The Effects of Import Competition on Unionization

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Online Appendix

Appendix

A1. Data

We rely on four data sources. First, we take Chinese import data from the ADH public replication files, extended through 2014 thanks to updates provided by Gordon Hanson. Second, we take NTR and non-NTR tariff rates from the PS public replication files. Third, we use the Annual Survey of Manufacturing (ASM) for (SIC) industry-level employment and capital-labor ratios. Fourth, we use the Current Population Survey (CPS) for data on union membership.[36] Our core employment results for both states and industries are based on Census-defined industries.

Adjusting industry codes. — There are two industry classification systems in the United States. Data based on firms (the ASM, CBP, LBD, and more) use the Standard Industrial Classification (SIC) and the North American Industrial Classification (NAICS, which replaced SIC in 1997). The original ADH paper (using the CBP) and PS paper (using the LBD) use these industry codes. They are detailed and easy to connect to product-level import and tariff data. Surveys of individuals use a less granular classification system based on Census-defined categories.[37]

To link NAICS/SIC-based import and tariff data with CPS-based union membership, we construct a crosswalk from the 1997 NAICS to 1990 Census industry codes using the 2000 Census and the 2001-2002 American Community Survey (ACS, again from IPUMS), which has included both industry codes since 2000. We identify the Census industry accounting for the largest share of a NAICS industry's employment. We then use files available on David Dorn's website to map SIC industries into NAICS, again using the NAICS industry accounting for the largest share of a SIC industry's employment. Throughout, when we refer to "SIC industries," we use the "sic87dd" scheme used by ADH. These codes are slightly coarser than the original 1987 SIC codes (used by PS). We therefore aggregate the PS SIC-based tariff measures to the ADH scheme based on unweighted averages across HS codes (as PS themselves do).

Summary statistics. —

[Table A1 about here.]

[36]We use the Integrated Public Use Microdata Sample (IPUMS) versions of the CPS, which has cleaned the data and made variables as consistent as possible over time (Flood et al., 2017). Since the industry- and state-level sample sizes can be small, we follow the common practice and pool three consecutive years for all calculations based on CPS employment, i.e., "1990 employment" is based on the 1989-1991 CPS samples.

[37]The Census Bureau's industry codes are re-evaluated every 10 years following the decennial census. The IPUMS project provides a crosswalk of all Census-based industry classifications back to the 1990 scheme (Flood et al., 2017; Ruggles et al., 2018), which we use.

Replicating existing results with Census industries. — Aggregating imports to Census-based industry codes means we go from 357 SIC-based manufacturing industries comparable over time to 64 under the Census codes. Thus, we lose a great deal of variation. As a first step we demonstrate that the core findings from ADH and PS still hold under coarser industrial classification.

Table A2 shows the relationship between both the PS and ADH import exposure measures and the changes in industry imports and employment over the full 1991-2014 period.[38] The upper panel (A) uses the change in China-Other trade as the measure of import penetration.[39] Panel B uses the NTR gap.

Column 1 regresses the change in China-US trade on these instruments at the SIC-industry level, and finds that both are strongly and significantly predictive of increased imports. Column 2 replicates this using 64 Census-defined industries. The table shows that the standard deviation of both instruments falls slightly going from SIC to Census industries (5% for China-Other trade, 15% for the NTR gap); i.e., aggregation costs us only a small amount of variation. Both instruments continue to predict import growth ($p < .05$) and the coefficients actually grow.

[Table A2 about here.]

Columns 3-6 display the estimated reduced form effects of both instruments on the change in industry-level employment. Column 3 estimates the effects of each instrument on changes in SIC-based employment (from the ASM).[40] A one standard deviation increase in China-Other trade implies a 20% (22 log point) decrease in industry employment. Similarly, Panel B estimates that a one standard deviation increase in the NTR gap leads to a 19% reduction in employment. These results, like most that we report in the paper, are strikingly similar between the two identification strategies.

Column 4 aggregates the ASM data into the 64 Census-based industries and estimates larger effects, with 23% and 28% employment declines for each standard deviation increase in China-Other trade and the NTR gap, respectively. Why might we find larger import effects when we aggregate data to the Census industry level? We investigate the possibility of spillovers across SIC-industries due to product substitutability.[41] SIC industry codes are quite granular. For instance, there is one Census-based code for the manufacturing of any meat product whereas there are 3 SIC industries for meat product manufacturing (meat packing, sausages and prepared meats, and poultry slaughtering and processing). From

[38] This updates both the Acemoglu et al. (2016) and PS results, which end in 2011 and 2005, respectively.

[39] Specifically, the change in Chinese imports divided by lagged employment.

[40] Pierce and Schott (2016) use similar but restricted access employment data. Acemoglu et al. (2016) use SIC-based industries and the ASM.

[41] Pierce and Schott (2016) study spillovers along the supply chain using input-output tables. Our spillovers are fundamentally different. Ours reflect the substitutability between different products that are similar enough to be in the same broad industry.

1990-2000, US imports of Chinese meat packing products increased by 160%, while US imports of Chinese poultry products increased by 1,130%. If different types of prepared meats are substitutes, then increased availability of inexpensive poultry might affect demand for other packed meats.

To estimate import spillovers into SIC-based industry i, we calculate the total increase in China-Other trade in *other* SIC industries that map into the same Census industry as i (likewise for the NTR gap). We then regress changes in SIC industries' employment on import exposure within that SIC as well as in other, similar SIC industries. Results are in column 5. Imports from other industries have large employment effects (equally sized with ADH, over 3 times as large with PS). Thus, the coarser Census-based codes may perform better than the precise SIC codes for estimating employment effects.

All employment effects in columns 3-5 relied on ASM data, which is based on surveys of firms. Column 6 replicates column 4 and estimates the effects of the instruments on employment using the noisier CPS. These estimates are somewhat smaller than those using ASM employment but similar to the SIC-level effects reported in column 3. One standard deviation increase in exposure reduces employment by 14% (using the PS instrument) to 19% (using ADH).

In summary, the coarser Census industries–which we must rely on to study unionization–perform at least as well as the detailed industries from past work. While we lose some cross-industry variation through aggregation and the CPS estimates are noisier, results suggest significant trade-induced employment declines similar in magnitude to existing estimates.

A2. Correlation with baseline union density

Autor, Dorn, Hanson (2013). — The ADH identification strategy fundamentally relies on Chinese productivity growth concentrated in certain industries. These industries were not chosen randomly. For instance, import growth was concentrated in labor-intensive industries where China held a comparative advantage (Amiti and Freund, 2010). Figure A1 shows that these industries differ in their historical unionization rates. On average, industries with the most growth in China-Other trade had lower rates of unionization in 1990.[42]

[Figure A1 about here.]

We entertain three potential explanations for the negative relationship between Chinese export growth and lagged unionization. First, we consider industries' skill profile, measured as the non-production workers share of all workers (from the ASM). Production workers are more likely to unionize than non-production workers, so industries with relatively more non-production staff will have relatively low

[42] The negative correlation remains even excluding outlier industries.

unionization rates. Second, we consider capital-labor ratios since China's comparative advantage is concentrated in labor-intensive industries. Finally, we consider 6 industries in the textile, apparel, and leather sector, which had the lowest rate of unionization and which had distinctive patterns of both trade policy (Irene Brambilla, Amit K Khandelwal and Peter K Schott, 2010) and Chinese export growth.[43]

As shown in columns 1 and 2 of Table A3, these three controls eliminate virtually all of the relationship between baseline unionization and subsequent growth in China-OECD trade. The coefficient in column 2 is no longer statistically significant, and the magnitude is less than 20% that of column 1.

