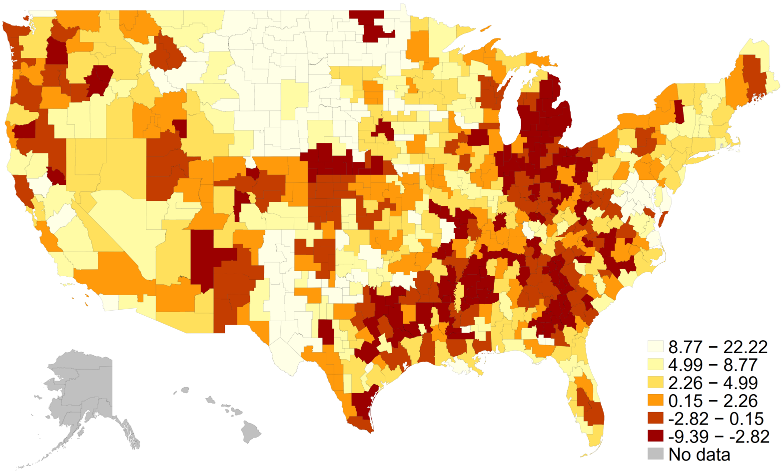
The Unequal Effects of Trade and Automation across Local Labor Markets

Simon Galle
BI Norwegian Business School

Linnea Lorentzen
BI Norwegian Business School

Oslo Macro Group
Oslo

Figure: Percent change in labor income per worker by commuting zone (2000 - 2007)



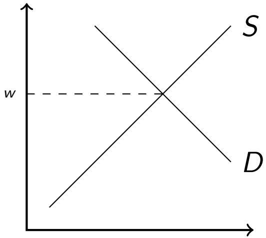
Labor income per worker aged 25-60. Persons employed in public administration, non-profits, or non-paid family workers are excluded, as are institutionalized individuals. Source: IPUMS.

Sector-specific shocks and regional inequality

- Dramatic inequality across US local labor markets during 2000-2007.
- Simultaneously, “surprisingly swift decline” in manufacturing employment, by 20.5%, or 3.5 million jobs.
- Both trade and technology likely contributed to these patterns:
  - Surge in import competition from China.
  - Manufacturing employment falls while manufacturing value-added continues to grow.
- This paper presents a unifying framework to examine the joint impact of trade and automation at the macro level and across local labor markets.

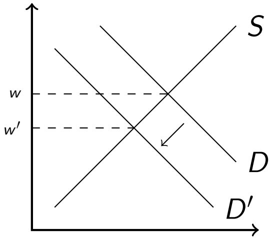
Central ingredients of the paper

- **Sectoral labor supply:** workers are imperfectly mobile across sectors (Discrete choice setup: Roy-Fréchet).
- **Sectoral labor demand:** downward sloping in the sector's wage (multi-sector gravity model of trade).



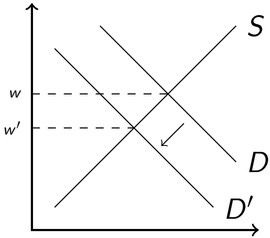
Central ingredients of the paper

- **Sectoral labor supply:** workers are imperfectly mobile across sectors (Discrete choice setup: Roy-Fréchet).
- **Sectoral labor demand:** downward sloping in the sector's wage (multi-sector gravity model of trade).
- Both an increase in equipment efficiency (**automation**) and an increase in foreign productivity (**import competition**) shift sectors' labor demand down.



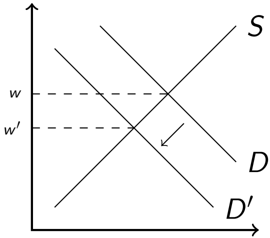
Central ingredients of the paper

- **Sectoral labor supply:** workers are imperfectly mobile across sectors (Discrete choice setup: Roy-Fréchet).
- **Sectoral labor demand:** downward sloping in the sector's wage (multi-sector gravity model of trade).
- Both an increase in equipment efficiency (**automation**) and an increase in foreign productivity (**import competition**) shift sectors' labor demand down.
- Commuting zones (CZs) more specialized in sectors with a contracting labor demand experience a relative decline in income,
  - amplified by a relative increase in frictional unemployment and a reduction in hours worked.



Central ingredients of the paper

- **Sectoral labor supply:** workers are imperfectly mobile across sectors (Discrete choice setup: Roy-Fréchet).
- **Sectoral labor demand:** downward sloping in the sector's wage (multi-sector gravity model of trade).
- Both an increase in equipment efficiency (**automation**) and an increase in foreign productivity (**import competition**) shift sectors' labor demand down.
- Commuting zones (CZs) more specialized in sectors with a contracting labor demand experience a relative decline in income,
  - amplified by a relative increase in frictional unemployment and a reduction in hours worked.
- Both shocks also reduce prices, which entail aggregate consumer gains.



Contribution to literature

- Motivated by reduced-form work on impact of trade or technical change across local labor markets.
  - e.g. Autor-Dorn-Hanson 2013-2015, Acemoglu-Restrepo 2020, ...
- Our unifying GE framework introduces automation in a gravity model of trade with a Roy-Fréchet labor supply side,
  - Caliendo-Dvorkin-Parro 2019, Lee 2020, Galle-Rodríguez-Clare-Yi 2023,...
- and distributional effects due to a specific-factors mechanism in models of technical change.
  - e.g. Acemoglu-Autor 2011, Acemoglu-Restrepo 2018, Burstein-Morales-Vogel 2019, Guner-Ruggieri-Tybout 2021, Hémous-Olsen 2022, ...

Limitations of the model

- Focus on inequality across commuting zones (CZs),

  with no implications for within-group inequality.

- Trade and automation shocks are exogenous.

- Mobility across sectors, but no mobility across commuting zones.

- All goods are tradable.

- Static model, so no dynamics.

