Increasing Chinese Exports and U.S Labor Market Outcomes

by

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Abstract

China's major economic upraise over the last decades has created both positive and negative consequences (economically speaking) for other countries. Perhaps the country who has gotten affected the most by this sudden change of hub for world manufacturing is the U.S. It is well known by both scholars and policy makers that the progressive shrinking the U.S manufacturing sector has experienced over the last 20 years or so is in part a product of China's astonishingly rapid economic development. This paper touches on the subject of estimating the impact of such rapid economic development (particularly increasing Chinese exports) on U.S labor markets specifically.

The purpose of this paper is to exemplify some of the more notable methods used in the economic literature through the last decade to estimate the impact of increasing Chinese exports on U.S labor markets. The first strategy discussed is "The Commuting Zone approach" used by Autor, Dorn, and Hanson (ADH 2013) for estimating the impact of increasing Chinese import penetration by relating changes in labor-market outcomes throughout a specific period of time across US local labor markets to changes in exposure to import competition. The second strategy relies on adding what is known as "Input-Output Linkages", which is what Autor, Dorn, Hanson, and Price (AADHP 2016) used to estimate the impact of increasing Chinese exports on U.S labor markets depending on the position of industries on the production chain. And finally, the last strategy mentioned in this paper relies on "Accounting for Value-Added Exports" in which Da Silva and Shen (DS 2018) compare the magnitude of Chinese exports on U.S labor markets when considering value-added exports instead of gross exports as well as incorporating input-output linkages like AADH (2016) did.

All three studies find increasing Chinese exports to have a negative effect on U.S labor markets. Even though their specifications for such general claim are slightly different from each other (the last two build up on the specifics provided by ADH 2013). ADH (2013) finds that increasing import penetration of Chinese goods yields negative effects on manufacturing employment as well as non-manufacturing. AADHP (2016) find the same results as ADH (2013), and their further specifications suggest that industries

with higher degree of upstreamness are the ones more negatively affected, and that the effect of industries with a high degree of downstreamness is ambiguous. Finally, DS (2018) find the same results as ADH (213) but their further specifications imply that industries with high degree of downstreamness are the ones more negatively affected by increasing Chinese imports, and also that accounting for gross exports (instead of value-added) overstates the negative impact caused by increasing Chinese exports on U.S labor markets. As I move on into the latter sections of this paper, I will explain in greater detail the models and strategies (with their respective results) each study used to reach such conclusions.

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Chapter 1 - Introduction/Historical Perspective

The astonishingly rapid economic development of China achieved over the last decades is no secret nowadays. It has been well covered by the media for several years now that China has returned to the post of the world's greatest manufacturing producer by the end of 2010, a title they last held in the first half of the 19th century. This incredible turnaround can be attributed to their successful transition from being a central planned economy to becoming a global trading partner by the end of the 1990's, which greatly helped consolidate their position as the top manufacturing country as well as their introduction to the World Trade Organization (WTO) as a full-time member in December of 2001. The shift in the world manufacturing base towards China has been a topic of much interest and apprehension among both scholars and policy makers alike.

One of the most discussed/analyzed topics within the economics literature has been that of the impact of increasing Chinese imports on the U.S economy, particularly the U.S labor market. This is a very interesting topic since China's rapid economic growth over the last decades coincides with a progressive contraction in the manufacturing employment in the U.S as well as a substantial increase in the U.S trade deficit with the same country which was at a sky high record of $273 billion in 2010.

Many scholars have looked into the matter with different methods finding somewhat similar results. Today I will discuss and explain 3 particular studies that built up on each other's strategies assess the actual impact of increasing Chinese imports on U.S labor market outcomes. In other words, I will exemplify the changes of thinking that have taken place over the years in the economics literature regarding the impact of Chinese import penetration on U.S labor markets. I will start off with the paper named "The China Syndrome: Local Labor Market Effects of Import Competition in the U.S" by Autor, Dorn, and Hanson (ADH 2013) which was mainly based on the repercussions of increasing Chinese imports on Commuting Zones (CZ's) across the U.S.

Then, I will move on to the study named "Import Competition and the Great U.S Unemployment Sag of the 2000's" by Acemoglu, Autor, Dorn, Hanson, and Price (AADHP 2016) which builds on ADH

2013 by incorporating input-output linkages and determining if industries at the beginning or bottom of the production chain are the ones more affected by increasing Chinese imports. And finally, I will discuss the most recent study published by Da Silva, and Shen titled “Value-Added Exports and US Local Labor Markets: Does China Really Matter?” (DS 2018). This particular study was created based on the basics of the ADH (2013), but it also includes input-output linkages as well as looking at the subject with a different perspective than the previous two studies. DS 2018 base their analysis on (as said on the title of their publication) value added Chinese exports that come into the U.S instead of looking at gross Chinese exports.

All three of these studies agree on that increasing Chinese imports are hurting the US labor market (particularly the manufacturing industry), but the extent at which each of them says so differs from the others on certain specifics. On the upcoming sections I will show with greater details the quantitative models with their respective results to back up such claims, to then conclude this paper by comparing the results found by each of these studies.

Chapter 2 - The Commuting Zone Approach

2-1-Introduction

In this section, I will discuss the methods and results found by Autor, Dorn, and Hanson (2013) when using the CZ approach to determine the effects of increased import penetration from China on the United States labor market (mostly in the manufacturing industry). I will discuss the method they use and the comparison of it to some other ones found in literature.

The Commuting Zone Approach (known as CZ) is a method in which the researchers relate changes in labor-market outcomes throughout a specific period of time across US local labor markets to changes in exposure to import competition. The CZ approach was developed by Tolbert and Sizer (1996), who used county-level commuting data from the 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. The current analysis includes the 722 CZs that cover the entire mainland United States (both metropolitan and rural areas). ADH (2013) treats local labor markets as sub-economies subject to differential trade shocks according to initial patterns of industry specialization. Commuting zones (referred to as CZs from this point), which encompass all metropolitan and nonmetropolitan areas in the United States, are logical geographic units for defining local labor markets (Tolbert and Sizer 1996; Autor and Dorn 2013). In the case of ADH (2013), they look at data ranging from 1990 to 2007.

They relate changes in exposure to low-income-country imports to changes in CZ wages, employment levels, industry employment shares, unemployment, labor force participation rates, and take-up of unemployment, disability, welfare, and other publicly funded benefits, where impacts vary by age, gender, and education. Their local labor market approach to analyzing the impacts of trade exposure is based on work by Borjas and Ramey (1995), who highlight the role of trade imbalances in mapping trade shocks to labor market outcomes, as well as the more recent work by Chiquiar (2008), Topalova (2005, 2010), and Kovak (2013), who looked into the effects of trade liberalizations on poverty, wages, and migration in both local and regional labor markets in Mexico, India, and Brazil.

When examining local labor markets economic outcomes, ADH (2013) captured both the direct effect of trade shocks on employment and earnings at import-competing employers as well as the net effects on employment, earnings, labor force participation, geographic mobility, and take-up of public transfer benefits in the surrounding geographic area (i.e CZ).

2-2-Theoretical Framework and Empirical Approach

This section will encompass the theoretical framework use in ADH (2013) to explain how an increase in U.S imports from China affects the demand for U.S produced goods, and U.S labor markets outcomes.

Throughout this study, region i was treated as a small open economy so they could derive how shocks in China affect region i's labor market in terms of employment and wages. In applying the monopolistic competition model, the authors assume trade to have a "gravity" structure (similar to Arkolakis, Costinot, and Rodriguez-Clare 2012), so one can map changes in trade quantities into labor-market outcomes. Another option would be to use a Heckscher-Ohlin or a specific-factors model, as was the case in Topalova (2005, 2010) or Kovak (2013), in which the mapping is strictly from trade prices to wages and employment. Given that they lack access to suitable US industry import price data, they argue that the quantity-based approach is the more appropriate for this case.

The outcomes of interest for region i are the change in the wage ($\widehat{W}_i$), the change in employment in traded goods ($\hat{L}_{Ti}$), and the change in employment in non-traded goods $\hat{L}_{Ni}$. China's productivity growth or falling trade costs affect region i through two channels: (I) increased competition in the markets in which region i sells its output, captured by the change in China's export-supply capability in each industry j ($\hat{A}_{Cj}$), which the authors treated as exogenous and which is a function of changes in labor costs, trade costs, and the number of product varieties made in China, and (II) increased demand for goods in China, captured by the change in expenditure in China on each industry j ($\hat{E}_{Cj}$), which they also treated as exogenous.

The impacts of export-supply and import-demand shocks in China on region i's wages and employment are as follow in the equations that will form (2.1)

$$\widehat{W}_i = \sum_j C_{ij} \frac{L_{ij}}{L_{Ni}} \left[\theta_{ijC} \hat{E}_{Cj} - \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} \right] \qquad (2.1)$$

$$\hat{L}_{Ti} = p_i \sum_j C_{ij} \frac{L_{ij}}{L_{Ni}} \left[\theta_{ijC} \hat{E}_{Cj} - \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} \right]$$

$$\hat{L}_{Ni} = p_i \sum_j C_{ij} \frac{L_{ij}}{L_{Ni}} \left[-\theta_{ijC} \hat{E}_{Cj} - \sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} \right]$$

Wage and employment outcomes are the sum of the increase in demand for region i's exports to China, given by the change in expenditure in China ($\hat{E}_{Cj}$) times the initial share of output by region i that is shipped to China ($\theta_{ijC} \equiv X_{ijC}/X_{ij}$); and the decrease in demand for region i's shipments to all markets in which it competes with China. The latter is given by the growth in China's export-supply capability ($\hat{A}_{Cj}$) times the initial share of output by region i that is shipped to each market k ($\theta_{ijk} \equiv X_{ijk}/X_{ij}$) and the initial share of imports from China in total purchases by each market k ($\phi_{Cjk} \equiv M_{kjC}/E_{kj}$). These shocks are summed across sectors, weighted by the initial ratio of employment in industry j to total employment in non-traded or traded industries (L_{ij}/L_{Mi}, M = N, T) and a general-equilibrium scaling factor ($C_{ij} > 0$). The employment equations are scaled further by p_i, the share of the current-account deficit in total expenditure in region i.

In (2.1), positive shocks to China's export supply decrease region i's wage and employment in traded goods and increase its employment in non-traded goods. In a similar way, positive shocks to China's import demand increase region i's wage and employment in traded goods as well as decreasing its employment in non-traded goods. Under balanced trade, a labor demand decrease in US regions that are more exposed to import competition from China would be offset by labor demand growth in US regions that enjoy expanded export production to China, so that for the aggregate US economy labor demand may result unchanged. On the other hand, with imbalanced trade this might not be the case. The import demand shock in China is not a function of growth in its income, but on its expenditure. Remember that the impact of trade shocks on the division of employment between traded and nontraded sectors depends on $p_i \neq 0$, or trade imbalance.

In order to use (2.1) for empirical analysis, ADH (2013) assume that the share of the trade imbalance in total expenditure (p_i) and the general equilibrium scaling factor (C_{ij}) are the same across US regions (such that $p_i C_{ij}$ = α). Moreover, the researchers begin by focusing on a single channel through which trade with China affects region i: greater import competition in the US market, thus ignoring (temporarily) the effects of greater US exports to China or greater import competition in the foreign markets that US regions serve.

These restrictions are imposed as base specifications simply because US imports from China vastly exceed US exports to China and because the US market accounts for the large majority of demand for most US industries. With these restrictions in place, the change in employment for traded goods in region i becomes the following expression:

$$\hat{L}_{Ti} = -\alpha \sum_j \frac{L_{ij}}{L_{Ti}} \frac{X_{ijU}}{X_{ij}} \frac{M_{CjU}}{E_{Uj}} \hat{A}_{Cj} \approx -\tilde{\alpha} \sum_j \frac{L_{ij}}{L_{Uj}} \frac{M_{CjU} \hat{A}_{Cj}}{L_{Ti}} \qquad (2.2)$$

with the wage change and the change in non-traded employment defined analogously. In (2.2), traded-sector employment in region i depends on growth in US imports from China mandated by growth in China's export-supply capability ($M_{CjU}\hat{A}_{Cj}$), scaled by region i's labor force (L_{Ti}), and weighted by the share of region i in US employment in industry j (L_{ij}/L_{Uj}).

Moving on to the empirical approach, following (2.2), the authors main measure of local labor market exposure to import competition is the change in Chinese import exposure per worker in a specific region, where imports are apportioned to the region according to its share of national industry employment:

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ucjt}}{L_{it}} \qquad (2.3)$$

In equation (2.3), L_{it} is the start of period employment (year t) in region i and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period.

Expression (2.3) makes clear that the difference in ΔIPW_{uit} across local labor markets comes entirely from variation in local industry employment structure at the start of period t. This variation arises from two sources. First, differential concentration of employment in manufacturing. And second, nonmanufacturing activities and specialization in import-intensive industries within local manufacturing. Differences in manufacturing employment shares are not the primary source of variation. However, ADH (2013) argue that in a bivariate regression, the start-of-period manufacturing employment share explains less than 25 percent of the variation in ΔIPW_{uit}. When the main specifications are applied, they will control for the start-of-period manufacturing share within CZs to focus on variation in exposure to Chinese imports stemming from differences in industry mix within local manufacturing sectors.

To identify the supply-driven component of Chinese imports, the authors instrument for growth in Chinese imports to the United States using the contemporaneous composition and growth of Chinese imports in eight other developed countries. They specifically instrument the measured import exposure variable ΔIPW_{uit} with a non-US exposure variable ΔIPW_{oit} that is constructed using data on contemporaneous industry-level growth of Chinese exports to other high-income markets:

$$\Delta IPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{ujt-1}} \frac{\Delta M_{ocjt}}{L_{it-1}} \qquad (2.4)$$

Equation (2.4) for non-US exposure to Chinese imports differs from equation (2.3) in two ways. First, instead of realized US imports by industry (ΔM_{ucjt}), it employs realized imports in other high-income markets from China (ΔM_{ocjt}). Second, instead of start-of-period employment levels by industry and region, this equation employs employment levels from the prior decade.

