Revisiting the drivers of US labor market polarization

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Motivation

- High (and rising) levels of inequality afflict many countries.
- In the US, employment polarization is one of the most striking features of the labor market in recent decades and a significant driver of wage inequality.
  Evidence
- The decline of the middle class has been connected to a wide variety of outcomes from voting, to health, marriage and fertility.
- At the same time, there is a considerable backlash against globalization.

Motivation (ct'd)

- Drivers of employment polarization are not yet fully understood.
- Three competing explanations put forward in the literature to explain employment polarization:

1. Routine-biased technological change (RBTC) (Autor et al., 2003): routine tasks, typically performed by middle-skilled workers, are easier to automate.
2. GVCs/Offshoring (Blinder and Krueger, 2013): tasks that do not require the physical presence of the worker are more prone to be offshored and subsequently imported. This tends to affect mostly middle-skilled workers.
3. The Rise of China (Autor et al., ADH, 2015): import competition from China has particularly hit middle-skilled manufacturing workers.

Our contribution

- Using a standard local labor market approach, we estimate the effect of all three factors on labor market outcomes in the US. We contribute to the literature in three ways:

  1. We look at all three factors simultaneously.
  2. We use accurate measures of the three factors.
  3. We instrument for all three factors.

- We therefore get a consistent estimate of each factor's contribution to labor market polarization in the US.

Literature review

- We speak to several strands of literature:
  - GVC integration and its effects: Hummels et al. (2001); Amiti and Wei (2005); Crinò (2010); Harrison and McMillan (2011); Johnson and Noguera (2012a,b); Ebenstein et al. (2014); Koopman et al. (2014); Timmer et al. (2014); Wright (2014); Baldwin and López-González (2015) ...
  - RBTC and labor market polarization: Autor et al. (2003); Acemoglu and Autor (2011); Autor and Dorn (2013); Goos and Manning (2007); Goos et al. (2009, 2014); Oldenski (2014); Harrigan et al. (2016); Keller and Utar (2016); Graetz and Michaels (2018) ...
  - The rise of China: Autor et al. (2013, 2014, 2015, 2016); Acemoglu et al. (2016); Chetverikov et al. (2016); Pierce and Schott (2016); Handley and Limão (2017); Jakubik and Kummritz (2017); Wang et al. (2018) ...
  - More generally, we contribute to the literature on how trade and technology impact within-country inequality (see Helpman, 2018 for a recent overview).