[Table A3 about here.]

Pierce and Schott (2016). — PS show that after 2001, US imports from China rose in the industries where the NTR gap was largest. They also show that lagged unionization is negatively correlated with the NTR gap (their Table A.2), but that controlling for lagged unionization has no effect on their main results (their Table 2). Although PS devoted little attention to this relationship, it is obviously more important here.

The NTR gap depends on both NTR tariffs (applied to WTO members) and the non-NTR tariffs that would be applied to non-market economies absent a Congressional waiver. Either could produce a correlation between unionization and the NTR gap. Figure A2 shows that it is the non-NTR tariffs that drive this relationship: Historically unionized industries had *lower* nonmarket tariff rates in 1999 (the opposite of what a simple political economy explanation based on union power would suggest).

[Figure A2 about here.]

In the bottom panel of Table A3 we show that, like China-OECD trade, capital-intensity, skill-intensity, and the textile/apparel sector explain this correlation. Conditioning on all three we see that unioniztion-NTR gap relationship is no longer statistically significant at conventional levels ($p = .11$). In summary, across both the ADH and Pierce-Schott instruments, it appears that more unionized manufacturing industries were relatively insulated from the Chinese import penetration. This is largely due the fact that the pockets of unionization still remaining in US manufacturing by 1990 were in relatively capital-intensive industries that Chinese exporters avoided, and that unions in labor-intensive industries (like textiles) had been under pressure for decades by this time (Silver, 2003).

[43] We classify manufacturing industries into 9 sectors based on two-digit Census industry codes. This sector has the lowest union density.

A3. Robustness

Industry-level. —

[Table A4 about here.]

[Table A5 about here.]

[Table A6 about here.]

State-level. —

[Table A7 about here.]

[Table A8 about here.]

[Table A9 about here.]

[Table A10 about here.]

[Table A11 about here.]

[Table A12 about here.]

A4. Decomposition

Derivation. — For the manufacturing decomposition, note that we can write the change in union density within manufacturing as

$$\begin{aligned}
\Delta u = u_1 - u_0 &\equiv \sum_i w_{i,1}u_{i,1} - \sum_i w_{i,0}u_{i,0} \\
&= \sum_i w_{i,1}u_{i,1} - \sum_i w_{i,0}u_{i,0} + \sum_i w_{i,1}u_{i,0} - \sum_i w_{i,1}u_{i,0} \\
&= \sum_i w_{i,1}(u_{i,1} - u_{i,0}) + \sum_i (w_{i,1} - w_{i,0})u_{i,0} \\
&= \sum_i w_{i,1}\Delta u_i + \sum_i \Delta w_i u_{i,0}
\end{aligned}$$

or equivalently as:

$$\begin{aligned}
\Delta u = u_1 - u_0 &\equiv \sum_i w_{i,1}u_{i,1} - \sum_i w_{i,0}u_{i,0} \\
&= \sum_i w_{i,1}u_{i,1} - \sum_i w_{i,0}u_{i,0} + \sum_i w_{i,0}u_{i,1} - \sum_i w_{i,0}u_{i,1} \\
&= \sum_i u_{i,1}(w_{i,1} - w_{i,0}) + \sum_i (u_{i,1} - u_{i,0})w_{i,0} \\
&= \sum_i u_{i,1}\Delta w_i + \sum_i \Delta u_i w_{i,0}
\end{aligned}$$

where $u_{i,t}$ is the union density in industry i at time t and $w_{i,t}$ is industry i's share of employment at time t.

Then we can use these two expressions for Δu and the fact that:

$$\begin{aligned}
\Delta u &= \frac{1}{2}\Delta u + \frac{1}{2}\Delta u \\
&= \frac{1}{2}\sum_i w_{i,1}\Delta u_i + \frac{1}{2}\sum_i \Delta w_i u_{i,0} + \frac{1}{2}\sum_i u_{i,1}\Delta w_i + \frac{1}{2}\sum_i \Delta u_i w_{i,0} \\
&= \frac{1}{2}\sum_i (w_{i,1} + w_{i,0})\Delta u_i + \frac{1}{2}\sum_i \Delta w_i(u_{i,0} + u_{i,1}) \\
&= \sum_i \bar{w}_i \Delta u_i + \sum_i \Delta w_i \bar{u}_i
\end{aligned}$$

where $\bar{x}_i$ is the average level of $x \in \{w, u\}$ in industry i between the two time periods. This is a standard decomposition of the sort popularized by Eli Berman, John Bound and Zvi Griliches (1994).

Similarly, letting m_t denote the manufacturing share of employment in time t and letting subscript m denote manufacturing, we can write union density in the full labor market as:

$$\begin{aligned}
\Delta u &= \bar{m}\Delta u_m + (1-\bar{m})\Delta u_{-m} + \Delta m \bar{u}_m + \Delta(1-m)\bar{u}_{-m} \\
&= \bar{m}\sum_i \bar{w}_i \Delta u_i + \bar{m}\sum_i \Delta w_i \bar{u}_i + (1-\bar{m})\Delta u_{-m} + \Delta m \bar{u}_m + \Delta(1-m)\bar{u}_{-m} \\
&= \bar{m}\sum_i \bar{w}_i \Delta u_i + \bar{m}\sum_i \Delta w_i \bar{u}_i + (1-\bar{m})\Delta u_{-m} + \Delta m \bar{u}_m - \Delta m \bar{u}_{-m} \\
&= \bar{m}\sum_i \bar{w}_i \Delta u_i + \bar{m}\sum_i \Delta w_i \bar{u}_i + (1-\bar{m})\Delta u_{-m} + \Delta m(\bar{u}_m - \bar{u}_{-m}) \\
&= \bar{m}\sum_i \bar{w}_i \Delta u_i + \bar{m}\sum_i \Delta w_i \bar{u}_i + \Delta m(\bar{u}_m - \bar{u}_{-m}) + (1-\bar{m})\Delta u_{-m}
\end{aligned}$$

which is the decomposition appearing in the paper.

A5. Manufacturing-type workers

Methodological approach. — We use a machine-learning approach to identify workers most directly affected by the manufacturing decline. We use a Lasso approach, with λ selected using the eBIC (selecting λ using cross-validation produces estimates of the probability of manufacturing employment which have a correlation, across individuals, with our preferred measure above .995). We use a rich set of demographic and geographic variables to predict the likelihood that 1989-1991 ORG respondents work in manufacturing, including: state fixed effects; a cubic in age; 5 education dummies; dummies for Hispanic, Black, other non-White race, and being married; and a series of interactions. Specifically, we interact each state dummy with {age, male, 5 education dummies, Hispanic, Black, other non-White race, married}. We each education dummy with {age, male, Hispanic, Black, other non-White race, married}. We interact male with {age, Hispanic, Black, other non-White race, married}. We interact age with {Hispanic, Black, other non-White race, married}.

To illustrate why we use such a flexible model (including all of the interactions), consider that manufacturing employment accounted for 20% of North Carolina's working-age population in 1990, compared to only 3% of Wyoming's. Thus, there are dramatic cross-state differences in the likelihood that observationally similar individuals work in manufacturing.

We use a linear probability model in the Lasso estimation for simplicity. We define manufacturing-type workers as those with estimated probability above the 90^{th} percentile of the cohort-specific distribution because this is most effective. Table A13 compares the performance of different approaches for defining "manufacturing-type workers," as a function of the same estimated probabilities.