Model

Demand: gravity model of trade (Caliendo-Parro 2015)

- Multi-sector version of Eaton-Kortum (2002).
- Preferences across sectors are Cobb-Douglas with shares β_{ds}.
- Trade shares for destination country d from origin country o have a gravity form:

$$\lambda_{ods} = \frac{T_{os}\left(\tau_{ods} c_{os}\right)^{-\theta}}{\sum_i T_{is}\left(\tau_{ids} c_{is}\right)^{-\theta}}$$

Demand: gravity model of trade (Caliendo-Parro 2015)

- Multi-sector version of Eaton-Kortum (2002).
- Preferences across sectors are Cobb-Douglas with shares β_{ds}.
- Trade shares for destination country d from origin country o have a gravity form:

$$\lambda_{ods} = \frac{T_{os}\left(\tau_{ods}c_{os}\right)^{-\theta}}{\sum_i T_{is}\left(\tau_{ids}c_{is}\right)^{-\theta}}$$

- Sectoral demand is downward sloping in marginal cost:

$$R_{os} = \sum_d \lambda_{ods} X_{ds}$$

- Critical question: what is the share of revenue R_{os} going to labor?

Production and labor demand

- Upper-tier Cobb-Douglas with structures, intermediates, and F_{os} as inputs.
- F_{os} is a lower tier CES of labor Z_{os} and equipment M_{os}:

$$F_{os} = \xi_{os}^{\upsilon} \left[\xi_{os}^{\frac{1}{\rho}} M_{os}^{\frac{\rho-1}{\rho}} + Z_{os}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}.$$

Production and labor demand

- Upper-tier Cobb-Douglas with structures, intermediates, and F_{os} as inputs.
- F_{os} is a lower tier CES of labor Z_{os} and equipment M_{os}:

$$F_{os} = \xi_{os}^{\upsilon} \left[\xi_{os}^{\frac{1}{\rho}} M_{os}^{\frac{\rho-1}{\rho}} + Z_{os}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}.$$

- The resulting labor compensation share:

$$\omega_{os} \equiv \frac{w_{os}^{1-\rho}}{\left[\xi_{os} P_o^{1-\rho} + w_{os}^{1-\rho} \right]}.$$

- We model automation as an increase in ξ_{os}, which lowers ω_{os}.
- υ regulates the productivity increase associated with an automation shock.

Roy-Fréchet Labor Supply (Lagakos-Waugh 2013)

- Roy model: workers sort into sectors to maximize their earnings.
- Earnings are a function of a worker's effective units of labor z_s and the sector-level wage w_{os} per effective unit of labor.

Roy-Fréchet Labor Supply (Lagakos-Waugh 2013)

- Roy model: workers sort into sectors to maximize their earnings.
- Earnings are a function of a worker's effective units of labor z_s and the sector-level wage w_{os} per effective unit of labor.
- A worker from group (CZ) og has z_s in sector s drawn iid from a Fréchet dist. with shape parameter $\kappa > 1$ and level parameter A_{ogs}.
  - The Fréchet distribution (extreme value Type II) makes this discrete choice setup highly tractable.
- Variation in the A_{ogs} leads to differences in specialization across CZs.
  - These differences in specialization lead to differential exposure to sector-specific shocks.

Worker sorting and labor revenue

- Share of workers in group g who choose to work in sector s is

$$\pi_{ogs} = \frac{A_{ogs} w_{os}^{\kappa}}{\Phi_{og}^{\kappa}} \text{ with } \Phi_{og} \equiv \left(\sum_{k} A_{ogk} w_{ok}^{\kappa} \right)^{1/\kappa}$$

  - Sectoral reallocation elasticity κ.
  - Φ_{og} is an index of sectoral wages, with weights A_{ogs}.

- We find that the average hourly wage is proportional to $\frac{\Phi_{og}}{P_o}$.

Intensive and extensive margin of labor adjustment

(Kim-Vogel 2021)

- The model features a standard labor-leisure choice,
  - where the average number of hours per worker supplied in group *og* is:

$$h_{og} \propto \left(\frac{\Phi_{og}}{P_o}\right)^{\frac{1}{\mu}}.$$

Details

- And a bare-bones search-and-matching model,
  - where the employment rate increases with real labor surplus:

$$e_{og} \propto \left(\frac{\Phi_{og}}{P_o}\right)^{\frac{\chi}{1-\chi}\frac{1+\mu}{\mu}}$$

Details

Labor Market Equilibrium

- Roy-Fréchet: upward-sloping labor supply to each sector.
- Trade side: downward-sloping demand in each sector.
- Automation and trade shocks shift labor demand.
- Use hat algebra to solve for the counterfactual equilibrium as a function of the shocks, trade and labor market data, and the six elasticities.

Counterfactual equilibrium

Comparative Statics: Real Income

- Change in a group's real income:

$$\frac{\widehat{I}_{og}}{\widehat{P}_o} = \left(\frac{\widehat{\Phi}_{og}}{\widehat{P}_o}\right)^{\frac{1}{1-\chi}\frac{1+\mu}{\mu}},$$

with $\widehat{\Phi}_{og} = \left(\sum_s \pi_{ogs}\widehat{w}_{os}^{\kappa}\right)^{\frac{1}{\kappa}}$.

- Distributional effects are driven by a generalized specific factors intuition:
  - Wage changes are weighted by a group's degree of specialization in a sector.
  - Distributional effects are largest when labor is a specific factor $(\kappa \to 1)$,
  - and disappear when workers are perfectly mobile $(\kappa \to \infty)$.

- Amplification due to changes in unemployment (χ), and hours worked $(1/\mu)$.

Shift-share approximation

- Inequality in groups' income changes is driven by $\widehat{\Phi}_{og} = \left(\sum_s \pi_{ogs} \widehat{w}_{os}^{\kappa}\right)^{\frac{1}{\kappa}}$.

- While the $\hat{w}_{os}$ are unobservable, the model says we can approximate them with $\hat{r}_{os}$, where $r_{os} \equiv I_{os}/I_o$:

$$\frac{\hat{I}_{og}}{\hat{I}_o} \approx \left(\sum_s \pi_{ogs} \hat{A}_{ogs} \hat{r}_{os}\right)^{\frac{1+\mu}{\kappa(1-\chi)\mu}}.$$

- Our model provides a GE framework for the shift-share impact of trade and automation shocks:
  - Relative income changes depend on local exposure to national-level reallocation.

- Close approximation for different κ, χ, μ.