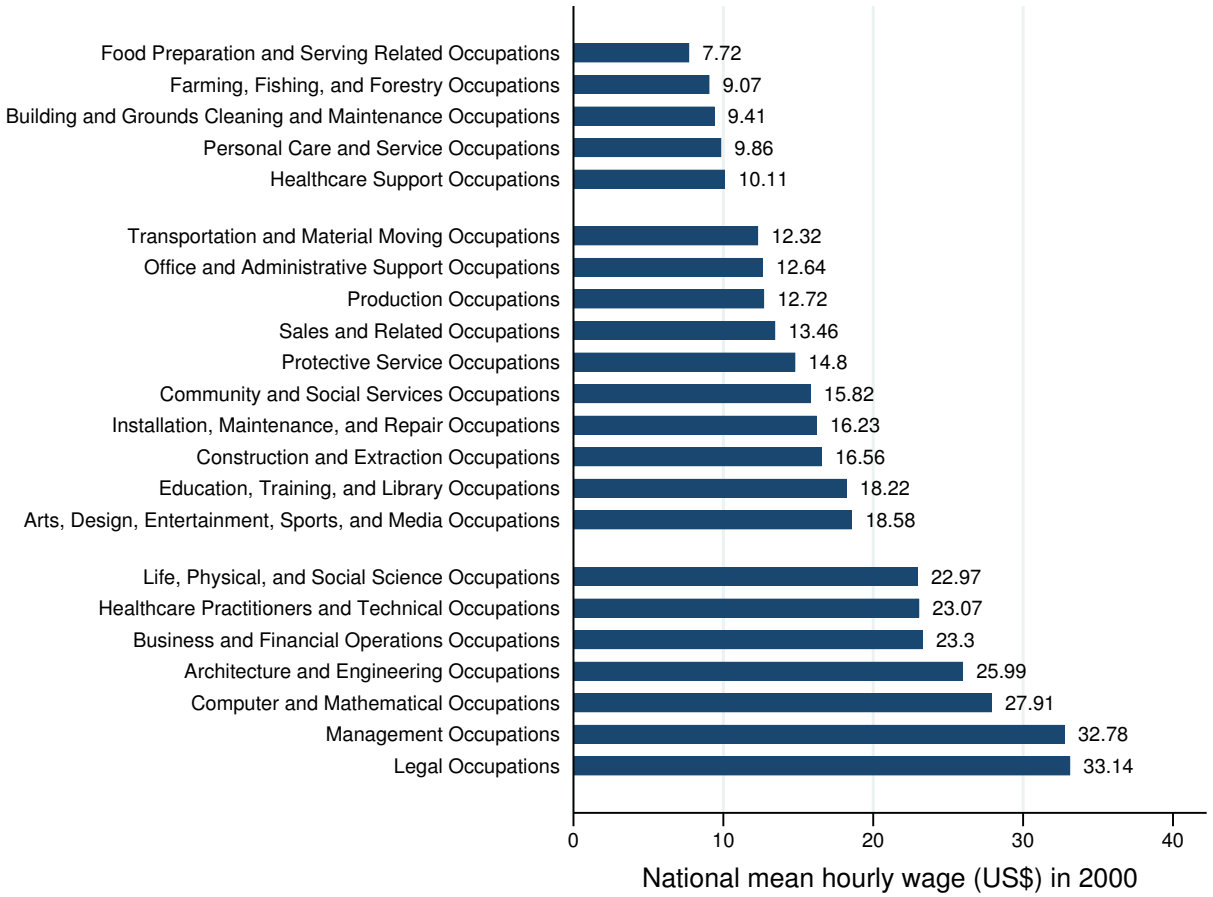
Empirical framework

$$\Delta Y_i^S = \alpha + \beta_1 \mathit{GVC}_i + \beta_2 \mathit{China}_i + \beta_3 \mathit{Automation}_i + \mathbf{x}_i' \boldsymbol{\gamma} + \varepsilon_i$$

- Dependent variable – Change in the share of wage group $S = \{Low, Middle, High\}$ in total employment or in the working-age population of commuting zone (CZ) i between 2000 and 2014.
- GVC_i – Local (i.e. CZ-level) exposure to GVCs, constructed from foreign value added (FVA) in US exports.
- $China_i$ – Local exposure to Chinese import competition, constructed as imports of Chinese value added consumed in the US.
- $Automation_i$ – Local exposure to automation.
- **x** – Fixed effects and CZ-level control variables (baseline manufacturing share and demographics).

Construction of wage groups

- US SOC occupations (23 Major Groups) are ordered by US national average wage in 2000 (our baseline year).
- Classification of occupations into three groups: Low, Middle, and High (see Goos et al., 2009 for a similar approach).



Local automation exposure

- Baseline automation exposure measure is local exposure to routinization (ADH, 2015).

- Beginning-of-period fraction of CZ employment that falls in routine task-intensive occupations.

Local GVC exposure

- Baseline GVC exposure measure is local exposure to foreign value added in US exports (FVAX):

$$GVC_i \equiv \frac{1}{L_i} \sum_j \frac{L_{ij}}{L_j} \Delta FVAX_j^{US}$$

- $FVAX_j^{US}$ is FVA in US exports (final + intermediate) from the source industry j, summed over all source countries (except the US), all exporting industries and all destination countries.

- Following the ADH methodology, we assign $FVAX_j$ to CZ's by summing across all source industries j, weighting the sum by the CZ i's baseline-year (2000) share of national industry employment in j (L_{ij}/L_j), and normalizing by total employment in CZ i (L_i).

Local China exposure

- Baseline Chinese import competition exposure measure is local exposure to Chinese domestic value added (DVA) in China's exports to the US that is absorbed in the US:

$$China_i = \frac{1}{L_i} \sum_j \frac{L_{ij}}{L_j} \Delta DVA_j^{CN}$$

- DVA_j^{CN} is DVA in China's exports (final + intermediate) to the US from the source industry j, summed over all exporting industries.
- As for GVC exposure, the assignment to CZ's is a weighted normalized sum.
- $China_i$ proxies for Chinese import competition because it allocates the national change in industry-level Chinese *DVA* to CZ's according to their baseline industry employment structure.
- Since j represents industries where value added originates, we are able to correctly assign exposure to Chinese import competition across local labor markets.

Novelties in GVC and China exposure

- We calculate local China and GVC exposure with j representing industries where value added originates rather than the exporting industry following (Jakubik and Stolzenburg, 2018). We therefore correctly assign trade-related shocks to CZ's.

- To capture exposure to China we use only Chinese value added in Chinese exports that are absorbed in the US in order to:
  - have mutually exclusive China and GVC measures
  - account for insights from (Jakubik and Stolzenburg, 2018) that this part has driven labour market adjustments in the US.

