Economics 250a
Lecture 9, Fall 2016
Impacts of Trade-Induced Shocks on Local Areas and Workers

1. **ADH**: David Autor, David Dorn and Gordon Hanson. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States" *American Economic Review* 103(6), 2121-2168, 2013

2. **ADHS**: David Autor, David Dorn, Gordon Hanson, and Jae Song. "Trade Adjustment: Worker Level Evidence" *Quarterly Journal of Economics*, 129(4), 1799–1860, 2014.

3.**ADH2:** David Autor, David Dorn and Gordon Hanson. "The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade." NBER WP #291006, January 2016

ADH

The analysis in ADH is motivated by a trade model outlined in the online theory appendix to the paper. It is worth reading this appendix if you are interested in trade and labor, since papers in trade always have to have a "front end" that defends the empirical approach. The setup of the model is that each local labor market has one type of labor and 3 industries: a non-traded sector, and 2 traded sectors. Within each of the two traded sectors there are multiple differentiated products (one per firm). Consumers spend a share $1-\gamma$ of income on the nontraded good, and shares $\gamma/2$ on each of the traded goods – so their utility function is a "nested" form, with Cobb Douglas at the top, and 2 CES sub-utilities for the traded good aggregates. Labor is freely mobile across sectors within a local labor market so there is only *one wage per market.* The nontraded sector has decreasing returns to scale, so if labor is "shed" from the traded sectors, wages have to fall. Firms in the traded sectors have a very simple labor demand functions of the form: $l = \alpha + \beta x$, where l is units of labor demanded and x is output of the firm, and use markup pricing. Each traded sector firm ends up having a unique output choice if it is active that is independent of wages (or local income). Equilibrium sets the number of active firms in each sector so each firm just covers their fixed costs.

The key feature of this model is that trade impacts are mediated through the "number of varieties" produced by a trade competitor i.e., the "quantity" of trade – which is a huge plus because it escapes the horror of the classic HO model, in which trade impacts arise through sector-specific output prices.

The "impact" measure that ADH use (equation 3) is:

$$\Delta IPW_{it} = \sum_j \frac{L_{ijt}}{L_{jt}} \times \frac{\Delta M_{jt}}{L_{it}}$$

where L_{ijt} is employment in tradeable sector j in region i at the start of period t, L_{jt} is total US employment in that sector, ΔM_{jt} is the change in the real value of imports from China to the US in sector j during period t, and L_{it} is total employment in region i at the start of period t. Note that this is just a share shift type measure of the potential "damage" of import in each sector, *per worker in region i.*

To deal with endogeneity of ΔM_{jt} ADH develop an instrument, which is:

$$\Delta IPW_{Oit} = \sum_j \frac{L_{ijt-1}}{L_{jt-1}} \times \frac{\Delta M_{Ojt}}{L_{it-1}}$$

where all the initial employment levels are replaced by lagged values (in their application, lagged 10 years), and ΔM_{Ojt} is change in imports from China in sector j in 8 other countries – Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, Switzerland. This is a pretty good instrument because the sectors where China was exporting to the US are more or less the same ones that China was also exporting to other rich countries. In fact, as shown in ADH-2, Table 1, the correlation across 397 4-digit industries between import growth from China to the US and import growth from China to other countries is extremely high:

US-Japan: 0.86
US-Germany: 0.91
US-Spain: 0.68
US-Australia: 0.96
US-8 other countries: 0.92

Their interpretation of these very high correlations is that Chinese producers in certain sectors were very low cost, allowing them to compete in all developed economies very effectively.

Table-by-table Commentary Most of their models are TSLS models fit across "commute zones" (CZ's), for dependent variables in changes, combining 1990-2000 and 2000-2007 changes (2 stacked changes per CZ). The data are measured from 1990 and 2000 Census and 2006-2009 ACS (which they call "2007"). There are 722 CZ's so there are lots of data.

Table 3: dep var = change in manufacturing employment over total working age population (mean = -2.1 1990 to 2000; -2.7 2000 to 2007)

bottom line: \$1,000 increase in ΔIPW_{it} (dollars of Chinese imports per worker in a CZ) causes loss of around 0.6 ppt in Mfg empl share. (which trended down from 13 to 9 pct). Corresponding OLS estimate is only 1/3 as big – so IV strategy reveals much bigger trade impacts than OLS.

Since the IV is much *more negative*, it appears that the unobserved determinants of the trend in the local employment share in Mfg in a CZ are **positively correlated** with the share-weighted growth in Chinese imports, biasing the estimated impact of trade shocks upward (toward 0). CZ's with a larger share of industries that were hit by Chinese imports would have had less of a decline in Mfg employment in the absence of the shocks – so these local shocks "hide" the impact of Chinese imports.

Table 4: dep var = change in log population

bottom line: once controls for Census division are added, *NO EFFECT.* Important because it seems to contradict the "conventional" view that local shocks are arbitraged by population mobility.

Table 5: dep var = changes in log counts of workers who are: in MFG; in other sectors; unemployed; NILF; on SSDI

and parallel models for changes in shares in each category, overall and by education group

bottom line: *fall in MFG is not offset by rise in non-mfg.* In fact, very large negative effect on employment of lower-education workers in both sectors!

Table 6: dep var = changes in log weekly wages of workers, by education

bottome line: wages fall – *about the same drop for college and non-college. No effect on widening wage inequality!*

Table 7: dep var = changes in log employment and log weekly wages of workers, by MFG and non-mfg

bottome line: no wage fall in MFG; all the decline is in other sectors.

