfare effect for that worker type in the US, in percentage terms $100(\widehat{W}_{US,m} - 1)$, and columns 2 and 5 show the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,mg} - 1)$. The third column shows the coefficient of variation (CV). For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of all the above statistics. Standard errors, computed using the delta method and numerical derivatives for each of the statistics, in parentheses.

I.2 Heterogeneity by gender and education

We have also considered the case with worker types defined by gender and education level. The main difference is that the female non-college workers have an estimated $\kappa_m = 2.5$, whereas it is close to 1.2 for the other worker types (See Table I.5). These female non-college workers gain the least from the China shock, and this is true both with the estimated κ_m for each group and setting $\kappa_m = 1.5$ for all groups. Appendix Table I.6 has the full results. As in the case with groups defined by age and education, when we define groups by gender and education most of the variance in the welfare changes comes from commuting zone fixed effects, which explain 72.0% of the variance, while worker-type fixed effects explain only 9.1% of the variance.

Table I.5: Estimates for κ_m by gender and education level

	(1)	(2)	(3)	(4)
$\ln \hat{\pi}_{NM}$	-0.407*	-0.870	-0.804**	-0.850**
	(0.226)	(0.616)	(0.280)	(0.359)
Implied κ	2.455	1.149	1.243	1.177
First Stage Coeff.	3.035	1.542	2.252	1.574
First Stage F	140.1	113.7	77.73	43.17
College educated	No	Yes	No	Yes
Male	No	No	Yes	Yes
Observations	1444	1444	1444	1444

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing for group g. Groups are now defined by commuting zones and worker type m (non-college vs. college, and below male vs. female). We estimate the model separately for each worker type τ: column (1) presents estimates for female non-college workers, column (2) for female college workers, while columns (3) and (4) present results for male non-college and college workers, respectively. The shift-share insruments are constructed using contemporaneous group-specific employment shares at the 13-sector level obtained from ACS data (this is the only available level of disaggregation available that contains worker demographic data). Our instruments are $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age and education groups. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fourth row displays the F-statistic from the first stage. All regressions include the same controls employed in ADH's preferred specification: lagged manufacturing shares, period fixed effects, Census division fixed effects, and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

Table I.6: Heterogeneity in Welfare Effects by Gender and Education

	The rise of China			Gains from trade		
	$\widehat{W}_{US,m}$	Mean	CV	$\widehat{W}_{US,m}$	Mean	CV
All	0.22	0.31	0.87	1.56	1.58	0.62
	(0.002)	*(0.01)*	*(0.072)*	*(0.028)*	*(0.033)*	*(0.147)*
Female, Non-college	0.12	0.18	1.56	1.08	1.12	1.27
	(0.022)	*(0.016)*	*(0.336)*	*(0.085)*	*(0.076)*	*(0.402)*
Male, Non-college	0.31	0.39	0.61	1.33	1.43	0.60
	(0.009)	*(0.016)*	*(0.04)*	*(0.041)*	*(0.014)*	*(0.175)*
Female, College	0.28	0.35	0.52	2.05	2.06	0.22
	(0.013)	*(0.019)*	*(0.034)*	*(0.141)*	*(0.145)*	*(0.054)*
Male, College	0.15	0.34	0.95	1.64	1.69	0.35
	(0.013)	*(0.011)*	*(0.076)*	*(0.052)*	*(0.066)*	*(0.077)*

The first three columns display the welfare effects for the counterfactual rise of China, while the final three columns show the gains from trade. Columns 1 and 4 displays, for the relevant worker type, the aggregate welfare effect for that worker type in the US, in percentage terms $100(\widehat{W}_{US,m} - 1)$, and columns 2 and 5 show the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,mg} - 1)$. The third column shows the coefficient of variation (CV). For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of all the above statistics. Standard errors, computed using the delta method and numerical derivatives for each of the statistics, in parentheses.

Online Appendix J Model with voluntary and involuntary unemployment

J.1 Equilibrium system for model with employment effects

For the model in Section 8, the equilibrium system to solve for wages $\{w_{is}\}$ is still given by Equation (6):

$$ELD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ijs} \beta_{js} X_j - \sum_{g \in G_i} \mathcal{Z}_{igs}.$$

The difference is that now we have $\mathcal{Z}_{igs} = \frac{\pi_{igs} \pi_{igF} W_{ig} L_{ig}}{\nu \omega_{is}}$, where $\omega_{is} = w_{is}/P_i$ is the real wage,

$$\pi_{igs} = \frac{A_{igs} \omega_{is}^{\kappa}}{\sum_{k \in F} A_{igk} \omega_{ik}^{\kappa}},$$

and π_{igF} and W_{ig} are given by Equations (28) and (29) respectively , where the latter depends on the employment rate e_{ig}, given by Equation (30).