IV for automation exposure

- Exposure to automation is instrumented as in ADH (2015).
- The fraction of employment that falls in routine task-intensive occupations (*RSH*) is instrumented using historical information for 1950 on the local industry mix and the nationwide occupational structure of industries:

$$RSH_i^{IV} = \sum_{j=1}^{J} E_{j,i,1950} \times R_{j,-i,1950}$$

- $E_{j,i,1950}$: employment share of industry j in CZ i in 1950.
- $R_{j,-i,1950}$: routine occupation share among workers in industry j in 1950 in all US states except the state that includes CZ i.
- The validity of the instrument stem from the fact that it is determined three decades prior to the onset of rapid computerization, so it should be correlated with the long-run component of the routine occupation share but uncorrelated with contemporaneous innovations to this share (ADH, 2015).

IV for GVC exposure

- In the spirit of Frankel and Romer (1999), we build an exogenous predictor for trade (in value added) which is then used to construct an exogenous measure of CZ-level GVC exposure.

- Following Kummritz (2016), we use a directional value added trade resistance index that combines third country bilateral trade costs with the distance between the involved industries within the value chain.

Details

IV for China exposure

- Following in spirit ADH (2013), we use Chinese DVA in exports of goods which are exported to and consumed in seven non-US developed countries (Australia, Denmark, Finland, Germany, Japan, Spain, and Switzerland) as an instrument for Chinese DVA in exports of goods which are exported to and consumed in the US.

- The identification assumption is that growth in imports of Chinese DVA in high-income countries other than the US is correlated with growth in imports of Chinese DVA in the US, but uncorrelated with shocks to US product demand.

IV for China exposure (ct'd)

- Important difference with ADH (2013):
  - ADH use growth in gross imports from China in eight non-US developed countries as an instrument for the growth in gross imports from China in the US.
  - Both gross Chinese exports to the US and gross Chinese exports to non-US developed countries embody US value added.
  - Since US employment is a major contributor to US value added, and US employment is correlated with shocks to US product demand, ADH's identification assumption is likely violated (Jakubik and Stolzenburg, 2018)
  - We only use Chinese DVA in exports, which:
    1. Is relevant because Chinese DVA in exports to other countries and Chinese DVA in exports to the US both reflect positive supply shocks (e.g. productivity growth) in China. (The same reason why ADH's instrument is also relevant) .
    2. Is valid because, by construction, it does not include value added from other countries, so it is uncorrelated with shocks in US product demand.

Data

- VA trade flows, export shares and industrial distances: World Input-Output Database (WIOD) from the Research Centre for GVCs at the University of International Business and Economics (UIBE) in Beijing.
- US employment data by CZ (722 used for estimations), industry, and occupation: American Community Survey (ACS).
- US wage data by occupation to construct wage groups: Occupational Employment Statistics (OES) of Bureau of Labor Statistics (BLS).
- Control variables (baseline manufacturing share and demographics): David Dorn and ACS.
- Industry concordances: United Nations Statistics Division.
- Occupation concordances: US Census Bureau.
- Bilateral trade costs from the ESCAP-World Bank Trade Cost Database.

Descriptive evidence

- Patterns of exposure measures across CZ's vary considerably, without clear overlap between them. Details

- Employment polarization (unconditionally) positively correlates with exposure to automation, and (unconditionally) loosely correlates with GVC and China exposure. Details

OLS estimations

	Low-wage group			Middle-wage group			High-wage group		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GVC exposure		-0.0034***	-0.0029***		0.0023**	0.0014		0.0010	0.0015*
		(0.0008)	(0.0008)		(0.0010)	(0.0009)		(0.0008)	(0.0008)
China exposure		0.0012***	0.0012***		-0.0011	-0.0010		-0.0002	-0.0002
		(0.0004)	(0.0004)		(0.0008)	(0.0006)		(0.0006)	(0.0005)
Automation exposure	0.1750***		0.1465***	-0.2996***		-0.2903***	0.1247***		0.1438***
	(0.0497)		(0.0433)	(0.0570)		(0.0501)	(0.0335)		(0.0345)
Standardized beta coefficients									
GVC exposure		-0.415	-0.359		0.229	0.141		0.117	0.167
China exposure		0.361	0.346		-0.247	-0.225		-0.047	-0.060
Automation exposure	0.311		0.260	-0.425		-0.412	0.202		0.232
N	722	722	722	722	722	722	722	722	722
R^2	0.288	0.295	0.327	0.253	0.179	0.261	0.259	0.244	0.271

Notes: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. State-level clustered standard errors in parentheses. Dependent variable: change in the share in total employment of the respective wage group between 2000 and 2014. Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

