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Chinese Import Exposure and U.S. Occupational Employment

Marco Del Angel, Sanjana Goswami, and Antonio Rodriguez-Lopez*
University of California, Irvine

Abstract

Import competition has heterogenous impacts across occupations. This paper estimates the effects of import exposure from China on employment in U.S. occupations from 2002 to 2014. After obtaining occupation-specific measures of Chinese import exposure and sorting occupations in tertiles from low to high wage, from routine to non-routine, and from low to high education, we find that Chinese import competition reduces employment in lower-indexed occupations under each sorting criteria. The employment reduction in the lowest tertile of occupations occurs in Chinese-trade exposed and unexposed sectors, which suggests the existence of local labor market effects in the presence of a strong regional concentration of lower-indexed occupations.

JEL Classification: F14, F16

Keywords: import exposure, employment, occupations

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1 Introduction

Occupations differ along several characteristics such as their pay, degree of routineness, and required level of education. These differences should lead to heterogeneous responses of occupational employment levels to technology or international trade shocks. For example, automation is more likely to replace highly-routine occupations, and an international offshoring relationship with an unskilled-labor abundant country is more likely to replace low-skilled occupations in the source country. For the U.S., the greatest trade shock in the last few decades comes from the rise of China as the world's largest trader. In influential papers, Autor, Dorn, and Hanson (2013), Acemoglu, Autor, Dorn, Hanson, and Price (2016), and Pierce and Schott (2016) find a large negative impact of Chinese import competition on U.S. employment.[1] Contributing to this literature, the goal of this paper is to estimate the impact of the 'China shock' on U.S. occupational employment from 2002 to 2014 by distinguishing occupations according to their wage, non-routineness, and education characteristics.

After sorting about 750 occupations from low to high wage, from routine to non-routine, and from low to high education, we document the decline in the share of lower-indexed occupations in total U.S. employment from 2002 to 2014, and an increase in the share of higher-indexed occupations during the same period. At the industry level, we show that the composition of employment in the vast majority of our industries changes in favor of higher-indexed occupations. Our empirical analysis confirms that Chinese import exposure is an important driver of these results, mainly through its large negative employment impact on lower-indexed occupations.

Following Acemoglu, Autor, Dorn, Hanson, and Price (2016), henceforth AADHP, we construct industry-level measures of direct, upstream, and downstream import exposure from China. An industry's direct import exposure is simply related to the change in the industry's real imports from China, while upstream and downstream import exposure take into account input-output linkages across industries. The upstream measure captures Chinese exposure effects flowing from affected buying industries to domestic selling industries, while the downstream measure captures Chinese exposure effects flowing from affected selling industries to their domestic buying industries. From those industry-level variables, we construct occupation-specific measures of Chinese import exposure using industry shares of occupational employment as weights.

Our first empirical specification, which ignores occupational sorting, obtains large and negative

[1] For the 1999-2011 period, Acemoglu, Autor, Dorn, Hanson, and Price (2016) attribute to Chinese import exposure the loss of about 2.4 million jobs.

employment effects of Chinese import exposure on U.S. occupational employment. We estimate the employment effects of direct import exposure, and of two combined measures of import exposure—the first combined measure adds the direct and upstream exposures, while the second measure adds the direct, upstream, and downstream exposures. From 2002 to 2014, the predicted employment losses are 1.05 million jobs from direct exposure, 1.51 million when we consider upstream exposure, and 2.12 million when we consider downstream exposure. These numbers are well in line with the employment losses calculated by AADHP from 1999 to 2011 in their industry-level analysis.

Our second empirical specification considers occupational sorting under our three criteria (real wage, non-routineness, and education). Occupations are arranged into tertiles (low, middle, and high) under each criteria, and we estimate the impact of Chinese import exposure on each occupational tertile—a regression is individually estimated for each occupation-sorting criteria. Our estimation obtains a large negative effect of all types of Chinese exposure on lower-indexed (low wage, routine, low education) occupations, suggesting that a high content of these occupations is embodied in U.S. imports from China.