[Table A13 about here.]

We apply our estimated probability model (based on the 1990 data) to the 2013-2015 CPS sample, calculating the predicted probabilities of manufacturing for each respondent. We refer to respondents in the top 10% of predicted probabilities as "manufacturing-type workers." We think of these as the individuals who likely *would have* worked in manufacturing had they looked the same in the past and had the labor market not changed; thus, they were particularly acutely affected by import competition. Our approach follows in the tradition of the well-known John DiNardo, Nicole M Fortin and Thomas Lemieux (1996) decomposition.

To define retail-type workers, we use this exact same approach, except predicting retail employment in 1990 instead of manufacturing employment.

We also use of the estimated probability model is to identify household members of manufacturing-type workers. Specifically we refer to anyone with below median predicted manufacturing probability but who lives with a manufacturing-type worker as a "household member."

Who are manufacturing-type workers?. — Panel A of Table A14 characterizes manufacturing-type workers and household members, comparing them to the general population in 1990 and 2014. Our estimated probability model performs well; in both time periods, manufacturing-type workers are two and a half times more likely than the full population to work in manufacturing. These workers differ from the full population in many ways. They are almost almost entirely male, somewhat older, more likely to be married, more likely to be White, and less educated, on average. Household members, on the other hand, are overwhelmingly female (85%), and are younger than and similarly educated to the full population. Our sample of household members is younger, more gender-balanced, and less likely to be married than the manufacturing-type workers, suggesting household members includes children in addition to spouses.

[Table A14 about here.]

A6. Interpreting household adjustment

[Figure A3 about here.]

[Figure A4 about here.]

[Table A15 about here.]

[Table A16 about here.]

[Figure A5 about here.]

[Table A17 about here.]

A7. Right-to-Work results

[Figure A6 about here.]

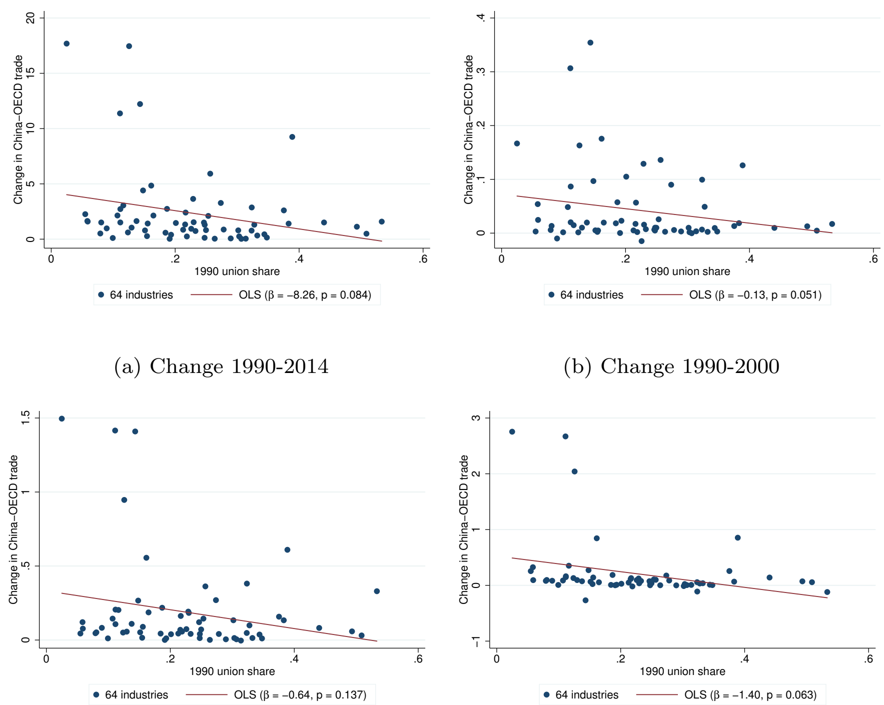
[Table A18 about here.]

[Table A19 about here.]

[Table A20 about here.]

[Figure A7 about here.]

Figure A1. : Autor-Dorn-Hanson instrument and lagged unionization



(a) Change 1990-2014

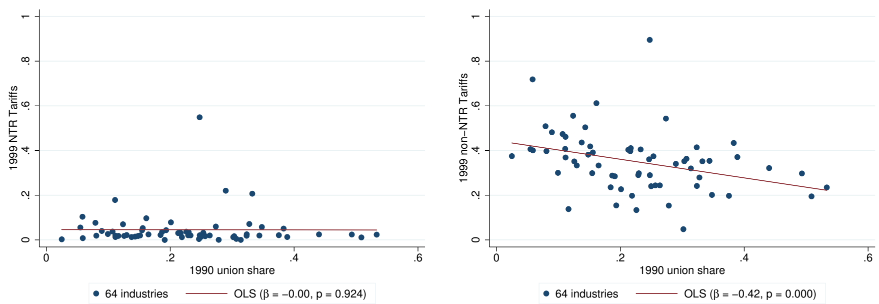
(b) Change 1990-2000

(c) Change 2000-2007

(d) Change 2007-2014

Each dot is an industry (for Census defined industries). Figure shows the relationship between baseline union density (1990) and subsequent changes in exports from China to eight "comparable" OECD countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) used by ADH in the construction of their instrument. All eight had established permanent NTR with China prior to 1990.

Figure A2. : Pierce-Schott instrument and lagged unionization

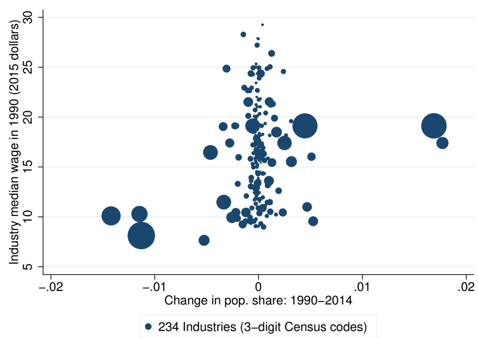


(a) NTR tariffs

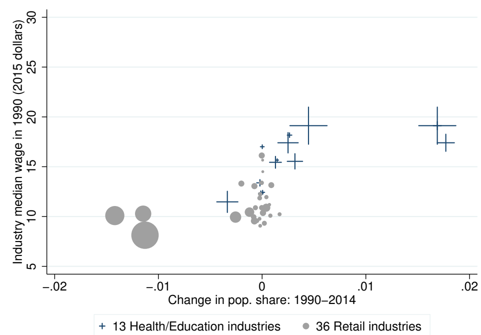
(b) non-NTR tariffs

Each dot is an industry (for Census defined industries). Figure shows the relationship between baseline union density (1990) and tariffs measured by Pierce-Schott. We note that Pierce-Schott showed a correlation between their NTR gap measure and 1999 unionization in their paper (see Table A.2).