They use ten-year-lagged employment levels because to the degree that contemporaneous employment by region is affected by anticipated China trade, the use of lagged employment to apportion predicted Chinese imports to regions will reduce the simultaneity bias.

2-3-Results

In this section, I will discuss the econometric method used by the authors to measure the effect of increasing Chinese imports in the manufacturing sector. I will show how increasing Chinese imports affect wages, the quantity of labor within the manufacturing industry, and labor mobility to other industries. I will show and discuss the trends of the data within the 2SLS and reduced form estimates (OLS) of the model in addition to the significance it may have on the manufacturing industry given some control variables.

Table 2.1 show the initial estimates of the relationship between US manufacturing employment and Chinese import exposure. By employing the full sample of 722 CZs and weighting each observation by start of period CZ population, the researchers fit models of the following expression:

$$\Delta L_{it}^{m} = \gamma_t + \beta_1 \Delta IPW_{uit} + X'_{it}\beta_2 + e_{it}, \qquad (2.5)$$

where ΔL_{it}^{m} is the change in decades that takes place in the manufacturing employment share of the working-age population in commuting zone i. When estimating this model for the 1990-2007 interval, the authors stack the ten-year equivalent first differences for the two periods, 1990 to 2000 and 2000 to 2007, and also include separate time dummies for each decade (in γ_t). The change in import exposure ΔIPW_{uit} is instrumented by the variable ΔIPW_{oit} as described before. Since the model is estimated in first differences, the decade-specific models are equivalent to CZ fixed effects regressions, while the stacked first difference models are similar to a three period fixed effects model with slightly less restrictive assumptions made on the error term. Moreover, the vector X_{it} contains a rich set of controls for CZs start-of-decade labor force and demographic composition that might independently affect manufacturing employment. Standard errors are clustered at the state level to account for spatial correlations in commuting zones.

The first two columns of Table 2.1 estimate equation (2.5) separately for the 1990–2000 and 2000–2007 periods, and the third column provides stacked first differences estimates. The −0.75 coefficient in column 3 indicates that a \$1,000 exogenous decadal rise in a commuting zones import exposure per worker is predicted to decrease its manufacturing employment per working-age population by three-quarters of a percentage point.

Throughout the examined time-span, US manufacturing suffered a considerable decline. Concern exists regarding that increased imports from China could be a symptom of this decline rather than a cause. In order to make sure that the results capture the period-specific effects of exposure to China trade, and not some long-run common causal factor behind both the fall in manufacturing employment and the rise in Chinese imports, a falsification exercise is performed by regressing past changes in the manufacturing employment share on future changes in import exposure. Column 4 shows the correlation between changes in manufacturing employment in the 1970s and the change in future import exposure averaged over the 1990s and 2000s. On the other hand, column 5 shows the corresponding correlation for the 1980s and column 6 shows the results of the stacked first differences model. These recently mentioned correlations provide little evidence suggesting reverse causality. There is a weak negative relationship between the change in manufacturing employment and future import exposure in the 1980s. It is also worth noting that in the prior decade, this relationship is positive. While this exercise does not rule out the possibility that other factors contribute to the contemporaneous commuting zone level relationship between rising China trade exposure and decreasing manufacturing employment, the Table 2.1 estimates demonstrate that this relationship was not present in the decades immediately prior to China's rise.

Table 2.1: Imports From China and Change of Manufacturing Employment in CZ's, 1970-2007: 2SLS Estimates

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

	I. 1990-2007			II. 1970-1990 (pre-exposure)		
	1990-2000	2000-2007	1990-2007	1970-1980	1980-1990	1970-1990
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ current period imports from China to US)/worker	-0.89***	-0.72***	-0.75***			
	(0.18)	(0.06)	(0.07)			
(Δ future period imports from China to US)/worker				0.43***	-0.13	0.15
				(0.15)	(0.13)	(0.09)

Note: N=722, except columns 3 and 6 where N= 1,444. "Future period imports is defined as the average of the growth of a CZ's import exposure during 1990*-2000 and 2000-2007. All regressions include a constant and the models in column 3 and 6 include a time dummy. Robust standard errors in parenthesis are clustered on state. Superscripts ***, ** and * represent significance at 1, 5, and 10 percent levels respectively. Source, **ADH 2013**

Moving on to Table 2.2, the stacked first difference model for the period 1990–2007 is augmented with a set of demographic and labor force measures which test robustness and potentially eliminate confounds. In column 2, a share of manufacturing in a commuting zone's start-of-period employment control is added. This specification further addresses the concern that the China exposure variable may in part be picking up an overall trend decline in US manufacturing rather than the component that is because of differences across manufacturing industries in their exposure to increasing Chinese competition. The column 2 estimate suggests that a commuting zone with a one percentage point higher initial manufacturing share suffers a differential manufacturing employment share decrease of 0.04 percentage points over the next decade. This specification finds a slightly smaller effect of import exposure on manufacturing employment than the estimate in column 1, although the relationship remains economically large and statistically significant. Seeing that the interquartile range in commuting zone level import exposure growth in the 2000-2007 time-span was approximately $1,000 per worker, the column 2 point estimate suggests that the share of manufacturing employees in the working-age population of a commuting zone at the 75th percentile of import exposure declined by −0.65 percentage points more than in a commuting zone at the 25th percentile from 2000, through 2007.

Column 3 augments the regression model with geographic dummies for the nine Census divisions that absorb region-specific trends in the manufacturing employment share. These dummies decrease the estimated effect of import exposure on manufacturing employment. Column 4 also controls for the start-of-period share of a commuting zone's population with college education, the share of foreign-born population, and the share of working-age women that are employed. These controls do not affect the main result.

Moreover, column 5 introduces two variables that capture the susceptibility of a commuting zone's occupations to substitution by technology or task offshoring. Both variables are based on occupational task data, which are explained in greater detail in Autor and Dorn (2013). There are two types of routine-intensive occupations. One of them refers to white collar positions whose primary job tasks involve routine information processing (e.g., accountants and secretaries) and the other refers to blue-collar production occupations that primarily involve repetitive motion and monitoring tasks. If commuting zone's that have a large start-of-period employment share in routine occupations experience strong displacement of manufacturing jobs due to automation, it would be natural to expect a negative relationship between the routine share variable and the change in manufacturing share. The column 5 estimates indicate that the population share in manufacturing declines by about 0.23 percentage points for each additional percentage point of initial employment in routine occupations.

Table 2.2: Imports From China and Change of Manufacturing Employment in CZ's, 1990-2007: 2SLS Estimates

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

	I. 1990-2007 stacked differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/worker	-0.746***	-0.610***	-0.538***	-0.508***	-0.562***	-0.596***
	(0.068)	(0.094)	(0.091)	(0.081)	(0.096)	(0.099)
Percentage of employment in manufacturing		-0.035	-0.052***	-0.061***	-0.056***	-0.040***
		(0.022)	(0.020)	(0.017)	(0.016)	(0.013)
Percentage of college-educated population				-0.008		0.013
				(0.016)		(0.012)
Percentage of foreign-born population				-0.007		0.030***
				(0.008)		(0.011)
Percentage of employment among women				-0.054***		-0.006
				(0.025)		(0.024)
Percentage of employment in routine occupations					-0.230***	-0.245***
					(0.063)	(0.064)
Average offshorability index of occupations					0.244	-0.059
					(0.252)	(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***	0.664***	0.652***	0.635***	0.638***	0.631***
	(0.079)	(0.086)	(0.090)	(0.090)	(0.087)	(0.087)
R^2	0.54	0.57	0.58	0.58	0.58	0.58

Note: N=1,444 (722 CZ x 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 emp in 1980. The offshorability index is standardized to mean 0 and standard deviation 10 in 1980. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of period CZ share of national population. Superscripts ***, ** and * represent significance at 1, 5, and 10 percent levels respectively. Source, **ADH 2013**

If offshoring of occupations were an important factor for the decline in manufacturing within commuting zone's, it would be natural to expect a negative relationship between the offshorability index and the change of the manufacturing employment share. However, the column 5 estimate does not find a negative or statistically significant coefficient for occupational offshorability. The fully augmented model in column 6 indicates a considerable robust negative impact of increasing import exposure on manufacturing employment. The decrease in manufacturing is also bigger in commuting zone's with a bigger initial manufacturing employment share and in local labor markets where employment is concentrated in routine-task intensive occupations. It is smaller in places where the initial foreign-born population is larger.

Table 2.3: Means and Standard Deviations of CZ Level Variables

	I. Levels			II. Ten-year equivalent Δ's	
	1990/1991	2000	2007	1990-2000	2000-2007
	(1)	(2)	(3)	(4)	(5)
(Imports from China to US)/ (workers inn 1990) (in kU$$)	0.29	1.32	3.58	1.14	n/a
	(0.32)	(1.18)	(2.84)	(0.99)	n/a
(Imports from China to US)/ (workers inn 2000) (in kU$$)	0.25	1.08	2.92	n/a	2.63
	(0.27)	(0.90)	(2.13)	n/a	(2.01)
Percentage of working-age population employed in manufacturing	12.69	10.51	8.51	-2.07	-2.73
	(4.80)	(4.45)	(3.60)	(1.63)	(1.80)
Percentage of working-age population employed in nonmanufacturing	57.75	59.16	61.87	1.29	3.7
	(5.91)	(5.24)	(4.95)	(2.38)	(2.71)

Notes: N = 722 CZs. Statistics in columns 1 and 4 are weighted by 1990 population, statistics in columns 2 and 5 are weighted by 2000 population, and statistics in column 3 are weighted by 2007 population. The first two rows of column 1 report import volumes for the year 1991, all other variables in column 1 are based on 1990 data. Information on employment composition, wages, and income in column 3 is derived from pooled 2006–2008 ACS data. Source, **ADH (2013)**

The preferred specification with full controls in Table 2.2 column 6 suggests that a $1,000 per worker rise in import exposure over a decade decreases manufacturing employment per working-age population by 0.596 percentage points. Table 2.3 exemplifies that Chinese import exposure increased by $1,140 per worker between 1990 and 2000 and by an additional $1,839 per worker between 2000 and 2007. Thus, based on the estimates from ADH (2013) an increase in exposure to import competition from China helps explains 33 percent of the US manufacturing employment decline between 1990 and 2000, 55 percent of such decline between 2000 and 2007, and 44 percent of the same decline for the complete 1990 through 2007 period.

Moving on to table 2.4, the authors look at the population effect on local labor markets caused by increasing Chinese imports. Table 2.4, which deals with the employment status over the years of the working-age population given the increase in Chinese imports. Panel A of Table 2.4 portrays the impact of import shocks on the log change in the number of non-elderly adults in four mutually exclusive categories such as employment in manufacturing, employment in nonmanufacturing, unemployment, and labor force nonparticipation. The researchers find that a \$1, 000 per worker increase in import exposure decreases the amount of workers in manufacturing employment by 0.42 log points (~ 4.2 percent, t = 4.04) (Note this is because ADH reported the coefficients estimated from multiplying the dependent variable by 100 in table 2.4). Perhaps surprisingly, this effect is not offset by an increase in non-manufacturing employment in the commuting zone affected; instead, there is a modest decrease in local nonmanufacturing employment on the order of 0.27 log points. This point estimate is not statistically significant, although the authors show below that there is a significant decrease in non-college employment in nonmanufacturing. These net declines in manufacturing and nonmanufacturing employment are echoed by sharp rises in the number of unemployed workers and labor force nonparticipants: a \$1,000 per worker import shock increases the number of unemployed and nonparticipating individuals by 4.9 and 2.1 percent. Then, Panel B of Table 2.4 shows a corresponding set of models for employment, unemployment, and non-employment employing the share of the non-elderly adult population in each category as a dependent variable: declines in the population share in one category (e.g., manufacturing employment) must produce equivalent gains in other categories. Since population is not systematically affected by the shock, normalizing by this measure is not problematic.

The sum of the first two coefficients in panel B indicate that a \$1,000 per worker increase in a commuting zone's import exposure decreases its employment to population rate by 0.77 percentage points. About three-quarters of that decrease is because of the loss in manufacturing employment, with the remainder due to a (not significant) decrease in nonmanufacturing employment. The next two columns show that one-quarter of the decrease in the employment to population ratio is accounted for by an increase in the unemployment to population rate (0.22 percentage points) while the remaining three-quarters accrue to labor force nonparticipation (0.55 percentage points). Hence, the shock to manufacturing employment leads to a more than one-for-one rise in non-employment.

Table 2.4: Imports From China and Employment Status of Working-Age Population Within CZ's, 1990-2007: 2SLS Estimates

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

	Mfg emp	Non-mfg emp	Unemp	NILF	SSDI receipt
	(1)	(2)	(3)	(4)	(5)
Panel A. 100 x 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 educational 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)	

Note: N=1,444 (722 CZ x 2 time periods). All statistics based on working age individuals (age 16 to 24). The effect of import exposure on the overall employment/population ratio can be computed as the sum of the coefficients of manufacturing employment. All regressions include the full vector control of variables from column 6 Table 2. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of period CZ share of national population. Superscripts ***, ** and * represent significance at 1, 5, and 10 percent levels respectively. Source, **ADH 2013.**

The next two rows of panel B show that a $1,000 import shock decreases college and non-college manufacturing employment per population by equivalent amounts but has a unique effect on college versus non-college employment in nonmanufacturing employment, unemployment and non-employment. More specifically, a $1,000 import exposure shock decreases non-college employment in nonmanufacturing by a highly significant 0.53 percentage points. On the other hand, college employment in nonmanufacturing increases modestly by 0.17 percentage points (t = 1.37). A potential explanation for this pattern is that the decline of manufacturing industries decreases the demand for non-traded services that are typically provided by low-skilled workers. On net, a $1,000 import exposure shock decreases the employment to population rate of college adults by 0.42 percentage points and of non-college adults by 1.11 percentage points.