Table 4 from ADH2 summarizes some of the employment and earnings results in a nice way. Note the data for annual wage and salary income per adult. The results suggest $1,000 increase in dollars of Chinese imports per worker in a CZ causes a loss of $550 in wage and salary income per adult.

Figure 7 from ADH2 shows the offsets in transfer income. Notice these are very small. The "loser areas" from trade shocks are hardly compensated for the losses.

ADHS

ADHS builds on the same idea as ADH, but focuses on the impact of trade shocks on workers by using longitudinal data from Social Security earnings records (hence the addition of Song, who is essentially the "owner" of all SSA data for the US) assigning each worker to their industry in 1991. For a worker who is observed working in industry j in 1991 they define the import shock:

$$\Delta IP_j = \frac{\Delta M_j}{D_{j,1991}}$$

where ΔM_j is the change in imports from China from 1991 to 2007 in industry j and $D_{j,1991}$ is US "absorption" (i.e., net domestic demand = total industry shipments + imports - exports) in 1991 in the industry. NOTE that the focus is on people who were working in one of 397 Mfg industries in 1991. The most heavily impacted industries are toys (mean value of $\Delta IP_j = 33\%$) textiles and apparel (mean=17%), wood products and furniture (mean=15%) and machinery (mean=15%). The least impacted sectors are paper, petroleum, chemicals, and food. People outside Mfg are in the "control group."

They then instrument this with

$$\Delta IPO_{j(1988)} = \frac{\Delta M_{Oj(1988)}}{D_{j(1988),1988}}$$

where $j(1988)$is the industry the individual was employed in 1988, $\Delta M_{Oj(1988)}$ is the change in imports from China to the other countries (same list as in ADH) from 1991 to 2007 in industry $j(1988)$, and $D_{j(1988),1988}$ is net domestic demand in sector $j(1988)$ in 1988.

The person-level data is based on a 1% sample of SSA data for people born 1943-70 (who were 22-64 in the years between 1992 and 2007), and who had a minimum level of earnings in each year from 1988-1991. The main outcome variable is

$$\widetilde{E}_i = \frac{1}{E_{i0}} \sum_{t=1992}^{2007} E_{it}$$

where E_{it}= SSA earnings in year t and E_{i0} are average earnings in the 4-year base period 1988-1991. The mean value of this is 19. They also look at #years with positive earnings, #years with DI income, etc. Table I shows their summary stats. (The extended sample adds an additional group of workers who had some labor income in 1988-91).

The main estimating equation is:

$$\widetilde{E}_i = \beta_0 + \beta_1 \Delta IP_j + \beta_2 IP_{j,1991} + controls \tag{1}$$

where $IP_{j,1991}$ is import penetration in 1991.

Table-by-table Commentary Table 2: shows that being in a trade-impacted industry in 1991 was bad for subsequent earnings. The coefficient β_1 from (1) is around -2.9 from OLS and -6.86 from IV models. They interpret this as follows: a worker in a highly impacted Mfg industry had ΔIP_j 6.7 ppts higher than in a low-impacted Mfg sector. Multiplying by -6.86 leads to a loss of earnings equal to 46% of initial annual earnings over the 16 years from 1992 to 2007 (i.e. about 1/2 of a year of earnings over 16 years). These are big losses for the people in the heavily impacted sectors! Again, as in ADH, the IV estimates are a lot bigger than the OLS, suggesting that industries that had positive demand shocks had a bigger growth in imports, hiding some of the negative impact of trade.

Table 3 Panel A shows being in a trade-impacted industry in 1991 had a negative effect on #years with positive earnings but the coefficient is not significant. Panel B shows a "placebo test" checking that the same sectors were not trending down in 1976-1991

Table 4 is a nice way to try to "decompose" the loss in earnings into losses at the initial employer, at employers in the same Mfg sector, and in other "sectors". Being in a trade-impacted industry in 1991 causes a big loss in earnings from the initial employer (column 2) that is partially offset by gains in employment in other sectors in Mfg (column 4), but no significant gain in earnings outside Mfg (column 5).

Table 5 does a similar analysis breaking down income by where it is earned: same (initial) CZ or somewhere else. Here we see that the losses are spread across both the initial CZ and other CZ's – what this means is that movements across CZ's are not working in such a way to offset the losses.

Table 3—Imports from China and Change of Manufacturing Employment in CZs, 1990–2007: 2SLS Estimates

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % pts)

	I. 1990–2007 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/worker	−0.746*** (0.068)	−0.610*** (0.094)	−0.538*** (0.091)	−0.508*** (0.081)	−0.562*** (0.096)	−0.596*** (0.099)
Percentage of employment in manufacturing$_{-1}$		−0.035 (0.022)	−0.052*** (0.020)	−0.061*** (0.017)	−0.056*** (0.016)	−0.040*** (0.013)
Percentage of college-educated population$_{-1}$				−0.008 (0.016)		0.013 (0.012)
Percentage of foreign-born population$_{-1}$				−0.007 (0.008)		0.030*** (0.011)
Percentage of employment among women$_{-1}$				−0.054** (0.025)		−0.006 (0.024)
Percentage of employment in routine occupations$_{-1}$					−0.230*** (0.063)	−0.245*** (0.064)
Average offshorability index of occupations$_{-1}$					0.244 (0.252)	−0.059 (0.237)
Census division dummies	No	No	Yes	Yes	Yes	Yes
	II. 2SLS first stage estimates					
(Δ imports from China to OTH)/worker	0.792*** (0.079)	0.664*** (0.086)	0.652*** (0.090)	0.635*** (0.090)	0.638*** (0.087)	0.631*** (0.087)
R^2	0.54	0.57	0.58	0.58	0.58	0.58