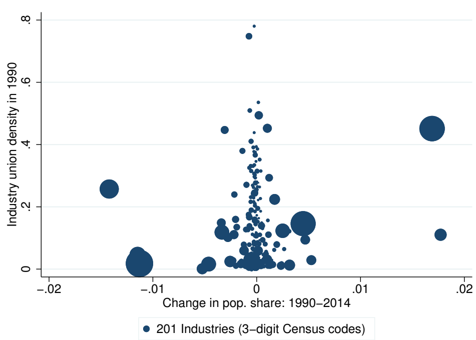
Figure A3. : Characteristics of industries seeing largest changes in household members' employment



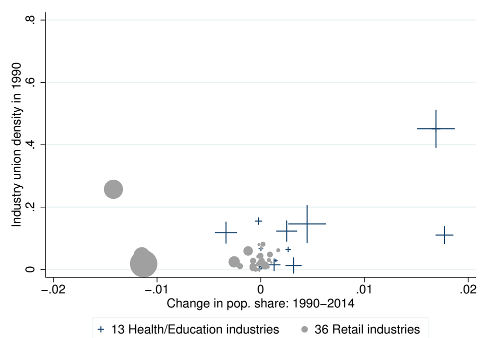
(a) Median wages (all industries)



(b) Median wages (retail, ed., health)



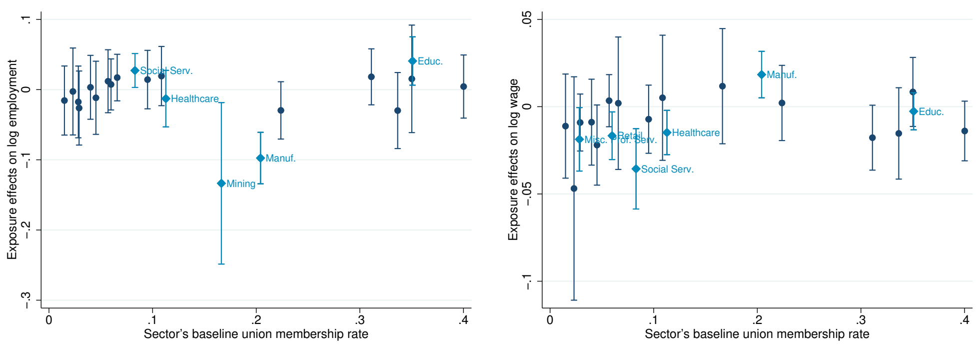
(c) Union density (all industries)



(d) Union density (retail, ed., health)

Sample is based on individuals for whom the estimated probability of working in manufacturing (based on demographics, state-of-residence, and a probability model estimated on the 1990 sample) is below the cohort-specific median, but for whom at least one household member has an estimated probability above the cohort-specific 90^{th} percentile. For these individuals, we calculate changes in the share of the population working in each 3-digit Census industry, from 1990 to 2014 (shown on the x-axis). We relate this to the median wage in the industry in 1990 (in 2015 dollars) and the union density in the industry in 1990. The three points furthest to the left (i.e., showing the largest decline) are department stores, grocery stores, and eating and drinking places.

Figure A4. : Sector specific effects of import competition



(a) Log employment

(b) Log wage

Figure presents coefficient estimates (and 90% confidence intervals) for effects of import exposure (at the state level) on log employment and log wage for 21 sectors ordered by baseline (1991) union membership rate.

Figure A5. : Effects of import competition on within-sector unionization rates

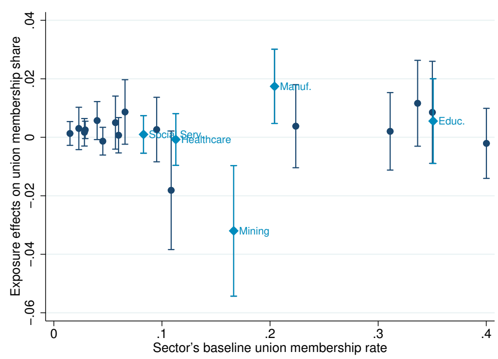
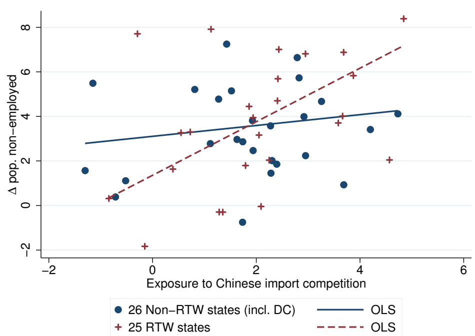
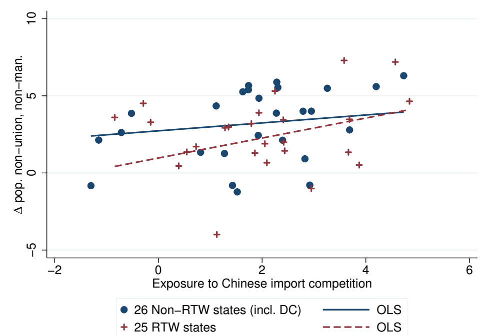


Figure presents coefficient estimates (and 90% confidence intervals) for effects of import exposure (at the state level) on union density for 21 sectors ordered by baseline (1991) union density.

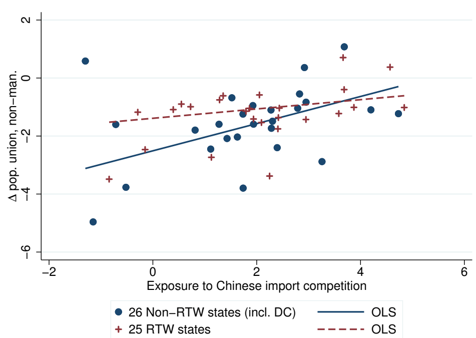
Figure A6. : Non-parametric heterogeneity by RtW status



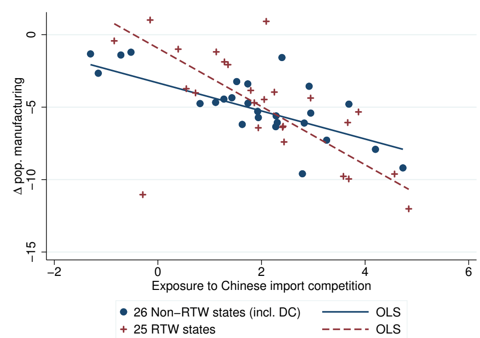
(a) Non-employed



(b) Non-union, non-man.



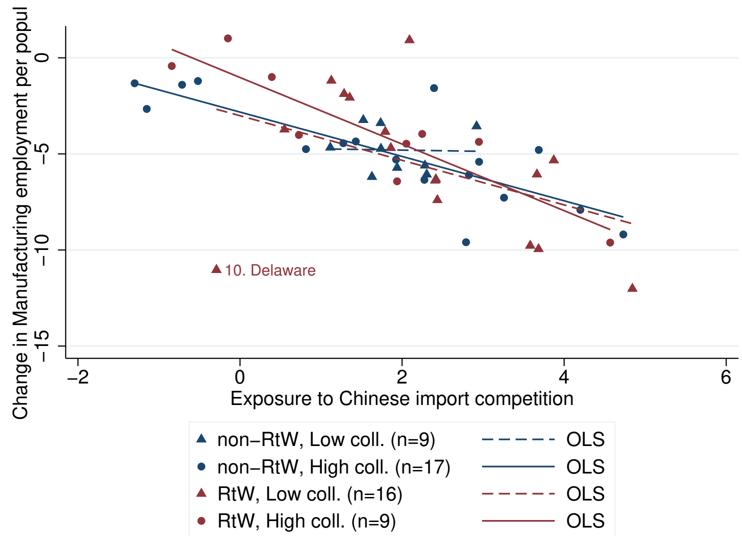
(c) Union, non-man.