J.2 Additional counterfactual results for the model with unemployment

Table J.7: Impact of the rise of China with voluntary and involuntary unemployment

(a) Changes in real income

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.23	0.29	1.37	-1.87	2.37	0.14
1.5	0.21	0.26	1.15	-1.54	1.72	0.15
3.0	0.20	0.23	0.81	-0.98	1.03	0.16
$\kappa \to \infty$	0.20	0.20	0.11	0.11	0.25	0.20

(b) Changes in home production share

κ	$\widehat{\pi}_{US,HP}$	Mean	CV	Min.	Max.
$\to 1$	-0.56	-0.72	-1.38	-5.70	4.82
1.5	-0.54	-0.65	-1.16	-4.18	3.96
3.0	-0.52	-0.58	-0.81	-2.54	2.49
$\kappa \to \infty$	-0.49	-0.49	-0.11	-0.61	-0.27

(c) Changes in employment rate

κ	$\widehat{e}_{US}$	Mean	CV	Min.	Max.
$\to 1$	0.08	0.10	1.37	-0.63	0.79
1.5	0.08	0.09	1.15	-0.52	0.57
3.0	0.07	0.08	0.81	-0.33	0.34
$\kappa \to \infty$	0.07	0.07	0.11	0.04	0.08

The tables show summary statistics for the effect of the China shock for the model with frictional unemployment and home production, with $\mu = 2.5$. Panel (a) documents the aggregate real income gains for the US as $100(\widehat{W}_{US}-1)$ (column 1) and the mean gains as $100\frac{1}{G}(\sum_g \widehat{W}_{US,g}-1)$ (column 2). Panel (b) shows the aggregate and mean change in π_{gHP} as $100(\widehat{\pi}_{US,HP}-1)$ (column 1) and $100\frac{1}{G}(\sum_g \widehat{\pi}_{USg,HP}-1)$ (column 2). Finally, Panel (c) shows the change in the employment rate $100(\widehat{e}_{US}-1)$ (column 1) and $100(\widehat{e}_{USg,HP}-1)$. In each panel, the third column shows the coefficient of variation (CV), and the fourth and fifth column show the minimum and maximum change Min.$\equiv \min_g 100(\widehat{x}_{US,g}-1)$ and Max.$\equiv \max_g 100(\widehat{x}_{US,g}-1)$, where x is the relevant variable for that panel. The final column in Panel (a) shows the aggregate ACR gains for the US, in percentage terms.

Table J.8: Impact of trade with home production and frictional unemployment

(a) Real income gains from trade

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	1.57	1.61	0.80	-6.28	3.91	1.45
1.5	1.52	1.54	0.58	-3.77	3.15	1.45
3.0	1.47	1.48	0.33	-1.23	2.36	1.45
$\to \infty$	1.42	1.41	0.11	0.78	1.76	1.45

(b) Changes in home production share

κ	$\widehat{\pi}_{US,HP}$	Mean	CV	Min.	Max.
$\to 1$	-3.16	-4.20	-0.77	-10.50	14.11
1.5	-3.28	-4.00	-0.57	-8.32	8.83
3.0	-3.43	-3.81	-0.33	-6.16	3.02
$\to \infty$	-3.60	-3.62	-0.11	-4.54	-1.98

(c) Changes in employment rate

κ	$\widehat{e}_{US}$	Mean	CV	Min.	Max.
$\to 1$	0.43	0.54	0.79	-2.05	1.32
1.5	0.44	0.52	0.57	-1.24	1.06
3.0	0.46	0.50	0.33	-0.41	0.79
$\to \infty$	0.48	0.47	0.11	0.26	0.59