Table 2.5: 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	College	Noncollege	All workers	College	Noncollege
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Log change in number of workers						
(Δ imports from China to US)/worker	-4.231***	-3.992***	-4.493***	-0.274	0.291	-1.037
	(1.047)	(1.181)	(1.243)	(0.651)	(0.590)	(0.764)
R^2	0.31	0.3	0.34	0.35	0.29	0.53
Panel B. Change in average log wage						
(Δ imports from China to US)/worker	0.15	0.458	-0.101	-0.761***	-0.743**	-0.822***
	(0.482)	(0.340)	(0.369)	(0.260)	(0.297)	(0.246)
R^2	0.22	0.21	0.33	0.6	0.54	0.51

Note: N=1,444 (722 CZ x 2 time periods). All regressions include the full vector control of variables from column 6 Table 2. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of period CZ share of national population. Superscripts ***, ** and * represent significance at 1, 5, and 10 percent levels respectively. Source, **ADH 2013.**

One way that could potentially accommodate the increase in labor force nonparticipation following a rise in import exposure is enrollment in the Social Security Disability Insurance (SSDI) program, which gives transfer benefits and Medicare coverage to working-age adults who are able to establish that their disabilities preclude gainful employment. The panel B estimates of Table 2.4 imply that 9.9 percent (0.076/0.77) of those who lose employment following an import shock obtain some sort of federal disability insurance benefits. As large as this fraction looks, it is not implausible. As of 2010, 4.6 percent of adults age 25 to 64 received SSDI benefits, and SSDI applications and awards are elastic to adverse labor market shocks (Autor and Duggan 2003 and 2010).

Finally, they look at the wage effects of increase import penetration from China. In Table 2.5, the researchers explore wage effects separately for workers employed in manufacturing and nonmanufacturing. To make interpretation easier, the upper panel of the table shows estimates of the effect of import exposure on log employment counts in both sectors. Consistent with the earlier estimates, Table 2.5 confirms that import exposure reduces head counts in manufacturing but has little employment effects outside of manufacturing, more specifically in college workers.

The effect of import exposure on mean wages found in Table 2.5 panel B is the complement of the employment effects estimated in panel A. Although import exposure decreases manufacturing employment, it looks to have no significant effects on mean manufacturing wages in commuting zones. This finding is similar to the outcomes of industry-level studies such as Edwards and Lawrence (2010) or Ebenstein et al. (2014), which do not find negative wage effects of imports on US workers in import-competing manufacturing industries. One possible explanation for this pattern is that the most productive workers retain their jobs in manufacturing. Hence, biasing the estimates against finding a decrease in wages within manufacturing. Another 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 as a result, wages may rise.

On the other hand, Chinese import exposure significantly decreases earnings in non-manufacturing sectors. Nonmanufacturing wages fall by 0.76 log points for a $1,000 rise in Chinese import exposure per worker, an effect that is comparable for college and noncollege workers. This result implies that a negative shock to local manufacturing decreases the demand for local non-traded services in addition to increasing the available supply of workers, creating downward pressure on wages in the sector. The results of this section demonstrate that a rise in the exposure of local US labor markets to imports from China stemming from rising Chinese comparative advantage leads to a considerable decline in employment and wages in local labor markets.

2-4-Conclusion

In this particular study, the authors find that local labor markets that are exposed to rising low-income-country imports due to China's rising competitiveness experience increased unemployment, decreased labor-force participation, and increased use of disability and other transfer benefits, as well as lower wages. Comparing two CZs over the period of 2000 through 2007, one at the 25th percentile and the other at the 75th percentile of exposure to Chinese import growth, the more exposed CZ would be expected to experience a differential 4.5 percent fall in the number of manufacturing employees, a 0.8 percentage point larger reduction in the employment to population rate, a 0.8 percent larger decline in mean log weekly earnings, and larger increases in per capita unemployment, disability, and income assistance transfer benefits on the order of 2 to 3.5 percent.

After looking more carefully at the results, Autor, Dorn and Hanson (ADH, 2013) conclude that the growing exposure of the U.S. economy to Chinese gross exports has had a negative effect on manufacturing and non-manufacturing employment levels, as well as on wages, across U.S. local labor markets (commuting zones). Their results suggest that increasing exposure to Chinese competition can explain 26 percent of the decline in U.S. manufacturing employment for the years 2000 to 2007.

Chapter 3 - Incorporating Input-Output Linkages

3-1-Introduction:

This section will exemplify the effect of increasing import penetration of Chinese goods on the U.S labor market with an emphasis in the manufacturing sector just as in the previous section. Only that this time, the analysis will have a new feature. The difference for this section is that the study in question adds a new dimension to the analysis. In order to better portray the effect of increasing Chinese imports, Acemoglu, Autor, Dorn, Hanson, and Price build up on the work done by ADH (2013) by accounting for input-output linkages of each separate industry they looked at in their 2016 paper titled "Import Competition and the Great Unemployment Sag of the 2000's" (AADHP 2016). The analysis will encompass the effects in quantity of labor in manufacturing and non-manufacturing, wages, and how susceptible are industries to this increase in imports depending on their level of upstreamness or downstreamness.

Within the analysis, their direct industry-level employment estimates come from comparing changes in employment across four-digit manufacturing industries from 1991 to 2011 as a function of industry exposure to Chinese import competition similar to the ones mentioned in the previous section. The first part of the article shows that there is a sizable and robust negative effect of growing Chinese imports on US manufacturing employment.

The full general equilibrium impact of growing Chinese imports on US employment encompasses several indirect channels through which rising exposure to import competition may affect employment levels. One source of indirect effects, also studied by Pierce and Schott (2015), is industry input-output linkages. Which can generate either positive or negative changes in US industry labor demand by creating a net employment change that is ambiguous in sign. If an industry downsizes because of Chinese competition, it may reduce its demand for U.S made intermediate as well as its supply of inputs to other domestic industries. Hence, an industry may be affected in a negative way by trade shocks either to its domestic suppliers or buyers. The sign of the "downstream effect" (exposure to import competition that propagates downstream from an industry to its customers) is theoretically ambiguous. While competition may reduce the domestic supply of certain inputs, those reductions may be offset by the increased supply of imported inputs. On the other hand, the "upstream effect" (exposure to import competition that propagates upstream from an industry's buyers) should avoid having contractionary consequences for the upstream industry. The US input-output table for 1992 was used to estimate the effects of upstream and downstream import exposure for manufacturing industries as well as for nonmanufacturing industries.

3-2-Theoretical Framework

This section will go more into the details of the theoretical framework used on the study to determine the impact of increased Chinese imports in the US market. As mentioned before, in the same way as in the previous case, this study also uses an import penetration variable as one of the foundations of the analysis. The baseline measure of trade exposure is the change in the import penetration ratio for a US manufacturing industry over the period 1991–2011 which is defined as

$$\Delta IP_{jt} = \frac{\Delta M_{j,t}^{UC}}{Y_{j,91}+M_{j,91}-E_{j,91}} \tag{3.1}$$

where for US industry j, $\Delta M_{j,t}^{UC}$ is the change in imports from China over the period 1991–2011 (which in most of the analysis is divided into two subperiods, 1991–99 and 1999–2011) and $Y_{j,91} + M_{j,91} - E_{j,91}$ is initial absorption (measured as industry shipments, $Y_{j,91}$, plus industry imports, $M_{j,91}$, minus industry exports, $E_{j,91}$).

One concern about (3.1) as a measure of trade exposure is that observed changes in the import penetration ratio may in part reflect domestic shocks to US industries that affect US import demand. Even if the dominant factors driving China's export growth are internal supply shocks, US industry import demand shocks may still contaminate bilateral trade flows. To capture this supply-driven component in US imports from China, the authors instrument for trade exposure in (3.1) with the variable

$$\Delta IPO_{jt} = \frac{\Delta M_{j,t}^{OC}}{Y_{j,88}+M_{j,88}-X_{j,88}} \tag{3.2}$$

where $\Delta M_{j,t}^{OC}$ is the growth in imports from China in industry j during the period t (in this case 1991–2011 or some subperiod thereof) in eight other high-income countries excluding the United States. The denominator in (3.2) is initial absorption in the industry in 1988. The motivation for the instrument in (3.2) is that high-income economies are similarly exposed to growth in imports from China that is driven by supply shocks in the country. The identifying assumption is that industry import demand shocks are uncorrelated across high-income economies and that there are no strong increasing returns to scale in Chinese manufacturing (which might imply that US demand shocks will increase efficiency in the affected Chinese industries and induce them to export more to other high-income Countries).

A potential concern about the analysis is that US exports to China are mostly ignored, with greater focus set primarily on trade flows in the opposite direction. This is for the simple reason that the instrument, has little predictive power for US exports to China.

3-3-Results

Now I will move onto the direct impact of trade exposure on employment by showing the direct effect of trade exposure on employment the authors found over the period 1991–2011 using aggregate, industry-level regressions. The initial specification for the regression is as follows

$$\Delta L_{jt} = \alpha_t + \beta_1 \Delta IP_{jt} + \gamma X_{j0} + e_{jt}, \qquad (3.3)$$

where ΔL_{jt} is 100 times the annual log change in employment in industry j over time period t; ΔIP_{jt} is 100 times the annual change in import penetration from China in industry j over period t as defined in (1); X_{j0} is a set of industry-specific start-of-period controls (specified later); α_t is a period-specific constant; and e_{jt} is an error term. Even though the authors calculate values on import penetration by first differences on each period separately, they also fit equation (3.3) to get stacked first differences covering the two subperiods 1991–99 and 1999– 2011, where in some specifications they shrink the subperiod 1999-2011 to 1999–2007 to evaluate impacts on employment before the Great Recession. Variables specified in changes (denoted by D) are annualized since expression (3.3) is estimated on periods of different lengths. When including the elements in the vector of controls X_{j0}, all of them normalize with mean zero so that the constant term in expression (3.3) reflects the change in the outcome variable conditional only on the variable of interest, ΔIP_{jt}. Almost all outcome variables are measured at the level of 392 four-digit manufacturing industries, while later models also estimate spillovers to 87 nonmanufacturing industries. Regression estimates are weighted by start-of-period industry employment, and standard errors are clustered at the three-digit industry level to allow for arbitrary error correlations within larger industries over time.

Now to show the impact of US import exposure to Chinese goods calculated in the previous expression I turn to table 3.1. Which presents a simple stacked first-difference model for the two time periods 1991–99 and 1999–2011, with the change in import penetration and a dummy for each time period as the sole regressors. Along with these estimates, there are also the results from stacking the time periods 1991–99, and 1999–2007 and from fitting the model separately for the three subperiods 1991–99, 1999–2011, and 1999–2007. These additional specifications allow for the results to be examined both before and after the commencement of the 2000s US employment sag and allow for comparison of the results for the 2000s with and without the Great Recession years. AADHP (2016) also present results for the single long difference, 1991–2011, for comparison against the stacked first differences.

In column 1, which excludes the import penetration variable from equation (3.2), the time dummies reflect the mean annual within-industry change in employment in each period. Column 2 adds the observed import exposure measure previously mentioned without instrumentation. This variable is negative and highly statistically significant, consistent with the idea that increasing import penetration lowers domestic industry employment. Nevertheless, this OLS point estimate could be biased because growth in import penetration is partly driven by changes in domestic supply and demand. Column 3 mitigates this simultaneity bias by instrumenting the observed changes in industry import penetration with contemporaneous changes in other-country China imports as noted in expression (3.2). The estimate in column 3 implies that a 1 percentage point rise in industry import penetration decreases domestic industry employment by 1.3 percentage points (t-ratio of 3.2). Column 4, which stacks the periods 1991–99 and 1999–2007, shows that the coefficient of import penetration is very similar if attention is only centered in the years preceding the Great Recession.

The remaining columns of table 3.1 present bivariate estimates of this relationship separately by subperiod. The trade exposure coefficient is negative and statistically significant in all time periods and is largest in absolute value for 1991–99 and smallest for 1999–2007. Even though the responsiveness of employment to import penetration is greater before 2000, the even faster growth in Chinese imports after 2000 produces an overall impact of trade on employment that is substantially larger in the latter period. The sensitivity of employment to trade for 1999– 2011 is similar to the estimate for 1999–2007, despite the global financial crisis in 2007 and the associated dislocation of worldwide trade patterns.