Additionally, we obtain a mildly-significant positive employment effect of Chinese direct import exposure on high-education occupations. These gains are either the result of *(i)* strong productivity effects—as described by Grossman and Rossi-Hansberg (2008)—by which firms importing cheaper inputs from China increase their productivity and market shares, allowing an expansion in occupations that remain inside the firm, or *(ii)* market share reallocation effects as in Melitz (2003), by which contracting or dying firms are displaced by more productive firms that hire high-education workers more intensively, or *(iii)* a combination of both. The associated employment gains in high-education occupations are sufficiently large to make up for the employment losses in low-education occupations.

Our third and last empirical specification investigates the effects of Chinese import exposure on occupational employment across different sectors. After classifying industries into three sectors (Chinese-trade exposed, non-exposed tradable, and non-exposed non-tradable), this paper finds large and negative employment effects of Chinese exposure on lower-indexed occupations across all sectors, with the exposed sector accounting for 55 to 63 percent of employment losses due to direct exposure. Although the losses in the exposed sector's lower-indexed occupations are expected, the losses in lower-indexed occupations in the non-exposed sector are a novel result. The most likely explanation of this result is the existence of local-labor-market effects as in Autor, Dorn, and Hanson (2013) along with a heavy regional concentration of lower-indexed occupations. Importantly, we find no evidence of Chinese-induced job reallocation of lower-indexed occupations from the exposed sector to the non-exposed sector.

The rest of the paper is organized as follows. Section 2 briefly describes the relevant literature. In section 3 we discuss our data sources, and present a brief overview of the 2002-2014 changes in occupational employment and in our occupation-specific measures of Chinese import exposure. Section 4 presents our empirical analysis for the impact of Chinese import exposure on U.S. occupational employment. Lastly, section 5 concludes.

2 Literature Review

As mentioned above, this paper builds on the recent contributions of Autor, Dorn, and Hanson (2013), AADHP, and Pierce and Schott (2016), who study the impact of the China shock on U.S. employment. The main difference with those papers is that we use occupational employment data, which allows us to exploit differences in occupational characteristics to estimate differential effects of Chinese exposure.[2]

Related to our focus on occupations, there are papers that link trade exposure to U.S. outcomes at the occupational level. Ebenstein, Harrison, and McMillan (2015) estimate the impact of trade exposure on occupational wages using worker-level data from the Current Population Survey (CPS). Similar to our approach, they construct occupation-specific measures of import penetration. Also focusing on U.S. wages, Ebenstein, Harrison, McMillan, and Phillips (2014) find that the negative effects of globalization affect routine occupations the most, and argue—while highlighting the importance of labor reallocation across sectors and into different occupations—that globalization affects wages by pushing workers out of the manufacturing sector to take lower-paying jobs elsewhere. Using also CPS data, Liu and Trefler (2011) examine the impact of trade in services with China and India on U.S. unemployment, occupational switching, and earnings. They also find that routine occupations are the most adversely affected by service imports. Along those lines, Oldenski (2012) shows that U.S. firms are more likely to offshore routine tasks, while less routine tasks are more likely to be performed in their U.S. headquarters. More generally, we find that Chinese import exposure negatively affects employment in lower-indexed occupations whether they are classified by wage, non-routineness, or education.

Keller and Utar (2016) link Chinese import competition and occupational employment. Using Danish employer-employee matched data from 1999 to 2009, they show that import competition

[2]While Pierce and Schott (2016) use the U.S. policy change of granting Permanent Normal Trade Relations (PNTR) status to China as its measure of the China shock, our empirical analysis uses AADHP's measure of Chinese import exposure. However, we are not able to perform a local-labor-market analysis as in AADHP and Autor, Dorn, and Hanson (2013) because our occupational employment data does not have geographical information.

from China explains a large part of the increase in job polarization. They document the decline in employment in mid-wage occupations as well as the rise in employment in both low-wage and high-wage occupations. They also report that in the process of Danish job polarization there is substantial worker reallocation from the manufacturing sector to services. In contrast, in this paper we find that Chinese import exposure reduces employment in low-wage occupations in every sector, and there is not statistically significant evidence of Chinese-induced job creation in the highest-wage occupations. Hence, we do not find evidence of Chinese-induced job polarization based on the wage criterion. We find, however, evidence of strong job destruction in mid-routine occupations in all sectors, which indicates Chinese-induced polarization under the non-routineness criterion. The last result points out that the adversely affected mid-routine occupations are more related to low-wage (and low-education) occupations than to mid-wage occupations.