IV baseline estimations

	Low-wage group			Middle-wage group			High-wage group		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GVC exposure		-0.0026**	-0.0031***		-0.0034*	-0.0018		0.0060***	0.0049***
		(0.0012)	(0.0012)		(0.0020)	(0.0016)		(0.0018)	(0.0016)
China exposure		0.0008	0.0015**		0.0019	0.0002		-0.0028**	-0.0017
		(0.0007)	(0.0007)		(0.0014)	(0.0012)		(0.0011)	(0.0011)
Automation exposure	0.1537		0.1717*	-0.4480***		-0.4723***	0.2942*		0.3006*
	(0.0971)		(0.0960)	(0.1154)		(0.1342)	(0.1521)		(0.1651)
Standardized beta coefficients									
GVC exposure		-0.314	-0.385		-0.333	-0.177		0.665	0.552
China exposure		0.244	0.429		0.451	0.043		-0.736	-0.440
Automation exposure	0.273		0.305	-0.635		-0.670	0.475		0.486
N	722	722	722	722	722	722	722	722	722
R^2	0.287	0.291	0.325	0.231	0.076	0.206	0.221	0.146	0.205

Notes: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. State-level clustered standard errors in parentheses. Dependent variable: change in the share in total employment of the respective wage group between 2000 and 2014. Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

First stage results

IV extensive margin regressions

	Total employed (1)	Low-wage employed (2)	Middle-wage employed (3)	High-wage employed (4)
GVC exposure	0.0072***	-0.0008	0.0029	0.0051***
	(0.0025)	(0.0007)	(0.0019)	(0.0013)
China exposure	-0.0028**	0.0007	-0.0016	-0.0018**
	(0.0012)	(0.0005)	(0.0011)	(0.0009)
Automation exposure	-0.0606	0.1481**	-0.4093***	0.2007
	(0.1640)	(0.0640)	(0.1253)	(0.1290)
Standardized beta coefficients				
GVC exposure	0.420	-0.122	0.209	0.801
China exposure	-0.383	0.254	-0.272	-0.691
Automation exposure	-0.051	0.343	-0.425	0.457
N	722	722	722	722
R^2	0.693	0.451	0.654	0.034

Notes: *p<0.10, **p<0.05, ***p<0.01. State-level clustered standard errors in parentheses. Dependent variable: change in the share in total employment of the respective wage group between 2000 and 2014. State dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

Robustness and further analysis

- Alternative construction of the GVC and of the China exposure variables.
  - China exposure built in a way similar to ADH (2013)'s – without US as source country to avoid mechanical correlation between US employment and Chinese import competition, and with adjustment of the GVC exposure variable to avoid overlapping with China exposure.
  - GVC exposure measure built as FVA in production – without Chinese DVA in intermediate exports used by the US to produce local final products to avoid overlapping with China exposure.

    Results

- EP index constructed as in Reijnders and de Vries (2017) as dependent variable. Results
- State dummies instead of Census division dummies. Results
- Estimations with shares in total hours worked. Results

Conclusions

1. GVC integration has increased the share of high-wage jobs in total employment (skill upgrading).
2. The rise of China has increased the share of low-wage jobs in total employment (skill downgrading).
3. Automation is responsible for labor market polarization in the US.

Next steps

- Include a fourth main trend of the last two decades – servicification of the economy – as yet another possible driver of employment polarizations in the US (see Eckert, 2019).

- Control for SBTC (fraction of workers reporting using a computer at their job as in Oldenski, 2014).

Thank you

Changes in the US employment composition, 2000-2014

Occupation	SOC code	Share in 2000	Share in 2014	Wage group
Food Preparation and Serving Related	35	3.85	4.87	Low
Farming, Fishing, and Forestry	45	0.77	0.85	Low
Building and Grounds Cleaning and Maintenance	37	2.84	3.55	Low
Personal Care and Service	39	2.25	3.11	Low
Healthcare Support	31	1.81	2.24	Low
Transportation and Material Moving	53	6.54	6.65	Middle
Office and Administrative Support	43	14.36	12.17	Middle
Production	51	8.93	6.60	Middle
Sales and Related	41	10.78	10.06	Middle
Protective Service	33	2.11	2.38	Middle
Community and Social Services	21	1.50	1.67	Middle
Installation, Maintenance, and Repair	49	4.46	3.53	Middle
Construction and Extraction	47	5.89	5.49	Middle
Education, Training, and Library	25	5.38	5.81	Middle
Arts, Design, Entertainment, Sports, and Media	27	1.84	1.80	Middle
Life, Physical, and Social Science	19	0.96	0.87	High
Healthcare Practitioners and Technical	29	4.70	5.94	High
Business and Financial Operations	13	4.50	4.96	High
Architecture and Engineering	17	2.24	1.95	High
Computer and Mathematical	15	2.58	2.93	High
Management	11	10.51	11.37	High
Legal	23	1.20	1.18	High
Averages by wage group				
Low		11.51	14.62	
Middle		61.79	56.18	
High		26.70	29.21	

Notes: SOC stands for Standard Occupational Classification. Shares in 2000 and 2014 expressed as percentages of total usual hours worked per week. In the upper panel, shares are weighted averages across commuting zones (with commuting zone, CZ population in 2000 as weights). In the lower panel, shares are weighted averages across occupations belonging to the same wage group and across commuting zones (with CZ population in 2000 as weights).