Table 3.1: Effect of Import Exposure on Log Employment in US Manufacturing Industries OLS and 2SLS Estimates

	Stacked Differences (N =784)				Separately by period (N =392)			
	1991-2011			1991-2007	1991-99	1999-2011	1999-2007	1991-2011
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
100 x annual Δ in US exposure to Chinese imports		-0.81**	-1.30***	-1.24***	-2.30**	-1.16***	-1.12***	-1.49***
		(0.16)	(0.41)	(0.37)	(1.12)	(0.37)	(0.34)	(0.47)
1{1991-99}	-0.3	-0.08	0.05	0.04				
	(0.37)	(0.36)	(0.36)	(0.36)				
1{1999-2011}	-4.32***	-3.79***	-3.46***					
	(0.37)	(0.33)	(0.33)					
1{1991-2007}				-2.58***				
				(0.38)				
Constant					0.32	-3.55***	-2.68***	-1.96***
					(0.43)	(0.34)	(0.39)	(0.27)
Estimation method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

Note: Columns 1– 4 report results from stacking log employment changes and changes in US exposure to Chinese imports over the periods 1991–99 and either 1999–2011 or 1999–2007, as indicated (N=784=392 four-digit manufacturing industries x 2 periods). Columns 5–8 report results from regressing the employment change over the indicated period on the change in US exposure to Chinese imports over the same period (N=392). Employment changes are computed in the CBP and are expressed as 100 x annual log changes. In 2SLS specifications, the change in US import exposure is instrumented as described in the text. In all specifications, observations are weighted by 1991 employment. Standard errors in parentheses are clustered on 135 three-digit industries in all specifications. Superscripts *** and ** refer to significance at the 1 and 5 percent levels. **Source, AADHP (2016)**

A simple long-difference model for the change in manufacturing employment over the full 1991–2011 period (col. 8) also suggests a negative relationship between import penetration and US manufacturing employment. The coefficient estimates in column 3, for the stacked first differences, and column 8, for the long-time difference, are quite similar, reflecting strong persistence in the growth in Chinese import penetration within industries. Replacing stacked first differences with the long difference may remove cyclical variation in the data, accounting for the mildly larger coefficient estimates in the latter case.

Going back to the results in column 3 of table 3.1, the authors analyze the economic magnitude of these estimates by constructing counterfactual changes in employment that would have occurred in the absence of increases in import competition from China. Using equation (3.3), they wrote the difference between actual and counterfactual manufacturing employment in year t as

$$\Delta L_t^{cf} = \sum_j L_{jt} \left(1 - e^{-\widehat{\beta}_1 \widetilde{\Delta IP_{Jt}}}\right), \qquad (3.4)$$

where $\hat{\beta}_1$ is the 2SLS coefficient estimate from (3.3) and $\widetilde{\Delta IP_{Jt}}$ is the increase in import penetration from China that is attribute to China's improving competitive position in industry j between 1991 (or 1999) and year t. Following Autor et al. (2013), the authors estimate $\widetilde{\Delta IP_{Jt}}$ by multiplying the observed increase in import penetration ΔIP_{jt} with the partial R-squared from the first-stage regression of expression (3.1) on the instrument in expression (3.2), which has a value of 0.56 in their baseline specification in column 3 in table 3.1. When their instrument is valid and there is no measurement error, this partial R-squared adjusted $\widetilde{\Delta IP_{Jt}}$ variable is a consistent estimate of the contribution of Chinese import supply shocks to changes in import penetration.

3-3-1-Controlling for Industry Confounds and Pre-trends

AADHP (2016) state that a challenge in their analysis is that industries that face greater import competition may be exposed to other economic shocks that are correlated with China trade. They address this concern by incorporating controls for potential industry confounds. A set of additional falsification tests are shown as well.

AADHP (2016) consider three control variable groups for their analysis. First, they probe the robustness of the results by including dummies for 10 one-digit manufacturing sectors. Since regressions are in first differences, including these dummies amounts to allowing for differential trends across these one-digit sectors. Regressions including these dummies therefore identify the industry-level impacts of trade exposure while purging common trends within the one-digit sectors and using only variation in import growth across industries with relatively similar skill intensities.

Another important thing to point out is that technological progress within manufacturing has been among the fastest in recent decades, more specifically in computer and skill-intensive sectors (Doms, Dunne, and Troske 1997; Autor, Katz, and Krueger 1998). A second set of control variables is added to capture the extent to which industries are exposed to technical change. This set of control variables is drawn from the NBER-CES database. It measures the intensity of their use of production labor and capital. These variables include the share of production workers in total employment, the log of the average wage, the ratio of capital to value added (all measured in 1991), as well as computer and high-tech equipment investment in 1990, each expressed as a share of total 1990 investment.

US manufacturing as a share of employment has been declining since the 1950s, and the number of manufacturing employees has also been decreasing since the 1980s. This trend highlights a concern by the authors that the correlation between rising industry trade penetration and contemporaneous, within-industry declines in manufacturing employment during 1991–2011 could potentially predate the recent rise in import exposure. Since this could overstate the impact of increased trade exposure nowadays, then pre-trend measures were added in industry employment and earnings in Table 3.2, specifically the change in the industry's share of total US employment and the change in the log of the industry average wage.

The first seven columns of table 3.2 alternate among combinations of these three groups of industry controls: the one-digit sector dummies, industry-level controls for production structure, and industry-level controls for pre-trends. Column 1 replicates results from column 3 of table 3.1 to use as a benchmark. Among the other groups, only the one-digit sector dummies have a substantial impact on the point estimates, reducing the (instrumented) estimates by about 40%. Even though the inclusion of the sectoral dummies is an important robustness check, the researchers say that there are two reasons why these specifications may underestimate the impact of Chinese import competition. First, trade exposure at the four-digit industry level is likely to be measured with error, and the inclusion of the one-digit sector dummies will then cause significantly greater attenuation of the estimates of the impact of Chinese import growth. Second, if there

Table 3.2: 2SLS Estimates of Import Effects on Log Employment Industry-Level Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
100 x annual Δ in US exposure to Chinese imports	-1.30***	-0.75***	-1.10***	-1.33***	-0.80***	-0.76***	-0.74***	-0.60**
	(0.41)	(0.22)	(0.35)	(0.43)	(0.25)	(0.22)	(0.23)	(0.29)
1{1991-99}	0.05	-0.09	0.00	0.06	-0.08	-0.09	-0.1	
	(0.36)	(0.32)	(0.37)	(0.36)	(0.30)	(0.32)	(0.30)	
1{1999-2011}	-3.46***	-3.82***	-3.59***	-3.44***	-3.79***	-3.82***	-3.83***	-3.79***
	(0.33)	(0.27)	(0.35)	(0.32)	(0.28)	(0.26)	(0.27)	(0.45)
One-digit manufacturing sector controls	No	Yes	No	No	Yes	Yes	Yes	No
Production controls	No	No	Yes	No	Yes	No	YES	No
Pretrend controls	No	No	No	Yes	No	Yes	Yes	No
Industry fixed effects	No	No	No	No	No	No	No	Yes

Note: Each column reports results from stacking log employment changes and changes in US exposure to Chinese imports over the periods 1991–99 and 1999–2011 (N=784=392 four-digit manufacturing industries x 2 periods). The dependent variable is 100 x the annual log change in each industry's employment in the CBP over the relevant period. The regressor is 100 x the annual change in US exposure to Chinese imports over the same period. Pretrend controls are changes in the log average wage and in the industry's share of total employment over 1976–91. The final column includes a full set of four-digit industry fixed effects. Covariates are demeaned to facilitate interpretation of the time effects. Standard errors in parentheses are clustered on 135 three-digit industries. Superscripts *** and ** refer to significance at the 1 and 5 percent levels. Source **AADHP (2016)**

is a significant increase in imports in some industries within a one-digit sector, then employers in other similar industries within this broad sector may anticipate greater competition both from the current substitutes imported from China and also from future waves of Chinese imports and thus industries will likely downsize and close existing plants and will also be less likely to open new plants. On the other hand, neither the production nor the pre-trend variables have an important effect on the magnitude or precision of the coefficient of interest. As another robustness test, column 8 includes a full set of dummies for the 392 four-digit manufacturing industries in their data. These variables serve as industry-specific trends in the stacked first-difference specification, so the effect of import competition on industry employment in this specification is identified by changes in the growth rates of industry employment and import penetration in 1999–2011 relative to 1991–99. The addition of an exhaustive set of industry-specific trends only slightly reduces the point estimate and precision of the coefficient of interest relative to specifications that include one-digit sector dummies, thus highlighting the robustness of the relationship. To sum up, while the authors preferred industry-level model from column 3 of table 3.1 allows for an impact of Chinese trade competition on employment both within and across broad manufacturing subsectors, the estimates in table 3.2 document that a sizable negative employment effect remains even when focusing only on the within-subsector or within industry, over-time variation in trade exposure.

3.3.2-Accounting for sectorial linkages

Now, I'll move into the expansion of the scope of the inquiry to encompass the effects of trade shocks on employment in both manufacturing and nonmanufacturing industries when incorporating input-output linkages.

To study these inter-industry linkages, the researchers envisage an economy similar to the one studied by Long and Plosser (1983) and Acemoglu et al. (2012), where each industry uses with different intensities the output of other industries as inputs. They apply this methodology to the BEA's input-output table for 1992. They chose the 1992 input-output table since it largely predates the China trade shock and hence measures linkages that are unlikely to be endogenous to the subsequent shock. To estimate the upstream effect, they calculated the following quantity for each industry j:

$$\Delta IP_{jt}^{U} = \sum_{g} w_{gj}^{U} \Delta IP_{gt}, \tag{3.5}$$

which is equal to the weighted average change in import penetration during time interval t across all industries, indexed by g, that purchase from industry j. It is also worth noting that the upstream effect portrayed in expression (3.5) represents the effect of import exposure faced by j's downstream industries (industries that j sells to) on industry j. Not to be confused with the effect of industry j's import exposure on those upstream industries, because the weight $\mu_{g'j}^{U}$ represents the value of industry j's output purchased by industry g' (i.e. j's output that is sold to industry g). AADH (2016) refer to expression (3.5) as the "upstream effect" because j is the upstream industry in this case. The weights w_{gj}^{D} on expression (3.5) are defined as:

$$w_{gj}^{D} = \frac{\mu_{gj}^{U}}{\sum_{g'} \mu_{g'j}^{U}} , \tag{3.6}$$

where μ_{gj}^U is the 1992 "use" value in the BEA input-output matrix for the value of industry j's output purchased by industry g, such that the weight in (3.6) is the share of industry j's total sales that are used as inputs by industry g. Thus, (3.5) is a weighted average of the trade shocks faced by the purchasers of j's output. When industry j's purchasers suffer a negative trade shock, they are likely to reduce demand for j's output.

Similarly, to compute the downstream effect ΔIP_{jt}^D experienced by each industry j the authors make the same calculation after reversing the j and g indexes in the numerator of (3.6). Expression (3.6) represents the actual effect of import exposure faced by j's upstream industries (industries that j buys from). Since the left-hand side variable is j's employment, expression (3.6) looks at the effect of import exposure faced by j's upstream industries in industry j. The authors refer to expression (3.6) as the "downstream exposure" because j is the downstream industry in this case. They instrument both the upstream and downstream exposure measures analogously to the main import shock measure: using contemporaneous changes in China imports in eight other high-income countries to calculate predicted upstream and downstream exposure for each industry, where these predictions serve as instruments for the measured domestic values. Concretely, they constructed these instruments by replacing the term ΔIP_{gt} with ΔIPO_{gt} in equation (3.5) while retaining the same weights.

Equation (3.5) accounts for the direct (first-order) effect on output demand of an industry j stemming from trade-induced changes in demand from its immediate buyers. But it ignores further indirect effects on industry j's demand stemming from changes in demand from its buyers' buyers, and so on. To account for the full chain of linked downstream and upstream demands, the authors replace ΔIP_{jt}^U and ΔIP_{jt}^D (and their instruments) with the full chain of implied responses from the input-output matrix, which is given by the Leontief inverse of the matrix of upstream and downstream linkages (see, e.g., Acemoglu et al. 2012).

As expected, the indirect exposure measures are substantially smaller in magnitude, and have a much smaller cross-industry variation than the direct exposure measures. In the average manufacturing industry, direct trade exposure is five times as large as the first-order downstream exposure measure and over three times as large as the first-order upstream exposure measure. To include higher-order linkages significantly increases the magnitude of the upstream and downstream exposure measures. The full indirect upstream exposure measure (given by the Leontief inverse) is approximately half as large as the direct exposure measure, while the full Indirect downstream exposure measure is about one-third as large as the direct exposure measure.

Table 3.3 present instrumental variable estimates of the effects of import exposure on industry employment. These estimates are similar to those in table 3.2, column 1 (without the one-digit sector dummies) and column 2 (with the one-digit sector dummies). In table 3.3, these estimates are augmented with the upstream and downstream import exposure measures. Panel A of table 3.3 employs the first-order upstream and downstream measures, ΔIP_{jt}^{U} and ΔIP_{jt}^{D}, while panel B uses the full Leontief exposure measures. Results are presented with and without the one-digit sector dummies previously mentioned.

Columns 1–3 of table 3.3 consider the impact of upstream and downstream linkages on employment in the 392 manufacturing industries while columns 4 and 5 consider these impacts on employment in the 87 nonmanufacturing industries. Columns 6–10 present results for manufacturing and nonmanufacturing pooled. All regressions employ the stacked first differences specification: columns 1–8 and 10 cover the time periods 1991– 99 and 1999–2011, while column 9 shortens the second period to 1999– 2007. Downstream import effects are not statistically significant in any specification and are unstable in sign, showing up as positive in the manufacturing only specification (col. 2) and negative in the nonmanufacturing and pooled specifications (cols. 5 and 7). The authors say this imprecision may be due to the fact that the downstream effects combine the offsetting effects of reduced domestic input supply and increased foreign input supply. Given the instability of effects working through downstream linkages, attention is focused on the upstream effects, which are quite stable across specifications and are similar qualitative-wise both for manufacturing and nonmanufacturing sectors.

As mentioned above, growth in an industry's upstream trade exposure is found to reduce industry employment. For manufacturing industries, the coefficient of the upstream linkage effect is considerably large without the one-digit sector dummies (col. 2) and has a magnitude similar to that of the direct trade shock coefficient as well as more precisely estimated when the one-digit sector dummies are added in column 3. In the case of nonmanufacturing industries, upstream linkages are also negative and statistically significant (cols. 4 and 5), and larger in magnitude than the estimates of manufacturing. Pooling manufacturing and non-manufacturing, coefficients on upstream linkages are negative and statistically significant either without (cols. 6 and 7) or with (col. 8) the one-digit sector dummies. Results for the period 1991–2007 (col. 9) are quantitatively similar.