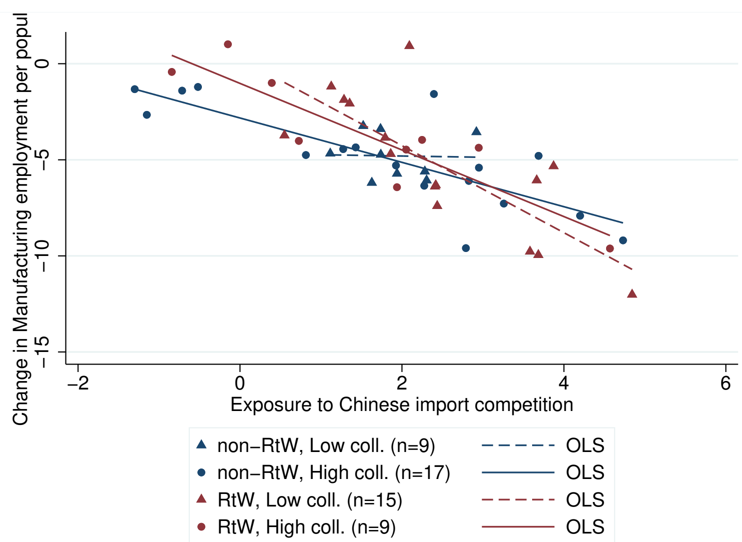
(d) Manufacturing

Figure reflects changes in share of the working age population (1990-2014) as a function of state-level import exposure. Formal regressions included in Table 3. Outlier in Panel (d) is Delaware.

Figure A7. : Right-to-Work vs. Baseline (1990) education (non-parametric)



(a) All states



(b) Excluding Delaware

Figure reflects changes in manufacturing share of the working age population (1990-2014), as a function of state-level import exposure, separately depending on RtW status (our focus) and average education levels (the focus of Bloom et al. (2019)). Formal regressions included in Table A20.

Table A1—: Summary statistics

				Percentiles				
Variable	Mean	SD	N	10	25	50	75	90
Δ China-US Trade (SIC)	0.16	0.67	1121	0.00	0.00	0.03	0.12	0.36
1990-2000	0.10	0.36	364	0.00	0.00	0.01	0.05	0.17
2000-2007	0.23	0.65	376	0.00	0.01	0.06	0.19	0.43
2007-2014	0.15	0.87	381	-0.03	0.00	0.03	0.14	0.36
Δ China-US Trade (Cen.)	0.17	0.50	199	0.00	0.01	0.04	0.12	0.34
1990-2000	0.08	0.20	68	0.00	0.00	0.01	0.06	0.26
2000-2007	0.22	0.45	65	0.00	0.03	0.07	0.17	0.50
2007-2014	0.22	0.72	66	-0.00	0.01	0.05	0.12	0.41
Δ China-Other. Trade (SIC)	0.16	0.83	1157	0.00	0.00	0.03	0.12	0.34
1990-2000	0.06	0.18	385	0.00	0.00	0.01	0.05	0.14
2000-2007	0.20	0.50	384	0.00	0.01	0.06	0.17	0.40
2007-2014	0.23	1.33	388	-0.00	0.00	0.04	0.14	0.41
Δ China-Other. Trade (Cen.)	0.14	0.37	199	0.00	0.01	0.05	0.13	0.27
1990-2000	0.05	0.08	68	0.00	0.00	0.01	0.06	0.14
2000-2007	0.19	0.32	65	0.01	0.04	0.07	0.18	0.38
2007-2014	0.20	0.53	66	0.00	0.01	0.07	0.13	0.33
NTR Gap (SIC)	0.33	0.14	382	0.13	0.24	0.34	0.41	0.48
NTR Gap (Cen.)	0.31	0.12	69	0.14	0.22	0.33	0.38	0.44
Δ ln(Emp) (ASM, SIC)	-1.00	3.33	1170	-3.09	-1.20	-0.33	-0.01	0.56
1990-2000	-0.05	3.43	386	-1.43	-0.29	-0.03	0.44	1.49
2000-2007	-1.22	2.60	390	-3.26	-1.39	-0.50	-0.10	0.21
2007-2011	-1.72	3.65	394	-3.67	-1.75	-0.65	-0.20	-0.03
Δ ln(Emp) (ASM, Cen.)	-0.30	0.43	197	-0.95	-0.52	-0.23	-0.01	0.15
1990-2000	-0.00	0.28	66	-0.28	-0.16	0.01	0.14	0.25
2000-2007	-0.33	0.42	65	-0.99	-0.42	-0.28	-0.10	0.07
2007-2011	-0.56	0.39	66	-1.11	-0.80	-0.51	-0.23	-0.14
Δ ln(Emp) (CPS, Cen.)	-0.16	0.65	203	-0.70	-0.35	-0.10	0.05	0.21
1990-2000	-0.09	0.43	68	-0.57	-0.20	-0.04	0.05	0.18
2000-2007	-0.25	0.98	67	-1.06	-0.69	-0.21	0.01	0.21
2007-2016	-0.13	0.33	68	-0.48	-0.31	-0.10	0.06	0.23
Δ Union share (Cen.)	-0.05	0.06	203	-0.13	-0.08	-0.05	-0.02	0.00
1990-2000	-0.05	0.06	68	-0.13	-0.08	-0.06	-0.03	0.00
2000-2007	-0.07	0.07	67	-0.18	-0.11	-0.05	-0.02	0.01
2007-2016	-0.04	0.04	68	-0.09	-0.05	-0.03	-0.01	0.00

Δ China-US Trade is change in real import volume (in $10,000) per worker (same as Autor, Dorn and Hanson (2013)). NTR Gap is gap between China tariff the Normalized Trade Relations tariff rate applied to WTO members (same as Pierce and Schott (2016)). ASM = Annual Survey of Manufacturing, CPS = Current Population Survey, SIC = Standard Industrial Classification. Imports are annual changes, everything else is a decadal change.

Table A2—: Replicating existing results

	(1)	(2)	(3)	(4)	(5)	(6)
DV:	Δ China-US Trade		Δ log(Employment)			
	Panel A: Autor-Dorn-Hanson identification strategy					
Δ China-Other Trade	1.340***	1.561***	-0.052***	-0.064***	-0.035**	-0.051***
	(0.110)	(0.061)	(0.012)	(0.017)	(0.014)	(0.010)
Δ Ch.-Oth. (other ind.)					-0.034**	
					(0.015)	
R^2	0.869	0.963	0.115	0.203	0.137	0.136
N	357	64	357	64	357	64
F-stat	148.7	655.9				
St. dev. of X_{own}	4.36	4.17	4.36	4.17	4.36	4.17
St. dev. of X_{other}					3.53	
	Panel B: Pierce-Schott identification strategy					
NTR Gap	8.901***	14.276**	-1.794***	-3.254***	-0.582	-1.471*
	(2.549)	(6.188)	(0.376)	(1.138)	(0.362)	(0.816)
NTR Gap (other ind.)					-2.140***	
					(0.482)	
R^2	0.029	0.049	0.113	0.323	0.194	0.068
N	350	64	350	64	350	64
F-stat	12.2	5.3				
St. dev. of X_{own}	0.12	0.10	0.12	0.10	0.12	0.10
St. dev. of X_{other}					0.11	
Industries	SIC	Census	SIC	Census	SIC	Census
Emp. data			ASM	ASM	ASM	CPS

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014. All regressions weighted by industry employment in 1990. "Other industries" refers to other SIC industry codes within the same census industry code. "F-stat" refers to the F-statistic testing the null that ΔChina-Other Trade or the NTR Gap has no effect on ΔChina-US Trade.