Notes: $N = 1{,}444$ (722 commuting zones × 2 time periods). All regressions include a constant and a dummy for the 2000–2007 period. First stage estimates in panel II also include the control variables that are indicated in the corresponding columns of panel I. Routine occupations are defined such that they account for 1/3 of US employment in 1980. The offshorability index variable is standardized to mean of 0 and standard deviation of 10 in 1980. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

share. These dummies modestly decrease the estimated effect of import exposure on manufacturing employment. Column 4 additionally controls for the start-of-period share of a CZ's population that has a college education, the share of population that is foreign born, and the share of working-age women that are employed. These controls leave the main result unaffected.

Column 5 introduces two variables that capture the susceptibility of a CZ's occupations to substitution by technology or task offshoring. Both variables are based on occupational task data, which are described in detail in Autor and Dorn (2013). Routine-intensive occupations are a set of jobs whose primary activities follow a set of precisely prescribed rules and procedures that make them readily subject to computerization. This category includes white collar positions whose primary job tasks involve routine information processing (e.g., accountants and secretaries) and blue collar production occupations that primarily involve repetitive motion and monitoring tasks. If CZs that have a large start-of-period employment share in routine occupations experience strong displacement of manufacturing jobs due to automation, one would expect a negative relationship between the routine share variable and the change in manufacturing share. Indeed, the estimates in column 5 suggest that the

TABLE 4—IMPORTS FROM CHINA AND CHANGE OF WORKING-AGE POPULATION IN CZ, 1990–2007: 2SLS ESTIMATES

Dependent variables: Ten-year equivalent changes in log population counts (in log pts)

	I. By education level			II. By age group		
	All (1)	College (2)	Noncollege (3)	Age 16–34 (4)	Age 35–49 (5)	Age 50–64 (6)
Panel A. No census division dummies or other controls						
(Δ imports from China to US)/worker	−1.031**	−0.360	−1.097**	−1.299	−0.615	−1.127***
	(0.503)	(0.660)	(0.488)	(0.826)	(0.572)	(0.422)
R^2	—	0.03	0.00	0.17	0.59	0.22
Panel B. Controlling for census division dummies						
(Δ imports from China to US)/worker	−0.355	0.147	−0.240	−0.408	−0.045	−0.549
	(0.513)	(0.619)	(0.519)	(0.953)	(0.474)	(0.450)
R^2	0.36	0.29	0.45	0.42	0.68	0.46
Panel C. Full controls						
(Δ imports from China to US)/worker	−0.050	−0.026	−0.047	−0.138	0.367	−0.138
	(0.746)	(0.685)	(0.823)	(1.190)	(0.560)	(0.651)
R^2	0.42	0.35	0.52	0.44	0.75	0.60

Notes: $N = 1,444$ (722 CZs × two time periods). All regressions include a constant and a dummy for the 2000–2007 period. Models in panel B and C also include census division dummies while panel C adds the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

substantial changes in population. The regressions in Table 4 are analogous to our earlier models for the manufacturing employment share except that our dependent variable is the log of the working-age population ages 16 through 64 in the CZ, calculated using Census IPUMS data for 1990 and 2000 and American Community Survey for 2006 through 2008.

The specifications in panel A, which include no controls except a constant and a time dummy for the 2000–2007 time period, find a significant negative relationship between exogenous increases in Chinese import exposure and CZ-level population growth. A $1,000 per worker increase in trade exposure predicts a decline of 1.03 log points in a CZ's working-age population. In specifications that add Census division dummies (panel B)—which are equivalent to trends in our first-difference model—and in specifications that further include the full set of controls from Table 3, we find no significant effect of import shocks on local population size. This null is found for the overall working-age population (column 1), for college and noncollege adults (columns 2 and 3), and for age groups 16 through 34, 35 through 49, and 50 through 64 (columns 4 through 6). In moving from panel A to C, the point estimates on import exposure fall while the standard errors rise. These estimates suggest that the effect of trade exposure shocks on population flows is small, though the imprecision of these estimates does not preclude more substantial responses.

The lack of a significant effect of trade exposure on population flows is consistent with several hypotheses. One is that shocks to manufacturing from China trade are too small to affect outcomes in the broader CZ. A second is that goods markets are sufficiently well integrated nationally that local labor markets adjust to adverse

Table 5—Imports from China and Employment Status of Working-Age Population within CZs, 1990–2007: 2SLS Estimates

Dependent variables: Ten-year equivalent changes in log population counts and population shares by employment status

	Mfg emp (1)	Non-mfg emp (2)	Unemp (3)	NILF (4)	SSDI receipt (5)
Panel A. 100 × log change in population counts					
(Δ imports from China to US)/worker	−4.231***	−0.274	4.921***	2.058*	1.466***
	(1.047)	(0.651)	(1.128)	(1.080)	(0.557)
Panel B. Change in population shares					
All education levels					
(Δ imports from China to US)/worker	−0.596***	−0.178	0.221***	0.553***	0.076***
	(0.099)	(0.137)	(0.058)	(0.150)	(0.028)
College education					
(Δ imports from China to US)/worker	−0.592***	0.168	0.119***	0.304***	—
	(0.125)	(0.122)	(0.039)	(0.113)	
No college education					
(Δ imports from China to US)/worker	−0.581***	−0.531***	0.282***	0.831***	—
	(0.095)	(0.203)	(0.085)	(0.211)	