Finally, the last specification in panel B (col. 10) regresses changes in industry employment on the sum of the direct and upstream exposure measures. The estimated coefficient on the combined shock is between the coefficients on the direct and upstream effects in column 6. Comparing the two panels of table 6, which employ the first-order (panel A) and full (panel B) upstream and downstream measures, a similar pattern of coefficient estimates was spotted. In all cases, the coefficients on the full exposure measures are smaller in magnitude than those on the first order exposure measures. Of course, the full exposure measures are considerably larger in magnitude than the first-order exposure measures, so the smaller coefficients do not imply smaller quantitative effects.

Table 3.3: 2SLS Estimates of Import Effects on Employment Incorporating Input-Output Linkages

	Manufacturing Industries (N = 784)			Nonmanufacturing Industries (N = 174)		Pooling Manufacturing and Nonmanufacturing Industries (N = 958)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	A. First-Order Input-Output Linkages									
Direct import exposure	-1.17***	-1.28***	-0.72***			-1.14***	-1.11**	-0.69***	-1.07***	
	(0.42)	(0.49)	(0.22)			(0.42)	(0.48)	(0.22)	(0.38)	
Upstream import exposure	-2.21*	-2.44**	-1.03**	-6.63**	-6.88**	-2.70**	-2.64**	-1.72**	-3.06***	
	(1.14)	(1.13)	(0.45)	(2.79)	(2.97)	(1.26)	(1.32)	(0.75)	(1.09)	
Downstream import exposure		2.31			-5.8		-0.67			
		(2.66)			(7.43)		(3.69)			
Combined import exposure (direct + upstream)										1.35***
										(0.38)
	B. Full (High-Order) Input-Output Linkages									
Direct import exposure	1.20***	-1.30***	-0.72***			-1.18***	-1.14**	-0.71***	-1.12***	
	(0.42)	(0.49)	(0.22)			(0.42)	(0.48)	(0.22)	(0.38)	
Upstream import exposure	-1.64*	-1.78**	-0.85**	-3.19	-3.17	-1.90**	-1.86**	1.29**	-2.10***	
	(0.84)	(0.82)	(0.37)	(2.14)	(2.27)	(0.86)	(0.91)	(0.59)	(0.75)	
Downstream import exposure		1.74			-4.26		-0.68			
		(2.10)			(5.94)		(2.95)			
Combined import exposure (direct + upstream)										-1.32***
										(0.37)
Sector x period effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
One-digit manufacturing sector controls	No	No	Yes	No	No	No	No	Yes	No	No
Exclude 2007-11	No	No	No	No	No	No	No	No	Yes	No

Note: Each column stacks changes in log employment and changes in import exposure over the periods 1991–99 and either 1999–2011 (cols. 1–8, 10) or 1999–2007 (9). The dependent variable is 100 x the annual log change in employment. The direct import exposure of industry i equals 100 x the annual change in US exposure to Chinese imports. In panel A, upstream (respectively, downstream) import exposure for a given industry is a weighted average of the direct import exposure experienced by its customers (suppliers). Panel B uses the Leontief inverse of the input-output matrix to incorporate higher-order linkages. Columns 1–5 include dummies for each time period. Columns 6–10 include sector x period interactions. Observations are weighted by 1991 industry employment, and standard errors in parentheses are clustered on three-digit industry (with each nonmanufacturing industry constituting its own cluster). Superscripts ***, ** and * refer to 1, 5, and 10 percent significance respectively. **Source AADHP 2016**

3-4-Conclusion:

As mentioned in section one, all three of the studies in question had different strategies to estimate the impact of increasing Chinese imports in U.S labor markets. Instead of looking at the impact of increasing Chinese exports from the employee side of labor markets like ADH (2013) did, AADH (2016) approached the matter more from the industry side by looking at the impact of Chinese imports based on the degree of upstreamness or downstreamness of specific industries.

Their estimates indicate that upstream effects have considerably negative effects on labor markets while the impact of downstream magnitudes are imprecisely estimated because of their sign instability. They found that applying their direct and full input-output measure of exposure increased their estimates of trade-induced job losses for 1999–2011 to 985,000 workers in manufacturing alone and to 1.98 million workers in the entire economy. Hence, interindustry linkages magnify the employment effects of trades hocks, doubling the impact within manufacturing and yielding an equally large employment effect outside of manufacturing. To sum up, the overall results provided by AADH (2016)'s methods indicate that the effects of traded shocks on employment increase substantially when accounting for upstream linkages.

Chapter 4 - Accounting for Value-Added Exports

4-1-Introduction

When thinking of the astonishingly rapid increase Chinese exports have had in the last decade or so, a grand number of papers that looked into the impact of such growth usually consider gross exports rather than value added exports. A considerable number of papers in the literature such as the ones mentioned in the previous two sections have found the impact of increasing gross Chinese exports on US labor markets to be negative. However, the direct contribution of China to U.S. labor market outcomes has to be taken with caution. This is very important since the world economy has become more integrated and access to imported materials and technologies has never been more important. For example, Kee and Tang (2016) show that most Chinese exports emerge from so called “export processing firms", which refers to firms that have the privilege of importing materials free of duty for assembling and exporting purposes. This information suggests that the direct contribution of China to changes in labor market outcomes in other countries should consider two important features. First, the value added by companies exporting from China may be considerably different from Chinese gross exports. Second, Chinese exported goods can be, in many cases, close to the bottom of the production chain, and thus be characterized as having a high degree of downstreamness.

The strategy for the analysis in this particular study is based on an international trade model with G regions, where N of these regions represent commuting zones in the U.S. economy, and where firms in a particular sector and country are assumed to have access to the same technology. By following specifications of Halpern, Koren and Szeidl (2015), the authors assume that the production of final goods requires the use of intermediate goods which can be produced inside or outside of the country in question. Wage rates are assumed to be fixed throughout the analysis.

Da Silva and Shen’s empirical analysis builds on the insights provided by the empirical strategy used by ADH (2013), as well as their theoretical framework and assumptions. The Chinese value-added exports information across countries and products used for the analysis comes from KWW (2014). The main focus lies on the change in U.S. exposure to value-added exports from China between the years 2000 and 2007. Another important feature of the analysis (as was in the study discussed in section 3) is to distinguish exporting sectors according to their degrees of downstreamness (low or high). Most of the analysis distinguishes between these groups according to the usage of exported products (final versus intermediate), which is also based on the definition used in KWW (2014).

4-2-Theoretical Framework

For the model developed for the analysis, Da Silva and Shen take into account commuting zones (CZ's) just as the previous studies discussed in this paper. They developed a partial equilibrium model that considers how increased import competition from China affects employment in U.S. commuting zones. Within the model there are a total of G regions; which can be interpreted as having N regions representing commuting zones in the U.S., another region representing China, and G - N - 1 other regions. Following specifications of Antras and Helpman (2004), producers of traded goods face a perfectly elastic supply of labor in each of the regions. Wage rate is denoted in region k by W^k and it is assumed to be fixed.

There are J traded-good sectors, indexed by j, where consumers allocate J share of spending on each. For each traded good sector, there are intermediate and final goods. The demand for product varieties for final goods is derived from a CES sub-utility function, such that total demand for a variety y_j^i is the sum over the demand in each destination market k (y_j^{ik}) given by,

$$y_j^i = \sum_k y_j^{ik} = \sum_k \frac{(p_j^{ik})^{-\sigma_j}}{(P_j^k)^{1-\sigma_j}} \frac{E^k}{J} \ ,$$

where p_j^{ik} is the delivered price in market k of a variety in sector j produced in region i. E^k is the total expenditure in market k. P_j^k is the price index for final goods in sector j of market k which captures the intensity of competition in a market. $\sigma_j > 1$ is the elasticity of substitution between any pair of varieties in the final good sector j.

The production of final goods requires the use of intermediate goods. As was the case in Halpern, Koren and Szeidl (2015) and Blaum, Lelarge, and Peters (2016),

$$y_j^i = \prod_k \prod_s (m_{sj}^{ki})^{\eta_{sj}^{ki}},$$

where m_{sj}^{ki} is the intermediate good produced in sector s in region k and used for sector j in region i, and η_{sj}^{ki} is the exogenous input-output linkages with η_{sj}^{ki} ϵ [0; 1] and $\sum_k \sum_s \eta_{sj}^{ki} = 1$. One unit of intermediate good (m_{sj}^{ki}) requires one unit of labor in region k with wage W^k. Cost minimization leads to the following demand for intermediate goods:

$$m_{sj}^{ki} = y_j^i \left(\frac{\eta_{sj}^{ki}}{W^k}\right)^{1-\eta_{sj}^{ki}} \prod_{k'} \prod_{s'} \left(\frac{W^{k'}}{\eta_{s'j}^{k'i}}\right)^{\eta_{s'j}^{k'i}}, \qquad (4.1)$$

which can be used to obtain the following total cost (TC_j^i) and marginal cost functions (MC_j^i),

$$TC_j^i = y_j^i \prod_k \prod_s \left(\frac{W^k}{\eta_{sj}^{ki}}\right)^{\eta_{sj}^{ki}} \qquad MC_j^i = \prod_k \prod_s \left(\frac{W^k}{\eta_{sj}^{ki}}\right)^{\eta_{sj}^{ki}} \qquad for\ \eta_{sj}^{ki} \neq 0.$$

To produce a final good variety y_j^i, there is a fixed labor cost α_j^i. Under monopolistic competition, the price of each variety is a constant markup over marginal cost as described by $p_j^{ik} = \left(\frac{\sigma_j}{(\sigma_j - 1)}\right) \tau_j^{ik} MC_j^i, where\ \tau_j^{ik} \geq 1$ is the transportation cost (based on the iceberg transport cost model) of delivering one unit of a final good in sector j from region i to region k. L_T^i denotes the labor used in region i to produce final and intermediate goods. This implies that $L_T^i = \sum_j M_j^i \alpha_j^i + \sum_j \sum_s \sum_k m_{js}^{ik}$ where M_j^i is the number of final good varieties produced by sector j in region i.

From this point they start to consider the contribution of the degree of downstreamness in determining labor market outcomes. Throughout the first part of the study, they mostly consider a good to display either high or low degree of downstreamness depending on its usage as a final good or intermediate good. The strategy they use disregards the presence of trade in intermediate goods in the status quo situation, to later allow for an external shock to either lead to more trade in final goods or to some marginal trade in intermediate goods. Then, they move on to considering a more general case where the trade in intermediate goods is present in the status quo.

First, they consider three cases. On the first one, production of the final good variety (y_j^i) requires all intermediate inputs to be produced in region i (i.e.,$\sum_s \eta_{sj}^{ki} = 1 \; for \; k = i$). The price of each variety of final good depends only on the wage in region i, on the iceberg transportation cost τ_j^{ik} and on exogenous parameters σ_j and η_{sj}^{ki}. Notice that free entry in each sector drives profits to zero for a given production technology in sector j region i, so the level of output for each final good variety is fixed, $y_j^i = \alpha_j^i(\sigma_j - 1)/\prod_s (1/\eta_{sj}^{ii})^{\eta_{sj}^{ii}}$. Therefore, any adjustment in sectorial output and employment occurs at the extensive margin, through changes in the number of final good varieties (i.e. $\Delta y_j^i/y_j^i = 0$ and adjustment occurs through $\Delta M_j^i/M_j^i$). In this case, an increase in Chinese import competition (with goods with high downstreamness) leads to an increase in the number of final goods varieties produced in China for each market served by region i. This outcome lowers the labor demand in the traded-good sector in region i.

The second case implies that intermediate inputs can suddenly be sourced from China (represented by superscript c) in sector s due to trade liberalization, such that $\eta_{sj}^{ci} \neq 0$ for some region i. This assumption represents an increase in exposure to Chinese exports in goods with low degree of downstreamness. This lowers the marginal cost of production (MC_j^i) which means final good producers can earn a positive profit, which means new final good producers can enter the market in region i, leading to an ambiguous total effect on employment in region i since imports of intermediate goods from region c may lower total employment (L_T^i) in region i while the increase in demand for this variety from all markets may lead to an increase in total employment in that region.

The third case considers an external shock from China (e.g. a reduction in W^C) with existing trade in intermediate and final goods. Gross output of sector s in region i is the sum of intermediate goods produced plus the sum in final goods produced,

$$x_s^i = \sum_k \sum_j m_{sj}^{ik} + M_s^i \sum_k y_s^{ik}$$

This can be re-written in block matrix notation following KWW (2014) specifications as

$$\begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^G \end{bmatrix} = \begin{bmatrix} A^{11} & A^{12} & \ldots & A^{1G} \\ A^{21} & A^{22} & \ldots & A^{2G} \\ \vdots & & & \\ A^{G1} & A^{G2} & \ldots & A^{GG} \end{bmatrix} \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^G \end{bmatrix} + \begin{bmatrix} \sum_k^G Y^{1k} \\ \sum_k^G Y^{2k} \\ \vdots \\ \sum_k^G Y^{Gk} \end{bmatrix}$$

where X^i is a $J \times 1$ vector $\left[x_1^i, \ldots, x_s^i, \ldots x_j^i\right]^T$ that gives region i's gross output. A^{ik} is a $J \times J$ block input-output coefficient matrix, where a_{sj}^{ik} is an element in the A^{ik} matrix and is the direct input-output coefficient that gives units of the intermediate goods produced in sector s of region i that are used in the production of one unit of gross output in sector j of region k (i.e., $a_{sj}^{ik} = a = m_{sj}^{ik}/x_s^i$). Y^{ik} is a $J \times 1$ vector that gives final goods produced in region i and that are consumed in region k. $Y^i = \sum_k^G Y^{ik}$ is also a $J \times 1$ vector that gives the global use of region i's final goods.

