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ABSTRACT

The United States imports intermediate inputs from China, helping downstream US firms to expand employment. Using a cross-regional reduced-form specification but differing from the existing literature, this paper (a) incorporates a supply chain perspective, (b) uses intermediate input imports rather than total imports in computing the downstream exposure, and (c) uses exporter-specific information to allocate imported inputs across US sectors. We find robust evidence that the total impact of trading with China is a positive boost to local employment and real wages. The most important factor is employment stimulation outside the manufacturing sector through the downstream channel. This overturns the received wisdom from the reduced-form literature and provides statistical support for a key mechanism hypothesized in general equilibrium spatial models.

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1. Introduction

Trade in intermediate goods has been growing steadily over time (Hummels, Ishii, and Yi, 2001; Johnson and Noguera, 2017; Koopman, Wang, and Wei, 2014). This can alter how imports affect the labor market of the importing countries. In this paper, we show that incorporating a supply chain perspective in a cross-regional reduced-form specification can overturn the received wisdom in the literature with a similar specification that looks only at the direct competition channel (Autor, Dorn, and Hanson, 2013). The paper also provides statistical support for a key mechanism hypothesized (but not tested) in recent general equilibrium spatial models used to assess the effects of trade shocks on labor markets.

In 2000, US imports of intermediate goods from China was 14.8 billion US dollars, accounting for 28.6% of that year's total imports from China. This number increased to 63.2 billion USD in 2007, and doubled again to 130.2 billion USD in 2014 (accounting for 37.5% of total imports from China that year). Across industries, those that experience a high rate of growth in total imports from China tend to see an even higher growth rate in intermediate inputs (see Figure 1). US firms that use these inputs potentially expand their employment.

Antràs, Fort, and Tintelnot (2017) estimate that US manufacturing firms that source intermediate inputs from abroad tend to increase their production and may even buy more inputs from domestic manufacturing firms simultaneously. In this paper, we suggest that many non-manufacturing firms also use imported inputs from China and increase their operational scale as a result. Indeed, the employment gains by non-manufacturing firms that can be traced to trading with China will be shown to dominate those of manufacturing firms.

An influential paper by Autor, Dorn, and Hanson (2013), using a cross-regional reduced-form regression specification, shows that US regions with greater exposure to competition from China experience a greater decline in employment. Pierce and Schott (2016), another well-published paper that also focuses on the direct competition channel, reach the same conclusion that imports from China has reduced US manufacturing jobs and total employment.

This paper adopts an explicit supply chain perspective, which is missing in Autor, Dorn, and

Hanson (2013). We find that while the direct competition effect reduces manufacturing sector employment, an indirect upstream channel further exacerbates job losses in both manufacturing and non-manufacturing sectors. In other words, those US firms that do not compete directly with Chinese imports but sell their output to other US firms that are squeezed by Chinese imports also experience job losses. However, the job gains from the downstream channel are not only statistically significant but also economically powerful enough to more than offset the combined negative effects from direct competition and the upstream channel. Once we account for all three channels of exposure to trading with China, the total effect for an average region is a net job increase of 1.27% (as a share of working age cohort) a year relative to a hypothetical region with no exposure to trading with China. We also find that 75% of the workers in an average region experience a real wage growth as a result of exposure to the China trade.

To place this paper in the literature, it is useful to discuss four questions. First, how is it different from the previous attempt to incorporate a supply chain perspective in a cross-regional reduced-form specification? Second, how is it related to the emerging literature that uses a general equilibrium spatial model? Third, why would an indirect (positive) employment effect from a downstream channel be powerful enough to overwhelm a direct (negative) employment effect from import competition? Fourth, how to address possible endogeneity of US imports from China?

Let us start with a comparison with the previous attempt to incorporate supply chain channels, namely Acemoglu et al. (2015). Methodologically, our paper differs from theirs in two ways. First, they do not separate intermediate goods from final goods in computing downstream exposure to China trade. Since the downstream effect is about how input costs are affected by imported Chinese inputs, that distinction is important. Second, Acemoglu et al. (2016) do not use exporter-specific information to allocate imports from China to the downstream sectors in the United States. In other words, they effectively assume that the imported inputs from China are allocated in the same way across US sectors as imported inputs from Germany or any other countries. Correcting these two items makes our approach better in line with a supply chain perspective. They turn out to make a big difference in the conclusion too. In particular, while Acemoglu et al (2016) reaffirm the conclusion of Autor, Dorn, and Hanson (2013) that trading with China causes a net job loss, we overturn this result. In addition, we find that the total real wage in the United States has been made higher by trading with China.

We now relate our paper to the new literature on general equilibrium (GE) spatial models. Caliendo, Dvorkin, and Parro (2018) develop a dynamic multi-regional and multi-sector model with an important methodological innovation that solves for comparative statics without having to solve for the steady state values of the variables. Adao, Arkolakis, and Esposito (2018) develop a static general equilibrium model with multiple regions and multiple sectors and solve for changes in labor shares (comparative statics) following a trade shock. Note that the cross-regional reduced-form specification used in this paper (as well as in Autor, Dorn, and Hanson, 2013) does not by itself speak about general equilibrium effects. Without information on inter-regional linkages, it would be misleading to extrapolate the results from the reduced-form regressions to a national aggregate effect on the labor market. GE spatial models, on the other hand, allow for inter-market linkages and can therefore speak meaningfully about the effects of trade shocks on national labor market and on welfare.

Our paper is a useful complement to the GE spatial models for four reasons. First, a key potential shortcoming of our specification is assessed to be unimportant quantitatively. In particular, Caliendo et al., (2018) find that labor mobility across regions is very modest (with the median mobility across states being less than one half of one percent per quarter). (Autor, Dorn, Hanson, and Song, 2016, also report low inter-regional labor mobility.) Adao et al., (2018) state that, because the inter-regional mobility is low, the inferences from the cross-regional reduced-form regressions are in principle valid. Since they are much easier to implement, it is useful to do them as a check on the performance of the GE models. Second, our paper provides a useful statistical test on a key mechanism hypothesized in Caliendo et al. (2018). In particular, firms using imported inputs in the GE spatial models would expand their employment and much of the job expansion takes place in the service sectors (see, for example, Figures 1, 6, and 8 of Caliendo et al, 2018, and the associated discussions in the text). Their model is calibrated to fit the input-output linkages.

This mechanism is crucial for their conclusion that the overall effect of trading with China is an increase in the aggregate employment and aggregate welfare. However, their paper does not provide a statistical test for the presence of such a mechanism. Indeed, the existing test in Acemoglu et al. (2016) appears to reject the significance of this mechanism. Our paper provides the first affirmative evidence that the downstream channel, especially outside the manufacturing sector, is statistically significant and economically powerful. Third, GE models make several assumptions that our paper does not. For example, Caliendo et al., 2018; and Adao, et al., 2018 assume that agents in their models have perfect foresight (in order for the models to be solved). Without having to make these assumptions, our results are potentially robust to alternative assumptions. Fourth, by using a specification that is essentially the same as Autor, Dorn, and Hanson (2013) except for the addition of two supply chain terms, our paper makes it transparent about what may be the crucial missing items in the existing reduced-form literature. In particular, stripped of multiple sources of complexity in GE models, our paper makes it easier to see that it is not the cross-regional mobility but rather downstream/upstream linkages (a particular form of cross-market linkages) that are responsible for the differences in the conclusions between the GE models of Caliendo et al. (2018) and Adao et al. (2018) and the reduced-form results of Autor, Dorn, and Hanson (2013).

The third comment is about how an indirect downstream effect on employment can be stronger than the direct competition effect. Intuitively, since a subset of the manufacturing sectors are responsible for most of the US imports from China, the direct competition channel only affects these sectors, which collectively constitute a small part of the US labor market. In comparison, the downstream channel benefits almost all sectors in the economy, including service sectors. Even research institutes, hospitals, schools, banks, law firms, government departments, and restaurants use imported Chinese made laptops, desktop computers, electric cables, communication devices, steel parts, tables and chairs, light bulbs, bed sheets, uniforms, or wash towels. This is true not only for the economy as a whole, but also for the vast majority of local labor markets. Note that the upstream channel also affects more sectors than the direct competition channel. Therefore, whether the downstream channel can ultimately overturn the existing results is an empirical question.

The fourth comment is about possible endogenous nature of US imports from China. We employ three instrumental variable (IV) approaches to address this issue. The first is to use sector variations in imports from China by other high-income countries as instruments for the sector variations in US imports from China. This follows the spirit of the IV approach in ADH (2013). The second is to add routine job share and offshorability index developed by Autor and Dorn (2013) as additional IVs； they are (partial) predictors of the exposures to China, and the three IVs collectively pass the over-identification test. The third IV approach is to expand the set of IVs further to include "PNTR Gaps," which use the sector variations in the reduction of uncertainty after the United States granted permanent normal trading relations (PNTR) status to China in 2000 to predict subsequent growth of US imports from China by sector. This follows the idea from Pierce and Schott (2017). Again, we perform an over-identification test for the validity of the instruments.

We also investigate the effects of the China trade on real wages, another important labor market outcome that has also been studied by Autor, Dorn, and Hanson (2013), Ebenstein, Harrison, McMillan, and Phillips (2014), and Chetverikov, Larsen, and Palmer (2016). We show that the supply chain perspective makes a difference as well. In particular, if one focuses just on the direct competition effect, as Autor, Dorn, and Hanson (2013) and Chetverikov, Larsen, and Palmer (2016) do, one would find that workers in almost all initial income groups either experience a decline in real wage or no increase in real wage. In contrast, our supply chain perspective uncovers a different picture. For a region with an average exposure to trading with China relative to a region with no exposure, while there are winners and losers, the total effect of trading with China is an increase in the real wage for 75% of American workers as well as an increase in the aggregate real wage.

It might be useful to take note of the estimated impact of the China trade shock on employment in other countries. Using linked employer-employee data for (almost) the entire labor market in Denmark, Trailberman (2017) finds that trading with China does not result in a net increase in unemployment. Since the United States has a more flexible labor market than Denmark, it would seem surprising if the labor market outcome is indeed worse for the United States than for Denmark.

We organize the rest of the paper in the following way. Section 2 provides some motivating facts about US-China trade. Section 3 introduces our empirical approach and data sources. Estimation results, model extensions and a set of robustness checks are presented in Sections 4-6, and Section 7 concludes.

2. Some Basic Facts about US Imports from China

For US firms to benefit from imported inputs from China, one might conjecture that the Chinese imports are associated with cost savings for US firms. To check for plausibility of this channel, we examine unit import values at the HS 6-digit level. In the top graph in Figure 2, we present a binned scatter plot of changes in average unit value from 2000 to 2007 against increases in the share of China in US imports. More precisely, we divide all the increases in China's share in US imports at the HS 6-digit level into 20 equal-sized bins, and then plot the average value of the changes in the unit import values (on the vertical axis) for all observations in a bin against the mid-point of all changes in China's shares in the same bin (on the horizontal axis). The resulting binned scatter plot purges the noise from having too many data points on a raw scatter plot. We can clearly see a negative relationship between the two variables: those products for which China has become a relatively more important source tend to exhibit a greater decline in unit import values.

As the supply chain perspective is about trade in intermediate goods, the bottom graph in Figure 2 presents a different binned scatter plot focusing on US imports of intermediate goods at the HS 6-digit level. We see the same pattern: Imported intermediate inputs become relatively cheaper when China becomes relatively more important as a source country.

The data pattern can be confirmed more formally with the following regression model:

$$\Delta \ln UnitPrice_{i,2000\text{-}2007} = \beta_0 + \beta_1 \times \Delta CHN\text{-}Share_{i,2000\text{-}2007} + u_{i,2000\text{-}2007}$$

where i represents a 6-digit product under the HS classification system. $\Delta \ln UnitPrice_{i,2000\text{-}2007}$ is the change in log import unit price for product i averaged across all source countries from 2000 to 2007 (multiplied by 100). $CHN\text{-}Share_{i,2000\text{-}2007}$ is the change (in percentage points) in the quantity share (i.e., share in total weight or total physical units) of China in US imports of product i.

We have done the regressions that give equal weights to all products as well as weighting each product in proportion to its total import values at the start of the sample period. They yield qualitatively similar results. In the first column of Table 1, we report the equal-weighted result in the first row, and the value-weighted results in the second row. In both cases, a negative coefficient means that an increase in the share of China in US imports and a decline in average unit value tend to go together. The effect is stronger when we weight the products according to their relative importance. Based on the coefficient in the first column, second row, an increase in the China share by one percentage point is approximately corresponding to a decline in the unit value by one percent. Note that the regression is done with all available observations (i.e., more than those in the binned scatter plots).

To address endogeneity of the change in China's share in US imports, we use the change in China's share in other high-income countries' imports as an instrumental variable[2]. The IV results are reported in Column 2 of Table 1. We continue to find a negative and significant coefficient. Indeed, the point estimates are bigger than the corresponding OLS estimates. Based on 2SLS estimate in the value-weighted regression, an increase in the China share by one percentage point leads to a reduction in unit import price by 1.8%.

In Columns 3 and 4, we re-do the regressions by focusing on intermediate inputs only. We find the slope estimates tend to be larger than the corresponding estimates in the first two columns. Based on the 2SLS estimate from a value weighted regression (last column, last row), an increase in China's share in US imports of intermediate inputs by one percentage point tends to reduce the average US intermediate import price by 2.1%. Across all intermediate inputs, the median increase

[2] Other high-income countries are five G7 countries: Japan, Germany, United Kingdom, France, and Italy (hereafter referred to as "G5"). We exclude Canada as it is effectively an extension of the US economy due to its proximity and close supply chain relationships. As a robustness check, we have also added Australia, Denmark, Finland, New Zealand, Spain, and Switzerland to the set and found little change in the key results (results are not reported to save space).

in China's share in US imports during 2000-2007 was 8.23 percentage points; this translates to a reduction in intermediate import price by 17.4%.

The top three most important intermediate inputs for the United States by import values are "portable automatic data processing machines" (i.e., laptops), "transmission apparatus", and "parts & accessories for data processing machinery" (including computer parts), respectively. For these three intermediate inputs, the Chinese shares in US intermediate imports have increased by 67.6, 14.4, and 42.6, percentage points, respectively, during 2000-2007. This leads to a much greater decline in intermediate import prices than the average or median across products[3].

To summarize, the data on unit import values and China's shares in US imports are consistent with the notion that trading with China has generated substantial cost savings for US firms.

It may also be useful to look at some macro facts regarding the relationship between US unemployment and the US trade deficit. Appendix Figure 1 plots the time series of US unemployment rate and US trade deficit as a share of total trade from 1960 to 2015. A striking feature that emerges from this graph is that the two variables tend to be negatively correlated: the US trade deficit tends to be large when the US labor market is strong (low unemployment) and small when the US labor market is weak. In other words, an increase in US net imports is unlikely to be associated with an increase in national unemployment.