Notes: N = 1,444 (722 CZs × two time periods). All statistics are based on working age individuals (age 16 to 64). The effect of import exposure on the overall employment/population ratio can be computed as the sum of the coefficients for manufacturing and nonmanufacturing employment; this effect is highly statistically significant ($p \leq 0.01$) in the full sample and in all reported subsamples. All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

shocks without a mobility response. This would occur, for example, in a Heckscher-Ohlin setting if local labor markets operated within a single cone of diversification, such that factor price equalization pins down the wage in all markets, making local factor prices independent of local factor demands and supplies. A third possibility is that population adjustments to local economic shocks are sluggish because mobility is costly or because factors other than labor (including government transfer benefits or house prices) bear part of the incidence of labor demand shocks (Blanchard and Katz 1992; Glaeser and Gyourko 2005; Notowidigdo 2010). Costs to labor of moving between sectors (as in Artuç, Chaudhuri, and McLaren 2010, and Dix-Carneiro 2011) may contribute to costs of moving between regions. In this third case, we would expect to see local labor markets adjust along margins other than intersectoral or geographic mobility. Our evidence below is most consistent with the third interpretation.

If working-age adults do not depart from CZs facing adverse trade shocks, then the trade-induced decline in manufacturing employment must yield a corresponding rise in either nonmanufacturing employment, unemployment, labor force exit or some combination of the three. In the first panel of Table 5, we study the impact of import shocks on the log change in the number of non-elderly adults in four exhaustive and mutually exclusive categories that sum up to the total working-age population as studied in column 1 of Table 4: employment in manufacturing, employment in nonmanufacturing, unemployment, and labor force nonparticipation. We find that

TABLE 6—IMPORTS FROM CHINA AND WAGE CHANGES WITHIN CZs, 1990–2007: 2SLS ESTIMATES

Dependent variable: Ten-year equivalent change in average log weekly wage (in log pts)

	All workers (1)	Males (2)	Females (3)
Panel A. All education levels			
(Δ imports from China to US)/worker	−0.759***	−0.892***	−0.614***
	(0.253)	(0.294)	(0.237)
R^2	0.56	0.44	0.69
Panel B. College education			
(Δ imports from China to US)/worker	−0.757**	−0.991***	−0.525*
	(0.308)	(0.374)	(0.279)
R^2	0.52	0.39	0.63
Panel C. No college education			
(Δ imports from China to US)/worker	−0.814***	−0.703***	−1.116***
	(0.236)	(0.250)	(0.278)
R^2	0.52	0.45	0.59

Notes: $N = 1{,}444$ (722 CZs × two time periods). All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

employed, and bearing in mind that we have already established that import exposure shocks reduce employment, the wage estimates must be interpreted with caution. If, plausibly, workers with lower ability and earnings are more likely to lose employment in the face of an adverse shock, the observed change in wages in a CZ will understate the composition-constant change in wages. This concern is likely to be relevant for workers with lower education levels, among whom job losses are concentrated.[39]

Despite the potential for upward bias, Table 6 finds a significant negative effect of import exposure on average weekly earnings within CZs. A $1,000 per worker increase in a CZ's exposure to Chinese imports during a decade is estimated to reduce mean weekly earnings by −0.76 log points. While the point estimates are somewhat larger overall for males than for females, with the largest declines found among college males and noncollege females, we do not have sufficient precision to reject the null hypothesis that impacts are uniform across demographic groups.

In Table 7, we explore wage effects separately for workers employed in manufacturing and nonmanufacturing. To aid interpretation, the upper panel of the table presents estimates of the effect of import exposure on log employment counts in both sectors. Consistent with the earlier estimates, Table 7 confirms that import exposure reduces head counts in manufacturing but has little employment effects outside of manufacturing, particularly for college workers.

[39] Another concern, which data limitations prevent us from addressing, is that the impact of import competition on local prices of non-traded goods and services may move in the same direction as the impact on local nominal wages, possibly attenuating the consequences of trade exposure for real earnings. See also note 13 and the related analysis in Notowidigdo (2010).

Table 7—Comparing Employment and Wage Changes in Manufacturing and outside Manufacturing, 1990–2007: 2SLS Estimates

Dependent variables: Ten-year equivalent changes in log workers and average log weekly wages

	I. Manufacturing sector			II. Nonmanufacturing		
	All workers (1)	College (2)	Noncollege (3)	All workers (4)	College (5)	Noncollege (6)
Panel A. Log change in number of workers						
(Δ imports from China to US)/worker	−4.231*** (1.047)	−3.992*** (1.181)	−4.493*** (1.243)	−0.274 (0.651)	0.291 (0.590)	−1.037 (0.764)
R^2	0.31	0.30	0.34	0.35	0.29	0.53
Panel B. Change in average log wage						
(Δ imports from China to US)/worker	0.150 (0.482)	0.458 (0.340)	−0.101 (0.369)	−0.761*** (0.260)	−0.743** (0.297)	−0.822*** (0.246)
R^2	0.22	0.21	0.33	0.60	0.54	0.51