Estimation

Data

- Period: 2000 - 2007
- 23 sectors, with 11 manufacturing sectors
- US Labor Market:
  - 722 Commuting Zones (CZs)
  - Data from IPUMS-USA (Census and American Community Survey)
- Trade data from WIOD
- Data on labor compensation share from WIOD-SEA
- Data from EU-KLEMS and OECD to help construct cost shares

Estimating the shift-share approximation

- Starting from our approximation, taking logs and assuming $\hat{A}_{gs} = \hat{A}_g$:

$$\ln \hat{I}_g = \ln \hat{I} + \frac{(1+\mu)}{\kappa(1-\chi)\mu} \ln \left(\sum_s \pi_{gs} \hat{r}_s \right) + \ln \hat{A}_g^{\frac{(1+\mu)}{\kappa(1-\chi)\mu}},$$

- The shift-share variable absorbs all national level shocks (e.g. due to trade or technology), so there are no confounding national shocks.
- 40% of the variation in $\ln\left(\sum_s \pi_{gs} \hat{r}_s\right)$ is explained by the ADH or Acemoglu-Restrepo trade or technology shocks. Regression results

Table: Estimating the model-implied shift-share approximation

	(1)	(2)	(3)	(4)
	$\ln \hat{I}_g$	$\ln \hat{I}_g$	$\ln \hat{I}_g$	$\ln \hat{I}_g$
$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$	1.23^{***}	1.18^{***}		
	(0.17)	(0.27)		
$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$			1.13^{***}	0.94^{***}
			(0.16)	(0.25)
Controls	No	Yes	No	Yes
Observations	722	722	722	722

The even-numbered specifications include the following control variables from ADH: dummies for the nine Census divisions, the average offshorability index of occupations, and percentages of employment in manufacturing, college-educated population, foreign-born population, and employment among women, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses. P-values: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Labor-side elasticities

- We estimate our three labor-side elasticities employing transparent 2SLS.
- We employ $\sum_s \pi_{gs} \hat{r}_s$ as an IV to parse out *local* shocks.
- We find:
  - Reallocation elasticity $\kappa \approx 1.4$. Results
  - Intensive margin elasticity $1/\mu \approx 0.4$. Results
  - Employment rate (matching) elasticity $\chi \approx 0.3$ Results

Values for the elasticities

- Trade elasticity $\theta = 5$ (Head-Mayer 2014)
- Elasticity of substitution between labor and equipment: $\rho = 1.28$ (Karabarbounis-Neiman 2014, Hubmer 2021)
- Productivity elasticity: $\upsilon = -1.96$
  - υ governs the elasticity of productivity changes to automation-induced declines in the labor share.
  - $\upsilon = -1.96$ ensures our model yields the same productivity elasticity as in Moll-Rachel-Restrepo (2022).
  - This value is also in line with our indirect inference estimation of υ. Details

Counterfactual Analysis

Joint calibration of the China and automation shocks

- Model the China shock as Chinese sector-level productivity growth:
  - Calibrate $\widehat{T}_{China,s}$ such that the model exactly matches increased US imports from China $(\hat{\lambda}_{China,US,s})$.
- The automation shock $(\hat{\xi}_{os})$ is labor saving:
  - Calibrate $\hat{\xi}_{os}$ such that the model exactly matches changes in US sectoral labor shares $(\hat{\omega}_{US,s})$.
- We jointly calibrate these shocks, since the joint impact of trade and automation on the targeted moments differs from their isolated impact.

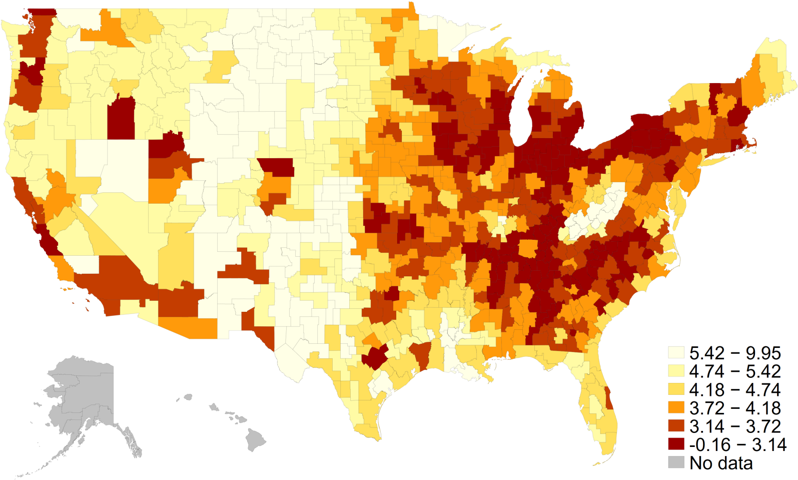
Targeted moments

Impact of automation and the China shock across CZs

	Aggregate	Mean	SD	Min.	Max.
$\widehat{I}_g / \widehat{P}$	3.62	4.33	1.41	-0.16	9.95
$\widehat{i}_g / \widehat{P}$	1.79	2.14	0.69	-0.08	4.86
$\widehat{h}_g$	0.72	0.85	0.27	-0.03	1.92
$\widehat{e}_g$	1.08	1.28	0.41	-0.05	2.89
$\Delta\pi_{gM}$	-0.79	-0.80	0.37	-2.44	-0.09

The table shows the impact of automation and the rise of China across US commuting zones. The first row displays the change in average real income, the second on the average hourly wage, the third row on hours worked per employee and the fourth on the employment rate. The final row shows the change in the share of employment in manufacturing. All variables are measured in percentage changes, except $\Delta\pi_{gM}$ which is measured in percentage points because $\hat{\pi}_{gM}$ is a very noisy measure in our data, especially for low initial π_{gM}.

Figure: Predicted changes in real income of the automation and China shock



Map for China shock
Map for automation

Table: Impact of the individual shocks on real income across US commuting zones

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
Only China Shock	0.94	1.83	1.18	-2.71	4.96	-0.59
Only Automation shock	2.46	2.34	0.70	0.40	5.68	-0.28
China and Automation Shock	3.62	4.33	1.41	-0.16	9.95	-0.79

All the changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing, in percentage points.