The above matrix can be re-arranged in the following way:

$$\begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^G \end{bmatrix} = \begin{bmatrix} B^{11} & B^{12} & \ldots & B^{1G} \\ B^{21} & B^{22} & \ldots & B^{2G} \\ \vdots & & & \\ B^{G1} & B^{G2} & \ldots & B^{GG} \end{bmatrix} \begin{bmatrix} \sum_k^G Y^{1k} \\ \sum_k^G Y^{2k} \\ \vdots \\ \sum_k^G Y^{Gk} \end{bmatrix},$$

where B^{ik} is the $J \times J$ block Leontief inverse matrix. An element in B^{ik} (b_{sj}^{ik}) is considered the total requirement coefficient in the input-output literature. Specifically, b_{sj}^{ik} gives the total amount of gross output in sector s in region i to produce an extra unit of final goods in sector j in region k, which is for consumption in region i as well as others. Note that $b_{sj}^{ik} \cdot y_j^{kr}$ gives the total amount of gross output in sector s in region i to produce final goods in sector j in region k for consumption in region r. B matrix is $GJ \times GJ$. X^i may be re-written in terms of matrices X^{ik}, which corresponds to $J \times 1$ gross output vector that gives gross output produced in region i and absorbed in region k.

The direct value-added coefficient v_s^i is defined by $1 - \sum_k \sum_j a_{js}^{ki}$ while country i's direct value-added vector can be written in matrix form as $V^i = \begin{bmatrix} v_1^i & v_2^i & \ldots & v_j^i \end{bmatrix}$ which corresponds to a $1 \times J$

row vector of direct-value-added coefficients. Let $\hat{V}^i$ be a $J \times J$ diagonal matrix with direct value-added coefficients v_s^i along the diagonal. Then, the authors define a $GJ \times GJ$ diagonal matrix $\hat{V}$ where each element of its diagonal is formed by a matrix $\hat{V}^i$. Then, they define the domestic value-added matrix in a region's gross output $\hat{V}X$, which equals the $GJ \times G$ matrix $\hat{V}BY$, as follows:

$$\begin{bmatrix} \hat{V}^1 \sum_g^G B^{1g} Y^{g1} & \hat{V}^1 \sum_g^G B^{1g} Y^{g2} & \dots & \hat{V}^1 \sum_g^G B^{1g} Y^{gG} \\ \hat{V}^2 \sum_g^G B^{2g} Y^{g1} & \hat{V}^2 \sum_g^G B^{2g} Y^{g2} & \dots & \hat{V}^2 \sum_g^G B^{2g} Y^{gG} \\ \vdots & & & \\ \hat{V}^G \sum_g^G B^{Gg} Y^{g1} & \hat{V}^G \sum_g^G B^{Gg} Y^{g2} & \dots & \hat{V}^G \sum_g^G B^{Gg} Y^{gG} \end{bmatrix},$$

where elements in the diagonal give each region's production of value-added absorbed at home. The off-diagonal elements of the $\hat{V}BY$ matrix gives each region i's production of value added that is absorbed in region k, or the value-added exports (VAX^{ik}), as note below

$$VAX^{ik} = \hat{V}^i X^{ik} = \hat{V}^i X^{ik} = \hat{V}^i \sum_g^G B^{ig} Y^{gk} = \hat{V}^i B^{ii} Y^{ik} + \hat{V}^i B^{ik} Y^{kk} + \hat{V}^i \sum_{g \neq k,i}^G B^{ig} Y^{gk}, \qquad (4.2)$$

where $\hat{V}^i B^{ii} Y^{ik}$ is value-added exports in final goods produced in i and absorbed in k. $\hat{V}^i B^{ik} Y^{kk}$ is value-added exports in intermediate goods produced in i and absorbed in k, and $\hat{V}^i \sum_{g \neq k,i}^G B^{ig} Y^{gk}$ is the value-added exports in intermediate goods that are first exported to region g to later be absorbed in region k. Notice also that VAX^{ik} is a $J \times 1$ vector.

The authors then proceed to use a three-country example to highlight the role of downstreamness in explaining labor market outcome changes. They think of the global economy as being divided in 3 regions. Those are region i (commuting zone i in U.S.), region k (rest of commuting zones in the U.S.), and region c (China). Moreover, they assume the presence of 2 sectors denoted by subscripts 1 and 2. A Chinese exposure increase affects the labor market in U.S. CZ i by changing the demand for labor (i.e., value added) used in producing goods in i exported to all regions for either final consumption or as an intermediate product. In this example, value-added exports from region i to region k can be defined based on (4.2) as

$VAX^{ik} = \hat{V}^i X^{ik} = \hat{V}^i X^{ik} = \hat{V}^i \sum_g^G B^{ig} Y^{gk} = \hat{V}^i B^{ii} Y^{ik} + \hat{V}^i B^{ik} Y^{kk} + \hat{V}^i \sum_{g \neq k,i}^G B^{ig} Y^{gk}$. This expression can be rewritten using matrix notation as noted below,

$$\begin{bmatrix} v_1^i b_{11}^{ii} Y_1^{ik} + v_1^i b_{12}^{ii} Y_2^{ik} \\ v_2^i b_{21}^{ii} Y_2^{ik} + v_2^i b_{22}^{ii} Y_2^{ik} \end{bmatrix} + \begin{bmatrix} v_1^i b_{11}^{ik} Y_1^{kk} + v_1^i b_{12}^{ik} Y_2^{kk} \\ v_2^i b_{21}^{ik} Y_1^{kk} + v_2^i b_{22}^{ik} Y_2^{kk} \end{bmatrix} + \begin{bmatrix} v_1^i b_{11}^{ic} Y_1^{ck} + v_1^i b_{12}^{ic} Y_2^{ck} \\ v_2^i b_{21}^{ic} Y_1^{ck} + v_2^i b_{22}^{ic} Y_2^{ck} \end{bmatrix}.$$

Where $v_1^i b_{11}^{ii} Y_1^{ik}$ is value added created in region i sector 1 used by region i's sector 1 in the production of final goods exported to region k. Similarly, $v_1^i b_{11}^{ik} Y_1^{kk}$ is value added created in region i's sector 1 used by region k's sector 1 to produce final goods absorbed in region k. The other terms can be defined in a similar way. As previously mentioned, the effects on region i’s labor market from an increase in its exposure to region c (China) depends on its labor demand across markets, which can be expressed by

$$\begin{aligned} \sum\nolimits_k^G VAX^{ik} &= \hat{V}^i \sum\nolimits_k^G \sum\nolimits_g^G B^{ig} Y^{gk} = \hat{V}^i \sum\nolimits_g^G B^{ig} Y^g \\ &= \begin{bmatrix} v_1^i b_{11}^{ii} Y_1^i + v_1^i b_{12}^{ii} Y_2^i \\ v_2^i b_{21}^{ii} Y_1^i + v_2^i b_{22}^{ii} Y_2^i \end{bmatrix} + \begin{bmatrix} v_1^i b_{11}^{ik} Y_1^k + v_1^i b_{12}^{ik} Y_2^k \\ v_2^i b_{21}^{ik} Y_1^k + v_2^i b_{22}^{ik} Y_2^k \end{bmatrix} + \begin{bmatrix} v_1^i b_{11}^{ic} Y_1^c + v_1^i b_{12}^{ic} Y_2^c \\ v_2^i b_{21}^{ic} Y_1^c + v_2^i b_{22}^{ic} Y_2^c \end{bmatrix} \end{aligned}$$

where Y_1^g denotes $Y_1^{gi} + Y_1^{gk} + Y_1^{gc}$ for every $g = \{i, c, g\}$.

It is important to note that the value of production of final goods produced by sector 1 in region i has to equal the value added in the production of inputs from all regions used in its production. Following Wang, Wei and Zhu (2014), this implies that the following repetition applies

$$v_1^i b_{11}^{ii} + v_2^i b_{21}^{ii} + v_1^k b_{11}^{ki} + v_2^k b_{21}^{ki} + v_1^c b_{11}^{ci} + v_2^c b_{21}^{ci} = 1 \qquad (4.3)$$

This expression helps in considering an increase in region i's exposure to exports in goods with low downstreamness from region c (China). To consider the case of exposure to final goods exported by region c, the authors consider an equation relating the value of production of final goods by sector 1 based in region c to the value-added contributions from all regions:

$$v_1^i b_{11}^{ic} + v_2^i b_{21}^{ic} + v_1^k b_{11}^{kc} + v_2^k b_{21}^{kc} + v_1^c b_{11}^{cc} + v_2^c b_{21}^{cc} = 1 \qquad (4.4)$$

Then, they consider an increase in value-added exports from region c in low downstreamness products, which is represented by an increase in intermediate goods with the assistance of expression (4.3). This case shows that an increase in value-added exports from China to region i in intermediate goods produced by sector 1 implies an increase in $v_1^c b_{11}^{ci}$ in (4.3), leading to three possible situations:

1. There is a decrease in intermediates used from region k in sector 1 or 2, represented by $\downarrow v_1^k b_{11}^{ki}$ or $\downarrow v_2^k b_{21}^{ki}$.

2. There is a decrease in intermediates used from region c in sector 2, $\downarrow v_2^c b_{21}^{ci}$.

3. There is a decrease in value added from region i in sector 1 or 2, $\downarrow v_1^i b_{11}^{ii}$ or $\downarrow v_2^i b_{21}^{ii}$.

Value-added shares in region i are not directly affected in the first two cases. Although import competing intermediate inputs from China in sector 1 could lower marginal costs, and, according to equation (4.1), could lead to an increase in Y_1^i and Y_2^i, which would then increase the demand for labor region i. In option 3, the domestic value-added shares in final goods decrease, which could lead to a decrease in employment in region i, depending on if the increase in the production of final goods increase in Y_1^i and Y_2^i enough according to (4.1). In this particular case, the net effect on the demand for labor in region i is unclear.

The authors empirical approach also characterizes the degree of downstreamness by using the share of foreign value-added content in gross exports. Defining the foreign value content in region c's gross exports of good j to region i, represented by FVA_j^{ci}, required them to extend their notation since gross exports may not be fully absorbed in the destination country. Foreign value added in final goods can be represented by $\left(\sum_{g\neq c}\sum_{m=1} v_m^g b_{mj}^{gc}\right) Y_j^{ci}$, while foreign value added in intermediate goods can be represented by $\left(\sum_{g\neq c}\sum_{m=1} v_m^g b_{mj}^{gc}\right) M_j^{ci}$. With that in mind, total foreign value added can be represented by

$$FVA_j^{ci} = \left(\sum_{g\neq c}\sum_{m=1}^{2} v_m^g b_{mj}^{gc}\right) Y_j^{ci} + \left(\sum_{g\neq c}\sum_{m=1}^{2} v_m^g b_{mj}^{gc}\right) M_j^{ci} \qquad (4.5)$$

$$= \left(\sum_{g \neq c} \sum_{m=1}^{2} v_m^g b_{mj}^{gc} \right) E_j^{ci},$$

where E_j^{ci} stands for region c's gross exports to region i in sector. Expression (4.5) shows that the foreign value-added content is lower than growth exports since expression $\sum_{g \neq c} \sum_{m=1}^{2} v_m^g b_{mj}^{gc}$ is less than one.

As shown in KWW (2014) and Wang, Wei and Zhu (2014), higher FVA_j^{ci} implies a greater degree of downstreamness for sector j in country c. They also note that higher FVA_j^{ci} may increase (or decrease) $v_m^i b_{mj}^{ic}$ for m = 1, 2, and lead to an increase (or decrease) in value-added exports from region i in sector j. A decrease in $v_m^i b_{mj}^{ic}$ may occur instead if region i does not hold a comparative advantage in producing inputs for downstream sector j. Hence, the effect on labor demand in region i is negative if higher FVA_j^{ci} leads to less intermediate inputs imported by region c from region i to use in region c's export to region i.