Geographic distribution of EP

Employment polarization in local labor markets

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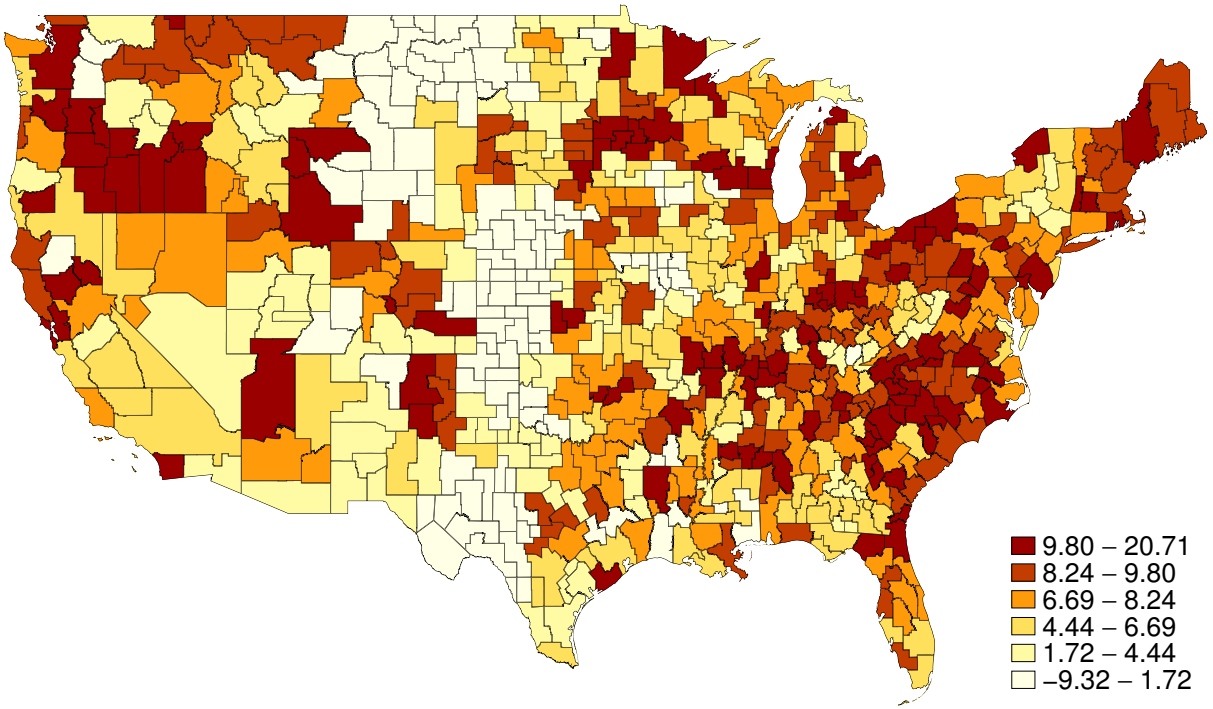
- Employment polarized in 643 out of 722 local labor markets in the US between 2000 and 2014.



Notes: The figure displays the EP index by Commuting Zone (CZ). The EP index is constructed as in Reijnders and de Vries (2017) (EP $>$ 0 if there was polarization, and higher the greater the fall in the employment share of the middle-skilled group relative to the other two).

Instrument for *FVAX*: construction

Example

- In a first step, we predict bilateral industry-level value added trade flows based on their exogenous determinants only:

$$\textit{vae}_{jlrkt} = \exp\left\{\alpha + \beta \ln(RI_{jlrkt}) + \gamma_{jk} + \phi_{kt} + \delta_{rt} + \varepsilon_{jlrkt}\right\}$$

where j, r index industries; k, l index countries; t indexes years.

  - *RI* is the value added trade resistance index:

$$\tau_{lkt} \times \textit{inddist}_{jr}$$

    - τ_{lkt} is a weighted average of country l's bilateral trade costs with all other c countries except k, where the weights are export shares of l to c.
    - $\textit{inddist}_{jr}$ – industrial distance – is the product of the upstreamness of source industry j and the downstreamness of using industry r.

- In a second step, we aggregate the fitted values across all k countries and r industries, to get $\textit{FVAX}^{IV}_{ljt}$ ($l = \textit{US}$).

Instrument for *FVAX*: example

Graph

- Say that the interest is to find exogenous variation in the value added of Indian steel in Japan's car exports.
- India exports steel to be embodied in Japan's car exports directly and also indirectly, in the form of Chinese and Thai exports of fabricated metals.
- Bilateral trade costs between India and China and between India and Thailand, being exogenous to the productivity or value added of the Japanese car industry, are good predictors of the exogenous component of India's value added in Japanese exports of cars.
- These costs are interacted with industrial distance between steel and cars because the larger this distance, the higher the probability that third countries (in this example, China or Thailand) affect a bilateral value added trade relationship since a large distance implies more stages that third countries can occupy.