Notes: $N = 1{,}444$ (722 CZs × two time periods). All regressions include the full vector of control variables from column 6 of Table 3. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

The effect of import exposure on mean wages found in panel B of Table 7 is the complement of the employment effects estimated in panel A. Although import exposure reduces manufacturing employment, it appears to have no significant effects on mean manufacturing wages in CZs. This finding mirrors the outcomes of industry-level studies such as Edwards and Lawrence (2010) or Ebenstein et al. (2010), which observe no negative wage effects of imports on US workers in import-competing manufacturing industries.[40] One explanation for this pattern is that the most productive workers retain their jobs in manufacturing, thus biasing the estimates against finding a reduction in manufacturing wages. An alternative possibility, suggested by Bloom, Draca, and Van Reenen (2011), is that manufacturing plants react to import competition by accelerating technological and organizational innovations that increase productivity and may raise wages.

By contrast, Chinese import exposure significantly reduces earnings in sectors outside manufacturing. Nonmanufacturing wages fall by 0.76 log points for a $1,000 increase in Chinese import exposure per worker, an effect that is comparable for college and noncollege workers. This result suggests that a negative shock to local manufacturing reduces the demand for local non-traded services while increasing the available supply of workers, creating downward pressure on wages in the sector.

The results of this section demonstrate that an increase in the exposure of local US labor markets to Chinese imports stemming from rising Chinese comparative advantage leads to a significant decline in employment and wages in local markets. These findings suggest that a variety of partial and incomplete labor market adjustments are operative. Because total CZ employment falls following a shock to local manufacturing, we conclude that labor and product markets are not sufficiently

[40] An exception to this generalization is McLaren and Hakobyan (2010), who find a wage impact on US industries exposed to increased competition from Mexico by NAFTA.

Figure 6B, which plots import exposure *conditional* on the share of manufacturing in CZ employment as of 1990, thus measuring import competition for the local set of manufacturing industries. When looking within manufacturing, Tennessee, owing largely to its concentration of furniture producers, is far more exposed to trade with China than is Alabama, which has agglomerations of relatively insulated heavy industry. This variation of import exposure *within* local manufacturing sectors is the basis for much of the econometric analysis we discuss.

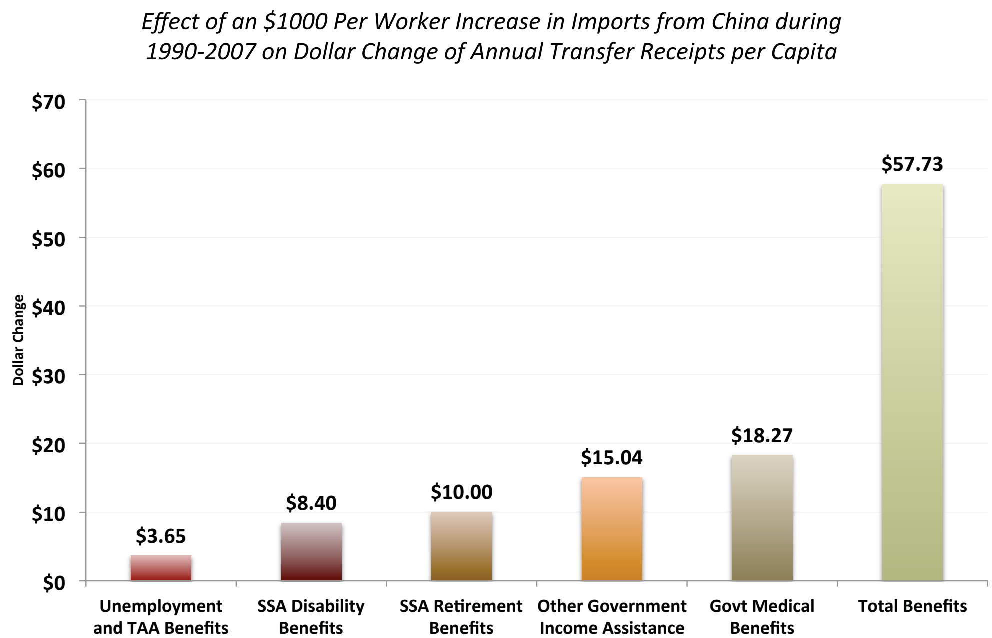
Table 4: Import Competition and Outcomes in U.S. Local Labor Markets, 1990 - 2007

A. Δ Fraction of Working Age Population in Manufacturing, Unemployment, NILF			
Employed in Manufacturing (1)	Employed in Non-Manufacturing (2)	Unemployed (3)	Not in Labor Force (4)
-0.60***	-0.18	0.22***	0.55***
(0.10)	(0.14)	(0.06)	(0.15)
B. Δ Log Population, Log Wages, Annual Wage and Transfer Income			
Δ Log CZ Population (log pts) (5)	Δ Avg Log Weekly Wage (log pts) (6)	Δ Annual Wage/Salary Inc per Adult (US$) (7)	Δ Transfers per Capita (US$) (8)
-0.05	-0.76***	-549.3***	57.7***
(0.75)	(0.25)	(169.4)	(18.4)