Table A3—: Explaining the correlation between 1990 density and exposure

	(1)	(2)	(3)	(4)
DV:	1990 Union Density (members as share of employment)			
Δ China-Other Trade	-4.112***	-0.743		
	(1.291)	(1.500)		
Non-NTR Tariff Rate (1999)			-4.963***	-2.504
			(1.593)	(2.027)
R^2	0.104	0.388	0.152	0.404
N	64	64	64	64
Controls		Yes		Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. Controls: Skill share, capital-labor ratios, and dummy for textile sector. Skill share is non-production workers as a share of all workers. Capital-labor ratios and skill shares are drawn from the Annual Survey of Manufacturing (ASM). Both measures of exposure are normalized to have unit standard deviation.

Table A4—: Industry-level effects separately by identification strategy

	(1)	(2)	(3)	(4)	(5)	(6)
DV:	Δ ln(Employment)			Change in Union member share		
	Total	Union mem.	Non-mem.			
	Panel A: Autor-Dorn-Hanson identification strategy					
Δ China-Other Trade	-0.184***	-0.370***	-0.174***	-0.007	-0.006**	-0.006*
	(0.050)	(0.093)	(0.049)	(0.004)	(0.003)	(0.003)
Exposure × Homogen. goods						-0.031
						(0.050)
R^2	0.158	0.272	0.261	0.843	0.864	0.874
N	64	64	64	64	64	62
Controls:						
Union mem. (1990)	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	Yes	Yes
	Panel B: Pierce-Schott identification strategy					
NTR Gap	-0.106	-0.291**	-0.100	-0.015***	-0.012*	-0.005
	(0.090)	(0.129)	(0.093)	(0.005)	(0.006)	(0.005)
Exposure × Homogen. goods						-0.017
						(0.013)
R^2	0.096	0.189	0.214	0.863	0.870	0.878
N	64	64	64	64	64	62
Controls:						
Union mem. (1990)	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	Yes	Yes
p for $H_0 : \beta_{ADH} = \beta_{PS}$	.403	.558	.440	.107	.438	.859

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014, weighted by 1990 industry employment; and condition on 1990 union share. Both the Pierce-Schott NTR Gap and the ADH ΔChina-Other Trade have unit standard deviation across industries. Results can be compared to Table 1 which pools both identification strategies. Columns 5 and 6 condition on the covariates considered in Table A3 (capital intensity, skill share, textiles).

Table A5—: Placebo (pre-1990) industry-level effects

	(1)	(2)	(3)	(4)	(5)	(6)
DV:	Change in Union member share (1985-1990)					
Δ China-Other Trade	0.003	-0.001				
	(0.004)	(0.004)				
NTR Gap			0.005	0.005		
			(0.004)	(0.004)		
Import exposure					0.005	0.002
					(0.004)	(0.005)
R^2	0.015	0.097	0.029	0.116	0.033	0.099
N	64	64	64	64	64	64
Controls:		Yes		Yes		Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1985 to 1990 and are weighted by 1990 industry employment. Controls include industry-level capital-labor ratios (from ASM), "skill intensity" (non-production workers as share of employment; from ASM), and a dummy for textiles, apparel, and leather. "Import exposure" refers to the composite measure combining the ADH and PS instruments. All three instruments have unit standard deviation (by construction).

Table A6—: IV effects of imports on industry-level unionization

	(1)	(2)	(3)	(4)	(5)
DV:		Δ ln(Employment)		Change in	
	Total	Union mem.	Non-mem.	Union member share	
$\frac{\Delta Imports_i}{Emp_{i,t-1}}$	-0.392**	-0.888**	-0.371**	-0.028*	-0.020**
	(0.188)	(0.368)	(0.187)	(0.015)	(0.009)
R^2	0.103	0.141	0.216	0.821	0.858
N	64	64	64	64	64
Effect of 1 SD change	-0.260	-0.590	-0.246	-0.018	-0.013
First stage F-stat.	11.5	11.5	11.5	11.5	32.5
Controls:					
Union mem. (1990)	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014, weighted by 1990 industry employment; and condition on 1990 union share. Change in imports is measured as the change in the dollar value of imports from China to the US between 1991 and 2014 (inflation adjusted; hundreds of thousands of dollars) normalized by 1990 industry-level employment. Columns 5 conditions on the covariates considered in Table A3 (capital intensity, skill share, textiles).

Table A7—: State-level effects separately by identification strategy

	(1)	(2)	(3)	(4)
DV: Δ share working age pop.	Non-emp.	Non-manuf., non-union	Non-manuf., union	Manufact.
	Panel A: Autor-Dorn-Hanson identification strategy			
Δ China-Other Trade	0.534*	0.457*	0.313***	-1.304***
	(0.298)	(0.270)	(0.101)	(0.279)
R^2	0.074	0.049	0.131	0.383
N	51	51	51	51
	Panel A: Pierce-Schott identification strategy			
NTR Gap	0.762**	0.324	0.271*	-1.357***
	(0.334)	(0.271)	(0.144)	(0.294)
R^2	0.150	0.025	0.098	0.414
N	51	51	51	51
p for H_0: $\beta_{ADH} = \beta_{PS}$	.612	.729	.810	.896

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014, are weighted by state employment in 1990, and are based on working age persons (age 16-64). "States" includes the District of Columbia. Coefficients in columns 1-4 sum to zero because the population shares sum to one (i.e., groups are mutually exclusive and exhaustive). "NTR Gap" and "ΔChina-Other Trade" have standard deviation 1 across states.

Table A8—: Robustness to state-level controls

	(1)	(2)	(3)	(4)	(5)
Numerator:	Non-emp.	Non-man., non-union	Non-man., union	Man.	Union
Denominator:	Pop.	Pop.	Pop.	Pop.	Emp.
	Panel A: Baseline				
Import exposure	0.721**	0.434	0.324***	-1.479***	0.538*
	(0.300)	(0.270)	(0.119)	(0.252)	(0.312)
R^2	0.134	0.044	0.140	0.492	0.053
N	51	51	51	51	51
	Panel B: 9 controls (see notes for details)				
Import exposure	0.160	-0.304	0.340**	-0.196	0.539**
	(0.315)	(0.285)	(0.165)	(0.250)	(0.264)
R^2	0.615	0.711	0.364	0.802	0.809
N	51	51	51	51	51

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014 in either population or employment shares. All regressions weighted by state employment in 1990. "States" includes the District of Columbia. All regressions based on working age persons (age 16-64). Panel B controls for fixed effects for four Census regions, 1990 share of population (26-64) with a college degree, 1990 manufacturing share of employment, and 1990 union share of employment, as well as variables from Table A3 converted to the state-level in the same way as import exposure (skill share, capital-labor ratio, and a dummy for textiles).

Table A9—: Placebo (pre-1990) state-level effects

	(1)	(2)	(3)	(4)
DV: Δ share working age pop.	Non-emp.	Non-manuf., non-union	Non-manuf., union	Manufact.
Import exposure	0.580**	0.062	-0.058	-0.584***
	(0.223)	(0.125)	(0.074)	(0.205)
R^2	0.143	0.003	0.011	0.222
N	51	51	51	51
DV mean in 1985	31.3	47.3	7.8	13.6
Avg change '85-'90	-3.3	3.8	-0.0	-0.5

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1985 to 1990, are weighted by state employment in 1990, and are based on working age persons (age 16-64). "States" includes the District of Columbia. Coefficients in columns 1-4 sum to zero because the population shares sum to one (i.e., groups are mutually exclusive and exhaustive). To calculate exposure, we standardized state-level measures of "NTR Gap" and "ΔChina-Other Trade" to have standard deviation 1 across states, sum them, and re-standardize the sum to have standard deviation 1 across states.