Instrument for *FVAX*: graph

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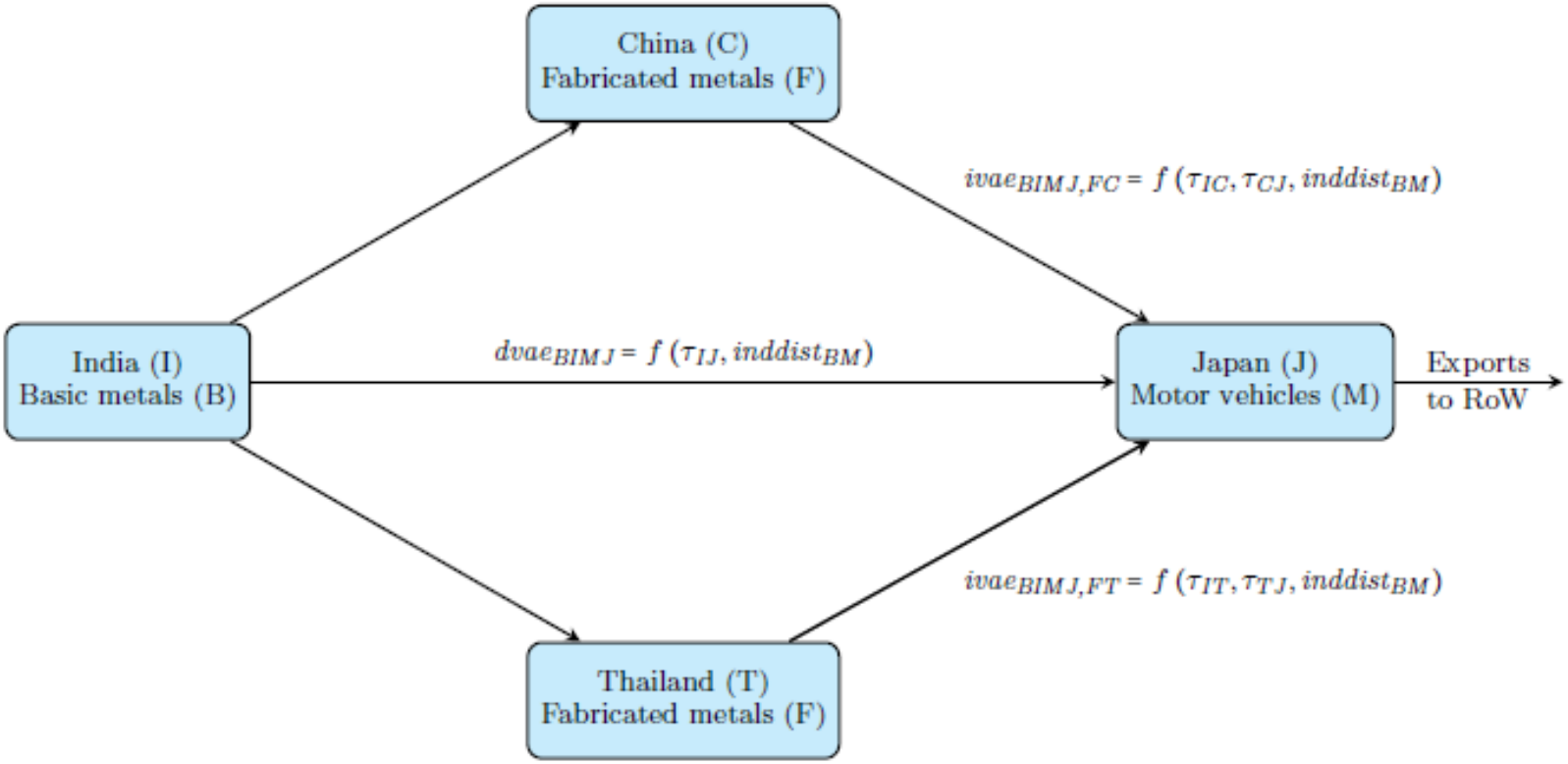

Note: Derived from Table 1 in Kummritz (2016).