- The China shock has weaker aggregate but stronger distributional effects than automation.
- Aggregate gain of combined shock is larger than sum of the parts.
- Distributional effect of combined shock (in variance) is slightly larger than the sum of the parts.
  - Follows from positive covariance of the CZ-level shocks (corr = 7.9%).

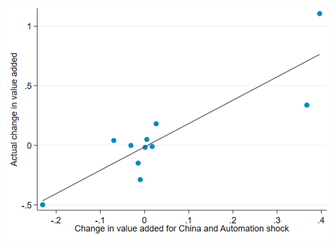
Table: Model fit of variation across commuting zones

	$\ln \widehat{l}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Predicted $\ln \widehat{l}_g$	1.92	1.24								
	(0.42)	(0.54)								
Predicted $\ln \widehat{i}_g$			1.37	1.94						
			(0.53)	(0.86)						
Predicted $\ln \widehat{h}_g$					6.04	4.92				
					(0.62)	(0.75)				
Predicted $\ln \widehat{e}_g$							3.31	2.07		
							(0.49)	(0.56)		
Predicted $\Delta\pi_{gM}$									3.79	2.34
									(0.33)	(0.34)
R^2	0.08	0.29	0.04	0.20	0.38	0.44	0.29	0.37	0.29	0.44
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	722	722	722	722	722	722	722	722	722	722

The even-numbered specifications include the following controls from ADH: dummies for the nine Census divisions, percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women and the average offshorability index of occupations, where these percentage are all measured at the start of the period. Standard errors, clustered at the state level, in parentheses.

Fit for individual shocks

Figure: Fit for changes in manufacturing value-added



- Combined shock: $R^2 = 76\%$; sign of value-added changes is roughly right.
- China shock: $R^2 = 35\%$; predicts falling value added for all sectors. Scatter
- Automation: $R^2 = 60\%$; predicts rising value added for most sectors. Scatter

Sensitivity Analysis

Our results are broadly robust to:

- Alternative value for ρ: 0.72 (Oberfield-Raval 2021) Results
- Alternative calibration of the shocks: Results
  - Calibrate automation shock based on labor share changes in Europe
  - Calibrate the China shock based on China's export growth to "other" countries
- Allowing for heterogeneity between college and non-college workers Results

Conclusion

- We develop a model to jointly examine the impact of trade and automation on local labor markets.
- The combined effect of the China shock and automation over 2000-2007 is:
  - a 3.62% increase in aggregate real income,
  - with a standard deviation of 1.41 percentage points;
  - a decline of manufacturing employment by 0.79 percentage points.
- The China shock has weaker aggregate but stronger distributional effects than automation.
- The model predictions fit well with the variation in the data, both across CZs and across sectors.

Background

Labor-leisure trade-off

Workers trade off consumption of the final good (C) versus the number of hours worked (H) in their utility function:

$$U(C, H; og) = \delta_{og} C - \frac{H^{1+\mu}}{1+\mu},$$

where consumption is funded by a worker's earnings. Back

Roy-Fréchet: details

- Average real income per worker in og is equalized across sectors:

$$\frac{\nu_{og} I_{ogs}}{\pi_{ogs} L_{og} P_o} = \eta \left(\frac{\nu_{og}}{P_o}\right)^{\frac{1+\mu}{\mu}} e_{og} \Phi_{og}^{\frac{1+\mu}{\mu}},$$

with $\eta \equiv \Gamma\left(1 - \frac{1+\mu}{\mu\kappa}\right)$

- So total nominal revenue per worker in group og is

$$\frac{\nu_{og} I_{og}}{L_{og} P_o} = \frac{\sum_s \nu_{og} I_{ogs}}{L_{og} P_o} = \eta \left(\frac{\nu_{og}}{P_o}\right)^{\frac{1+\mu}{\mu}} e_{og} \Phi_{og}^{\frac{1+\mu}{\mu}}.$$

Back

Frictional unemployment (DMP; Kim-Vogel 2021)

- Matching probability as a function of labor market tightness ψ_{og}:

$$e_{og} = A^{M}_{og} \psi^{\chi}_{og}$$

with $\psi_{og} = \psi_{ogs} \equiv \frac{V_{ogs}}{\pi_{ogs} L_{og}}$.

- Employers' ZPC implies that ψ_{og} increases with expected labor revenue, which is a function of Φ_{og}.

- Consequently, the employment rate increases with real labor surplus

$$e_{og} \propto \left(A^{M}_{og} \right)^{\frac{1}{1-\chi}} \left(\frac{\Phi_{og}}{P_o} \right)^{\frac{\chi}{1-\chi} \frac{1+\mu}{\mu}}$$

Back

Counterfactual Equilibrium

- Equilibrium at baseline

$$\underbrace{\sum_g \pi_{ogs} l_{og}}_{Labor\ \ income\ \ (supply\ \ side)} = \underbrace{\alpha_{os}\omega_{os}R_{os}}_{\substack{Payments\ \ to\ \ labor \\ (demand\ \ side)}}$$

- A counterfactual equilibrium (with $\hat{x} \equiv x'/x$)

$$\sum_g \hat{\pi}_{ogs}\pi_{ogs}\hat{l}_{og} l_{og} = \hat{\omega}_{os}\alpha_{os}\omega_{os}\sum_d \hat{\lambda}_{ods}\lambda_{ods} \left(\beta_{ds}\hat{V}_d V_d + \sum_{k=1}^{S}\gamma_{dsk}\hat{R}_{dk}R_{dk}\right)$$

- This is a function of: Shocks $\hat{T}_{os}, \hat{\xi}_{os}.$; Data: $\pi_{ogs} l_{og}, \alpha_{os}\omega_{os}, \lambda_{ods}, \beta_{ds}, \gamma_{dsk}, R_{dk}.$; Parameters $\kappa, \chi, \mu, \theta, \rho, \upsilon$; Hat variables, which are a function of the $\hat{w}_{os}$, data, and the shocks.