Table A10—: Robustness to non-manufacturing exposure

	(1)	(2)	(3)	(4)	(5)
Numerator:	Non-emp.	Non-man., non-union	Non-man., union	Man.	Union
Denominator:	Pop.	Pop.	Pop.	Pop.	Emp.
	Panel A: ADH: zero, PS: excluded (Baseline)				
Import exposure	0.721**	0.434	0.324***	-1.479***	0.538*
	(0.300)	(0.270)	(0.119)	(0.252)	(0.312)
R^2	0.134	0.044	0.140	0.492	0.053
	Panel B: ADH: zero, PS: zero				
Import exposure	0.486	0.760***	0.171*	-1.417***	-0.354
	(0.305)	(0.232)	(0.098)	(0.266)	(0.302)
R^2	0.061	0.135	0.039	0.452	0.023
	Panel C: ADH: excluded, PS: zero				
Import exposure	0.683**	0.302	0.369***	-1.354***	0.526*
	(0.304)	(0.283)	(0.100)	(0.273)	(0.266)
R^2	0.121	0.021	0.182	0.412	0.051
	Panel D: ADH: excluded, PS: excluded				
Import exposure	0.688**	-0.148	0.401***	-0.940***	1.273***
	(0.321)	(0.357)	(0.122)	(0.267)	(0.357)
R^2	0.122	0.005	0.215	0.199	0.300

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014 in either population or employment shares. All regressions weighted by state employment in 1990. "States" includes the District of Columbia. All regressions based on prime age persons (age 16-64). Panels differ in whether non-manufacturing industries are assigned zero exposure when creating state-level aggregate exposure, or are excluded from the calculation (i.e., whether exposure is based only on exposure among manufacturing industries).

Table A11—: Kirill Borusyak, Peter Hull and Xavier Jaravel (2018*a*) industry-level implementation

	(1)	(2)	(3)	(4)
DV: Δ share working age pop.	Non-emp.	Non-manuf., non-union	Non-manuf., union	Manufact.
Import exposure	0.753***	0.610***	0.286***	-1.650***
	(0.100)	(0.070)	(0.042)	(0.098)
R^2	0.254	0.234	0.266	0.624
N	330	330	330	330

* $p < .10$, ** $p < .05$, *** $p < .01$. Unit of observation is an industry (SIC 1987 with Dorn adjustment), where all non-manufacturing industries are combined into one single industry. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014. Coefficients in columns 1-4 sum to zero because the population shares sum to one (i.e., groups are mutually exclusive and exhaustive). See Kirill Borusyak, Peter Hull and Xavier Jaravel (2018*a*) for methodological details, and Kirill Borusyak, Peter Hull and Xavier Jaravel (2018*b*) for implementation. Results are nearly identical when omitting the non-manufacturing industry. Scatterplots (available upon request) show no outliers.

Table A12—: IV effects of imports on state-level population shares

	(1)	(2)	(3)	(4)
DV: Δ share working age pop.	Non-emp.	Non-manuf., non-union	Non-manuf., union	Manufact.
$\frac{\Delta Imports_i}{Emp_{i,t-1}}$	2.756**	1.661*	1.240***	-5.656***
	(1.189)	(0.993)	(0.459)	(1.062)
R^2	0.050	0.035	0.089	0.271
N	51	51	51	51
Effect of 1 SD change	0.823	0.496	0.370	-1.689
First stage F-stat.	163.5	163.5	163.5	163.5

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. All regressions are changes from 1990 to 2014, are weighted by state employment in 1990, and are based on working age persons (age 16-64). "States" includes the District of Columbia. Coefficients in columns 1-4 sum to zero because the population shares sum to one (i.e., groups are mutually exclusive and exhaustive). Change in imports is measured as the change in the dollar value of imports from China to the US between 1991 and 2014 (inflation adjusted; hundreds of thousands of dollars) normalized by 1990 industry-level employment, and then reweight this to the state-level based on 1990 employment shares.

Table A13—: Probabilities of manufacturing employment

	(1)	(2)	(3)	(4)	(5)
Share working in manuf. (1990)	.138	.161	.208	.274	.345
Weights	Sample	Pr(Manuf.)	Sample	Sample	Sample
Estimated Prob. above:			50^{th} pctl.	75^{th} pctl.	90^{th} pctl.

Calculations based on 1989-1991 ORG respondents and the lasso-based probability model estimated using demographic and geographic predictors. Column 1 gives the manufacturing employment share among all respondents based on the sample weights. Column 2 uses the estimated probabilities as weights, in a more conventional John DiNardo, Nicole M Fortin and Thomas Lemieux (1996) approach. Columns 3-5 restrict to the sample with estimated probabilities of working in manufacturing that are above the 50^{th}, 75^{th}, and 90^{th} percentiles.

Table A14—: Characteristics of manufacturing-type workers and household members

	(1)	(2)	(3)	(4)	(5)	(6)
Group:	Full sample	Manuf.-type person	Non-man. in manuf. household	Full sample	Manuf.-type person	Non-man. in manuf. household
	Panel A: Demographic characteristics					
Year:	1990			2014		
Manufacturing	.138	.345	.068	.073	.191	.044
Male	.472	.984	.157	.488	.970	.118
Age	36.4	40.0	29.2	39.7	43.3	34.3
Married	.560	.892	.552	.500	.811	.613
Black	.126	.083	.067	.141	.088	.071
Hispanic	.105	.104	.062	.173	.205	.109
Education						
HS or less	.605	.757	.548	.439	.693	.356
Some college	.204	.148	.278	.286	.202	.338
College degree	.191	.095	.173	.292	.138	.314
	Panel B: Labor market outcomes					
Year:	1990			2014		
Employed	.695	.875	.610	.655	.811	.601
Union membership						
Among all individuals	.113	.241	.067	.069	.102	.066
Among the employed	.163	.275	.110	.104	.126	.109
Among manufacturing workers	.209	.326	.112	.093	.136	.056
Among non-manufacturing workers	.152	.242	.110	.106	.123	.113

Calculations based on 1989-1991 and 2013-2015 CPS samples. "Manufacturing-type persons" are those with estimated probabilities of working in manufacturing (based on demographics and the 1990 probability model) above the cohort-specific 90^{th} percentile. "Non-manufacturing in manufacturing household persons" are those with estimated probabilities below the cohort-specific median, but for whom at least one household member has an estimated probability above the cohort-specific 90^{th} percentile.

Table A15—: Explaining household members' choice of industries

	(1)	(2)	(3)
DV:	100 × Δ Pop. share ('90-'14)		
Median wage (1990)	0.449***		0.347**
	(0.136)		(0.141)
Union density (1990)		0.378*	0.203
		(0.200)	(0.232)
R^2	0.321	0.227	0.370
N	201	201	201

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust standard errors in parentheses. Calculations based on 201 3-digit Census industries. Regressions weighted by industries' 1990 population share. We focus on "household members" (those for whom the estimated probability of working in manufacturing is below median, but for whom at least one household member has an estimated probability above the 90^{th} percentile), and calculate the change in each industry's employment share of this population, and relate that to industry median wages and union density, both measured in 1990. Both wages and union density have been normalized to have unit standard deviation across industries.