The tables show summary statistics for opening up to trade for the model with frictional unemployment and home production, based on a simulation of the return to autarky. Panel (a) documents the aggregate gains from trade for the US as $100(1-\widehat{W}_{US})$ (column 1) and the mean gains as $100\frac{1}{G}(\sum_g 1-\widehat{W}_{US,g})$ (column 2). Panel (b) shows the aggregate and mean change in π_{gHP} as $100(1-\widehat{\pi}_{US,HP})$ (column 1) and $100\frac{1}{G}(\sum_g 1-\widehat{\pi}_{USg,HP})$ (column 2). Finally, Panel (c) shows the change in the employment rate $100(1-\widehat{e}_{US})$ (column 1) and $100(1-\widehat{e}_{USg,HP})$. In each panel, the third column shows the coefficient of variation (CV), and the fourth and fifth column show the minimum and maximum change Min.$\equiv \min_g 100(1-\widehat{x}_{US,g})$ and Max.$\equiv \max_g 100(1-\widehat{x}_{US,g})$, where x is the relevant variable for that panel. The final column in Panel (a) shows the aggregate ACR gains for the US, in percentage terms.

Table J.9: Standard errors for results with home production and unemployment

(a) The rise of China

	Aggregate	Mean	CV	Min.	Max.
$\widehat{W}_g$	0.27	0.33	1.26	-2.08	2.42
	(0.03)	*(0.03)*	*(0.17)*	*(0.25)*	*(0.47)*
$\widehat{\pi}_{gHP}$	-0.72	-0.90	-1.28	-6.38	5.99
	(0.19)	*(0.27)*	*(0.17)*	*(2.51)*	*(2.15)*
$\widehat{e}_g$	0.14	0.17	1.26	-1.05	1.20
	(0.04)	*(0.05)*	*(0.17)*	*(0.28)*	*(0.31)*

(b) Gains from trade

	Aggregate	Mean	CV	Min.	Max.
$\widehat{W}_g$	1.84	1.87	0.68	-5.90	4.23
	(0.19)	*(0.18)*	*(0.17)*	*(1.99)*	*(0.57)*
$\widehat{\pi}_{gHP}$	-4.29	-5.45	-0.67	-12.69	14.65
	(1.17)	*(1.52)*	*(0.15)*	*(5.03)*	*(7.81)*
$\widehat{e}_g$	0.78	0.94	0.68	-2.91	2.14
	(0.24)	*(0.28)*	*(0.17)*	*(0.91)*	*(0.55)*

The tables show summary statistics for the variables listed in the first column for US groups for the model with home production and frictional unemployment. Panel (a) shows results for the counterfactual rise of China, and Panel (b) shows results for opening up to trade, starting from autarky. The first column of results shows the aggregate effect, and the second column the average effect. The third column displays the coefficient of variation (CV), and for the fourth and fifth column we show the minimum and maximum change. All results are in terms of percentage changes. Standard errors are computed using the delta method and shown in parentheses. Throughout, we use the estimation results specification 4 from Table 6, where $\alpha = 0.499$, $\mu = 2.762$ and $\kappa = 1.199$, since these coefficients are the most precisely estimated. We use the variance-covariance matrix obtained for this specification when computing the standard errors using the delta method.

Online Appendix K Mobility across Groups

Here we consider an extension of the benchmark model where workers can move across regions but not across countries. Assume that each worker gets a draw in each sector and each region. Workers also have an "origin region." We say that a worker with origin region g is "from region g." Each worker gets a draw z in each region-sector combination (h, s) from a Fréchet distribution with parameters κ and A_{ihs}. Workers are fully described by a matrix $\boldsymbol{z} = \{z_{hs}\}$ and an origin region g. A worker from region g in country i that wants to work in region h of country i suffers a proportional adjustment to income determined by ξ_{igh}, with $\xi_{igg} = 1$ and $\xi_{igh} \leq 1$ for all i, g, h. Thus, a worker from g that works in region h in sector s has income of $w_{is}\xi_{igh}z_{hs}$.

We now let

$$\Omega_{igfs} \equiv \{\boldsymbol{z} \text{ s.t. } w_{is}\xi_{igf}z_{fs} \geq w_{ik}\xi_{igh}z_{hk} \text{ for all } h, k\}.$$

A worker with productivity matrix $\boldsymbol{z}$ from region g in country i will choose region-sector (f, s) iff $\boldsymbol{z} \in \Omega_{igfs}$. The share of workers in group g in country i that choose to work in (f, s) is then

$$\pi_{igfs} \equiv \int_{\Omega_{gfs}} dF(\boldsymbol{z}) = \frac{A_{fs}\left(\xi_{igf}w_{is}\right)^{\kappa}}{\Phi_{ig}^{\kappa}},$$

where $\Phi_{ig}^{\kappa} \equiv \sum_{h,k} A_{ihk}\left(\xi_{igh}w_{ik}\right)^{\kappa}$.