Our other 11 hat equations Back

- Changes in labor supply

$$\hat{\pi}_{ogs} = \frac{\hat{A}_{ogs}\hat{w}_{os}^{\kappa_{og}}}{\sum_k \pi_{ogk}\hat{A}_{ogk}\hat{w}_{ok}^{\kappa_{og}}}$$

- Changes in labor demand

$$\hat{\lambda}_{ods} = \frac{\hat{T}_{os}\left(\hat{\tau}_{ods}\hat{c}_{os}\right)^{-\theta_s}}{\sum_i \lambda_{ids}\hat{T}_{is}\left(\hat{\tau}_{ids}\hat{c}_{is}\right)^{-\theta_s}}; \hat{\omega}_{os} = \frac{\hat{w}_{os}^{1-\rho}}{\left[(1-\omega_{os})\hat{\xi}_{os}\hat{P}_o^{1-\rho} + \omega_{os}\hat{w}_{os}^{1-\rho}\right]}$$

- which are functions of the changes in costs and price of the final good

$$\hat{c}_{os} = \hat{c}_{F,os}^{\alpha_{os}}\hat{P}_o^{1-\alpha_{os}-\gamma_{os}}\prod_k \hat{P}_{ok}^{\gamma_{oks}}$$

$$\hat{c}_{F,os} = \left[(1-\omega_{os})\hat{\xi}_{os}\hat{P}_o^{1-\rho} + \omega_{os}\hat{w}_{os}^{1-\rho}\right]^{\frac{1}{1-\rho}}$$

$$\hat{P}_o = \prod_s\left(\sum_i \lambda_{ios}\hat{T}_{is}\left(\hat{\tau}_{ios}\hat{c}_{is}\right)^{-\theta_s}\right)^{-\beta_{os}/\theta_s}$$

More Back

- Changes in income and employment

$$\hat{I}_{og} = \hat{E}_{og}\hat{\Phi}_{og}; \hat{E}_{og} = \left(\frac{\hat{\Phi}_{og}}{\hat{P}_o}\right)^{\frac{\chi}{1-\chi}},$$

- As a function of

$$\hat{\Phi}_{og} = \left(\sum_k \pi_{ogk}\hat{A}_{ogk}\hat{w}_{ok}^{\kappa_{og}}\right)^{\frac{1}{\kappa_{og}}}.$$

- Finally, changes in revenue and value added

$$\hat{R}_{os}R_{os} = \sum_d \lambda_{ods}\hat{\lambda}_{ods}\left(\beta_{ds}\left(\hat{V}_d V_d + \hat{D}_d D_d\right) + \sum_{k=1}^{S}\gamma_{dsk}\hat{R}_{dk}R_{dk}\right),$$

$$\hat{V}_d V_d = \sum_s (1-\gamma_{ds})\frac{\sum_g \hat{\pi}_{dgs}\pi_{dgs}\hat{I}_{dg}I_{dg}}{\alpha_{ds}\hat{\omega}_{ds}\omega_{ds}},$$

Back

Figure: Fit of approximation for various κ

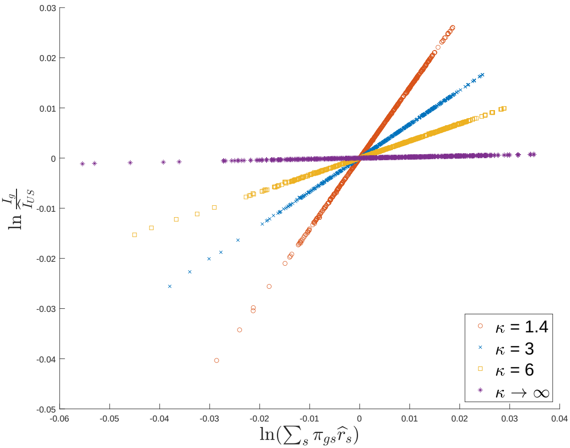


Figure: Fit of approximation for various χ

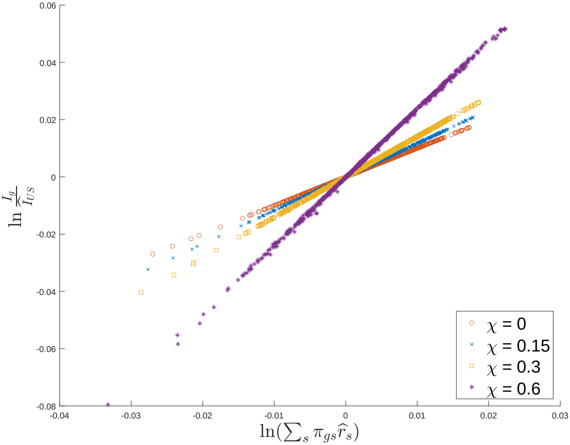


Figure: Fit of approximation for various μ

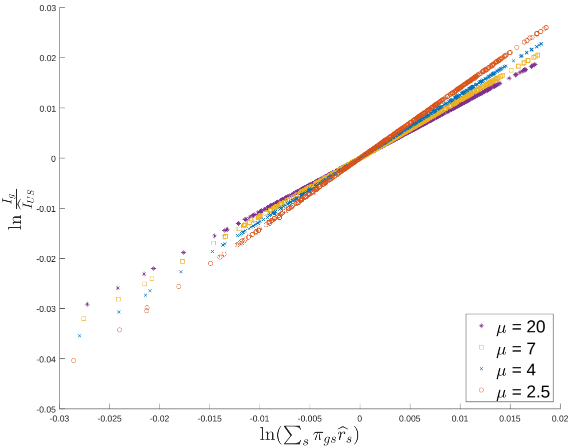


Table: Explaining the variation in the shift-share variable

	$\ln \sum_s \pi_{gs}^{hours} \hat{r}_s$				$\ln \sum_s \pi_{gs}^{income} \hat{r}_s$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to the China shock	-0.0056***			-0.0043***	-0.0058***			-0.0043***
	(0.0011)			(0.0010)	(0.0012)			(0.0010)
Exposure to computerization		-0.0042***		-0.0022***		-0.0044***		-0.0022***
		(0.0005)		(0.0006)		(0.0006)		(0.0006)
Exposure to robots			-0.0134***	-0.0060**			-0.0150***	-0.0076***
			(0.0043)	(0.0027)			(0.0045)	(0.0028)
R^2	0.29	0.21	0.16	0.40	0.27	0.21	0.18	0.40
F-stat	25.40	62.66	9.56	35.99	24.77	58.72	11.05	36.31
Controls	No	No	No	No	No	No	No	No
Observations	722	722	722	722	722	722	722	722