Table A16—: Exposure effects for manufacturing-type and retail-type workers

	(1)	(2)	(3)	(4)	(5)	(6)
DV:	Emp. (×100)	Service jobs (×100)	Health or Educ. (×100)	Retail (×100)	Industry union density	Industry median wages
$\text{Exposure}_s \times 1\{\text{Year} = 2014\}$	2.72***	-0.34***	0.33**	0.05	0.42***	0.15**
	(0.417)	(0.104)	(0.140)	(0.135)	(0.091)	(0.072)
$\text{Exp}_s \times \text{'14} \times \hat{P}_j(\text{Manuf.})$	-2.36***	1.05***	-0.49***	1.15***	-0.93***	-0.27***
	(0.414)	(0.085)	(0.101)	(0.105)	(0.095)	(0.028)
$\text{Exp}_s \times \text{'14} \times \hat{P}_j(\text{Retail})$	-3.99***	-0.07	0.34***	-0.86***	0.60***	-0.05***
	(0.131)	(0.069)	(0.086)	(0.066)	(0.052)	(0.018)
Conditional on emp.					Yes	Yes
R^2	0.070	0.022	0.054	0.029	0.044	0.097
N	1481638	1481638	1481638	1481638	1010775	1010775
DV mean (1990)	69.4	4.3	11.9	11.6	16.3	16.7
p for H_0: $\beta_1 + \beta_2 = 0$	0.229	0.000	0.204	0.000	0.000	0.088
p for H_0: $\beta_1 + \beta_3 = 0$	0.011	0.001	0.000	0.000	0.000	0.165

* $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors clustered at the state level are in parentheses. All regressions based on ORG respondents in 1989-1991 and 2013-2015 and use sample weights. "Manufacturing Probability" is an individual's estimated probability of working in manufacturing based on demographics, state-of-residence, and the probability model estimated on the 1990 sample. "Retail Probability" is analogous. "Service jobs" refers to eating and drinking places, landscaping, and automotive repair (see Table 5). Health and education based on 2-digit Census industry codes. Industry union density is based on 1990 average unionization within the 3-digit industry; industry wages refers to median wages within the 3-digit industry in 1990 (in 2015 dollars). Note that these can be calculated for all employed individuals based on the industry in which they are employed. Doing so provides a summary statistic for the characteristics of the industry in which the average worker (of a particular type) is employed. All regressions control for individual-level "Manufacturing Probability", "Retail Probability", and state and year fixed effects.

Table A17—: Employment of prime age married women depending on spouse's employment status and history

	(1)	(2)	(3)	(4)	(5)	(6)
DV:	Any emp.	Emp. in retail	Emp. in health or educ.	Any emp.	Emp. in retail	Emp. in health or educ.
Husband: Manufacturing	0.011***	-0.016***	-0.017***	0.011***	-0.016***	-0.017***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Husband: Displaced	0.012**	0.008*	-0.017***	0.012**	0.008*	-0.017***
	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)
H: Manuf. × H: Disp.	0.005	0.013*	0.018**	0.001	0.012*	0.012
	(0.010)	(0.007)	(0.009)	(0.011)	(0.007)	(0.010)
H: Manuf. × H: Disp. × Displaced job was unionized				0.034	0.007	0.046**
				(0.024)	(0.018)	(0.022)
R^2	0.053	0.013	0.046	0.053	0.013	0.046
N	201218	201218	201218	201218	201218	201218

* $p < .10$, ** $p < .05$, *** $p < .01$. Sample is married, female, prime age (26-55) CPS Displaced Worker Supplement Respondents (even numbered years from 1994-2014). Dependent variables refer to respondent's own employment. "Husband: Manuf." is a dummy indicating that respondent's spouse currently works in manufacturing or was displaced from a manufacturing job (following the post-1998 BLS definition of a Displaced Worker). "Husband: Displaced" is a dummy indicating that respondent's spouse was displaced from any job. The Displaced Worker Survey collects information about involuntary job loss over the past three years only. "Displaced job was unionized" is a dummy indicating that respondent's spouse was a member of a union at the displaced job. Columns 4-6 also control for the main effect of the displaced job having been unionized (i.e., the level effect without the interaction with manufacturing).

Table A18—: RTW-state heterogeneity in industry-level effects

DV: $\Delta \ln(Emp)_{i,s}$	(1)	(2)	(3)
Exposure_i	-0.357***		
	(0.094)		
RTW_s	-0.111	0.049	0.027
	(0.126)	(0.089)	(0.091)
$\text{Exp}_i \times \text{RTW}_s$	-0.266***	-0.159**	-0.188**
	(0.059)	(0.070)	(0.082)
$\text{RTW}_s \times \text{Homogeneous goods}_i$			0.290**
			(0.120)
$\text{Exp}_i \times \text{RTW}_s \times \text{Homogen}_i$			0.343**
			(0.130)
R^2	0.115	0.669	0.674
N	11062	11062	10516
Industry FE ($n = 293$)		Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Unit of observation is an industry-state (industries based on SIC 1987). Data drawn from CBP. Sample restricted to manufacturing industries. Panel is imbalanced; not all industries exist in all states. Two-way clustered standard errors (at the state and industry level) in parentheses. All regressions are changes from 1990 to 2014 and weighted by state-level total employment in 1990. Import exposure combines the NTR Gap and the ADH ΔChina-Other Trade, and has unit standard deviation across industries. Homogeneous goods classified by Rauch (1999). Adding the coefficient on $\text{Exp}_i \times \text{RTW}_s$ and the coefficient on $\text{Exp}_i \times \text{RTW}_s \times \text{Homogen}_i$ yields a sum that is positive (.154) and statistically significant ($p < .10$).

Table A19—: Wage differentials in Healthcare/Education

DV: ln(*wage*)	(1)	(2)	(3)	(4)
Health/Education	0.052***	0.072***	0.009	0.029***
	(0.010)	(0.008)	(0.009)	(0.008)
Health/Ed. × RTW		-0.056***		-0.050***
		(0.017)		(0.016)
R^2	0.002	0.020	0.211	0.212
N	138006	138006	138006	138006
Controls			Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors clustered at the state level are in parentheses. Sample is based on employed women with a high school education or less in years 1989-1991. All regressions weighted by sample weights. Column 2 includes a dummy for state RtW status. Columns 3 and 4 control for state fixed effects (which absorb the RtW dummy), a dummy for being married, a dummy for high school education, a quadratic in age, and dummies for black and hispanic. Unlike earlier results (based on the 1990-2014 change), right-to-work states excludes Oklahoma which didn't pass RtW legislation until 2001.

Table A20—: Right-to-Work vs. Baseline (1990) education

DV: Δ Manuf. emp./pop.	(1)	(2)	(3)
Import exposure	-0.968***	-0.113	-1.081**
	(0.147)	(0.615)	(0.520)
Right-to-work	2.391***	3.189***	2.212**
	(0.879)	(0.972)	(0.931)
RtW × exposure	-1.042***	-1.564***	-0.926*
	(0.372)	(0.445)	(0.466)
College share (normalized)		1.006	
		(2.096)	
College × exposure		-1.287	
		(0.967)	
High college (> median)			0.007
			(0.992)
High college × exposure			0.090
			(0.511)
R^2	0.553	0.577	0.555
N	51	51	51

* $p < .10$, ** $p < .05$, *** $p < .01$. Standard errors clustered at the state level are in parentheses. All regressions weighted by 1990 state population. Baseline education based on 4-year college degree among population age 26-64 in 1989-1991. Column 2 includes college share in levels, but for interpretability it has been normalized to have minimum zero (actual minimum: 13% in West Virginia) and maximum one (actual maximum: 39% Washington DC). Column 3 follows Bloom et al. (2019) and divides states into above and below median college share. Figure A7 shows non-parametric results graphically.