Exposure variables across CZ's

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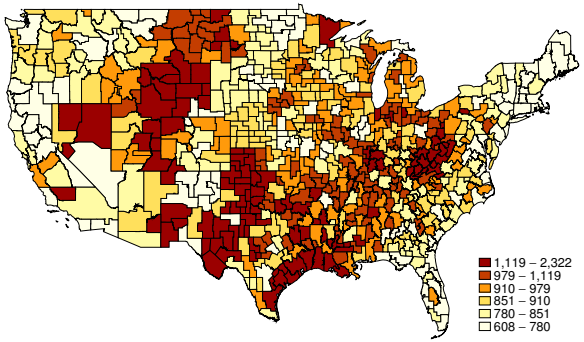
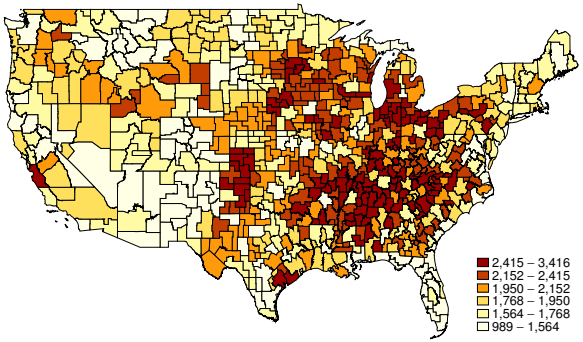
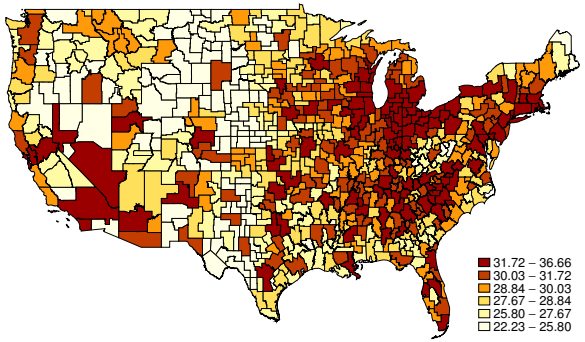


(i) GVC exposure



(ii) China exposure



(iii) Automation exposure

Unconditional correlations with the EP index

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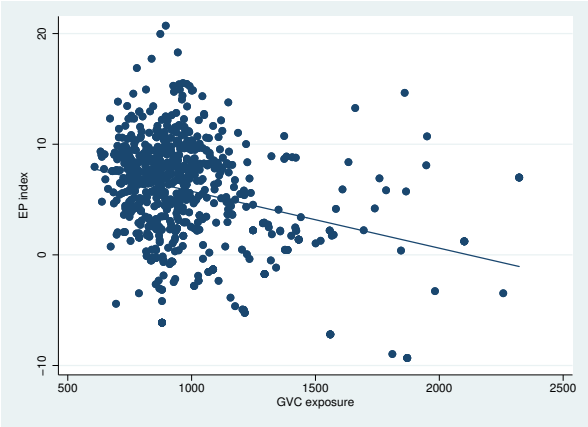
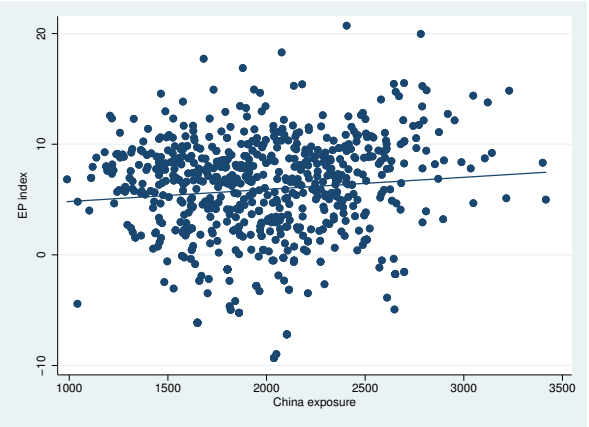
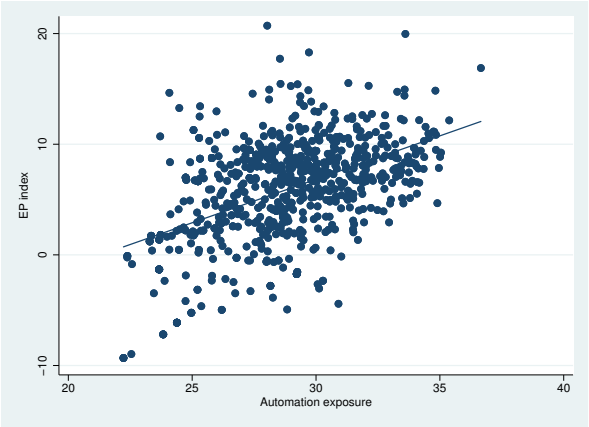


(i) GVC exposure



(ii) China exposure



(iii) Automation exposure

Note: EP index constructed as in Reijnders and de Vries (2017).