N=1444 (722 commuting zones x 2 time periods 1990-2000 and 2000-2007). Employment, population and income data is based on U.S. Census and American Community Survey data, while transfer payments are based on BEA Regional Economic Accounts. All regressions control for the start of period percentage of employment in manufacturing, college-educated population, foreign-born population, employment among women, employment in routine occupations, average offshorability index of occupations, and Census division and time dummies. Models are weighted by start of period commuting zone share of national population. Robust standard errors in parentheses are clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Over the period 1990 to 2007—considered either as a single long difference or as stacked changes for 1990 to 2000 and 2000 to 2007—CZs that were more exposed to increased import competition from China experienced substantially larger reductions in manufacturing employment. Columns 1 to 4 of Table 4, based on Autor, Dorn and Hanson (2013), show that the decline in manufacturing jobs was largely accommodated by an increasing share of a CZ's working-age population that was unemployed or out of the labor force. Specifically, a $\$1,000$ increase in a CZ's per-worker import exposure reduces the fraction of the working age population employed in manufacturing and non-manufacturing, respectively, by -0.60 and -0.18 percentage points (the latter of which is not significant), and raises the fraction unemployed and out of the labor force by 0.22 and 0.55 percent-income assistance, consistent with more households meeting the threshold for welfare payouts. Trade exposure also contributes to an increase in disability benefits, whose take-up is typically associated with permanent exit from the labor force (Autor and Duggan, 2003). Retirement benefits rise in more trade-exposed CZs, suggesting that adverse labor-market shocks induce more workers to retire earlier.[44]

Figure 7: Imports from China and Induced Government Transfer Receipts in Commuting Zones, 1990 - 2007



What is striking about the impact of trade shocks on benefit take-up is not just the size of these effects—for every extra $100 in local import exposure per worker transfer receipts rise by approximately $6 per capita—but their relative magnitudes across categories. Trade Adjustment Assistance, the primary federal government program intended to help workers who lose their jobs as a result of foreign competition (Baicker and Rehavi, 2004), is effectively inconsequential in local adjustment to trade shocks. Workers eligible for TAA receive extended unemployment benefits of up to 18 months, as long as they remain enrolled in a training program, and may obtain allowances toward relocation, job search, and healthcare.[45] Trade-exposed CZs certainly experience sharp

[44]See Kondo (2013) for a general equilibrium analysis of the welfare consequences of trade-related employment losses and Feler and Senses (2015) for results on the impact of the China trade shock on the provision of public services across local jurisdictions.

[45]To qualify for TAA, workers must show that their employer cut back production because of import competition, relocated production to a country with which the U.S. has a trade agreement, or lost business with a buyer or supplier that is TAA certified.

TABLE I
DESCRIPTIVE STATISTICS

	Main Sample		Extended Sample	
	All Workers	Manuf Workers	All Workers	Manuf Workers
Panel A: trade exposure, 1991–2007				
(Δ imports from China to U.S.)/U.S. consumption$_{91}$	1.60 (7.05)	7.72 (13.85)	1.30 (5.85)	6.30 (11.59)
P90, P10 interval	[2.72, 0.00]	[24.74, 0.06]	[1.99,0.00]	[18.75, 0.04]
P75, P25 interval	[0.00, 0.00]	[7.30, 0.62]	[0.00,0.00]	[6.28, 0.38]
(1991 imports from China to U.S.)/U.S. consumption$_{91}$	0.11 (0.94)	0.54 (2.00)	0.11 (0.88)	0.48 (1.78)
Panel B: main outcome variables, 1992–2007				
100*cumulative earnings (in mult of avg annual wage 88–91)	1,918.4 (1,181.7)	1,808.9 (1,025.7)	n/a	n/a
100*number of years with earnings > 0	1422.3 (342.1)	1428.6 (335.7)	1326.0 (428.3)	1355.8 (403.6)
100*cumul earn/yrs with earn > 0 (in mult of avg ann wage 88–91)	130.0 (69.9)	122.4 (59.7)	n/a	n/a
100*number of years with main income from SSDI	34.3 (168.3)	43.3 (188.6)	44.4 (200.0)	50.9 (211.4)
100*number of years with main income from self-employment	46.4 (175.9)	37.7 (152.2)	59.8 (200.4)	47.0 (170.2)
Panel C: worker characteristics in 1991				
Female	0.431	0.312	0.475	0.359
Nonwhite	0.207	0.200	0.236	0.235
Foreign-born	0.077	0.086	0.085	0.097
Employed in manufacturing	0.208	1.000	0.173	0.836
Tenure 0–1 years	0.269	0.236	0.418	0.425
Tenure 2–5 years	0.368	0.355	0.301	0.283
Tenure 6–10 years	0.169	0.187	0.129	0.134
Tenure 11+ years	0.194	0.221	0.153	0.158
Firm Size 1–99 employees	0.231	0.153	0.257	0.199
Firm Size 100–999 employees	0.237	0.289	0.231	0.285
Firm Size 1,000–9,999 employees	0.246	0.290	0.210	0.251
Firm Size 10,000+ employees	0.286	0.267	0.302	0.265
Average log wage 1988–1991	10.46	10.55	9.23	9.60
Sample size	508,129	105,625	880,465	181,900

Notes. The main sample in the first two columns includes all workers who had at least full-time minimum wage earnings during each of the years 1988 to 1991. The extended sample in the second two columns includes all workers who had a positive income in at least one year between 1987 and 1989 and one year between 1990 and 1992. Trade exposure for this sample and control variables for manufacturing employment, tenure, and firm size are computed and averaged over all years between 1990 and 1992 during which the worker is employed. Average log wage for this sample is computed based on years with positive earnings between 1988 and 1991. The outcome variables for main income sources are defined for the years 1993-2007 in the extended sample. Column (4) in Panel B provides statistics for the subset of workers from the extended sample who were employed in manufacturing during at least one year between 1990 and 1992.

that log earnings are undefined when income from some period or source is zero.