Back

Rotemberg weights for the χ estimation

(a) Instrument: $\sum_s \pi_{gs}^{hours} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	2.672	1.279	0.233	(0.20,0.50)	10.008	2.080
Agriculture, forestry, and fishing	2.022	1.064	0.265	(0.10,0.50)	13.640	6.644
Electricity, gas and water supply	0.170	0.979	0.473	N/A	1.327	1.257
Financial and insurance activities	0.057	1.244	-1.004	N/A	0.084	6.100
Construction	0.050	1.203	-1.102	N/A	0.013	9.705

(b) Instrument: $\sum_s \pi_{gs}^{income} \hat{r}_s$

	$\hat{\alpha}_s$	$\hat{r}_s$	$\hat{\beta}_s$	95 % CI	$\hat{F}_s$	$\pi_{US,s}$
Mining and quarrying	3.669	1.279	0.234	(0.10,0.50)	9.048	2.546
Agriculture, forestry, and fishing	1.652	1.064	0.287	(0.10,0.70)	9.669	5.387
Electricity, gas and water supply	0.350	0.979	0.456	N/A	1.907	1.810
Construction	0.160	1.203	-0.187	N/A	0.096	10.136
Rubber, plastics, and other non-metallics	0.034	0.886	-2.459	N/A	0.021	1.830

Back

Estimating the reallocation elasticity

- To estimate κ, we derive from the model:

$$\ln \hat{i}_g = \sum_s \omega_{\kappa,s} \ln \hat{w}_s - \frac{1}{\kappa} \sum_s \omega_{\kappa,s} \ln \hat{\pi}_{gs} + \sum_s \omega_{\kappa,s} \ln \hat{A}_{gs}^{\frac{1}{\kappa}},$$

- $\sum_s \omega_{\kappa,s} \ln \hat{\pi}_{ogs}$ is an inverse measure of the change in the degree of sectoral specialization.
  - It measures average percentage growth across sectors, which is higher if smaller sectors grow and larger sectors contract.
  - (More technically, it's the change in the Kullback-Leibler divergence.)
- As κ increases, a decline in sectoral specialization becomes less costly.
- We again employ our shift-share IV, to isolate variation in the regressor that is due to national shocks.

Back

Table: Estimation of $-\frac{1}{\kappa}$

	(1) $\ln \hat{i}_g$	(2) $\ln \hat{i}_g$	(3) $\ln \hat{i}_g$	(4) $\ln \hat{i}_g$
$\sum_s \pi_s^{hours} \ln \hat{\pi}_{gs}^{hours}$	-0.96***	-1.04***		
	(0.25)	(0.21)		
$\sum_s r_s \ln \hat{\pi}_{gs}^{income}$			-0.75***	-0.73***
			(0.21)	(0.19)
Implied κ	1.04	0.96	1.33	1.36
F-First Stage	71.9	95.7	53.7	34.5
Instrument	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$
Controls	No	Yes	No	Yes
Observations	722	722	722	722

- κ estimates are on the low side of common values in the literature, implying more costly reallocation.
- We set $\kappa = 1.4$, since the model requires $\kappa > (1 + \mu)/\mu$.

Back

Table: Estimation of $\frac{1}{\mu}$

	(1) $\ln \hat{h}_g$	(2) $\ln \hat{h}_g$	(3) $\ln \hat{h}_g$	(4) $\ln \hat{h}_g$
$\ln \hat{i}_g$	0.94^{***}	0.32^{***}	1.04^{***}	0.40^{***}
	(0.24)	(0.11)	(0.28)	(0.14)
Implied μ	1.07	3.12	0.96	2.48
F-First Stage	17.7	15.7	14.0	8.57
Instrument	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$
Controls	No	Yes	No	Yes
Observations	722	722	722	722

- Chetty (2012) provides bounds for $1/\mu$ between 0.28 and 0.54.
- We set $1/\mu = 0.4$, and therefore $\mu = 2.5$.
- Estimation equation here; Rotemberg weights analysis here.

Back

Table: Estimation of $\frac{\chi}{1-\chi}$

	(1)	(2)	(3)	(4)
	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$	$\ln \hat{e}_g$
$\ln \hat{i}_g \hat{h}_g$	0.39^{***}	0.20^{***}	0.42^{***}	0.27^{***}
	(0.053)	(0.054)	(0.059)	(0.079)
Implied χ	0.28	0.17	0.30	0.21
F-First Stage	39.4	17.0	33.3	11.1
Instrument	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{hours} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$	$\sum_s \pi_{gs}^{income} \hat{r}_s$
Controls	No	Yes	No	Yes
Observations	722	722	722	722

- Shimer (2005) estimates χ between 0.25 - 0.3; Barnichon & Figura (2015) find $\chi = 0.33$.
- We set $\chi = 0.3$.
- The just-identified regressions for the highest Rotemberg-weights sectors yield similar results. Details

Back

Indirect inference for υ

- In the data, we first estimate $\hat{\upsilon}$ the following model-implied relation:

$$d \ln Y_s + \frac{\alpha_s}{\rho - 1} d \ln \omega_s \approx -\upsilon \frac{\alpha_s d \ln \omega_s}{(1 - \omega_s)}.$$

OLS Results

- However, this estimate is biased since the relation above assumes constant factor prices.

- To account for this bias, we set υ such that the estimated $\hat{\upsilon}$ in the actual and the counterfactual data match with each other.
- For our OLS estimate of -1.07, via indirect inference we obtain $\upsilon = -2.48$, with a standard error of 0.38. So the value of $\upsilon = -1.96$ is well within the 95% confidence interval of our υ estimation.