To zoom in on US trading with China, Appendix Figure 2 presents the time series of US unemployment rate and US trade deficit with China as a share of US total trade from 1990 to 2015. Again, the relationship is negative. The US tends to run a larger trade deficit with China when its employment situation is good and vice versa[4]. While these macro facts are not a direct proof (as both are endogenous variables), they raise a question of whether trading with China systematically raises the US unemployment rate.

Total employment is the sum of manufacturing and non-manufacturing employment. While the US manufacturing employment has been declining over the last two decades, the employment

[3] For big changes in the China share, the Jensen's inequality sets in, and the difference in log is no longer a good approximation for calculating percentage change in the import prices.
[4] The same patterns are observed when we use US imports from China instead of US trade deficit with China.

outside the manufacturing sector has been on a rise. While Autor, Dorn, and Hanson (2013) makes a case that the observed decline in US manufacturing employment is to a significant part due to trading with China, it implicitly assumes that the equally dramatic rise of non-manufacturing employment is not related to China. (Indeed, most service sectors are typically labeled as non-traded.) One way to interpret what we do in this paper is to discover and document that the rise in the non-manufacturing jobs is to a significant part also due to trading with China.

3. Empirical Approach and Data Sources

We now turn to the framework for examining the effect of trading with China on local employment in the United States. To maintain maximum comparability with Autor, Dorn, Hanson (2013) and Acemoglu et al. (2016), we intentionally keep the methodology and the data as close as possible to theirs. In particular, we use changes in employment and changes in exposure to trading with China at the commuting zone level as units of observation.

We keep the differences at a minimum (by design), and they are introduced as a result of the supply chain perspective. First, we argument their specification by two additional terms capturing the downstream and upstream channels, respectively. Second, in computing the downstream exposure, we separate imported intermediate inputs from general imports. Third, we use a multi-country input-output table to capture the exporter-specific information on sector linkage. (This means that we do not have to assume that Chinese inputs are allocated across US sectors in the same way as German inputs or inputs from other countries.) These modifications make our measurement and framework more faithful to the spirit of a supply chain perspective.

3.1 Specification

We run (variants of) the following regression:

$$\Delta L\text{-}Share_{k,\tau} = \beta_0 + \beta_1 \Delta Direct_{k,\tau} + \beta_2 \Delta UP_{k,\tau} + \beta_3 \Delta Down_{k,\tau} + \beta_4 \Pi_{k,2000} + \varepsilon_{k,\tau}$$

where k stands for one of the 722 commuting zones that cover the mainland US. The concept

“Commuting Zone” was first developed by Tolbert and Sizer (1996), defined as an aggregation of counties that are characterized by strong internal commuting ties. This can be taken as a geographic area that constitutes a local labor market. It is the basic unit of observation in Autor, Dorn, and Hanson (2013).

We estimate this model for the period from 2000 to 2007 (t=2007), which is similar to Autor, Dorn, and Hanson (2013)[5]. To construct the dependent variable, we consider four mutually exclusive outcome variables, all measured as a share of the working age cohort in a commuting zone k: manufacturing employment, non-manufacturing employment, unemployment, and people not in the labor force. The four shares sum to 100%. $\Delta L\text{-}Share_{k,\tau}$ is 100 times the annualized change in each outcome variable over the relevant time interval.

$\Delta Direct_{k,\tau}$, $\Delta Up_{k,\tau}$ and $\Delta Down_{k,\tau}$ are 100 times the annualized change over the period τ (2000 to 2007) in direct, upstream and downstream exposures to trading with China in commuting zone k, respectively. They will be defined below in more detail. $\Pi_{k,2000}$ refers to a vector of start-of-period control variables at the commuting zone level, including initial employment share in working-age population (age 16-64) and census divisions fixed effects[6].

3.2 Three Channels of Exposure to the China Trade Shock

To quantify the three channels of trade exposure (in terms of direct competition, downstream effect, and upstream effect, respectively), we start with a sector level measure and then convert them to commuting zone level measures based on each a sector’s employment share in a region.

The Direct Competition Channel

The exposure to direct competition for Sector j is defined as the annualized change (in percentage point) in imports[7] from China of Sector j’s products as a share of the sector’s total

[6] The United States Census Bureau divides the country into nine census divisions, including East North Central, East South Central, Middle Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central and West South Central.
[7] Trade values are converted to 2000 US dollars using the Personal Consumption Expenditure (PCE) deflator.

absorption in year 2000:

$$\Delta Direct_{j,\tau} = \frac{100}{7} \times \frac{M^{C,U}_{j,2007} - M^{C,U}_{j,2000}}{Y^{U}_{j,2000} + M^{*U}_{j,2000} \text{ - } E^{U*}_{j,2000}}, \tag{1}$$

where $Y^{U}_{j,2000}$ is sector *j*'s total output in year 2000, $M^{*U}_{j,2000}$ - $E^{U*}_{j,2000}$ is sector *j*'s net imports (imports from all sources, $M^{*U}_{j,2000}$, minus exports to all destinations, $E^{U*}_{j,2000}$). Thus the denominator $Y^{U}_{j,2000} + M^{*U}_{j,2000}$ - $E^{U*}_{j,2000}$ equals sector *j*'s total absorption. The numerator $M^{C,U}_{j,2007} - M^{C,U}_{j,2000}$ measures the change in imports of sector *j*'s products from China from 2000 to 2007. This definition of direct competition channel is identical to the "Change in Import Penetration Ratio" in Acemoglu et al. (2016).

To control for US domestic demand factors in the US imports, we instrument the numerator in (1) with other high-income countries' imports from China and replace the denominator by its 5-year lagged value as:

$$\Delta Direct^{IV}_{j,\tau} = \frac{100}{7} \times \frac{M^{C,G5}_{j,2007} - M^{C,G5}_{j,2000}}{Y^{U}_{j,1995} + M^{*U}_{j,1995} \text{ - } E^{U*}_{j,1995}} \tag{2}$$

We then convert the direct exposure to Chinese imports from the sector level to the commuting zone level based on the composition of the working age population in various sectors in each commuting zone. An exposure to direct competition from China for commuting zone *k* from 2000 to 2007 is defined as:

$$\Delta Direct_{k,\tau} = \sum_{j} \frac{L_{k,j,2000}}{L_{k,2000}} \Delta Direct_{j,\tau} \tag{3}$$

where subscript *k* indexes commuting zones, $L_{k,j,2000}$ is the employment of sector *j* at commuting zone *k* in 2000, and $L_{k,2000}$ represents total employment of commuting zone *k* in 2000. In other words, the commuting zone level measure of exposure to direct competition is the weighted average of the changes in import penetration ratios across sectors, with weights proportional to each sector's initial employment share.

Following Autor, Dorn, and Hanson (2013), an instrumental variable version of the exposure to direct competition at the commuting zone level is defined as：

$$\Delta Direct_{k,\tau}^{IV} = \sum_{j} \frac{L_{k,j,1990}}{L_{k,1990}} \Delta Direct_{j,\tau}^{IV} \tag{4}$$

The weight on sector j's exposure to direct is the share of that sector in local employment in 1990 (the 10-year lag is proposed by Autor, Dorn, and Hanson, 2013[8]).

The Downstream Channel

The downstream exposure for a commuting zone describes how it benefits from being able to use imported intermediate goods. We also construct it in two steps. First, at the sector level, it is a weighted average of all of its input g' exposure to growth in China-sourced intermediate inputs (annualized to make it easy to compare across time periods):

$$\Delta Down_{j,\tau} = \frac{100}{7} \times \sum_{g} w_{g,j,2000}^{Down} \frac{M\text{-}int_{g,2007}^{C,U} - M\text{-}int_{g,2000}^{C,U}}{Y\text{-}int_{g,2000}^{U} + M\text{-}int_{g,2000}^{*U} - E\text{-}int_{g,2000}^{U*}} \tag{5}$$

The denominator is the total absorption of intermediate inputs by US sector j in 2000, whereas the numerator is the change of US imports of intermediates from China from 2000 to 2007. As pointed out before, our measure focuses on imported intermediate inputs whereas Acemoglu et al. (2016) use all imports including final goods.

The sectoral weights are proportional to each input sector's imports of intermediate goods from China：

[8] When we use the labor shares in 2000, we obtain similar results (not reported to save space).

$$w_{g,j,2000}^{\text{Down}} = \frac{Z_{g,j,2000}^{C,U}}{\sum_i Z_{i,j,2000}^{C,U}} \tag{6}$$

The numerator in the weight represents imports of intermediate input in sector g from China by US sector j in 2000, whereas the denominator is all intermediate inputs from China used by US industries j. Importantly, it does not assume that the Chinese and German intermediate inputs are allocated in the same way across US sectors (because we use an inter-country input-output table). In comparison, Acemoglu et al. (2016) and Feenstra et al. (2017) effectively make this assumption, and this assumption is rejected by the Inter-Country Input-Output Table.

The downstream exposure at a commuting zone level is the weighted average of the sector level downstream exposure, with the weights proportional to each sector's employment share in 2000:

$$\Delta Down_{k,\tau} = \sum_j \frac{L_{k,j,2000}}{L_{k,2000}} \Delta Down_{j,\tau} \tag{7}$$

The instrumented version of the downstream exposure at the sector level is constructed as：

$$\Delta Down_{j,\tau}^{IV} = \frac{100}{7} \times \sum_g w_{g,j,2000}^{Down} \frac{M\text{-}int_{g,2007}^{C,G5} - M\text{-}int_{g,2000}^{C,G5}}{Y\text{-}int_{g,1995}^{U} + M\text{-}int_{g,1995}^{*U} - E\text{-}int_{g,1995}^{U*}} \tag{8}$$

The instrumented version of the downstream exposure at a commuting zone level is the weighted average of the corresponding sector level measure, with employment share in 1990 as the sector weight. That is, the instrumented measure of downstream exposure for commuting zone k is:

$$\Delta Down_{k,\tau}^{IV} = \sum_j \frac{L_{k,j,1990}}{L_{k,1990}} \Delta Down_{j,\tau}^{IV} \tag{9}$$

The Upstream Channel

The upstream exposure captures how a commuting zone may be affected indirectly when their firms are at an upstream to those US firms that compete with Chinese imports directly.

For a given sector j, the upstream exposure is the annualized change in sales-weighted average of the direct competition exposure of all of its customers:

$$\Delta UP_{j,\tau} = \sum_{g} w^{UP}_{j,g,2000} \Delta Direct_{g,\tau} \tag{10}$$

where weight $w^{UP}_{j,g,2000}$ is computed as：

$$w^{UP}_{j,g,2000} = \frac{Z^{U,U}_{j,g,2000}}{\sum_{i} Z^{U,U}_{j,i,2000}} \tag{11}$$

where $Z^{U,U}_{j,i,2000}$ represents US sector j*'s* output sales to US sector i as the latter's intermediate input. Thus, the economic meaning of such a weight $w^{UP}_{j,g,2000}$ is the relative importance of US sector g for sector j as a percent of sector j's total sales in year 2000. The higher the percentage, the larger the impact of sector g's direct exposure to the China trade shock.

We convert the sector level measure of upstream exposure to commuting zone level by making use of each sector's initial share in local employment:

$$\Delta UP_{k,\tau} = \sum_{j} \frac{L_{k,j,2000}}{L_{k,2000}} \Delta UP_{j,\tau} \tag{12}$$

The corresponding instrumental variable version is:

$$\Delta UP^{IV}_{k,\tau} = \sum_{j} \frac{L_{k,j,1990}}{L_{k,1990}} \Delta UP^{IV}_{j,\tau} \tag{13}$$

$$\text{where } \Delta UP^{IV}_{j,\tau} = \sum_{g} w^{UP}_{j,g,2000} \Delta Direct^{IV}_{g,\tau} \tag{14}$$

3.3 Data Sources and Basic Statistics

The construction of the downstream and upstream exposures requires the use of inter-country input-output (ICIO) tables. We use ICIO tables from OECD[9], which cover 64 economies and 34 industries from 1995 to 2014. The structure of the ICIO Table is presented in Appendix Table 1.

The local employment data are derived from the U.S. Census microdata (5% sample for the year 1990 and 2000) and American Community Survey (ACS) microdata (for the year 2001 to 2014) provided by the IPUMS-USA database (Ruggles et al., 2015). These two datasets use a 5-digit numeric variable (PUMA code) to identify the Public Use Microdata Area where the respondent is located. The PUMA code is state-dependent, which must be read in conjunction with the 2-digit State FIPS code. We merge the Public Use Microdata Areas to 722 commuting zones by using the concordance between the 1990/2000 Census Public Use Micro Areas and 1990 commuting zones provided by Autor, Dorn, and Hanson (2013). Both census and ACS data provide information on a respondent's employment status: whether he/she is in the labor force, currently unemployed, and in which industry is the employment. The respondents' wage income, gender and educational attainment are also available.

Table 2 shows the three channels of exposure to China trade at the sector level in terms of annualized percentage changes in exposure to imports from China. Taking direct exposure to imports from China (ΔDirect) as an example, the mean of 0.224 represents an annual increase of 0.224% on average during 2000 to 2007.

In Figure 3, we plot the three channels of exposures at the sector level during 2000-2007 for all 34 industries in the OECD ICIO database. The direct competition channel only affects the manufacturing sectors in which China has comparative advantage or runs a large trade surplus from processing and assembling trade. Those manufacturing industries, such as Textile Products, Computer and Electronic Products and Electrical Equipment, account for a large portion of imports from China, but collectively only account for a small part of the US labor market. While the

[9] Our results also hold when we use the World Input-Output Database (WIOD) instead of the OECD database. We choose to report the results based on the OECD's Inter-country Input-Output database because the required data for our empirical exercise are more consistent across years in the OECD data (whereas WIOD changed sector definition and methodology in the middle of the sample).

upstream exposure is more important in the manufacturing sector than service and primary sectors, the downstream exposure benefits almost all sectors in the economy.

We now turn to commuting zone level measures. For all 722 commuting zones, as shown in Table 3, the exposure to direct competition has increased by an average of 0.112% a year during 2000-2007. The top five commuting zones that have experienced the most direct competition are Rome, GA; Hickory, NC; Morganton, NC; Martinsville, VA and Talladega, AL, respectively. The five commuting zones that exhibit the least exposure to direct competition are Gunnison CO; Granby CO; Winnemucca NV; Elko NV and Reno NV, respectively.

Interestingly, both the indirect upstream and downstream exposures have increased during the sample period. Similar to the sector level results, the increase in the downstream exposure is greater than those of the other two channels, partly because the imports of intermediate goods from China has grown faster than the imports of final goods.