The efficiency units supplied by this group in sector (f, s) are given by

$$\mathcal{Z}_{igfs} \equiv L_{ig}\int_{\Omega_{gfs}} z_{fs}dF_i(z) = \pi_{igfs}\eta L_{ig}\frac{\Phi_{ig}}{w_{is}\xi_{igf}}.$$

Total income of group g in country i is $Y_{ig} \equiv \sum_{f,s} w_{is}\xi_{gf}E_{igfs} = \eta L_{ig}\Phi_{ig}$. Moreover, the share of income obtained by workers in group g in country i in region-sector (f, s) is also given by π_{igfs}, while (ex-ante) per capita income for workers of group g in country i is $Y_{ig}/L_{ig} = \eta\Phi_{ig}$.

Let $\mu_{igh} \equiv \sum_s \pi_{ighs}$ be the share of workers from g that work in h. It is easy to verify that $\pi_{ighs}/\mu_{igh} = \pi_{ihhs}/\mu_{ihh}$ for all i, g, h, s. Thus, conditional on locating in region h, all workers irrespective of their origin have sector employment shares given by $\pi_{ihs} \equiv \pi_{ighs}/\mu_{igh}$. The shares π_{ihs} and μ_{igh} will be enough to characterize the equilibrium below.

The labor demand side of the model is exactly as in the case with no labor mobility across regions. Putting the supply and demand sides of the economy together, we see that excess demand for efficiency units in sector s of country i is

$$ELD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ijs} \beta_{js} Y_j - \sum_{g,h} E_{ighs}.$$

Noting that λ_{ijs}, Y_j and E_{ighs} are functions of the whole matrix of wages $\boldsymbol{w} \equiv \{w_{is}\}$, the system $ELD_{is} = 0$ for all i, s is a system of equations in $\boldsymbol{w}$ whose solution gives the equilibrium wages for a given choice of numeraire.

Turning to comparative statics, the implications of a trade shock can be characterized in similar fashion as before. Changes in wages can be obtained as the solution to the system of equations given by

$$\sum_{g,h} \hat{\pi}_{ihs} \hat{\Phi}_{ig} \mu_{igh} \pi_{ihs} Y_{ig} = \sum_j \lambda_{ijs} \hat{\lambda}_{ijs} \beta_{is} \sum_g \hat{\Phi}_{jg} Y_{jg} \tag{40}$$

with $\hat{\Phi}_{ig}^{\kappa} = \sum_{h,s} \mu_{igh} \pi_{ihs} \hat{w}_{is}^{\kappa}$, (9) and $\hat{\pi}_{ihs} = \hat{\pi}_{ighs}/\hat{\mu}_{igh}$, $\hat{\pi}_{ighs} = \hat{w}_{is}^{\kappa}/\hat{\Phi}_{ig}^{\kappa}$, and $\hat{\mu}_{igh} = \sum_s \pi_{ihs} \hat{\pi}_{ighs}$. Equation (40) can be solved for $\hat{w}_{is}$ given data on income levels, Y_{ig}, trade shares, λ_{ijs}, migration shares μ_{igh}, employment shares π_{ihs}, and the shocks, $\hat{\tau}_{ijs}$ and $\hat{T}_{js}$. In turn, given $\hat{w}_{is}$, changes in trade shares can be obtained from (9), while changes in migration and employment shares can be obtained from the expressions for $\hat{\pi}_{ihs}$ and $\hat{\mu}_{igh}$ above.

Given $\hat{w}_{ik}$, the following proposition analogous to Proposition 1 characterizes the impact of a trade shock on ex-ante real wages for different groups of workers.

Proposition 6. *Given some trade shock, the ex-ante percentage change in the real wage of group g in country i is given by* $\hat{W}_{ig} = \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta} \cdot \prod_s (\hat{\mu}_{igg} \hat{\pi}_{igs})^{-\beta_{is}/\kappa}$.

For the limit case $\kappa \to 1$ we again have $\lim_{\kappa \to 1} \hat{Y}_{ig}/\hat{Y}_i = 1/\hat{I}_{ig}$, except that now $I_g \equiv \sum_s v_{igs} \frac{\beta_{is}}{r_{is}}$, where $\nu_{igs} \equiv \sum_h \mu_{igh} \pi_{ihs}$ is the share of workers from region g that work in sector s.