Back

Table: Estimating υ using OLS

(a) OLS estimation of υ with $\rho = 1.28$

		$d \ln Y_s - \frac{\alpha_s}{\rho-1} d \ln \omega_s$		
	2010	2011	2012	2013
$-\frac{\alpha_s}{(1-\omega_s)} d \ln \omega_s$	-1.639	-1.205	-1.01	-1.074
	(0.396)	(0.46)	(0.445)	(0.368)

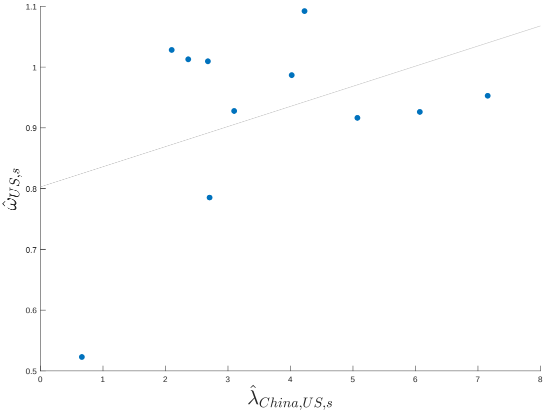
(b) OLS estimation of υ with $\rho = 0.72$

		$d \ln Y_s - \frac{\alpha_s}{\rho-1} d \ln \omega_s$		
	2010	2011	2012	2013
$-\frac{\alpha_s}{(1-\omega_s)} d \ln \omega_s$	1.171	1.891	1.975	1.764
	(0.524)	(0.437)	(0.453)	(0.421)

We use weighted OLS, with sectors' revenue in 2003 as weights. The data consists of 10 manufacturing subsectors. The start year of the period is always 2003, which is the first year where we have all the required data. The end year of the period is listed at the top of the column. In panel (a), we set $\rho = 1.28$ as in Karabarbounis-Neiman 2014, while in panel (b), we set $\rho = 0.72$ as in Oberfield-Raval 2021