DS (2018)'s analysis relies on how changes in exposure to value-added exports affect changes in U.S labor market outcomes. They express themselves to be highly interested in the relationship between changes in exposure and in the share of employment in this tradable (e.g., manufacturing) sector. Notice that, by definition, total employment equals the value added in gross output, $L_T^i = \sum_j v_j^i X_j^i$. In this case, X_j^i is sector j's gross output in region i. Hence, log differentiation leads to the following expression:

$$\tilde{L}_T^i = \sum_j \frac{1}{L_T^i} \Delta v_j^i X_j^i, \qquad (4.6)$$

where $\tilde{L}_T^i$ stands for $\Delta L_T^i / L_T^i$. This equation indicates that the total percent change in employment in region i is directly related to changes in value added in gross output. Moreover, total value added can be directly related to value added generated and absorbed in region i, and to domestic value added in region i that is absorbed in other regions by the following expression:

$$\hat{V}^i X^i = \sum_{g}^{G} \hat{V}^i B^{ig} Y^g = \hat{V}^i B^{ii} Y^i + \hat{V}^i B^{ik} Y^k + \sum_{g \neq i,k}^{G} \hat{V}^i B^{ig} Y^g,$$

where $\hat{V}^i X^i$ is a $J \times 1$ vector equal to $\left[v_1^i X_1^i .. v_j^i X_j^i \dots v_J^i X_J^i\right]^T$. This expression helps the authors to relate changes in total value-added output in region i's sector j to changes in value-added exports from region c (China) to region i in the following way:

$$\begin{aligned}
\Delta v_j^i X_j^i &\propto \pm \Delta VAX^{C,i} \\
\Delta v_j^i X_j^i &\propto -\Delta VAX^{C,i}_final \\
\Delta v_j^i X_j^i &\propto \pm \Delta VAX^{C,i}_intermediates.
\end{aligned}$$

With this, they approximate the effects of changes in labor demand due to changes in value-added exports from region c (China) to region i (U.S. CZ) using equation (4.6) according to the following expression:

$$\tilde{L}_T^i = \sum_j \frac{1}{L_T^i} \Delta VAX_j^{c,i},$$

where the total effect is ambiguous as mentioned before. However, DS (2018) do not observe China's value-added exports to region i, but only China's value-added exports to the U.S. Which is why their empirical strategy weights each region i in the U.S. by its own value-added share, or labor share of region i in the U.S. L_j^i / L_j^{US} in sector j as follows:

$$\Delta EXP\_VAX_i = \sum_j \frac{L_j^i}{L_j^{US}} \frac{1}{L_T^i} \Delta VAX_j^{C,US}, \qquad (4.7)$$

which can also be defined using changes in value-added exports in final and in intermediate goods

$$\Delta EXP\_VAX_i\_final = \sum_j \frac{L_j^i}{L_T^i} \frac{1}{L_j^{US}} \Delta \mathrm{VAX}_j^{C,US}\_final \qquad (4.8)$$

$$\Delta EXP\_VAX_i\_interim = \sum_j \frac{L_j^i}{L_T^i} \frac{1}{L_j^{US}} \Delta \mathrm{VAX}_j^{C,US}\_intermediates$$

4-3-Empirical Analysis (econometric model)

In this section I will describe the econometric method used by DS (2018) to analyze the effects of trade flows between China and the US labor markets. The analysis is mainly focused on trade flows between the two above-mentioned countries in the time period between the years 2000 and 2007. As mentioned in section 4.1, their strategy is mainly based in the CZ approach used by ADH (2013) while adding the new feature of incorporating value-added instead of gross exports, as well as the role/position of Chinese exports in the global value chains and on the effects it may cause on labor markets. They allow for different effects because of changes in both gross and value-added exports while exploring potentially different effects caused by exports with different degrees of downstreamness.

The key variable in the empirical analysis is the measure of U.S. local market exposure to Chinese value-added exports. This variable encompasses the direct contribution of the Chinese economy to the production of goods exported from China which are commercialized in the U.S. economy. The model described in section 4.2 suggests an approximation of the effects of an increase in value-added exports from China to the US labor markets on a per-worker basis can be achieved by using regression (4.7). In this particular case, the importance of sectorial trade in a specific labor market is weighted by the share of national sectorial employment for a particular labor market, which is similar to the approach used in ADH (2013). The author's basic measure of U.S. local labor market exposure can be described as follows:

$$\Delta LEXP\_VAX^{i} = \sum_{j} \frac{L_j^i}{L_j^{US}} \frac{\Delta VAX_j^{C,US}}{L_T^i}, \qquad (4.9)$$

where $\Delta VAX_j^{C,US}$stands for the change in Chinese value-added exports that go into the U.S. in industry (sector) j between the years 2000 and 2007. The value-added exports definition is taken from expression (2) in Section 4.2. For this reason, the year 2000 is taken as the base year. Consistent with the notation used in the model described in section 4.2, the variable L_T^i represents employment in local market i for the base year, while L_j^{US} stands for U.S. employment in industry j for the base year 2000.

The authors explore variations in the manner in which they measure the amount of exposure of US labor markets to international trade flows. They also compare measures of exposure based on changes in Chinese growth exports originally calculated by ADH (2013). This approach allows them to consider whether the effects of changes in value-added exports from China to the U.S. are different from the effects of changes in gross exports. In addition to being able to identify any differences, they also calculate the exposure measure (4.9) separately for value added exports according to their degree of downstreamness and they adopt two main approaches in considering this question. First, they consider value-added exports in terms of their usage in the production process where value-added exports in final goods reflect greater downstreamness relative to value-added exports in intermediate goods. In this case, the authors replace $\Delta VAX_j^{C,US}$ in expression (4.9) by the change in value added exports in final goods and by the change in value-added exports in intermediate goods as shown in expression (4.8) of the model shown in section 4.2.

Second, they identify sectorial exports from China that show greater and/or lower degrees of downstreamness with data on trade flows. Wang, Wei and Zhu (2014) argue the lengthening of the international production-chain is a product of the increasing degree of integration among national economies in economic terms. Which means bilateral trade flows may be significantly affected by the presence of foreign value-added from other countries, which is the case of the US with China in the case in question.

Following the insights outlined in Wang, Wei and Zhu (2014), DS (2018) opt to use the distribution of the sectorial ratio between Chinese growth exports and the foreign value added of Chinese exports in identifying sectors with greater and lower downstreamness. In this approach, sectors with relative high ratios are deemed to have a high degree of downstreamness. In other words, they are closer to the bottom of the global value chain, while sectors with low ratios portray a lower degree of downstreamness. In practical terms, the authors construct a variable I_j^d which equals 1 if a sector j is deemed to have high degree of downstreamness and equals 0 if otherwise. Expression (4.9) is then recalculated separately for sectors where I_j^d equals 0 and 1 as seen below,

$$\Delta LEXP\_VAX_{high}^i = \sum_j \frac{L_j^i}{L_j^{US}} \frac{\Delta VAX_j^{C,US}}{L_T^i} I_j^d, \qquad (4.10)$$

$$\Delta LEXP\_VAX_{low}^i = \sum_j \frac{L_j^i}{L_j^{US}} \frac{\Delta VAX_j^{C,US}}{L_T^i} \left(1 - I_j^d\right)$$

where the expression shown in the top (bottom) of (4.10) describes the change in U.S. exposure to value-added exports from China in sectors with high (low) degree of downstreamness.

For robustness purposes, the authors consider three definitions of downstreamness. They also substitute the change in value-added exports per worker $\left(\Delta VAX_j^{C,US}/L_T^i\right)$ in equation (4.9) by a measure based on the import penetration ratio ($\left(\Delta VAX_j^{C,US}/X_j^i\right)$, where X_j^i is the value of shipments/output), and, additionally, consider measures of changes in U.S. exposure to trade with high income and middle income countries. The basic econometric model used in this study is the following:

$$\Delta \frac{L_m^i}{WP^i} = \alpha + \gamma_1 LEXP\_VAE^i + \gamma_2' X^i, \qquad (4.11)$$

where $\Delta \frac{L_m^i}{WP^i}$ represents the change in the manufacturing employment share of the working age population in local market i. In this specification, China's direct contribution in terms of value-added originating and exported by that country, to changes in U.S. labor market outcomes is captured by parameter γ_1. As shown in equation (4.11), the authors also include a set of local market controls described in matrix X^i. These controls include characteristics of local labor markets measured during the base year that could be relevant, such as the percentage of employment in manufacturing, the percentage of college-educated population, the percentage of foreign-born population, among others. DS (2018) believe that by controlling for these local market characteristics, they will capture the effects of changes in market exposure on the manufacturing employment share. The same will be true to estimate the effects of local labor market exposure to trade on average wage and unemployment levels. In addition, all estimated versions of equation (4.11) weight observations by the local labor market's share of national employment at the base year 2000 and standard errors are clustered at the state level.

The main remaining problem is that there may be variables missing from expression (4.11) that are correlated with the measure of change in local market exposure to Chinese value-added exports, which could possibly generate biases in the econometric results from the estimation of this expression. To address this, the authors adopt the strategy proposed by ADH (2013) and use the following variable to instrument the change in local labor market exposure to value-added exports from China $\left(\Delta LEXP\_VAE^{i}\right)$

$$\left(\Delta IVEXP\_VAE^{i}\right) = \sum_{j} \frac{L_{jt-1}^{i}}{L_{jt-1}^{US}} \frac{\Delta VAE_{j}^{rich}}{L_{Tt-1}^{i}}, \tag{4.12}$$

variable ΔVAE_{j}^{rich} stands for the change in value-added exports from China to other selected developed countries in industry j between the years 2000 and 2007. The instrumental variable described by expression (4.12) uses employment-based variables measured in 1990, ten years prior to the base year (2000). This helps explain the application of subscript $t-1$ in expression (4.12). In this particular case, the idea is to mitigate possible simultaneity bias caused by the employment-based variables that were used in calculating the instrumental variable. The author's strategy consists in estimating equation (4.11) using a 2-stage least square approach where expression (4.12) instruments their change measure in labor market exposure described by expression (4.9). Their strategy also provides information about the quality of the instrumental variables, including a statistical test for weak instruments.

An additional (but also important) component of the empirical approach includes investigating the effects of traded products on labor market outcomes controlling for their degree of downstreamness. In these cases, the instrumental variable is calculated as described by (4.12) in line with the authors strategy. For instance, if the change in exposure described by (4.9) is measured using value-added exports from China to the U.S. in final goods, then they also use value-added exports in final goods from China to selected developed countries in order to construct their instrumental variable. A similar approach is used to relate changes in value-added exports in sectors where the binary variable I_{j}^{d} equals one (high downstreamness) and zero (low downstreamness). In addition to that, the authors also consider the effects of net trade flows between China and the U.S. on labor market outcomes on the analysis.

4-4-Econometric Results

The author's benchmark model is based on the estimation of (4.11) using a 2-stage least square strategy where they instrument the measure of exposure described in (4.9) using the variable represented by (4.12). Results are portrayed in Table 4.1 in which columns (1)-(3) show the results that account for gross exports from China to the U.S. to measure the change in trade exposure across U.S. labor markets. On the other hand, columns (4)-(6) show results involving value-added exports. The sample used in Table 4.1 covers (as in ADH 2013) information on 722 U.S. CZ's and covers the changes in exposure between the years 2000 and 2007.

The results displayed in columns (1)-(3) follow the results found in ADH (2013) where the contribution of China to changes in U.S. labor market outcomes is measured using gross exports. These results suggest that an increase in exposure to gross exports from China between the same time-span tends to decrease the share of manufacturing employment in U.S. labor markets. The results seem robust to the presence of U.S labor market controls as evident by comparing the parsimonious model used in column (1) relative to the more comprehensive model used in column (3). Moreover, results show that the instrumental variable is highly correlated with the measure of changes in trade exposure.

The results of these model suggest that using gross exports from China to measure trade exposure allows DS (2018) to explain 54 percent of the average decline in the share of manufacturing employment across U.S. labor markets. However, as explained in ADH (2013), this method would overstate the effect of the supply shock resulting from economic growth in China over the last decade. More specifically, this total effect combines changes in supply related to economic growth in China and changes in relative demand for products in which China has become a major exporter. To separate these effects, and more properly measure the contribution related to Chinese economic growth, the authors follow ADH's (2013) strategy that relies on an interplay between OLS and the IV estimations without using controls for CZ characteristics. This procedure concludes that about 59 percent of the change in U.S. exposure to gross exports from China is due to supply changes related to economic growth in China.

Table 4.1: Value-Added Exports from China and Change in U.S Manufacturing Employment

	I. 2000-2007 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ gross exports from China to US)/worker	-0.718***	-0.426***	-0.469***			
	(0.064)	(0.116)	(0.123)			
(Δ value-added exports from China to US)/worker				-1.391***	-0.382	-0.354
				(0.501)	(0.273)	(0.324)
Percentage of employment in manufacturing		-0.100***	-0.083***		-0.162***	-0.162***
		(0.027)	(0.025)		(0.019)	(0.021)
Percentage of college-educated population			0.000			-0.015
			(0.021)			(0.019)
Percentage of foreign-born population			0.057***			0.045***
			(0.013)			(0.011)
Percentage of employment among women			0.064*			0.065*
			(0.039)			(0.035)
Percentage of employment in routine occupations		-0.111	-0.143		-0.055	-0.078
		(0.105)	(0.093)		(0.094)	(0.084)
Average offshorability index of occupations		0.036	-0.670*		-0.601	-1.129***
		(0.368)	(0.344)		(0.396)	(0.353)
Census division dummies	No	Yes	Yes	No	Yes	Yes
R^2	0.14	0.52	0.53	0.19	0.57	0.6
	II. 2SLS first stage estimates					
(Δ value-added exports from China to OTH)/worker	0.767***	0.536***	0.528***	0.936***	0.799***	0.799***
	(0.088)	(0.094)	(0.097)	(0.050)	(0.036)	(0.039)
Adjusted R^2	0.45	0.52	0.53	0.75	0.85	0.85
Kleibergen-Paap's Weak IV Test	75.515	32.256	29.296	351.702	493.172	429.142
(pass 5 percent critical value?)	Y	Y	Y	Y	Y	Y

Note: Dependent variable is annual changes in manufacturing emp/working-age pop (in percentage points). Information on trade exposure available using thousands of US dollars per worker. VAX stands for value-added exports from China. Sample size in all columns is 722, which corresponds to the number of CZ's in the dataset. Superscripts ***, ** and * represent statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors are clustered at state level. **Source: DS (2018)**

A different picture can be seen when looking at the results of the effects of value-added exports from China on the share of manufacturing employment across U.S. labor markets. In this case, the results are shown in columns (4)-(6) of Table 4.1. Notice that the coefficient of the authors measures of changes in exposure based on value-added exports is also negative, which indicates that increases in exposure to value-added exports from China have led to a decrease in the share of manufacturing employment across

U.S. labor markets. The point estimates suggest that the average effect of changes in exposure to value-added exports from China is significantly smaller than the one obtained measuring exposure using gross exports. Such is the case when comparing the results in columns (3) and (6). Although this result is less statistically robust, since, as they move from the parsimonious model described in column (4) to the results described in the last 2 columns, the degree of statistical significance of the coefficient of changes in trade exposure decreases.