We model the cumulative shock due to trade exposure in equation (3) as a function of import penetration in 1991 ($IP_{j,91}$)

TABLE II

IMPORTS FROM CHINA AND CUMULATIVE EARNINGS, 1992–2007: OLS AND 2SLS ESTIMATES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS				2SLS				
(Δ China imports)/U.S. consumption$_{91}$	−2.939*	−5.726**	−6.017**	−6.099**	−6.883**	−6.436**	−5.695*	−6.728**	−6.864**
	(1.150)	(1.425)	(1.475)	(1.395)	(1.351)	(2.450)	(2.326)	(2.392)	(2.477)
Birth year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Demographic controls			yes	yes	yes	yes	yes	yes	yes
Employment history				yes	yes	yes	yes	yes	yes
Earnings history					yes	yes	yes	yes	yes
Initial import levels						yes	yes	yes	yes
10 mfg industry dummies							yes	yes	yes
Industry characteristics								yes	yes
Pretrends ind emp and wage									yes

Notes. Dependent variable: 100 × earnings 1992–2007 (in multiples of initial annual wage). $N = 508{,}129$. All regressions include a constant and a full set of birth year dummies. Demographic controls in column (3) include dummies for female, nonwhite, and foreign-born. Employment history controls in column (4) include dummies for tenure at 1991 firm (0–1, 2–5, 6–10 years), experience (4–5, 6–8, 9–11 years), and size of 1991 firm (1–99, 100–999, 1,000–9,999 employees). Earnings history controls in column (5) include the worker's annual log wage averaged over 1988–1991, an interaction of intial wage with age, and the change in log wage between 1988 and 1991, as well as the level and trend of the 1991 firm's log mean wage for the period 1988–1991. Columns (6)–(9) add controls for a worker's 1991 manufacturing industry, starting with initial trade penetration by Chinese and non-Chinese imports in column (6). Column (7) adds dummies for 10 manufacturing subindustries, column (8) adds 1991 levels for employment share of production workers, log average wage, capital/value added, and 1990 levels for computer investment, share of investment allocated to high-tech equipment, and fraction of intermediate goods among imports in 1990; column (9) additionally controls for changes in industry employment share and log average wage level during the preceding 16 years (1976–1991). Robust standard errors in parentheses are clustered on start-of-period three-digit industry. $\sim p \leq .10$, $^{*}p \leq .05$, $^{**}p \leq .01$.

TABLE III

Imports from China 1992–2007 and Cumulative Earnings, Years with Earnings, and Earnings per Year 1992–2007 and 1976–1991: 2SLS Estimates

	(1) Cumulative Earnings	(2) Years w/ Earnings > 0	(3) Earnings/ Year
Panel A: treatment period 1992–2007			
(Δ China imports)/U.S. consumption$_{91}$	−6.864**	−0.535	−0.393**
	(2.477)	(0.505)	(0.140)
Panel B: preperiod 1976–1991			
(Δ China imports)/U.S. consumption$_{91}$	−0.432	0.695	−0.064
	(1.996)	(0.856)	(0.112)

Notes. Dependent variables: 100 × cumulative earnings (in multiples of initial annual wage); 100 × years with earnings; 100 × earnings per year of employment (in multiples of initial annual wage), $N = 508{,}792$ in Panel A and $N = 301{,}490$ in Panel B, except $N = 506{,}339$ and $N = 300{,}239$ in column (3), where the dependent variable is not defined for individuals who are never employed during the entire outcome period. Regressions in Panel A include the full control vector from column (9) of Table II. Regressions in Panel B include the same controls except tenure, experience, and firm size; industry-level controls are measured either for 1975 or for 1972 (intermediate imports, computer investment, and high-tech equipment). Robust standard errors in parentheses are clustered on start-of-period three-digit industry. $\sim p \leq .10$, $^{*}p \leq .05$, $^{**}p \leq .01$.

the net reductions in cumulative earnings seen in column (9) of Table II (and replicated in Table III, column (1)) stem primarily from reductions in within-year earnings rather than from additional years with zero earnings. These within-year earnings declines are in turn a combination of reduced earnings per hour and reduced hours worked, the relative contributions of which we cannot disentangle with our data.

Could these results merely reflect the secular decline of labor-intensive U.S. manufacturing employment rather than the period-specific effects of exposure to China trade? We explore this concern in Panel B of Table III by testing whether the growth in import competition from China in the 1990s and 2000s "predicts" earnings and employment outcomes for an earlier cohort of workers that was not directly exposed to Chinese competition.[25]

25. We draw on an extended version of the Social Security data to construct cumulative earnings from 1976 to 1991 for workers who were between 22 and 64 years of age during this earlier period, and we use these data to examine whether their employment outcomes during 1976 through 1991 are correlated with later, post-1991 changes in Chinese import penetration that subsequently occurred in their initial industries. The sample for the analysis of the 1976–1991 period uses the same sampling criteria as our main sample, and hence comprises the workers who earned at least the equivalent of $8,193 at 2007 values in each of the four years preceding the outcome period.