Our baseline measures of upstream and downstream exposures keep the diagonal elements in the input-output matrix in computing the weights. There are two potential issues. First, since these elements are reflected in both the direct competition channel and the two indirect value chain channels, there is some double counting in these measures. Second, the double counting makes it more likely that the indirect channels and direct channel are collinear. Pairwise correlations among the three measures are presented in Table 4a. The multicollinearity problem appears most serious between the direct competition channel and the upstream channel. This makes it hard for the regression coefficients to be estimated precisely. Hence, as a robustness check, we exclude the diagonal elements in the input-output matrix in computing the weights. As shown in Table 4b, the correlation coefficient between direct exposure and upstream exposure at the commuting zone level has decreased from 0.97 to 0.78 after excluding the diagonal IO elements.

Table 5 presents the summary statistics for annualized changes in employment shares at the commuting zone level , there has been a trend decline in the manufacturing employment share. In comparison, non-manufacturing jobs exhibit a steady increase (at the rate of 0.231% a year during 2000-2007, offsetting the loss of manufacturing jobs, which was 0.23% a year). During this period, the labor force non-participation rate decreased at the rate of 0.048% a year, slightly more than offsetting an increase in the unemployment rate of 0.047% a year.

4. Estimation Results

4.1 An Incompletely-Specified Model that Only Looks at the Direct Competition Channel

This sub-section follows the specification in ADH (2013) by looking only at the direct competition channel, ignoring the downstream and upstream channels. This is to ensure that we can produce the same results as they do when the model specification is the same. The regression results are shown in Table 6.

On the impact on US manufacture employment, our estimation results are consistent with Autor, Dorn, and Hanson (2013) and Pierce and Schott (2017). Both the OLS and the 2SLS estimates indicate a negative impact on US manufacturing employment. Using the 2SLS estimates as an example, a one percentage point rise in direct exposure to Chinese imports will reduce manufacturing employment by 4.2 percentage points per year from 2000 to 2007. The magnitude of the estimate is also comparable to ADH (2013). (The point estimate is slightly larger than theirs because we scale our dependent variables by the working age cohort, whereas they scale everything by the labor force.) The results in Table 6 suggest that the slight difference in the definitions of the dependent variables does not make any qualitative difference.

In column 2 of Table 6, we report the results on non-manufacturing employment share. The same exposure to direct competition raises employment in the non-manufacturing sector (e.g., laid-off steel workers may be re-employed as restaurant waiters) but the increase is smaller than the decline of manufacture employment, resulting in a negative effect on total employment (Column 5). In Columns 3 and 4, we see that both the unemployment rate and the not-in-the-labor-force rate go up in response to the exposure to direct competition from the Chinese imports.

4.2 Accounting for Supply Chain Channels

We now introduce the upstream and downstream exposures to the regression specification. The benchmark results are reported in the upper panel of Table 7a, with the first stage regressions shown in Table 7b. The direct competition effect is negative on manufacturing employment (a decline with an elasticity of -3.5% in Column (1) of Table 7a). This number is smaller than the corresponding number (-4.2) in Column 1 of Table 6 without the supply chain variables.

The direct effect on non-manufacturing jobs is positive (Column 2), reflecting possibly laid-off manufacturing workers (from both a direct competition effect and an indirect upstream effect) working in service sector jobs such as restaurant servers. The direct effect leads to fewer people staying outside the labor force (Column 3), and the impact on officially recorded unemployment is small and not statistically significant (Column 4).

The supply chain perspective produces two terms with opposite signs. On the one hand, adding the upstream effect augments the negative impact on the US labor market. This is especially true for service sectors jobs that provide inputs to those manufacturing firms that compete with China imports directly (Column 2). On the other hand, the downstream channel produces a job gain, especially in the non-manufacturing sector (with an elasticity of 5.6%). The downstream channel also raises the labor force participation rate. Putting the results from Columns 1 and 2 together, we see that the downstream channel produces a net gain in jobs with an annualized elasticity of 5.9% during 2000-2007 (column 5).

It is noteworthy that the F statistics from the first stage for the three endogenous variables are 298.9, 142.8 and 269.8, respectively (Table 7b). They allow for an easy rejection of the weak IV null hypothesis. While the values of the F statistic are larger than many applications of the 2SLS technique, there is no theoretical upper bound for the statistics.

To interpret the results and translate the estimates into economic magnitude, let us consider a hypothetical "average" commuting zone whose three channels of exposure to trading with China are equal to the average values across all commuting zones, and compare it to another hypothetical commuting zone that has no exposure to trading with China. We can convert these estimates of the elasticities to estimates of the job market responses by combining with the mean values of the regressors reported in Table 3. The implied labor market reactions are reported in the lower panel of Table 7a.

The effect of the exposure to direct competition in the average commuting zone is a job loss in the manufacturing sector at the rate of 0.39% a year (Column 1 of Table 7a). Incorporating the upstream effect would raise the negative effect on manufacturing jobs to 0.63% a year (-0.39% - 0.24% = -0.63%). The sum of the direct and upstream effects also produces a loss of non-manufacturing sector jobs at the rate of 1.34% a year (0.87% - 2.21%= -1.34%). (Those service firms that used to provide inputs to the directly affected manufacturing firms also shed jobs.) The sum of the direct competition and upstream exposure produces a reduction in total employment (0.48% - 2.46%= -1.98%, Column 5). This reduction in total employment can be decomposed into some decrease in the labor force participation rate (Column 3) and some increase in the reported unemployment (Column 4).

However, this is not the whole story. In particular, the downstream channel produces large job gains in the non-manufacturing sector (at the rate of 3.08% a year, Column 2) and a small increase in jobs in the manufacturing sector (at the rate of 0.16% a year, Column 1). When we sum up all three channels (downstream, upstream, as well as the direct competition effects) in both manufacturing and non-manufacturing sectors, the total effect of trading with China is a net job gain of 1.27% a year as reported in Column 5.

Of course, many factors affect job market performance including technology and regulations besides trade. What the estimates in Table 7a suggest is that these other factors may well have led to job losses, but trading with China has mitigated the job loss.

Another way to provide economic interpretations to the estimation results is to compare two commuting zones whose exposure in terms of the direct competition channel is at the 25th and 75th percentiles of the entire distribution, respectively. To be concrete, the city of Plainview in Taxes - at the 25th percentile of the distribution - experienced a relatively small exposure to direct competition from Chinese imports during 2000-2007. In comparison, the city of Douglas in Illinois

- at the 75th percentile of the distribution - experienced a relatively large direct competition effect from Chinese imports. Unsurprisingly, by our estimation, Douglas loses more manufacturing jobs than Plainview due to competition with Chinese imports.

Once we have picked this pair of cities, their indirect exposure to Chinese imports in terms of the downstream and upstream exposures can also be calculated. We summarize the relative effects of trading with China on the job markets in these two commuting zones in Table 8.

First, if we use an incomplete specification that only looks at the direct competition channel (i.e., using the same specification as Autor, Dorn, and Hanson, 2013), we would have concluded that, relative to Plainview, Douglas has experienced an additional loss of manufacturing jobs at the rate of 0.22 percentage points a year, and an additional loss of total jobs at the rate of 0.15 percentage points a year. In other words, greater exposure to direct competition with China produces a greater relative job loss.

Second, when we use a more complete specification that takes into account the supply chain channels, we will find the opposite result. Even though Douglas suffered more from a combination of a direct competition effect and an indirect upstream effect in the manufacturing sector, this is completely offset by job expansion in the non-manufacturing sector[10]. In fact, taking into account all three channels of exposure to Chinese trade, Douglas has a small net job gain of 0.01% a year relative to Plainview.

Another way to see how the supply chain perspective alter the inference is to examine the commuting zones most negatively hit by a direct competition effect. An important feature to note is that in almost all commuting zones, non-manufacturing employment tends to dominate manufacturing employment. (At the commuting zone level, there are no single-factory towns.) For example, in Detroit in 2000, while 15% of the 790,000 people in the age cohort 18-64 are employed in the manufacturing sector, 53% are employed outside manufacturing. (Additionally, 5.4% are unemployed, and 29% are not in the labor force). As we noted earlier, most sectors, including those

[10] In this example, because the downstream exposure is big in both Plainview and Douglas, the difference in their downstream exposure is relatively small.

that are sometime labeled as non-tradable sectors, can in fact benefit from being able to use imported intermediate inputs from China.

In terms of the negative job effects from the direct competition channel, the Detroit commuting zone is not the worst hit in the country. The five commuting zones that are most severely affected by import competition are: Rome, GA; Hickory, NC; Morganton, NC; Martinsville, VA and Talladega, AL, respectively. Table 9 reports the estimated manufacturing job loss from the direct competition channel in these five places (relative to a hypothetical region with no exposure to Chinese imports). By construction, they all show a large negative job effect in the manufacturing sector.

Importantly, the table also reports the downstream and upstream effects in both the manufacturing and non-manufacturing sectors. (The calculations are done when each is compared to a hypothetical commuting zone that is unaffected by trading with China in any way.) An important take-away message is that the supply chain channels are important, and the job expansion effect in the non-manufacturing sector (that can be traced to trading with China) is economically powerful enough to offset any job loss in the manufacturing sector. In the end, the total effect of trading with China does not produce a net job loss in any of these five commuting zones.

It may be instructive to compare the total employment effect and the direct competition effect across all commuting zones through two graphs. In Figure 4, we plot the actual employment change against the direct exposure to imports from China across the 722 commuting zones from 2000 to 2007. We can see a negative relationship between the two: on average, those commuting zones that experience greater growth in imports from China tend to experience a greater decline in local employment. This of course is a graphic representation of the ADH result.

In Figure 5, we plot the change in local employment against the total China effect after taking into account all three channels of exposure to the China trade. The total China effect is computed by summing up all three channels using the estimated coefficients in Table 7a. Strikingly, the relationship between the employment change and the total China effect across all commuting zones is positive when the supply chain perspective is incorporated. In other words, those regions with greater exposure to total China effect tend to experience a relatively greater increase in local employment. Basically, non-manufacturing industries are a bigger part of a local labor market than manufacturing industries in all commuting zones, and the expansion of local non-manufacturing jobs can be systematically and statistically traced to the ability of the United States to import China made intermediate inputs.

Note that in the absence of information on cross-regional mobility, one cannot extrapolate the relative-relative results from such reduced-form regressions to the aggregate effect in local labor markets. However, the general equilibrium spatial model of Adao et al. (2018) has found a low degree of inter-regional mobility, and explicitly conclude that the results from the reduced-form regressions are in principle valid. Since US employment tends to be stronger when US imports more from China or when it runs a larger trade deficit with China (Appendix Figure 2), it would seem easier to reconcile the aggregate employment patterns with our conclusion than with that of Autor, Dorn, and Hanson (2013).

5. Extensions and Robustness Checks

5.1 Alternative Measures of Downstream and Upstream Exposures

Since the direct competition channel and supply chain channels are highly correlated, as a robustness check, we compute an alternative pair of downstream and upstream measures that exclude the diagonal elements in the input-output matrix. We re-do the regressions in Tables 7a and 7b with the new set of regressors, and report the corresponding results in Tables 10 and Appendix Table 5. As it turns out, our key results and interpretations are not affected. In particular, while a direct competition effect (and an upstream effect) produces a job loss, this is more than offset by a job expansion effect from a downstream channel. Overall, trading with China does not produce a net job loss once the supply chain channels are taken into account.

5.2 Additional Instrumental Variables and Controls

In addition to the initial employment share in working-age population and census divisions fixed effects, Autor, Dorn, and Hanson (2013) also consider start-of-period employment share in routine occupations, offshorability index, share of female workers, share of foreign-born population and education level in each commuting zone as control variables.

Occupations that are relatively intensive in routine tasks are jobs that follow precisely prescribed rules or procedures. Workers who do this kind of work are more likely to be replaced by foreign imports or computers. The offshorability index measures the degree to which an occupation that require neither a fixed office location nor face-to-face communication with other US workers. Viewed from the lens of the supply chain perspective, the initial routine occupation share and occupational offshorability may reflect subsequent downstream effects of trading with China. Indeed, the correlation matrix in Appendix Table 3 is consistent with this interpretation. Both the routine occupation share and offshorability index show a high and significant positive correlation with exposure to China trade. For this reason, we add these two variables as additional IVs to the first stage regressions, and include share of female workers, share of foreigners and education level as additional controls. (We will conduct an over-identification test to see if the routine occupation share and offshorability index are valid instruments.)

Both routine occupation share and offshorability index are taken from Autor and Dorn (2013), where routine occupation share is computed using the top 40 percent of occupations, and the offshorability index is the average offshorability score of employment that is normalized to have a mean of zero and a standard deviation of one cross 722 commuting zones in 1980. The three control variables are calculated from the 5% sample of U.S. Census microdata. (As an additional control, we also add the initial share of China-born in the local population, as well as the initial share of population over 64 years old.)

The main regression results, as well as the first stage coefficients, are shown in Table 11a and 11b, respectively. The results confirm the previous findings: while a direct competition effect produces a job loss, which is reinforced by an upstream channel, the total effect of trading with China, however, is a net job gain (of about 1.93% a year).

With the additional instrumental variables, we can perform an over-identification test (of whether the proposed IVs are uncorrelated with the error term in the main regressions). This serves as a check on whether the proposed IVs are valid. All regressions, except the one with NILF share as the dependent variable, have passed the over-identification test for the instrumental variables.

We can also expand the set of instrumental variables by using differential reductions in uncertainty facing imports from China across products following US granting Permanent Normal Trade Relations (NTR Gap) to China in 2000. This follows the idea in Pierce and Schott (2016).

We take five steps to calculate the NTR Gap for each sector (at the level of OECD ICIO sector). First, we aggregate the “Column 1” (MFN or NTR) tariff rates that the United States offers to WTO members and the “Column 2” (non-NTR) tariff rates to 6-digit HS level from the original 8-digit HS level provided by Feenstra, Romalis and Schott (2002)[11]. Second, using the concordance provided by OECD, we match the 6-digit HS code to OECD ICIO sector via ISIC revision 3 code. Third, the NTR gap for each OECD ICIO sector is calculated as the difference between the NTR and non-NTR tariff rates.

Fourth, we calculate the instrumented versions of the upstream and downstream exposures with NTR gaps for each commuting zone by using equation (9) and (13). It is worth noting that the uncertainty removed by the NTR affects both final consumption goods and intermediate goods. Based on our definition of downstream exposure, only the latter has a cost reduction effect on downstream sectors. We use the BEC classification to separate imports of intermediate goods and those of final goods, and calculate separately the NTR Gaps for consumption goods and intermediate goods. Finally, in the fifth step, we convert the sector level NTR gaps to the commuting zone level based on each commuting zone’s employment structure.