First stage IV results

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Dependent:	GVC exposure (1)	China exposure (2)	Automation exposure (3)
GVC exposure IV	3.7234***	-1.5007*	0.0104
	(0.5147)	(0.7889)	(0.0150)
China exposure IV	0.2788***	0.9170***	-0.0013
	(0.0450)	(0.0539)	(0.0015)
Automation exposure IV	2.1677*	4.7845***	0.1621***
	(1.1430)	(1.3083)	(0.0395)
N	722	722	722
F-test of excluded instruments	57.74	30.40	22.19

Notes: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. State-level clustered standard errors in parentheses. Census division dummies and the following controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and women's employment rate in 2000. F-test of excluded instruments is the Sanderson-Windmeijer F statistics (Sanderson and Windmeijer, 2016). Results refer to columns (3), (6) and (9) of the IV baseline estimations table.

IV with alternative GVC and China exposure

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	ADH (2013) China exposure			GVC exposure as FVA in production		
	Low-wage group (1)	Middle-wage group (2)	High-wage group (3)	Low-wage group (4)	Middle-wage group (5)	High-wage group (6)
GVC exposure	-0.0035*	-0.0038	0.0073***	-0.0003***	-0.0002	0.0005***
	(0.0019)	(0.0029)	(0.0025)	(0.0001)	(0.0002)	(0.0002)
China exposure	0.0009	0.0010	-0.0019	0.0014**	0.0001	-0.0015
	(0.0008)	(0.0014)	(0.0012)	(0.0007)	(0.0012)	(0.0011)
Automation exposure	0.1657	-0.4345***	0.2687	0.1717*	-0.4723***	0.3005*
	(0.1014)	(0.1393)	(0.1694)	(0.0971)	(0.1339)	(0.1653)
Standardized beta coefficients						
GVC exposure	-0.371	-0.329	0.713	-0.355	-0.164	0.509
China exposure	0.316	0.281	-0.609	0.402	0.031	-0.402
Automation exposure	0.294	-0.616	0.434	0.305	-0.670	0.486
N	722	722	722	722	722	722
R^2	0.325	0.179	0.160	0.323	0.206	0.201
F-test of excluded instruments	25.84	17.05	15.77	60.53	28.71	22.07

Notes: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. State-level clustered standard errors in parentheses. Dependent variable: change in the share in total employment of the respective wage group between 2000 and 2014. Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

Estimations with the EP index

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	OLS	Baseline IV	IV with ADH (2013) China exposure	IV with FVA in production
	(1)	(2)	(3)	(4)
GVC exposure	-0.0019	0.0026	0.0053	0.0002
	(0.0015)	(0.0026)	(0.0045)	(0.0003)
China exposure	0.0015	0.0000	-0.0011	0.0001
	(0.0009)	(0.0021)	(0.0023)	(0.0020)
Automation exposure	0.5017***	0.9301***	0.8785***	0.9301***
	(0.0759)	(0.2509)	(0.2566)	(0.2508)
Standardized beta coefficients				
GVC exposure	-0.120	0.162	0.289	0.149
China exposure	0.220	0.005	-0.201	0.018
Automation exposure	0.450	0.833	0.787	0.833
N	722	722	722	722
R^2	0.304	0.219	0.208	0.219

Notes: * p<0.10, ** p<0.05, *** p<0.01. State-level clustered standard errors in parentheses. Dependent variable: EP index constructed as in Reijnders and de Vries (2017). Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

IV with State dummies

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	Low-wage group (1)	Middle-wage group (2)	High-wage group (3)
GVC exposure	-0.0033***	-0.0006	0.0039**
	(0.0012)	(0.0021)	(0.0019)
China exposure	0.0016*	-0.0005	-0.0010
	(0.0008)	(0.0017)	(0.0015)
Automation exposure	0.2765***	-0.5972***	0.3207
	(0.1046)	(0.1814)	(0.2193)
Standardized beta coefficients			
GVC exposure	-0.398	-0.062	0.434
China exposure	0.454	-0.127	-0.269
Automation exposure	0.491	-0.847	0.518
N	722	722	722
R^2	0.453	0.338	0.327

Notes: * p<0.10, ** p<0.05, *** p<0.01. State-level clustered standard errors in parentheses. Dependent variable: change in the share in total employment of the respective wage group between 2000 and 2014. State dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

IV with shares in total hours worked

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	Low-wage group (1)	Middle-wage group (2)	High-wage group (3)
GVC exposure	-0.1097**	-0.0650	0.1747***
	(0.0456)	(0.0614)	(0.0596)
China exposure	0.0526*	0.0166	-0.0692
	(0.0281)	(0.0507)	(0.0493)
Automation exposure	0.0835	-0.4316***	0.3482*
	(0.1051)	(0.1309)	(0.1793)
Standardized beta coefficients			
GVC exposure	-0.401	-0.170	0.483
China exposure	0.423	0.096	-0.422
Automation exposure	0.159	-0.590	0.503
N	722	722	722
R^2	0.323	0.214	0.236

Notes: * p<0.10, ** p<0.05, *** p<0.01. State-level clustered standard errors in parentheses. Dependent variable: change in the share in total hours worked of the respective wage group between 2000 and 2014. Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.