Moving on to table 4.2, DS (2018) look into the effects of the changes in U.S. exposure to Chinese value-added exports accounting for the degree of downstreamness of traded goods. In this case, specification are the same ones used in columns 3 and 6 of Table 4.1. The ones used in columns (1) - (3) control for changes in exposure to Chinese value-added exports in sectors with high degrees of downstreamness, while the ones in (4)-(6) control for changes in exposure to Chinese value-added exports in sectors with low degrees of downstreamness. For this table, the specifications in columns (1) and (4) define the degree of downstreamness based on the usage of exported goods, the specifications in (2) and (5) measure the degree of downstreamness based on the median of the distribution of the ratio between the foreign value added contained in sectorial Chinese exports and the sectorial gross exports, while the specifications in (3) and (6) use the 75th percentile of the distribution of this ratio in defining the degree of downstreamness.

The results in columns (1)-(3) of Table 4 confirm that an increase in value added exports from China in sectors with high downstreamness tends to decrease the share of manufacturing employment across U.S. markets. This is true whether or not local labor market characteristics are controlled for. This effect is highly statistically significant for all measures used in specifications (1)-(3). Moreover, Table 4.1 indicates that the average increase in U.S. exposure to value-added exports from China in final goods was $0.93 thousand per worker, as well as also suggesting an average change in U.S. exposure to value-added exports with high degree of downstreamness using the median of the distribution of $0.91 thousand per worker. Keeping in mind that only 59 percent of the changes in U.S. exposure to exports from China is due to economic growth in that country, the authors conclude that the U.S. increase in exposure to value-added

Table 4.2: The Role of Downstreamness and the Share of Manufacturing Employment

	I. 2000-2007 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	Final goods	Above median	Above 75th	Intermediates	Below median	Below 75th
High downstreamness (Δ value-added exports from China to US)/worker	-1.558**	-1.881***	-2.698***			
	(0.706)	(0.563)	(0.427)			
Low downstreamness (Δ value-added exports from China to US)/worker				0.423	0.429	0.519
				(0.655)	(0.277)	(0.334)
Percentage of employment in manufacturing	-0.139***	-0.077**	-0.066***	-0.179***	-0.169***	-0.173***
	(0.020)	(0.033)	(0.022)	(0.022)	(0.023)	(0.022)
Percentage of college-educated population	-0.021	-0.004	0.000	-0.01	-0.006	-0.004
	(0.019)	(0.018)	(0.018)	(0.019)	(0.019)	(0.018)
Percentage of foreign-born population	0.045***	0.045***	0.049***	0.046***	0.047***	0.048***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
Percentage of employment among women	;0.059*	0.053	0.049	0.071**	0.071**	0.072**
	(0.036)	'(0.034)	(0.037)	(0.034)	(0.033)	(0.033)
Percentage of employment in routine occupations	-0.094	-0.054	-0.086	-0.061	-0.049	-0.053
	(0.081)	(0.074)	(0.063)	(0.087)	(0.088)	(0.087)
Average offshorability index of occupations	-1.023***	-0.913***	-0.824***	-1.228***	-1.218***	-1.229***
	(0.342)	(0.298)	(0.237)	(0.367)	(0.361)	(0.357)
Census division dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.61	0.61	0.6	0.59	0.59	0.6
	II. 2SLS first stage estimates					
(Δ value-added exports from China to OTH)/worker	0.777***	0.575***	0.709***	0.815***	0.783***	0.626***
	(0.040)	(0.055)	(0.061)	(0.049)	(0.054)	(0.054)
Adjusted R^2	0.85	0.86	0.74	0.82	0.8	0.69
Kleibergen-Paap's Weak IV Test	383.127	107.672	135.041	27.502	208.682	135.913
(pass 5 percent critical value?)	Y	Y	Y	Y	Y	Y

Note: Dependent variable is annual changes in manufacturing emp/working-age pop (in percentage points). Columns 1-3 do not use controls for local labor market characteristics, while columns 4-6 use the same local labor market controls used in column 6 of Table 10. Superscripts ***, ** and * represent statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors are clustered at state level. **Source, DS (2018).**

exports in high downstreamness sectors can (on average) explain between 38 and 44 percent of the decline in the share of manufacturing employment across local labor markets.

The results in columns (4)-(6) of Table 4.2 also follow the intuition discussed above related to the role played by the degree of downstreamness. In this case, an increase in U.S. exposure to value-added exports from China in sectors with low degree of downstreamness leads to an increase in the share of manufacturing employment. However, the results are not statistically significant, and they yield significantly smaller changes in the share of manufacturing employment than the results obtained in columns (1)-(3). So, the expected difference between the effects of an increase in U.S. exposure to exports in sectors with low downstreamness versus sectors with high downstreamness is confirmed.

Later on, the researchers move onto analyzing the impact of Chinese value-added exports on wages in US labor markets on table 4.3. More specifically, they look at the effects of changes in U.S. exposure to Chinese exports on average wages and on the share of unemployed workers across U.S. labor markets. Their initial strategy consists in substituting the dependent variable in equation (4.11) by the change in average wages for U.S. labor markets, while they calculate changes in U.S. exposure to trade using both gross and value-added exports from China just like for Tables 4.1 and 4.2. A similar approach is used to consider the effects of exposure on the share of unemployed workers.

The economics literature has not only considered the average effects of trade across all workers but has also considered the heterogeneity of trade effects across groups of workers. In particular, Hummels et al. (2014) consider the different effects of offshoring workers, while Ebenstein et al. (2014) investigates the effects of greater exposure to trade flows and offshoring activities on workers controlling for the degree of routineness of their occupations. Both of them find that an increase in exposure to trade flows and offshoring seems to have heterogeneous effects across groups of workers.

The authors consider the heterogeneous effects of changes in U.S. exposure to Chinese exports by looking into the effects it has on college educated workers and non-college educated workers following a method similar to ADH (2013). They replace the dependent variable used in equation (4.11) by the average

Table 4.3: Value-Added Trade with China and Effects on Wages across U.S Local Labor Markets

	(1)	(2)	(3) Final goods	(4) Above median	(5) Intermediate goods	(6) Below median
				All		
(Δ gross exports from China to US)/worker	-0.135					
	(0.359)					
(Δ value-added exports from China to US)/worker		0.97				
		(0.780)				
High downstreamness (Δ value-added exports from China to US)/worker			1.24	0.323		
			(1.799)	(1.843)		
Low downstreamness (Δ value-added exports from China to US)/worker					3.024**	1.234*
					(1.507)	(0.715)
				College		
(Δ gross exports from China to US)/worker	-0.205					
	(0.399)					
(Δ value-added exports from China to US)/worker		0.877				
		(0.933)				
High downstreamness (Δ value-added exports from China to US)/worker			0.928	0.842		
			(1.917)	(2.182)		
Low downstreamness (Δ value-added exports from China to US)/worker					3.047	0.84
					(2.152)	(0.735)
				Non-college		
(Δ gross exports from China to US)/worker	0.142					
	(0.383)					
(Δ value-added exports from China to US)/worker		1.738*				
		(0.914)				
High downstreamness (Δ value-added exports from China to US)/worker			2.542	0.438		
			(2.133)	(1.854)		
Low downstreamness (Δ value-added exports from China to US)/worker					4.953***	2.279***
					(1.747)	(0.835)

Note: Dependent variable is ten-year equivalent changes in average log weekly wage (in log pts). The same controls applied in column (6) of Table 10 are applied in all columns of this Table. Superscripts ***, ** and * represent statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors are clustered at state level. **Source: DS (2018)** change in weekly wages measured in log points, as well as by the change in the share of unemployed workers, across labor markets. The average of these variables across labor markets shows that average wages have increased by 3.84 log points between years 2000 and 2007, while the unemployed share has increased by 3.42 percent during the same time-span. However, there is considerable heterogeneity across groups of workers. More specifically, the wage of college educated workers tends to increase more than three times as much as the wages of non-college educated workers, while the unemployment rate among non-college educated workers grows more than three times as much as the unemployment rate of college educated workers.

The results of the author's econometric approach can be found in Tables 4.3 and 4.4. The results shown on columns (1) and (2) of Table 4.3 suggest that changes in exposure, either with gross or using value-added exports from China, are not statistically significant in explaining wage changes across U.S. labor markets. However, the results depend highly on the degree of downstreamness of exported goods. If comparing the results shown in columns (3) and (4) with the results shown in columns (5) and (6), the results suggests that increased U.S. exposure to exports from sectors with low downstreamness has a positive and statistically significant effect on wages, while greater exposure to goods exported by sectors with high downstreamness do not have a statistically significant effect. These results are important since they suggest that the average increase in the U.S. exposure to value-added Chinese exports in low downstreamness sectors tends to increase average wages by 0.62 log points according to column (6) of Table 4.3, which accounts for 16.1 percent of the increase in wages between 2000 and 2007. It is imperative to note that these effects tend to be stronger for non-college educated workers both in economic and in statistical terms.

Table 4.4 describes the econometric results exploring the causal relationship between U.S. exposure to Chinese exports and the unemployment rate across U.S. labor markets. The results shown in columns (1) and (2) of Table 4.4 suggest that changes in exposure, either using gross or value-added exports from China, are not very statistically significant in explaining changes in the unemployment rate across U.S. labor markets. However, the results depend highly on the degree of downstreamness of exported goods. The

Table 4.4: Value-Added Trade with China and Effects on Unemployment across U.S Local Labor Markets

	(1)	(2)	(3) Final goods	(4) Above median	(5) Intermediate goods	(6) Below median
				All		
(Δ gross exports from China to US)/worker	0.109					
	(0.099)					
(Δ value-added exports from China to US)/worker		-0.353				
		(0.250)				
High downstreamness (Δ value-added exports from China to US)/worker			-0.525	0.246		
			(0.506)	(0.421)		
Low downstreamness (Δ value-added exports from China to US)/worker					-0.975*	-0.630**
					(0.572)	(0.299)
				College		
(Δ gross exports from China to US)/worker	0.059					
	(0.063)					
(Δ value-added exports from China to US)/worker		-0.352*				
		(0.191)				
High downstreamness (Δ value-added exports from China to US)/worker			-0.56	-0.014		
			(0.377)	(0.368)		
Low downstreamness (Δ value-added exports from China to US)/worker					-1.342*	-0.901**
					(0.771)	(0.379)
				Non-college		
(Δ gross exports from China to US)/worker	0.115					
	(0.137)					
(Δ value-added exports from China to US)/worker		-0.516				
		(0.336)				
High downstreamness (Δ value-added exports from China to US)/worker			-0.827	0.322		
			(0.675)	(0.566)		
Low downstreamness (Δ value-added exports from China to US)/worker					-1.342*	-0.901**
					(0.771)	(0.379)

Note: For the dependent variable the authors use the Ten-Year equivalent change in the unemployed share (in percentage points). The same controls applied in column (6) of Table 4 are used in all columns of this Table. Superscripts ***, ** and * represent statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors are clustered at state level. **Source DS (2018)** results in columns (5) and (6) suggest that an increase in exposure to Chinese exported goods in low downstreamness sectors decreases the unemployment rate and this result is robust to using the sample that includes all employed workers, as well as using the different samples of workers controlling for their educational level. Lastly, the results in column (6) also show that this effect tends to be stronger in economic and in statistical terms for non-college educated workers.

4-5-Conclusion

To conclude the remarks made by DS (2018), the results provided by their study are in line with the ones discussed in sections 2 and 3 in the sense that they find that increasing Chinese exports are negatively affecting U.S labor markets. Their results suggest that an increase in value-added exports in goods with high degree of downstreamness tend to decrease employment levels in the economy exposed to these trade flows, while the effect in the case of goods with low degree of downstreamness is inherently ambiguous. Although the former statement holds for the manufacturing sector, DS (2018) find no statistical evidence that an increase in U.S. exposure to Chinese exports (either gross or value-added) causes either an average decline of wages, or an increase in unemployment levels across U.S. labor markets.

The authors find that the average increase in the U.S. labor market exposure to Chinese value-added exports is significantly lower than the average measure used in ADH (2013), which is based on gross exports. This supports the claim that the impact of increasing Chinese exports on U.S labor markets was being overstated by only considering Chinese gross exports. Keeping in mind that only 59 percent of the changes in U.S. exposure to exports from China is due to economic growth in that country, the authors conclude that the U.S. increase in exposure to value-added exports in high downstreamness sectors can explain (on average) between 38 and 44 percent of the decline in the share of manufacturing employment across U.S labor markets.

Chapter 5 - Conclusion

To conclude the paper, all of the main studies mentioned in the previous three sections were in line with the fact that increasing Chinese exports have a negative impact on U.S labor markets. However, although they all agree in the main result, their specifications, analysis methods, and strategies are slightly different from each other.

It is important to note that the three studies represented the progression the economics literature has taken in the analysis of this particular topic over the years. All of them adopted the commuting zone approach to a certain extent but added their own specifications building up on each other's work. It is also imperative to note that there are many other papers within the economics literature related to the topic that have found similar results, but I chose these three for two main reasons. First, the fact that they are all linked together since they build on each other's work, and second, the fact that they are all relatively recent since all of them were published within the current decade.

To sum up, the following points can be considered to be the highlights of this report. First, the undeniable fact that China's astonishingly quick economic development has negatively affected U.S labor markets. Second, the fact that the manufacturing sector was the more negatively affected industry in terms of both unemployment and wages. Third, the fact that in order to better account for the negative impact of increasing Chinse exports coming into the U.S, it is necessary to consider the place of the industry in question in the production chain (i.e, their degree of upstreamness/lowstreamness). And finally, that it is necessary to look at the whole issue taking into account value-added instead of gross-exports in order not to overestimate the impact of increasing Chinese exports on U.S labor markets.

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