The regression results with the enlarged set of instrumental variables, as well as the

[11] NTR and non-NTR rates are measured as the average across three years (1997-1999) before the policy change in year 2000.

corresponding first stage coefficients, are reported in Table 12a and 12b, respectively. We still see a significant positive downstream effect. In particular, while a direct competition effect and an upstream channel produce a loss of manufacturing jobs, an indirect downstream effect produces job expansion in the non-manufacturing sector. The total effect of trading with China, however, is a net job gain of about 1.62% a year. All regressions, except for the one on manufacturing employment, pass the over-identification J-test for the validity of the proposed instrumental variables.

5.3 Accounting for High-Order Input-Output Relationship

Conceptually, one can consider higher orders of downstream and upstream effects. That is, not only firms that use imported inputs from China can benefit, firms that buy inputs from other US firms that buy Chinese inputs can benefit too. Similarly, not only those US firms that sell output to US firms that compete directly with Chinese imports could suffer, other US firms that sell output to US firms that compete indirectly with Chinese imports may suffer too. Both the downstream and upstream effects can continue on higher orders. The Input-Output matrix allows us to compute supply chain effects at multiple rounds into infinity. A higher order downstream and upstream channels involve sums of power series of the input-output matrix.

In Table 13, we report the estimation results when we consider the high-order input-output relationship. The key take-away is that the China shock impacts from all three channels are amplified, especially for the positive downstream effect in the non-manufacturing sector (from job expansion of 3.08% a year during 2000-2007 as reported in Table 7a to 5.69% a year as reported in Table 13). The total effect of the China trade shock is a bigger increase in employment — 3.03% a year now relative to 1.27% a year before.

5.4 Net Instead of Gross Imports

In the regression results reported in Appendix Table 6, we use net imports (imports minus exports) rather than gross imports in computing the China exposure variables. As it turns out, some of the major importing sectors are also major exporting sectors to China, and the two are expected to have opposite effects on US employment in terms of the direct competition channel. For example, the United States simultaneously exports \$20.7 billion of transport equipment in 2014 and imports \$17.4 billion of similar products from China in the same year, and the cumulative growth of US exports of transport equipment to China at 615% exceeds that of US imports from China (at 386%) from 2000 to 2014. Naturally, those US regions that are over-represented by these sectors likely see their employment growth being helped by exporting to China. However, for most regions (as well as for the United States as a whole), the growth of imports from China exceeds that of exports to China. Moreover, since imports from China are more labor intensive than exports to China, one might conjecture that looking at the direct competition effect of net imports rather than gross imports from China might slightly reduce the negative employment consequence but not eliminate it[12]. We will show empirically that this is indeed the case.

We replace the measure of the annualized direct exposure to China trade shock from gross imports to net imports:

$$\Delta NetDirect_{j,\tau} = \frac{100}{7} \times [\frac{(M_{j,2007}^{C,U} - E_{j,2007}^{U,C}) - (M_{j,2000}^{C,U} - E_{j,2000}^{U,C})}{Y_{j,2000}^{U} + M_{j,2000}^{*U} - E_{j,2000}^{U*}}] \tag{15}$$

where $M_{j,2007}^{C,U}$ is US imports of sector j's products from China in 2007, and $E_{j,t}^{U,C}$ is US sector j's exports to China. This is similar to the measure of direct exposure to China imports in equation (1) except that we use US net imports from China to replace US gross imports from China in the numerator.

An instrumented version (IV) of this variable is as follows：

$$\Delta NetDirect_{j,\tau}^{IV} = \frac{100}{7} \times [\frac{(M_{j,2007}^{C,G5} - E_{j,2007}^{G5,C}) - (M_{j,2000}^{C,G5} - E_{j,2000}^{G5,C})}{Y_{j,1995}^{U} + M_{j,1995}^{*U} - E_{j,1995}^{U*}}] \tag{16}$$

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12 Feenstra, Ma, and Xu (2017) and Feenstra and Sasahara (2017) examine the employment effect of total US exports, and show that it partially offsets a negative employment effect from importing from China through a direct competition channel. They do not examine the employment effect of exporting to China alone, nor the employment effect of net imports from China across commuting zones. In a robustness check, Feenstra, Ma, and Xu (2017) estimate the employment effects of downstream and upstream channels and find no significant effects. However, their measures of the two channels have the same two limitations that we have explained about the Acemoglu et al. (2016) method.

The conversion from the sector level to the commuting zone level is also similar as before:

$$\Delta NetDirect_{k,\tau} = \sum_j \frac{L_{k,j,2000}}{L_{k,2000}} \Delta NetDirect_{j,\tau} \tag{17}$$

$$\Delta NetDirect^{IV}_{k,\tau} = \sum_j \frac{L_{k,j,1990}}{L_{k,1990}} \Delta NetDirect^{IV}_{j,\tau} \tag{18}$$

As shown in Appendix Tables 6, once one considers US exports to China as well as US imports from China, the negative direct competition effect on the manufacturing employment rate becomes smaller (-0.21% as opposed to -0.39% a year during 2000-2007). On the other hand, the positive employment effects from the downstream exposure channel are still significant. The effects on total employment when both the direct and indirect channels are considered together are very similar between Tables 7a and Appendix Table 6.

6. Effects on Real Wages

We now analyze the effect of trading with China on US wages. To do so, we follow the regression model discussed in section 3.1, and use 100 times the annualized change in log real weekly wage[13] as a dependent variable, and control for initial income level.

$$\Delta \ln Wage_{k,\tau} = \beta_0 + \beta_1 \Delta Direct_{k,\tau} + \beta_2 \Delta UP_{k,\tau} + \beta_3 \Delta Down_{k,\tau} + \beta_4 \Pi_{k,2000} + \varepsilon_{k,\tau}$$

For comparison, we report the results using the ADH specification in column 1 of Table 14. The direct competition channel clearly puts downward pressure on real wage growth. Regions with more exposure to growth of China imports experience a lower growth of real wage than regions with less exposure to growth of China imports. To help with economic interpretation, we convert the elasticity estimate to implied effects on the real wage growth for a hypothetical community zone whose exposure to trading with China is equal to the sample mean across all community zones relative to another hypothetical region with no exposure to China trade. The result is reported

[13] Pre-tax wage and salary are converted to be in 2000 US dollars using the Personal Consumption Expenditure (PCE) deflator.

in the lower panel of Table 14. Under the ADH specification, the average commuting zone experiences a decline in real wage by 0.85% a year during 2000-2007 due to its exposure to trading with China.

In Column 2 of Table 14, we report the results from a regression that includes the two additional supply chain variables. In this case, while the direct competition channel is no longer significant, the upstream channel (a form of indirect competition) exhibits a strong negative effect on real wage growth. On the other hand, the downstream channel produces a strong positive effect on real wage growth. Again, to help with economic interpretation, we convert the elasticity estimates to implied effects on the real wage growth for a hypothetical community zone whose exposure to trading with China is equal to the sample mean in all three channels (direct competition, downstream, and upstream channels) relative to another hypothetical region with no exposure to China trade. From the lower panel of Table 14, we can see that the downstream channel produces an increase in real wage by 8.5% a year, whereas the upstream channel produces a reduction in real wage by 4.1% a year. The overall effect of trading with China is a boost to the real wage growth by 4.9%.

Similar to the earlier discussion on the employment effect, it is useful to bear in mind that technological changes, regulatory changes, and other factors besides international trade could affect real wage during this period. Many factors could produce a declining or stagnant real wage. Our estimate suggests that the total effect of trading with China helps to raise the real wage, even though the sum of the direct competition channel and the upstream channel (which is a form of indirect competition from China) puts significant downward pressure on the real wage growth.

In Columns 3 and 4 of Table 14, we perform separate regressions for real wage growth in manufacturing and non-manufacturing sectors respectively. In the manufacturing sector, the upstream channel depresses the real wage growth (by 4.0% a year). It is not statistically significant mainly because the corresponding standard error is large. In any case, it is more than offset by the positive wage effect through the downstream channel (with an increase in real wage by 20.4% a year). The direct competition effect is modest and not statistically significant. Summing over all three channels of trading with China, the manufacturing real wage increases by 17.5% a year. Note that the estimated wage effect in the manufacturing sector likely reflects to a significant part a compositional change – relatively low skilled and lowly-paid workers are laid off through the upstream channel; the remaining workers are relatively more skilled and better paid than the previous average wage.

In the non-manufacturing sector, the downstream channel raises the real wage whereas the upstream channel depresses it. The overall effect of trading with China is an extra growth of non-manufacturing sector real wage by 4.4% (bottom of Column 4). Note that the overall effect on all workers (4.9% at the bottom of Column 2) is closer to that of the non-manufacturing workers (4.4% at the bottom of Column 4) than that of the manufacturing workers (17.5% at the bottom of Column 3) because most people work outside the manufacturing sector.

In Columns 5 and 6, we splice the workers by education level (with and without some college education[14]). There is a stark difference between these two groups. While the downstream channel produces a big real wage boost to college educated workers, it does not have a statistically significant effect on non-college educated workers. Overall, through trading with China, college educated workers see a faster wage growth by 7.2% a year whereas non-college educated workers see a decline by 4.3% a year. Without transfer, trading with China appears to enlarge the wage gap between the more and less educated workers.

In Columns 7 and 8 of Table 14, we splice workers by gender. Both groups of workers gain on average from trading with China. Female workers gain more (with an extra growth of real wage by 7.2% a year, bottom of Column 8), compare with male workers (with an extra wage growth of 3.5%). Therefore, trading with China appears to promote gender equality in pay.

We now move to investigate the effects on wage distribution, using grouped IV quantile regressions proposed by Chetverikov et al. (2016). Specifically, all US workers are grouped into

[14] We classify a worker as "college-educated" if he/she has completed at least 1 year of college.

20 quantiles according to their initial income levels. The overall effect of trading with China (summing over the three channels) is represented in Figure 6 together with a 95% confidence band. For comparison, we also plot the effect on the wage distribution when we only look at the direct competition effect, and this result is labeled as ADH specification. With the ADH specification, the effect of trading with China is a reduction in real wage for workers in almost all income groups. This is comparable to the results reported in Chetverikov et al. (2016)[15]. In comparison, with the supply chain perspective, we see that 75% of the workers benefit from trading with China, but the bottom 25% (in terms of initial income) are made worse off. This means, without income transfers, trading with China produces more winners than losers. (Based on the results in Table 14, we know that the sum of the gains by the winners outweigh the sum of the losses by the losers. Therefore, even without transfer between capital and labor, transfer within the labor group could make everyone better off.) Hence, incorporating the supply chain perspective or not makes an enormous difference.

With the supply chain perspective, we further decompose the effects on the wage distribution by channels and report the results in Figure 7. The direct competition channel is relatively modest, with losers in the middle of the distribution. The upstream channel causes wage loss in the entire distribution, with a greater loss on the two ends. In comparison, the downstream channel produces gains for workers outside the bottom 20%, with the size of the gains rising approximately with the initial income level.

We present similar results when the working age cohort is broken down by gender (Figure 8). Broadly speaking, workers with a low initial income (below 20% for males and 25% for females) tend to lose but an overwhelming majority of workers gain from trading with China even before transfer. For those workers above the median income level, females gain more from trading with China than males.

[15] Based on the point estimates in Chetverikov et al. (2016), the effect of trading with China – looking at the competition channel alone – is a reduction in real wage in 19 out of 20 income quantiles. For unclear reasons, the exception is the second highest income quantile which shows a positive wage effect in terms of the point estimate, although it is still statistically not different from zero.

The wage distribution effects separated by education levels are presented in Figure 9. The stark results in Table 14 can be seen more clearly in this graph. While an overwhelming majority of workers with some college education gain from trading with China, a majority of less educated workers appear to lose. Most of these less educated workers are in the bottom 25% of the initial income distribution.

To summarize, trading with China produces substantially more winners than losers. Losers are concentrated in the less educated group who are in the bottom 25% of the initial income distribution. Some income transfer could make them better off from trading with China, and such transfer seems feasible from an accounting point of view. This is because trading with China raises the total wage bill for the workers as a whole. Put it differently, shutting down trading with China would hurt workers as a group in terms of their real wage. Even without redistribution between capitalists and workers, there exists a redistribution among workers that would make every worker better.

Note that we have used a common price index to convert nominal wages to real wages for workers in all income groups. If trading with China produces a greater reduction in cost of living for low-income households than for high-income households[16], then the set of losers may shrink further and the set of winners may correspondingly become bigger.

7. Conclusions

US imports of intermediate inputs from China rose from about 1/4 of total imports in 2000 to more than 1/3 in 2014. Those US firms using imported inputs can improve efficiency and potentially expand their employment. Firms that use these imported inputs (e.g., computers, printers, telecommunication equipment, and parts and components of various office machinery)

[16] Amiti et al. (2018) show that trading with China has significantly reduced variety-adjusted prices in the United States. One third of the beneficial impact comes from Chinese exporters lower their prices, and two-thirds comes from entry of new Chinese exporters.

include those in what are traditionally labeled as “non-tradable sectors” such as banks, business services, research and educational institutions.

While we use a cross-regional reduced-form specification, our paper differs from the existing literature in a number of important ways. In particular, this paper explicitly considers downstream and upstream effects of imports from China, and uses more precise information on how imported intermediate inputs from China are allocated across US sectors. In contrast to the existing literature, we find strong evidence that the downstream effect is positive (i.e., the use of imported Chinese inputs raises US employment) and the effect is greater than the combined negative impact of a direct import competition channel and an indirect upstream channel. In addition, the US labor market is flexible enough that non-manufacturing employment is systematically stimulated by trading with China. The net employment effect from trading with China is found to be positive.

As important, once a supply chain perspective is applied, we find that American workers as a group experience an increase in real wage from trading with China. The effect is not the same across all workers; most college educated workers gain substantially, whereas many non-college-educated workers experience a decline in real wage. Still, even without redistribution between capital owners and workers, every worker can be made better off if the total wage bill can be redistributed.

If voters only understand the direct effects but not the general equilibrium or indirect effects, then it is possible that they mistakenly believe that trading with China produces a job loss and an income loss even though a majority of them gain in the general equilibrium.

We do not wish to claim that this paper represents the last word on the subject. Indeed, an important direction for future exploration is to construct estimation on how technology, local labor market institutions (e.g., strength of labor unions), and trade shocks jointly affect local labor market outcomes. Such estimation would be a useful complement to GE spatial models that study the same questions.