TABLE IV

IMPORTS FROM CHINA AND EARNINGS AND EMPLOYMENT BY FIRM, INDUSTRY, AND SECTOR, 1992–2007: 2SLS ESTIMATES

	(1)	(2)	(3)	(4)	(5)	(6)
	All Employers	Same Sector			Other Sector	N/A
Same 2-digit Industry		Yes	Yes	No	No	N/A
Same Firm		Yes	No	No	No	No
Panel A: cumulative earnings (in initial annual wage*100)						
(Δ China imports)/	−6.864**	−9.107**	−2.998~	5.914*	−2.253	1.579*
U.S. consumption$_{91}$	(2.477)	(3.395)	(1.671)	(2.326)	(3.049)	(0.800)
Panel B: cumulative employment (in years*100)						
(Δ China imports)/	−0.535	−6.204*	−2.036	4.654**	1.451	1.600*
U.S. consumption$_{91}$	(0.505)	(2.566)	(1.278)	(1.655)	(1.983)	(0.625)
Panel C: earnings per year of emp (in initial annual wage*100)						
(Δ China imports)/	−0.393**	−0.283	−0.543~	−0.551~	−0.655*	−0.606*
U.S. consumption$_{91}$	(0.140)	(0.093)	(0.304)	(0.300)	(0.291)	(0.245)

Notes. Dependent variables: 100 × cumulative earnings; 100 × years with earnings; 100 × earnings per year of employment. N = 508,129 in Panels A and B. N = 506,339, 424,027, 155,993, 263,158, 112,002, 119,989 in columns (1)–(6) of Panel C. Column (6) measures employment and earnings in firms with missing industry information. A large majority of these firms are new firms that have been incorporated between 2000 and 2007. All regressions include the full vector of control variables from column (9) of Table II. Robust standard errors in parentheses are clustered on start-of-period three-digit industry. $\sim p \leq .10$, $^{*}p \leq .05$, $^{**}p \leq .01$.

and insignificantly negative net estimate of trade exposure on years of employment (column (1), Panel B) that employment losses are almost entirely offset: trade-impacted workers make back their employment losses in the initial firm and industry through employment outside of the original two-digit industry. Column (4) in Panel B indicates that trade-exposed workers spend more years employed at firms that belong to a different two-digit industry within their initial sector of employment. But these offsetting employment gains from reallocation to other two-digit industries within manufacturing are only just over half as large as the losses incurred with the original employer and two-digit industry ($\frac{4.65}{6.20+2.04} = 0.56$), indicating that trade exposure in a worker's initial firm reduces the worker's total manufacturing employment net of mobility within the sector.[28] Columns (5) and (6) in Panel B complete the employment

28. Column (6), Panel B shows moderate employment gains at firms with a missing industry code, a large majority of which were incorporated in the years 2000–2007, when a new data collection process no longer recorded information on

TABLE V

IMPORTS FROM CHINA AND EARNINGS AND EMPLOYMENT BY GEOGRAPHIC LOCATION, 1994–2007: 2SLS ESTIMATES

	(1) All CZ	(2) Initial CZ	(3) Other CZ	(4) N/A CZ
Panel A: cumulative earnings (in initial annual wage*100)				
(Δ China imports)/U.S. consumption$_{91}$	−6.649**	−3.558*	−2.307~	−0.785
	(2.417)	(1.396)	(1.281)	(0.542)
Panel B: cumulative employment (in years*100)				
(Δ China imports)/U.S. consumption$_{91}$	−0.653	−0.008	−0.491	−0.154
	(0.513)	(0.599)	(0.539)	(0.253)
Panel C: earnings/year (in initial annual wage*100)				
(Δ China imports)/U.S. consumption$_{91}$	−0.418**	−0.344**	−0.741*	−1.010*
	(0.152)	(0.124)	(0.369)	(0.398)

Notes. Dependent variables: 100 × cumulative earnings; 100 × years with earnings; 100 × earnings per year of employment. N = 508,129, except smaller samples in Panel C. Column (1) shows aggregate results for earnings and employment. Columns (2)–(4) subdivide results into employment and earnings obtained while residing in the 1993 CZ of residence (column (2)), in all CZs other than the 1993 CZ of residence (column (3)), and in CZs than cannot be classified because either the 1993 location or subsequent location of the worker is unknown (column (4)). All regressions include the full control vector from column (9) of Table II, and a dummy for the 6% of workers whose 1993 CZ is unknown. Robust standard errors in parentheses are clustered on start-of-period three-digit industry. $\sim p \leq .10$, $^{*}p \leq .05$, $^{**}p \leq .01$.

A) but also for cumulative earnings in other CZs (column (3), Panel A), and for cumulative earnings in CZs that we cannot classify because information on a worker's initial or subsequent location is missing (column (4), Panel A). More trade-exposed workers thus receive less in total earnings from all local labor markets in which they reside, suggesting that geographic mobility is not a primary mechanism for adjusting to trade shocks.

Results for cumulative years of nonzero earnings in Panel B also fail to indicate that trade exposure causes geographic mobility to increase. Workers initially employed in industries subject to greater import competition have lower cumulative years with nonzero earnings not just in their initial CZ (column (2)) but also in other CZs (column (3)) and in unidentified CZs (column (4)), though none of these effects is significant. The decline in cumulative earnings by location in Panel A is instead driven largely by reduced earnings per year of employment in all CZs in which a worker resides (columns (2)–(4), Panel C). In sum, the results of Table V give further indication that regional mobility is of limited import as a mechanism through which workers adjust to changes in trade exposure.