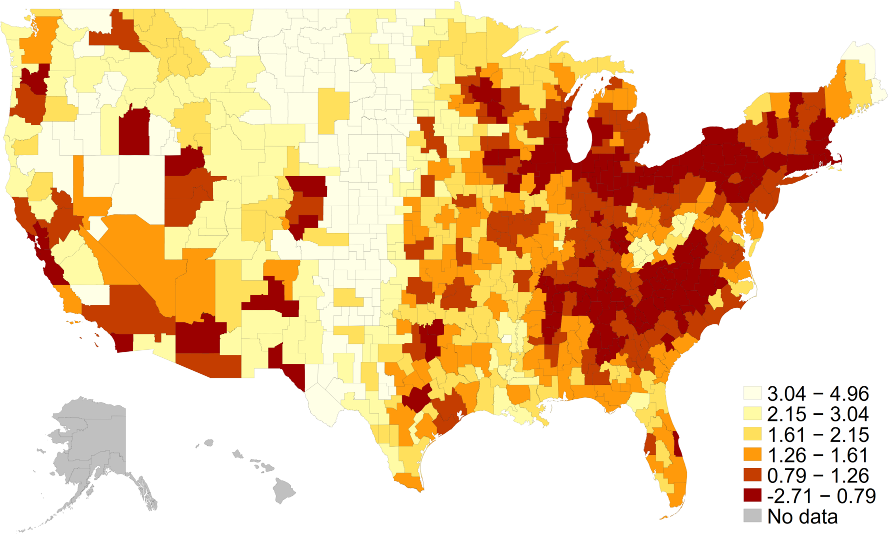
Back

Figure: Targeted moments for manufacturing subsectors



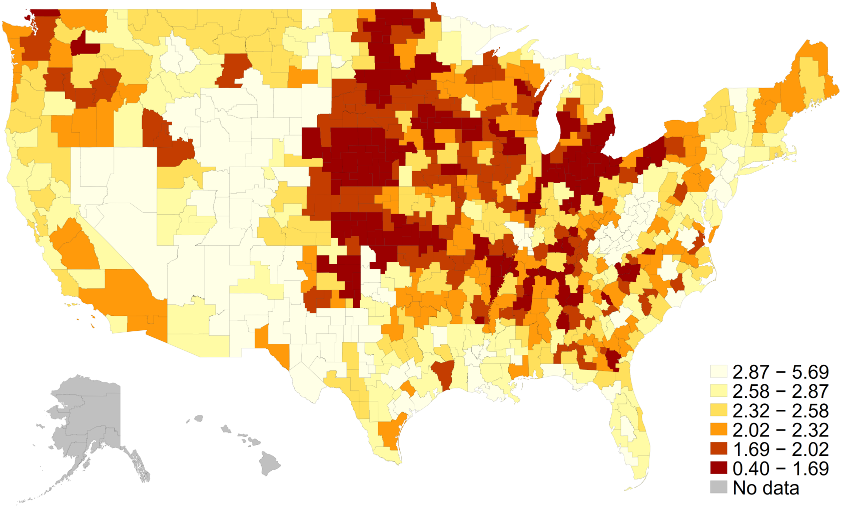
Correlation=0.39; Back

Change in real income due to the China shock



Back

Change in real income due to automation



Back

Table: Model fit to non-targeted moments - no controls

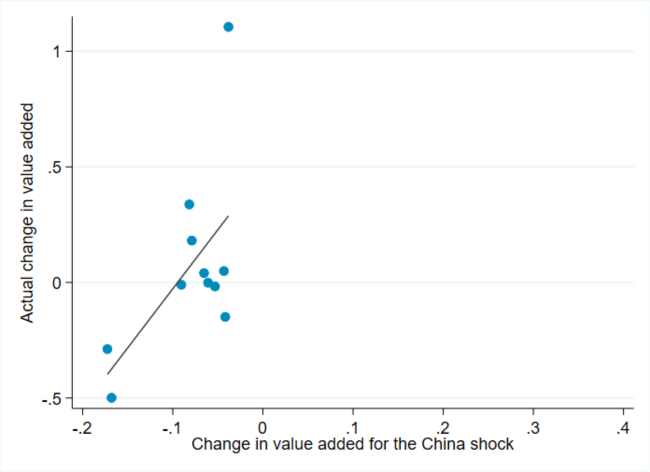
	$\ln \widehat{l}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln \widehat{l}_g$ - China	0.82									
	(0.56)									
$\ln \widehat{l}_g$ - Automation	4.37									
	(0.99)									
$\ln \widehat{l}_g$ - Both shocks		1.92								
		(0.42)								
$\ln \widehat{i}_g$ - China			1.13							
			(0.51)							
$\ln \widehat{i}_g$ - Automation			1.81							
			(1.07)							
$\ln \widehat{i}_g$ - Both shocks				1.37						
				(0.53)						
$\ln \widehat{h}_g$ - China					6.83					
					(0.68)					
$\ln \widehat{h}_g$ - Automation					3.69					
					(0.88)					
$\ln \widehat{h}_g$ - Both shocks						6.04				
						(0.62)				
$\ln \widehat{e}_g$ - China							3.60			
							(0.53)			
$\ln \widehat{e}_g$ - Automation							2.36			
							(0.79)			
$\ln \widehat{e}_g$ - Both shocks								3.31		
								(0.49)		
$\Delta\pi_{gM}$ - China									4.70	
									(0.45)	
$\Delta\pi_{gM}$ - Automation									1.91	
									(0.57)	
$\Delta\pi_{gM}$ - Both shocks										3.79
										(0.33)
R^2	0.12	0.08	0.04	0.04	0.41	0.38	0.31	0.29	0.32	0.29
Controls	No	No	No	No	No	No	No	No	No	No
Observations	722	722	722	722	722	722	722	722	722	722

Back Table with controls

Table: Model fit to non-targeted moments - with controls

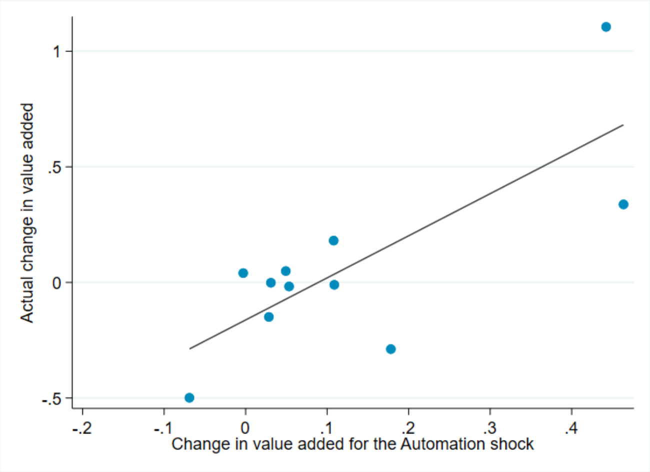
	$\ln \widehat{l}_g$		$\ln \widehat{i}_g$		$\ln \widehat{h}_g$		$\ln \widehat{e}_g$		$\Delta\pi_{gM}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln \widehat{l}_g$ - China	0.06									
	(0.70)									
$\ln \widehat{l}_g$ - Automation	3.06									
	(1.11)									
$\ln \widehat{l}_g$ - Both shocks		1.24								
		(0.54)								
$\ln \widehat{i}_g$ - China			1.20							
			(0.69)							
$\ln \widehat{i}_g$ - Automation			3.02							
			(1.30)							
$\ln \widehat{i}_g$ - Both shocks				1.94						
				(0.86)						
$\ln \widehat{h}_g$ - China					6.12					
					(0.90)					
$\ln \widehat{h}_g$ - Automation					2.84					
					(1.12)					
$\ln \widehat{h}_g$ - Both shocks						4.92				
						(0.75)				
$\ln \widehat{e}_g$ - China							2.49			
							(0.68)			
$\ln \widehat{e}_g$ - Automation							1.39			
							(1.01)			
$\ln \widehat{e}_g$ - Both shocks								2.07		
								(0.56)		
$\Delta\pi_{gM}$ - China									3.37	
									(0.42)	
$\Delta\pi_{gM}$ - Automation									1.00	
									(0.62)	
$\Delta\pi_{gM}$ - Both shocks										2.34
										(0.34)
R^2	0.31	0.29	0.20	0.20	0.46	0.44	0.38	0.37	0.46	0.44
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	722	722	722	722	722	722	722	722	722	722

Figure: Manufacturing value-added changes for the China shock, $R^2 = 35\%$



Back

Figure: Manufacturing value-added changes for the automation shock, $R^2 = 60\%$



Back

Table: Counterfactual results on real income across US CZs for $\rho = 0.72$.

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
Only China Shock	0.93	1.68	1.18	-3.12	4.48	-0.59
Only Automation shock	2.80	3.12	1.38	-6.14	8.35	-0.73
China and Automation Shock	3.72	4.82	1.80	-4.39	8.99	-1.32

For the model with $\rho = 0.72$, the table shows the impact of the individual China shock in the first row, of the individual automation shock in the second row and of the combined China and automation shock in the third row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing, in percentage points.

Back

Table: Impact of the individual shocks for the alternative calibration

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
Only China Shock	0.83	1.62	1.14	-2.21	4.78	-0.59
Only Automation shock	1.86	1.60	0.46	-0.21	2.40	-0.07
China and Automation Shock	3.05	3.50	0.69	-0.13	4.85	-0.55

The table shows the impact of the individual China shock in the first row, of the individual automation shock in the second row and of the combined China and automation shock in the third row, for the calibration of the shocks specified in this section. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing, in percentage points.

Back

Table: Heterogeneity across education groups for the combined shock

	Aggregate	Mean	SD	Min.	Max.	$\Delta\pi_{US,M}$
All groups	2.84	3.46	1.27	-1.59	8.79	-0.83
Non-college workers	2.78	3.44	1.56	-1.59	8.79	-0.98
College workers	2.87	3.48	0.88	-0.10	7.51	-0.66

The table shows the impact of the combined China and automation shock for the model with groups defined by commuting zone and education level (some college education or not). The first row shows the effect of the shock on all groups in the top row, on the groups where workers have no college education in the middle row, and on groups with college education in the bottom row. The first four columns display statistics for the changes in groups' real income, with the first column showing the aggregate change, the second the average change, the third the standard deviation, the fourth the minimum and the fifth the maximum change. All these changes in real income are reported as percentage changes. The final column lists the change in the aggregate US employment share in manufacturing, in percentage points. Back