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Tables and Figures

Table 1: Changes in US Import Prices versus Changes in China's Share in US Imports, across HS 6-digit Products

	Dependent Variable = Δ ln *Unit Price* (%)			
	Gross Imports		Intermediate Imports	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
China's Share (Equally-Weighted)	-0.594***	-1.203***	-0.628***	-1.137***
	(0.0596)	(0.214)	(0.0757)	(0.232)
China's Share (Weighted by Relative Values of the Products)	-1.044***	-1.773***	-1.358***	-2.116***
	(0.320)	(0.651)	(0.391)	(0.735)

Note: This table reports the coefficients on China's share in US imports at the HS 6 digit product from 8 separate regressions with changes in US import unit values at HS 6 digit level during 2000-2007 as the dependent variable. Intercepts are included but not reported. The regressions in the 2nd and 4th columns are two stage least square regressions with changes in China's share in the imports of Germany, France, Italy, Japan and the United Kingdom during the same period as an instrumental variable. The regressions in the second row are weighted in proportion to each product's total US import value from all sources in 2000. Robust standard errors in parentheses. *** denote statistically significant at the 1% level.

Table 2: Three Channels of Exposure to China Trade at the Sectoral Level
(Annualized Changes in Percentage Points)

Variable	Obs.	Mean	Std. Dev.	Min	Max
ΔDirect	34	0.224	0.386	-0.018	1.638
ΔDown	34	0.515	0.180	0.000	0.888
ΔUp	34	0.167	0.169	0.000	0.789

Table 3: Three Channels of Exposure to China Trade at the Commuting Zone Level
(Annualized Changes in Percentage Points)

Changes in Exposure to China Trade					
Variable	Obs	Mean	Std. Dev.	Min	Max
ΔDirect	722	0.112	0.041	0.052	0.319
ΔDown	722	0.546	0.012	0.505	0.595
ΔUp	722	0.128	0.015	0.101	0.222
Instrumental Variables					
Variable	Obs	Mean	Std. Dev.	Min	Max
G5 IV: ΔDirect	722	0.157	0.061	0.074	0.528
G5 IV: ΔDown	722	0.626	0.025	0.558	0.707
G5 IV: ΔUp	722	0.172	0.023	0.141	0.326

Note: We present in Appendix Table A2 an extended version of the summary statistics that include alternative IV measures (routine job share, offshoring index and PNTR IVs).

Table 4a: Correlation Matrix on the three measures and their three IVs
Upstream and downstream exposure measures that using Full Input-Output Matrix

	ΔDirect	ΔDownstream	ΔUpstream	ΔDirect (IV)	ΔDownstream (IV)	ΔUpstream (IV)
ΔDirect	1					
ΔDown	0.1342	1				
ΔUp	0.9666	0.1965	1			
G5 IV: ΔDirect	0.9226	0.166	0.92	*1*		
G5 IV: ΔDown	0.4304	0.7946	0.496	0.5125	1	
G5 IV: ΔUp	0.8737	0.2103	0.9071	0.9779	0.543	1

Note: We present in Appendix Table A3 an extended version of the correlation matrix that include a full set of control variables and alternative IV measures (routine job share, offshoring index and PNTR IVs)

Table 4b: Correlation Matrix on the three measures and their three IVs
Upstream and downstream exposure measures that excluding the diagonal IO elements

	ΔDirect	ΔDownstream	ΔUpstream	ΔDirect (IV)	ΔDownstream (IV)	ΔUpstream (IV)
ΔDirect	1					
ΔDownstream	-0.3135	1				
ΔUpstream	0.7773	0.0631	1			
G5 IV: ΔDirect	0.9226	-0.2715	0.7222	1		
G5 IV: ΔDown	-0.1659	0.8105	0.1698	-0.1974	1	
G5 IV: ΔUp	0.5945	0.2261	0.8566	0.6199	0.306	1

Table 5: Annualized Changes in Employment Shares at the Commuting Zone Level
(% of the Local Working Age Population)

Variables	Obs	Mean	Std. Dev.	Min	Max
Δ Manufacturing Employment	722	-0.230	0.279	-1.583	0.570
Δ Non-Manufacturing Employment	722	0.231	0.348	-0.091	1.625
Δ Not in Labor Force	722	-0.048	0.336	-1.640	1.276
Δ Unemployment	722	0.047	0.179	-0.656	0.716

Table 6: An Incompletely Specified Model That Only Looks at the Direct Competition Channel

Estimation Method	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
OLS Estimates:	-4.156***	1.339**	1.884***	0.934***	-2.817***
	(0.319)	(0.652)	(0.638)	(0.152)	(0.706)
2SLS Estimates:	-4.236***	1.393**	1.892***	0.951***	-2.844***
	(0.318)	(0.659)	(0.650)	(0.168)	(0.724)
First Stage F Statistics: 291.63					
Implied Labor Market Effects of the China Trade Shock					
2SLS Estimates:	-0.47%	0.16%	0.21%	0.11%	-0.32%

Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Table 7a: Accounting for Downstream and Upstream Effects

Dependent Variable = ΔEmp Share	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
ΔDirect	-3.534**	7.839**	-4.287	-0.0184	4.305
	(1.517)	(3.109)	(2.852)	(1.532)	(3.893)
ΔDown	0.298	5.648***	-7.520***	1.574**	5.946**
	(0.834)	(1.912)	(1.928)	(0.753)	(2.446)
ΔUp	-1.889	-17.24**	16.45**	2.686	-19.13*
	(3.843)	(8.103)	(7.464)	(4.038)	(10.01)
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.638	0.389	0.350	0.476	0.506

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.47%*	*0.16%*	*0.21%*	*0.11%*	*-0.32%*
Direct Competition Effect	-0.39%	0.87%	-0.48%	0.00%	0.48%
Downstream Effect	0.16%	3.08%	-4.10%	0.86%	3.24%
Upstream Effect	-0.24%	-2.21%	2.11%	0.35%	-2.46%
Total Effect	**-0.47%**	**1.74%**	**-2.47%**	**1.20%**	**1.27%**

Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Table 7b: First Stage Regressions

(a la Growth of Imports from China by Other High Income Countries, 2000-2007)

	ΔDirect (1)	ΔDown (2)	ΔUp (3)
G5 IV: ΔDirect	0.825***	-0.0445	0.0765***
	(0.0645)	(0.0283)	(0.0212)
G5 IV: ΔDown	-0.185***	0.557***	-0.0451***
	(0.0340)	(0.0184)	(0.0130)
G5 IV: ΔUp	-0.409**	-0.0175	0.460***
	(0.183)	(0.742)	(0.0661)
First Stage F Statistics	**298.92**	**142.78**	**269.78**

Note: The first stage regressions have the same controls as the second stage, and are also weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively.

Table 8: Relative Effects of the China Shock on Two Local Labor Markets

CZ1= 25th percentile of the direct competition effect (Plainview, TX), and

CZ2=75th percentile of the direct competition effect (Douglas, IL)

CZ2 – CZ1	Manufacturing	Non-Manufacturing	Total Employment
Actual Change	**-0.31%**	**0.21%**	**-0.10%**
Direct competition Effect (ADH Specification)	**-0.22%**	**0.07%**	**-0.15%**
Direct Competition Effect	-0.18%	0.41%	0.22%
Downstream Effect	0.01%	0.12%	0.13%
Upstream Effect	-0.03%	-0.30%	-0.34%
Total Effect	**-0.21%**	**0.22%**	**0.01%**

The employment effects are for Douglas IL relative to Plainview TX.

Table 9: Employment Effects of Trading with China on the Five CZs with the Largest Direct Competition Effects

Commuting Zone		Effect	Manufacturing	Non-Manufacturing	All Sectors
6600	**Rome (Georgia)**	Direct Competition Effect	-1.13%	2.50%	1.37%
		Downstream Effect	0.16%	3.05%	3.21%
		Upstream Effect	-0.42%	-3.82%	-4.24%
		Total Effect	**-1.38%**	**1.72%**	**0.34%**
1100	**Hickory (North Carolina)**	Direct Competition Effect	-1.10%	2.44%	1.34%
		Downstream Effect	0.16%	3.11%	3.27%
		Upstream Effect	-0.35%	-3.24%	-3.59%
		Total Effect	**-1.29%**	**2.31%**	**1.02%**
1002	**Morganton (North Carolina)**	Direct Competition Effect	-1.03%	2.28%	1.25%
		Downstream Effect	0.16%	3.07%	3.23%
		Upstream Effect	-0.34%	-3.11%	-3.46%
		Total Effect	**-1.21%**	**2.24%**	**1.03%**
402	**Martinsville (Virginia)**	Direct Competition Effect	-1.03%	2.28%	1.25%
		Downstream Effect	0.16%	3.05%	3.21%
		Upstream Effect	-0.35%	-3.21%	-3.57%
		Total Effect	**-1.22%**	**2.11%**	**0.89%**
9500	**Talladega (Alabama)**	Direct Competition Effect	-0.97%	2.14%	1.18%
		Downstream Effect	0.16%	3.05%	3.21%
		Upstream Effect	-0.37%	-3.39%	-3.76%
		Total Effect	**-1.18%**	**1.81%**	**0.63%**

Table 10: Excluding the Diagonal Elements in the IO Table in Computing Downstream/Upstream Exposures

Dependent Variable = ΔEmp Share	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
ΔDirect	-3.627***	4.505***	-1.843*	0.966*	0.878
	(0.574)	(1.043)	(1.067)	(0.498)	(1.394)
ΔDown	0.443	5.933**	-8.887***	2.511***	6.376**
	(1.148)	(2.418)	(2.491)	(0.924)	(3.179)
ΔUp	-3.904	-15.42***	16.34***	2.981	-19.32**
	(2.788)	(5.795)	(5.844)	(2.756)	(7.587)
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.645	0.405	0.366	0.486	0.529

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.47%*	*0.16%*	*0.21%*	*0.11%*	*-0.32%*
Direct Competition Effect	-0.40%	0.50%	-0.21%	0.11%	0.10%
Downstream Effect	0.25%	3.35%	-5.02%	1.42%	3.60%
Upstream Effect	-0.51%	-2.03%	2.15%	0.39%	-2.54%
Total Effect	**-0.67%**	**1.83%**	**-3.08%**	**1.92%**	**1.16%**

Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Table 11a: Expanding the Set of Instrumental Variables to Include Routine Job Share and Offshoring Index

Dependent Variable = ΔEmp Share	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
ΔDirect	-3.840**	4.332	-0.00883	-0.483	0.492
	(1.648)	(2.929)	(2.557)	(1.529)	(3.719)
ΔDown	1.158	5.144*	-9.334***	3.031***	6.303
	(1.545)	(3.046)	(3.436)	(0.955)	(4.012)
ΔUp	-1.603	-10.57	8.162	4.009	-12.17
	(4.106)	(7.643)	(6.949)	(4.014)	(9.901)
Female	-1.242**	-1.296	1.976	0.563	-2.539**
(% in Emp.)	(0.531)	(0.945)	(1.336)	(0.699)	(1.156)
Edu. Attainment	-0.0102	-0.349***	0.405***	-0.0451	-0.359***
(Years of Schooling)	(0.0522)	(0.0935)	(0.109)	(0.0367)	(0.118)
Foreign-Born	-0.0321	0.0570	-0.0524	0.0275	0.0249
(1=Above Average)	(0.0268)	(0.0363)	(0.0333)	(0.0231)	(0.0474)
Born in China	1.299	10.09**	-11.17**	-0.225	11.39**
(% in Pop.)	(0.993)	(4.669)	(4.740)	(0.973)	(5.395)
Age 64 and above	0.308	0.162	-1.657*	1.188***	0.469
(% in Pop.)	(0.436)	(0.596)	(0.919)	(0.305)	(0.913)
Hansen J Statistics	2.068	4.066	6.797	0.609	3.929
P-value	0.356	0.131	0.0334	0.738	0.140
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.647	0.462	0.442	0.492	0.563

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.47%*	*0.16%*	*0.21%*	*0.11%*	*-0.32%*
Direct Competition Effect	-0.43%	0.48%	0.00%	-0.05%	0.05%
Downstream Effect	0.63%	2.81%	-5.09%	1.65%	3.44%
Upstream Effect	-0.21%	-1.36%	1.05%	0.51%	-1.56%
Total Effect	**0.00%**	**1.93%**	**-4.05%**	**2.11%**	**1.93%**

Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Table 11b: First Stage Regressions
(a la Growth of Imports from China by Other High Income Countries,
Routine Job Share and Offshoring Index)

	ΔDirect	ΔDown	ΔUp
	(1)	(2)	(3)
G5 IV: ΔDirect	0.734***	-0.0349	0.0294
	(0.0623)	(0.0209)	(0.0193)
G5 IV: ΔDown	-0.167***	0.442***	-0.0546**
	(0.0571)	(0.0241)	(0.0250)
G5 IV: ΔUp	-0.278*	-0.00365	0.538***
	(0.162)	(0.0531)	(0.0533)
Routine	0.00222	-0.0206	-0.00614
	(0.0335)	(0.0166)	(0.0122)
Offshoring	0.00952***	0.00804***	0.00607***
	(0.00344)	(0.00195)	(0.00123)
First Stage F Statistics	**369.4**	**211.2**	**340**

Note: The first stage regressions have the same controls as the second stage, and are also weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively.

Table 12a: Expanding the Set of Instrumental Variables to Include PNTR Gaps

Dependent Variable = ΔEmp Share	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
ΔDirect	-3.866**	4.320	0.148	-0.602	0.454
	(1.596)	(2.827)	(2.462)	(1.509)	(3.497)
ΔDown	1.192	4.595*	-8.014**	2.227***	5.787*
	(1.459)	(2.662)	(3.167)	(0.707)	(3.486)
ΔUp	-1.695	-10.67	7.941	4.427	-12.37
	(3.991)	(7.289)	(6.505)	(4.004)	(9.207)
Female	-1.265**	-1.364	2.101	0.529	-2.630**
(% in Emp.)	(0.546)	(0.937)	(1.324)	(0.685)	(1.162)
Edu. Attainment (Years	-0.0147	-0.341***	0.384***	-0.0278	-0.356***
of Schooling)	(0.0517)	(0.0898)	(0.103)	(0.0353)	(0.111)
Foreign-Born	-0.0329	0.0590	-0.0580*	0.0319	0.0261
(1=Above Average)	(0.0271)	(0.0369)	(0.0338)	(0.0238)	(0.0487)
Born in China	1.354	10.29**	-11.62**	-0.0302	11.65**
(% in Pop.)	(0.939)	(4.617)	(4.746)	(0.865)	(5.283)
Age 64 and above	0.314	0.0848	-1.480	1.081***	0.399
(% in Pop.)	(0.434)	(0.614)	(0.949)	(0.321)	(0.923)
Hansen J Statistics	7.689	4.456	5.675	4.542	5.098
P-value	0.0529	0.216	0.129	0.209	0.165
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.647	0.462	0.445	0.496	0.563

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.47%*	*0.16%*	*0.21%*	*0.11%*	*-0.32%*
Direct Competition Effect	-0.43%	0.48%	0.02%	-0.07%	0.05%
Downstream Effect	0.65%	2.51%	-4.37%	1.22%	3.16%
Upstream Effect	-0.22%	-1.37%	1.02%	0.57%	-1.59%
Total Effect	**0.00%**	**1.62%**	**-3.34%**	**1.72%**	**1.62%**

Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock

Table 12b: First Stage Regressions
(a la Growth of Imports from China by Other High Income Countries and PNTR Gaps)

	ΔDirect	ΔDown	ΔUp
	(1)	(2)	(3)
G5 IV: ΔDirect	0.519***	-0.0355	0.0141
	(0.0865)	(0.0469)	(0.0358)
G5 IV: ΔDown	-0.135**	0.382***	-0.00534
	(0.0612)	(0.0540)	(0.0263)
G5 IV: ΔUp	0.297	0.253**	0.537***
	(0.238)	(0.125)	(0.0923)
PNTR IV: ΔDirect	0.487***	0.0691	0.0832
	(0.159)	(0.0763)	(0.0552)
PNTR IV: ΔDown	-0.308	0.120	-0.149
	(0.380)	(0.240)	(0.148)
PNTR IV: ΔUp	-1.173**	-0.771***	-0.0543
	(0.467)	(0.216)	(0.169)
First Stage F Statistics	**560.4**	**504.8**	**762.7**

Note: The first stage regressions have the same controls as the second stage, and are also weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively.

Table 13: Accounting for High-Order Input-Output Relationship

Dependent Variable = ΔEmp Share	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
	(1)	(2)	(3)	(4)	(5)
ΔDirect	-2.855**	7.832***	-4.799*	-0.177	4.977
	(1.449)	(2.986)	(2.724)	(1.583)	(3.825)
ΔDown	1.749	14.36***	-19.11***	2.994*	16.11***
	(1.872)	(4.410)	(4.425)	(1.659)	(5.563)
ΔUp	-5.055	-23.23**	23.90**	4.381	-28.28**
	(5.140)	(10.88)	(10.04)	(5.746)	(13.80)
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.640	0.397	0.370	0.478	0.516

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.47%*	*0.16%*	*0.21%*	*0.11%*	*-0.32%*
Direct Competition Effect	-0.32%	0.87%	-0.54%	-0.02%	0.56%
Downstream Effect	0.69%	5.69%	-7.57%	1.19%	6.38%
Upstream Effect	-0.70%	-3.21%	3.30%	0.61%	-3.91%
Total Effect	**-0.32%**	**3.35%**	**-4.80%**	**1.77%**	**3.03%**

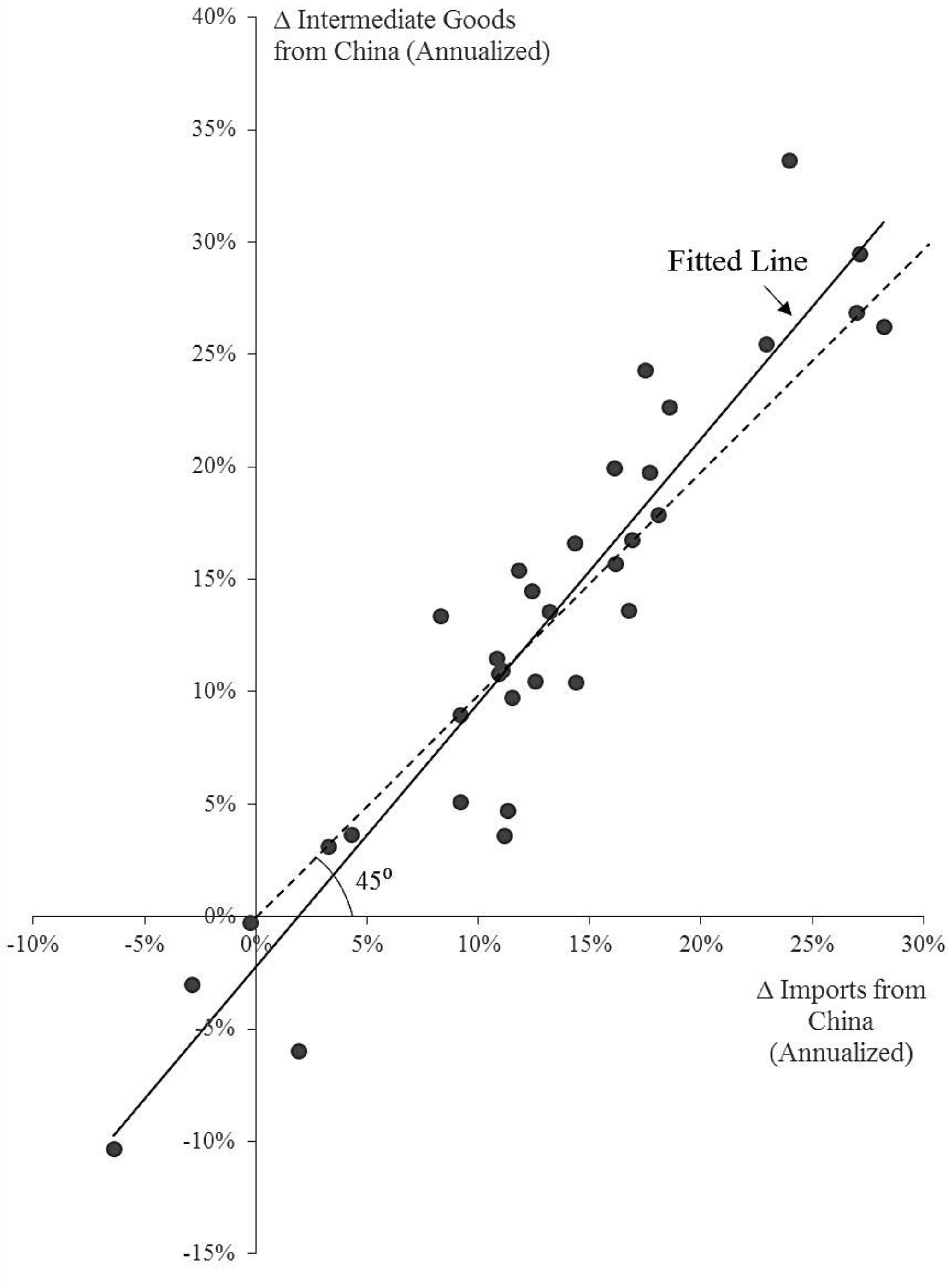
Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Table 14: Effect of the China Trade Shock on US Real Weekly Wage

Dependent Variable = Δ ln (Real Weekly Wage) (Annualized)	ADH Specification	Value Chain Perspective						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample	Full Sample	Manuf.	Non-Manuf.	College	Non-College	Male	Female
ΔDirect	-7.595***	3.912	9.398	0.484	10.49	-4.919	-3.723	13.29**
	(1.112)	(5.576)	(9.539)	(5.875)	(7.729)	(4.922)	(7.265)	(5.816)
ΔDown		15.67***	37.33***	13.62**	23.02***	-4.878	10.66	22.85***
		(5.602)	(14.35)	(5.525)	(7.171)	(7.085)	(6.624)	(6.508)
ΔUp		-32.17**	-30.81	-23.89	-50.88**	-8.234	-14.75	-52.73***
		(15.53)	(25.69)	(16.23)	(20.68)	(14.63)	(19.24)	(16.13)
Census Divisions Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	722	722	722	722	722	722	722	722
R-squared	0.194	0.216	0.053	0.203	0.227	0.213	0.197	0.123
Implied Real Wage Effects								
Direct Competition Effect	-0.85%	0.4%	1.0%	0.1%	1.2%	-0.5%	-0.4%	1.5%
Downstream Effect		8.5%	20.4%	7.4%	12.6%	-2.7%	5.8%	12.5%
Upstream Effect		-4.1%	-4.0%	-3.1%	-6.5%	-1.1%	-1.9%	-6.8%
Total Effect	**-0.85%**	**4.9%**	**17.5%**	**4.4%**	**7.2%**	**-4.3%**	**3.5%**	**7.2%**

Note: All regressions include a constant and control for the start-of-period real weekly wage and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. ** and *** denote coefficient statistically significant at the 5% and 1% levels, respectively. The implied real wage effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Figure 1: Growth in US Imports from China across Sectors
Intermediate Inputs vs Total Imports



Note: The annualized growth rate for gross imports and intermediate imports are measured over the period 2000-2014 by using the OECD ICIO table.

Figure 2: Binned Scatterplots of Change in the Share of China in US Imports and Change in US log Import Unit Price

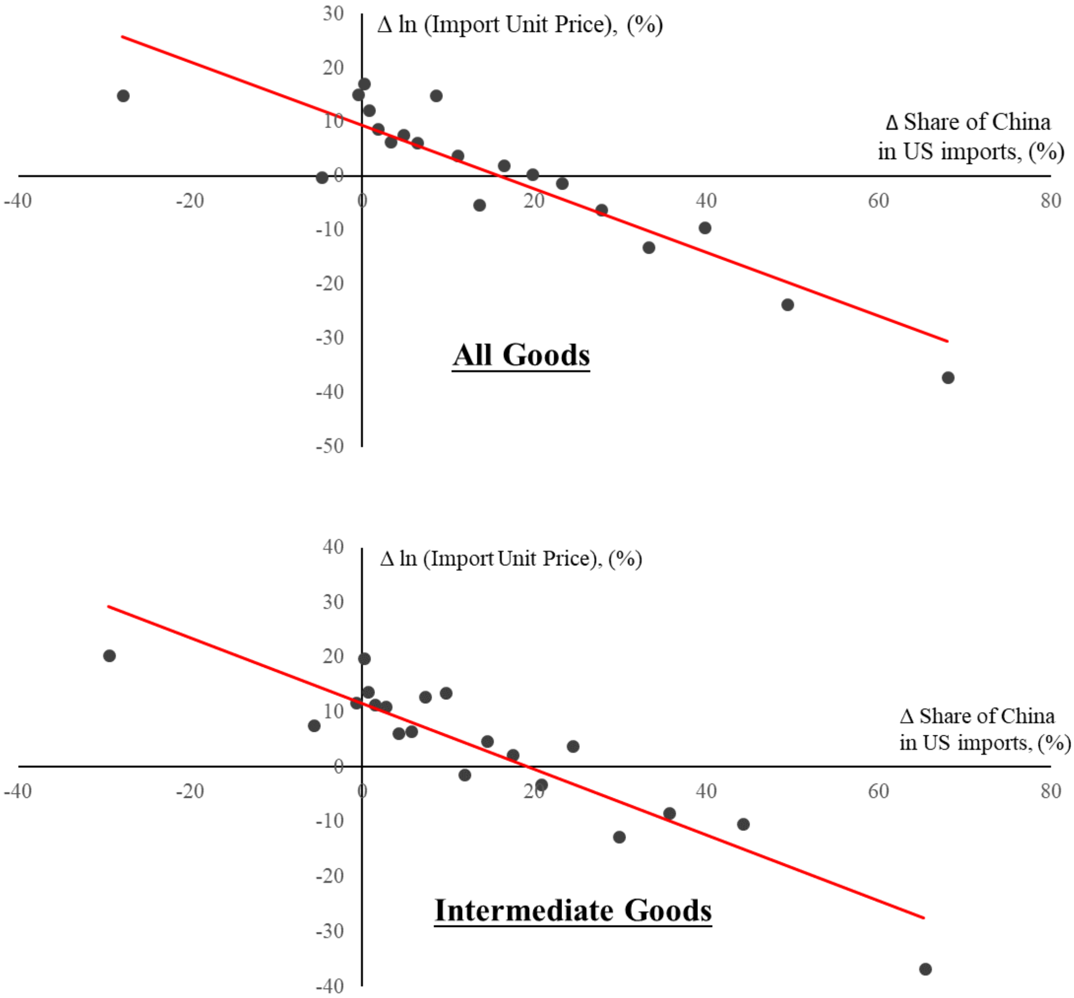


Figure 3: Three Channels across Sectors

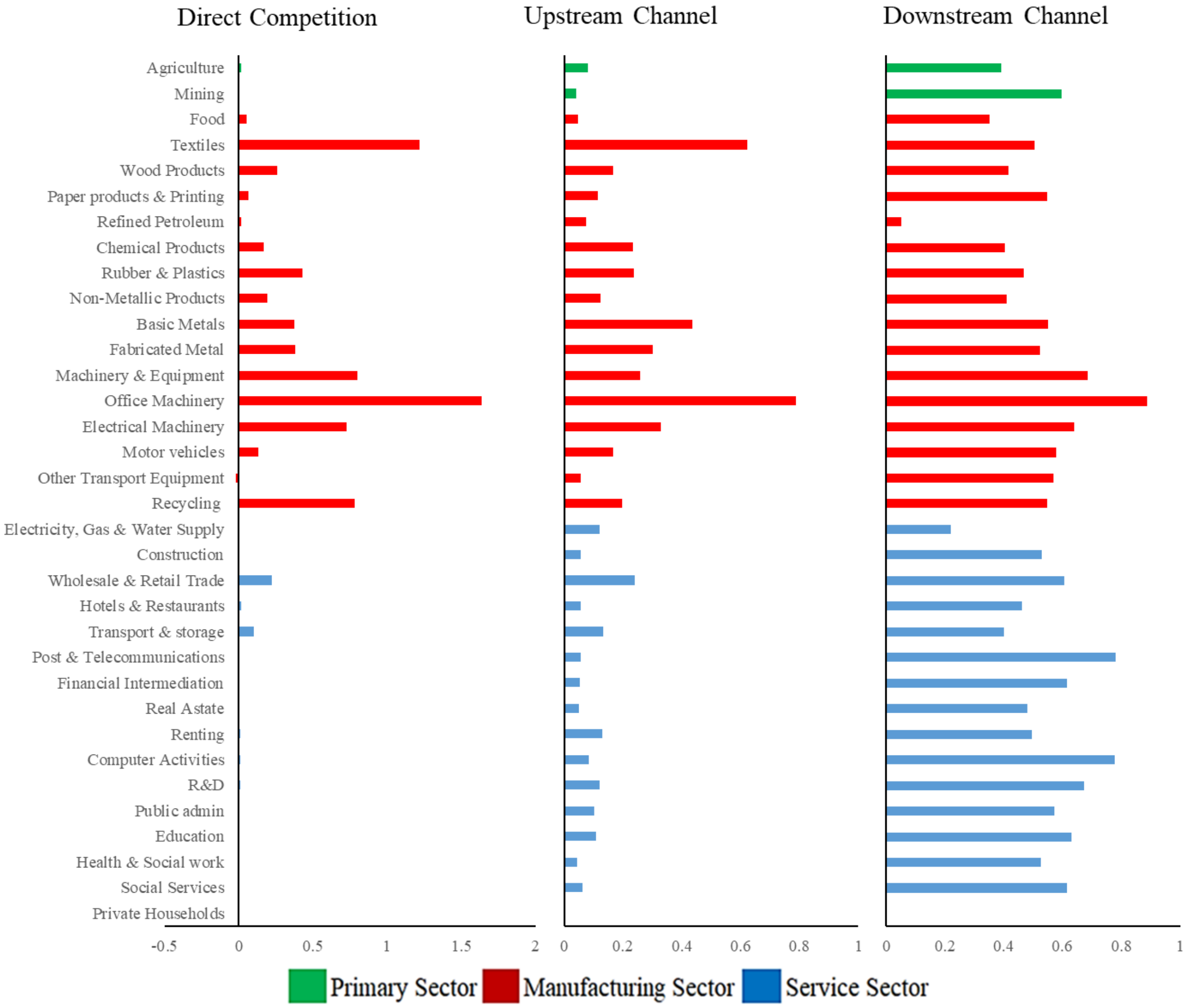


Figure 4: Employment Change against
the Direct Competition Exposure to China Imports across CZs
(% of the working age cohort, 722 Commuting Zones)

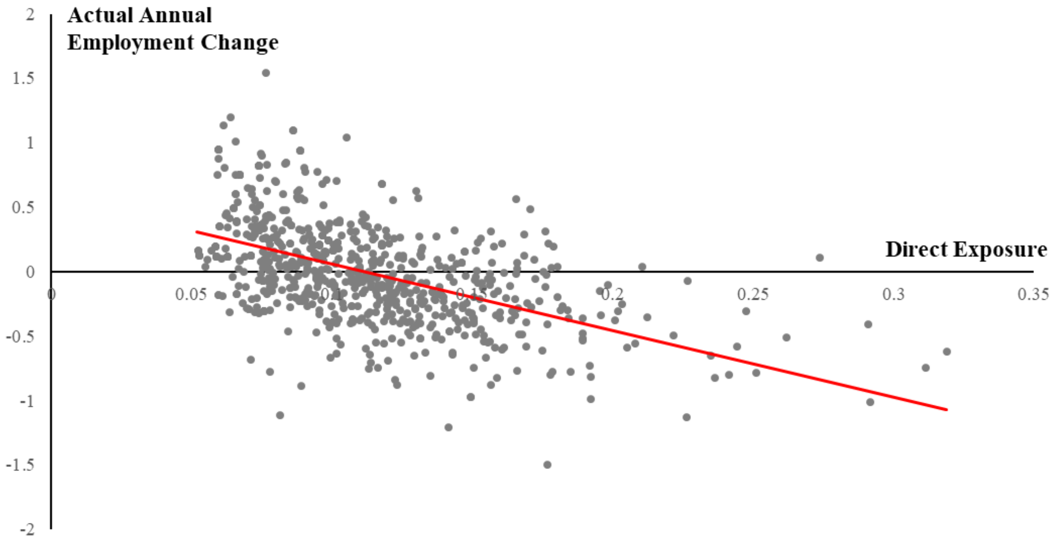


Figure 5: Employment Change against
the Total Effect of Trading with China across CZs
(% of the working age cohort, 722 Commuting Zones)

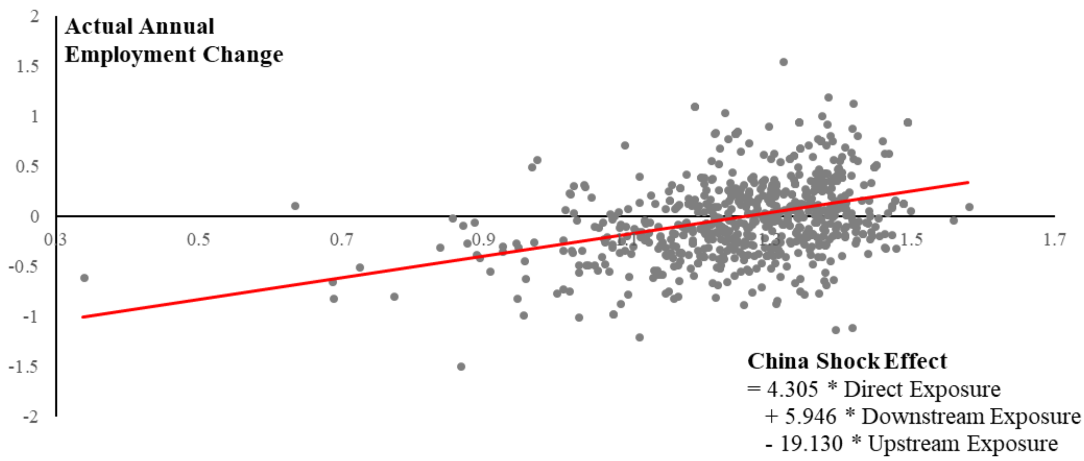


Figure 6: Effects of the China Trade Shock on US Wage Distribution: Comparing the ADH and Supply Chain Approaches

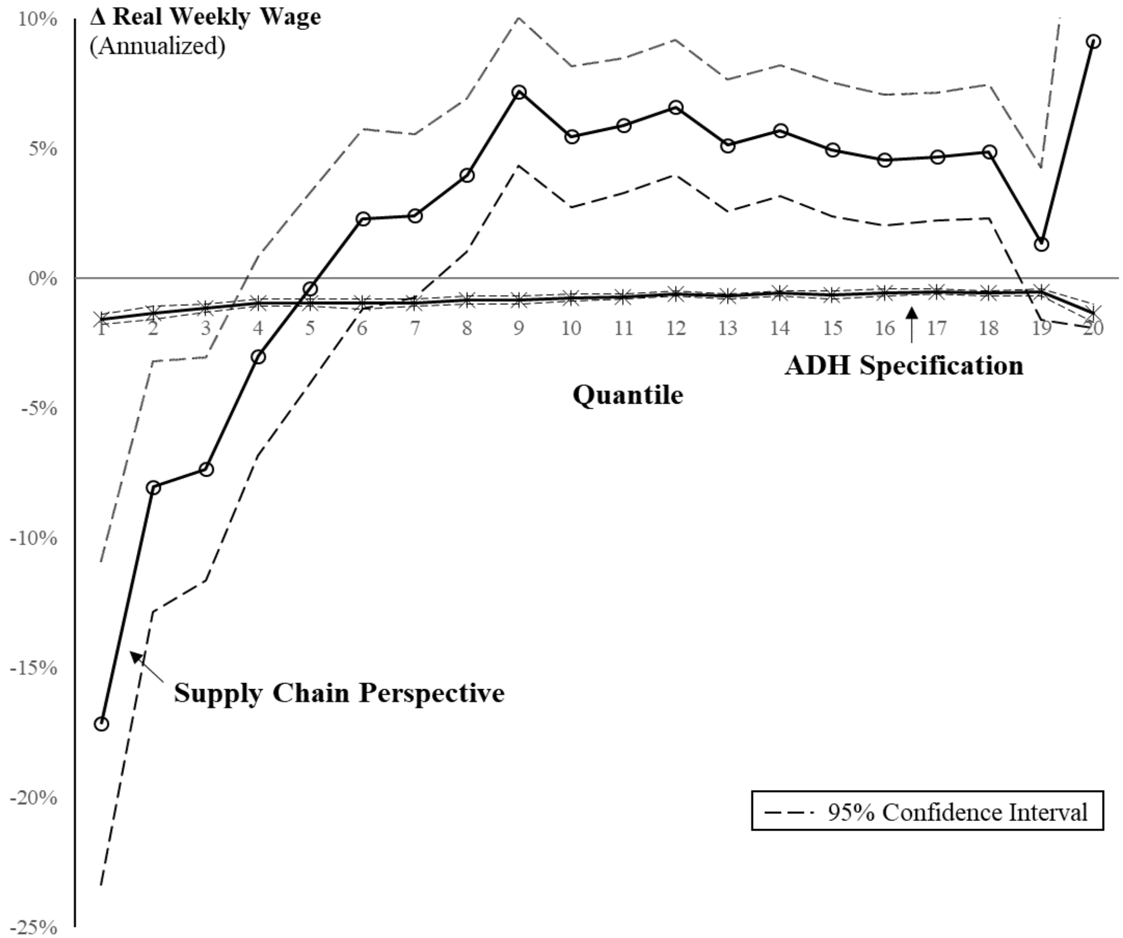


Figure 7: Effect of China Trade Shock on US Wage Distribution: Three Channels

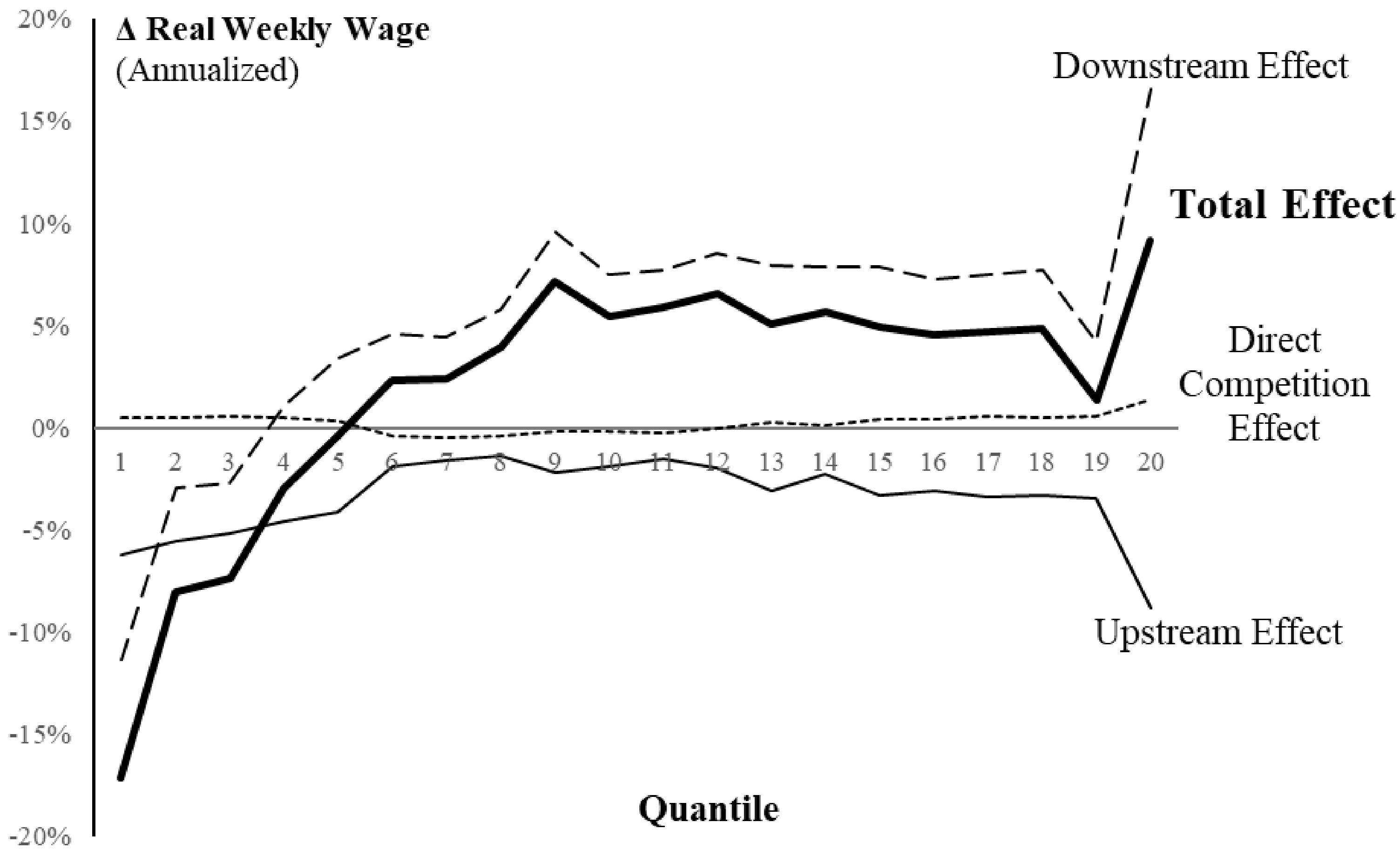


Figure 8: Effect of China Trade Shock on US Wage Distribution: Male and Female Workers

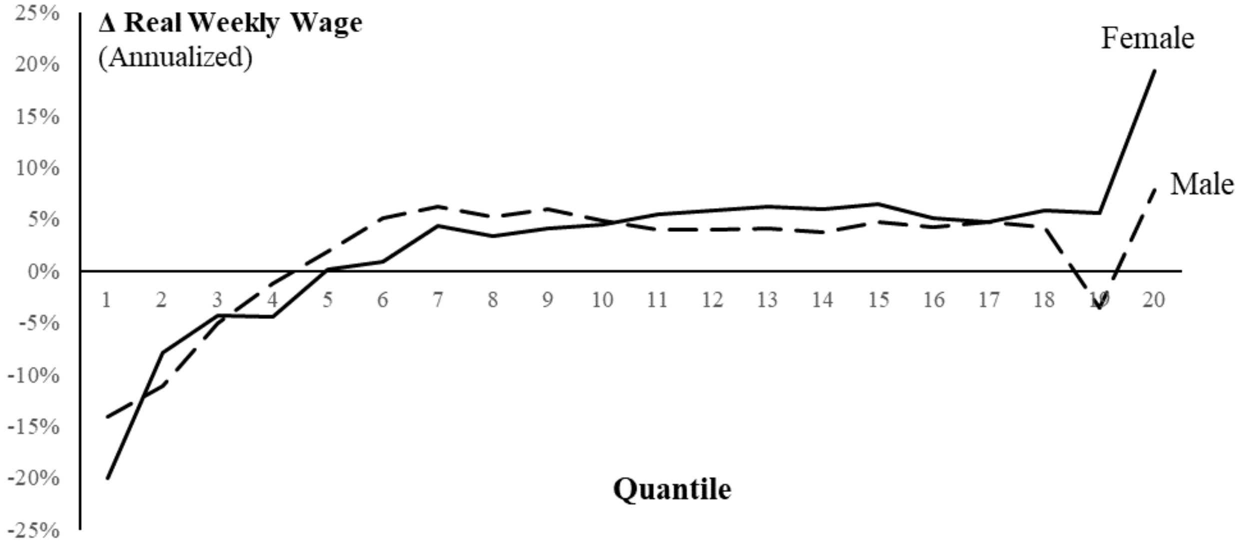
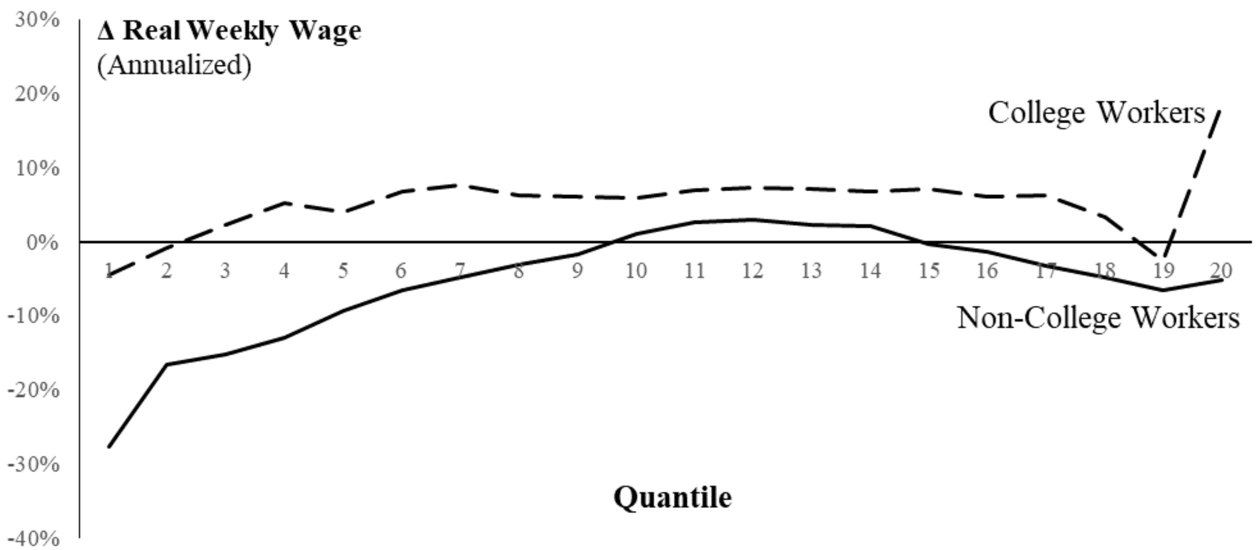


Figure 9: Effect of China Trade Shock on US Wage Distribution: College and Non-College Workers



Appendix Table 1: General Inter-Country Input-Output table

Inputs \ Outputs		Intermediate Use				Final Demand				Total Output
		1	2	⋯	g	1	2	⋯	g	
Intermediate Inputs	1	Z^{11}	Z^{12}	⋯	Z^{1g}	F^{11}	F^{12}	⋯	F^{1g}	Y^{1}
	2	Z^{21}	Z^{22}	⋯	Z^{2g}	F^{21}	F^{22}	⋯	F^{2g}	Y^{2}
	⋮	⋮	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
	g	Z^{g1}	Z^{g2}	⋯	Z^{gg}	F^{g1}	F^{g2}	⋯	F^{gg}	Y^{g}
Value-added		Va^{1}	Va^{2}	⋯	Va^{g}					
Total input		$(Y^{1})'$	$(Y^{2})'$	⋯	$(Y^{g})'$					

where Z^{sr} is an N×N matrix of intermediate input flows that are produced in country s and used in country r; F^{sr} is an N×1 vector giving final products produced in country s and consumed in country r; Y^{s} is also an N×1 vector giving gross outputs in country s; and VA^{s} denotes a 1×N vector of direct value added in country s.

Appendix Table 2: Extended Summary Statistics of Key Variables

	Obs	Mean	Std. Dev.	Min	Max
ΔDirect	722	0.112	0.041	0.052	0.319
ΔDown	722	0.546	0.012	0.505	0.595
ΔUp	722	0.128	0.015	0.101	0.222
G5 IV: ΔDirect	722	0.157	0.061	0.074	0.528
G5 IV: ΔDown	722	0.626	0.025	0.558	0.707
G5 IV: ΔUp	722	0.172	0.023	0.141	0.326
PNTR IV: ΔDirect	722	0.056	0.027	0.018	0.194
PNTR IV: ΔUp	722	0.253	0.004	0.241	0.272
PNTR IV: ΔDown	722	0.081	0.010	0.062	0.144
Routine	722	0.336	0.033	0.267	0.423
Offshoring	722	-0.617	0.289	-1.383	0.544
Female	722	0.462	0.016	0.412	0.498
Edu	722	5.144	0.370	3.767	6.488
Foreign	722	0.307	0.462	0	1
China-Born	722	0.001	0.003	0	0.046
Above 64	722	0.143	0.028	0.050	0.293

Appendix Table 3: Extended Correlation Matrix on the three measures and their three IVs

	ΔDirect	ΔDown	ΔUp	G5 IV: ΔDirect	G5 IV: ΔDown	G5 IV: ΔUp	PNTR IV: ΔDirect	PNTR IV IV: ΔUp	PNTR IV: ΔDown	Routine	Offshoring	Female	Edu	Foreign	China-born	Above 64
ΔDirect	1															
ΔDown	0.134	1														
ΔUp	0.967	0.197	1													
G5 IV: ΔDirect	0.923	0.166	0.920	1												
G5 IV: ΔDown	0.430	0.795	0.496	0.513	1											
G5 IV: ΔUp	0.874	0.210	0.907	0.978	0.543	1										
PNTR IV: ΔDirect	0.923	0.065	0.902	0.961	0.415	0.916	1									
PNTR IV: ΔUp	0.553	0.605	0.586	0.653	0.824	0.677	0.600	1								
PNTR IV: ΔDown	0.864	-0.104	0.873	0.920	0.271	0.902	0.939	0.461	1							
Routine	0.671	0.509	0.680	0.642	0.685	0.608	0.649	0.610	0.509	1						
Offshoring	0.576	0.258	0.544	0.493	0.397	0.420	0.509	0.386	0.441	0.712	1					
Female	0.092	0.257	0.090	0.048	0.235	0.009	0.049	0.030	0.025	0.300	0.156	1				
Edu	-0.182	0.486	-0.171	-0.172	0.361	-0.183	-0.221	0.110	-0.294	0.180	0.112	0.404	1			
Foreign	-0.146	0.444	-0.103	-0.106	0.427	-0.086	-0.153	0.260	-0.239	0.179	0.168	-0.027	0.448	1		
China-Born	-0.016	0.418	0.015	0.005	0.329	0.008	-0.054	0.173	-0.126	0.159	0.255	0.051	0.329	0.360	1	
Above 64	-0.003	-0.347	-0.055	-0.058	-0.283	-0.119	-0.018	-0.273	0.047	-0.187	-0.229	0.251	0.061	-0.353	-0.240	1

Appendix Table 4a: Accounting for Downstream and Upstream Effects: 2000-2014

Dependent Variable = ΔEmp Share	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
ΔDirect	-4.527***	7.672***	-2.276	-0.868	3.145
	(1.552)	(2.021)	(2.223)	(0.956)	(2.258)
ΔDown	0.863*	2.694***	-5.235***	1.678***	3.557***
	(0.480)	(0.995)	(1.123)	(0.368)	(1.318)
ΔUp	3.149	-16.34***	9.873*	3.323	-13.20**
	(3.979)	(5.280)	(5.466)	(2.512)	(5.564)
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.614	0.387	0.434	0.382	0.458

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.37%*	*0.16%*	*0.17%*	*0.04%*	*-0.21%*
Direct Competition Effect	-0.37%	0.63%	-0.19%	-0.07%	0.26%
Downstream Effect	0.45%	1.39%	-2.70%	0.87%	1.84%
Upstream Effect	0.34%	-1.74%	1.05%	0.35%	-1.41%
Total Effect	**0.41%**	**0.27%**	**-1.84%**	**1.15%**	**0.69%**

Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Appendix Table 4b: First Stage Regressions

(a la Growth of Imports from China by Other High Income Countries, 2000-2014)

	ΔDirect	ΔDown	ΔUp
	(1)	(2)	(3)
G5 IV: ΔDirect	0.617***	0.0985	0.0684*
	(0.102)	(0.0815)	(0.0376)
G5 IV: ΔDown	0.00831	0.873***	0.000472
	(0.0438)	(0.0401)	(0.0168)
G5 IV: ΔUp	-0.138	-0.495**	0.404***
	(0.259)	(0.197)	(0.101)
First Stage F Statistics	**127.43**	**69.76**	**102.21**

Note: The first stage regressions have the same controls as the second stage, and are also weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively.

Appendix Table 5: First Stage Regressions:
Excluding the Diagonal Elements in the IO Table in Computing Downstream/Upstream Exposures
(a la Growth of Imports from China by Other High Income Countries)

	ΔDirect	ΔDown	ΔUp
	(1)	(2)	(3)
G5 IV: ΔDirect	0.605***	-0.00783	0.0284***
	(0.0227)	(0.00972)	(0.00399)
G5 IV: ΔDown	-0.179***	0.512***	-0.0358***
	(0.0339)	(0.0188)	(0.00882)
G5 IV: ΔUp	0.186	0.0891*	0.654***
	(0.133)	(0.0520)	(0.0291)
First Stage F Statistics	**266.85**	**100.52**	**224.87**

Note: The first stage regressions have the same controls as the second stage, and are also weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively.

Appendix Table 6: Accounting for Net Imports

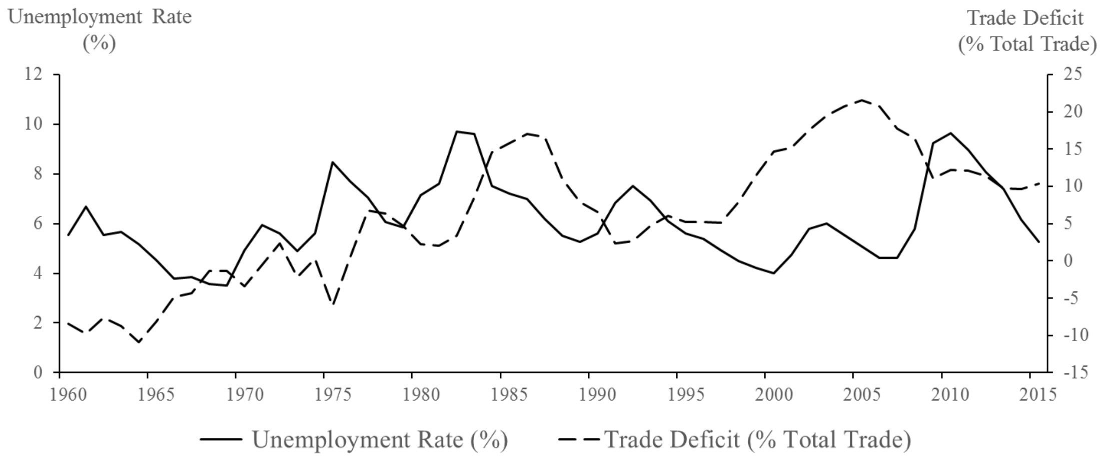
Dependent Variable = ΔEmp Share	Manufacturing (1)	Non-Manufacturing (2)	NILF (3)	Unemployment (4)	Total Employment (5)
ΔNetDirect	-2.562	6.001	-3.261	-0.177	3.439
	(2.201)	(4.119)	(3.920)	(2.031)	(5.017)
ΔDown	0.910	4.273**	-6.770***	1.586*	5.183**
	(0.844)	(1.840)	(1.817)	(0.823)	(2.404)
ΔUp	-4.903	-11.33	13.16	3.066	-16.23
	(4.969)	(10.61)	(9.802)	(5.067)	(12.86)
Census Divisions Fixed Effects	YES	YES	YES	YES	YES
Observations	722	722	722	722	722
R-squared	0.634	0.398	0.359	0.475	0.511

Implied Labor Market Effects of the China Trade Shock

	Manufacturing	Non-Manufacturing	NILF	Unemployment	Total Employment
(For comparison: ADH Specification) Direct Competition Effect	*-0.47%*	*0.16%*	*0.21%*	*0.11%*	*-0.32%*
Net Direct Competition Effect	-0.21%	0.49%	-0.27%	-0.01%	0.28%
Downstream Effect	0.50%	2.33%	-3.69%	0.87%	2.83%
Upstream Effect	-0.63%	-1.46%	1.69%	0.39%	-2.08%
Total Effect	**-0.34%**	**1.37%**	**-2.27%**	**1.24%**	**1.02%**

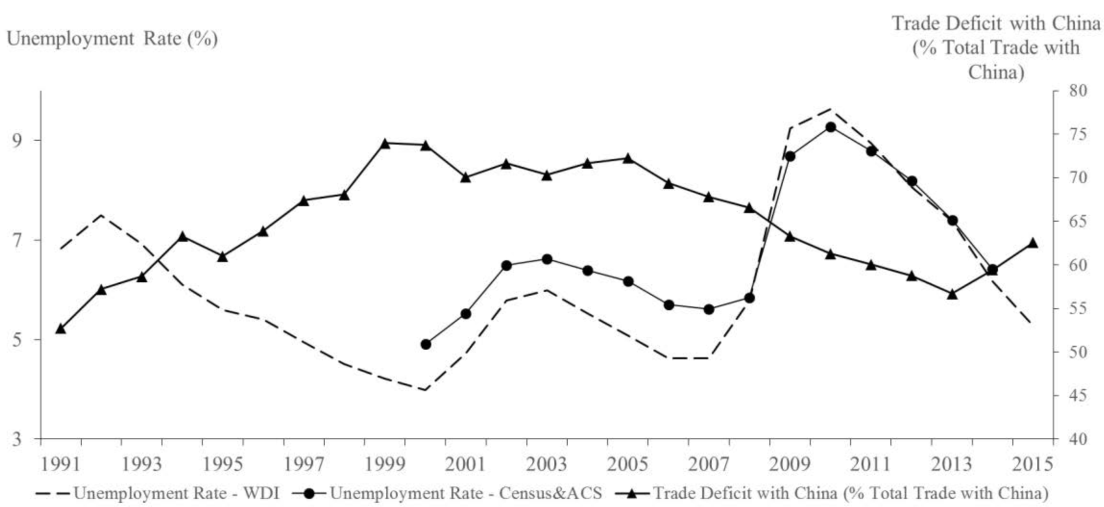
Note: All regressions include a constant and control for the initial employment share in working-age population and census divisions fixed effects. All models are weighted by each commuting zone's start of period working-age population. Robust standard errors clustered by states in parentheses. *, ** and *** denote coefficient statistically significant at the 10%, 5% and 1% levels, respectively. The implied labor market effects are calculated for a hypothetical commuting zone, whose exposure to the China shock is equal to the mean values across 722 Commuting Zones, relative to another hypothetical commuting zone that have no exposure to the China shock.

Appendix Figure 1: US Unemployment Rate vs. Trade Deficit /Total Trade, 1960-2015



Note: All data are taken from the World Bank WDI database.

Appendix Figure 2: US Unemployment Rate vs. Bilateral Trade Deficit with China/Total Trade with China, 1991-2015



Note: The US unemployment rate is taken from the World Bank WDI database, or calculated from the U.S. Census microdata (5% sample for the year 2000) and American Community Survey (ACS) microdata (for the year 2001-2014). The US-China bilateral trade data is taken from UN COMTRADE database.