Under the education criterion, this paper finds that Chinese direct import exposure yields net employment gains due to large job creation in high-education occupations, which dominates the job destruction in low-education occupations. Relatedly, Wright (2014) uses manufacturing data and finds that offshoring—which we interpret as imports of intermediate inputs from China—reduces low-skill employment but increases high-skill employment, with the net effect being positive. Similar to our interpretation, he attributes these results to strong productivity effects.

In terms of welfare, Artuç and McLaren (2015) estimate a dynamic structural model using CPS data and find that an offshoring shock harms low-education workers and benefits high-education workers. Using Danish data in the estimation of a dynamic model of occupational choice, Traiberman (2017) obtains similar evidence for the effects of lower import prices on earnings of low- and high-education workers. In a similar vein, Lee (2017) uses a multi-country Roy model and finds that "China effects"—measured by decreases in trade costs with China and increases in China's productivity—increase between-educational-type inequality in most of the 32 countries in her sample.

3 Data and Overview

Our analysis for the impact of Chinese import exposure on U.S. occupational employment relies on data from several sources. We obtain *(i)* occupational wage and employment data from the Occupational Employment Statistics (OES) database of the Bureau of Labor Statistics (BLS), *(ii)* data on occupation characteristics from the O*NET database, *(iii)* data on trade flows from the United Nations Comtrade database, and *(iv)* U.S. national and industry data from the Bureau of

Economic Analysis (BEA).

This section describes the construction of our occupational employment and Chinese import penetration variables, and provides an overview of their evolution during our period of study (2002-2014).

3.1 Occupational Employment and Occupation Characteristics

The OES database provides yearly occupational employment and mean hourly wage at the four-digit NAICS level. Although the classification of occupations changes across years, the BLS provides concordance tables that allow us to obtain 810 occupations at the six-digit 2010 Standard Occupational Classification (SOC) for the period 2002-2014. We also aggregate the data to 60 industries according to a three-digit NAICS classification of the BEA (see Table A.1 in the Appendix for the list of industries). In the end, our employment-wage data is an industry-occupation panel for years 2002 to 2014.

We construct time-invariant rankings of occupations along three dimensions: from low to high wage, from routine to non-routine, and from low to high education. For the wage ranking, we first obtain the average yearly wage of each occupation across all industries (weighted by employment), and then convert wages to real terms using the BEA's Personal Consumption Expenditure Price Index (PCEPI). Lastly, we obtain each occupation's median real wage throughout the 2002-2014 period, and then rank all occupations from the lowest to the highest median real wage.

The non-routineness and education rankings are based on O*NET data on occupation characteristics. Based on Costinot, Oldenski, and Rauch (2011), the non-routineness ranking is constructed from the O*NET's rating (on a 0 to 100 scale) of the importance of "making decisions and solving problems" for each occupation. On the other hand, the education ranking is created from the O*NET's "job zone" rating (on a 1 to 5 scale) of the level of preparation needed to perform each occupation.[3]

Out of 810, we are able to sort 757 occupations using the wage ranking, and 749 occupations using the non-routineness and education rankings. For illustration and comparison purposes, we convert the three occupation rankings to percentile ranks—in the (0,1) interval—so that, for example, a percentile wage rank of 0.4 for an occupation indicates that 40 percent of occupations have a lower median wage. Hence, for occupation i, we define w_i as its percentile wage rank, q_i

[3] According to the O*NET's website (https://www.onetonline.org/help/online/zones), occupations in job zone 1 need little or no preparation (some may require high school), occupations in job zone 2 need some preparation (usually require high school), occupations in job zone 3 need medium preparation (usually require vocational school or an associate's degree), occupations in job zone 4 need considerable preparation (usually require a bachelor's degree), and occupations in job zone 5 need extensive preparation (usually require a graduate degree).

as its percentile non-routineness rank, and e_i as its percentile education rank. As expected, the correlation between the three percentile ranks is high and positive: 0.65 between w and q, 0.75 between w and e, and 0.59 between q and e.

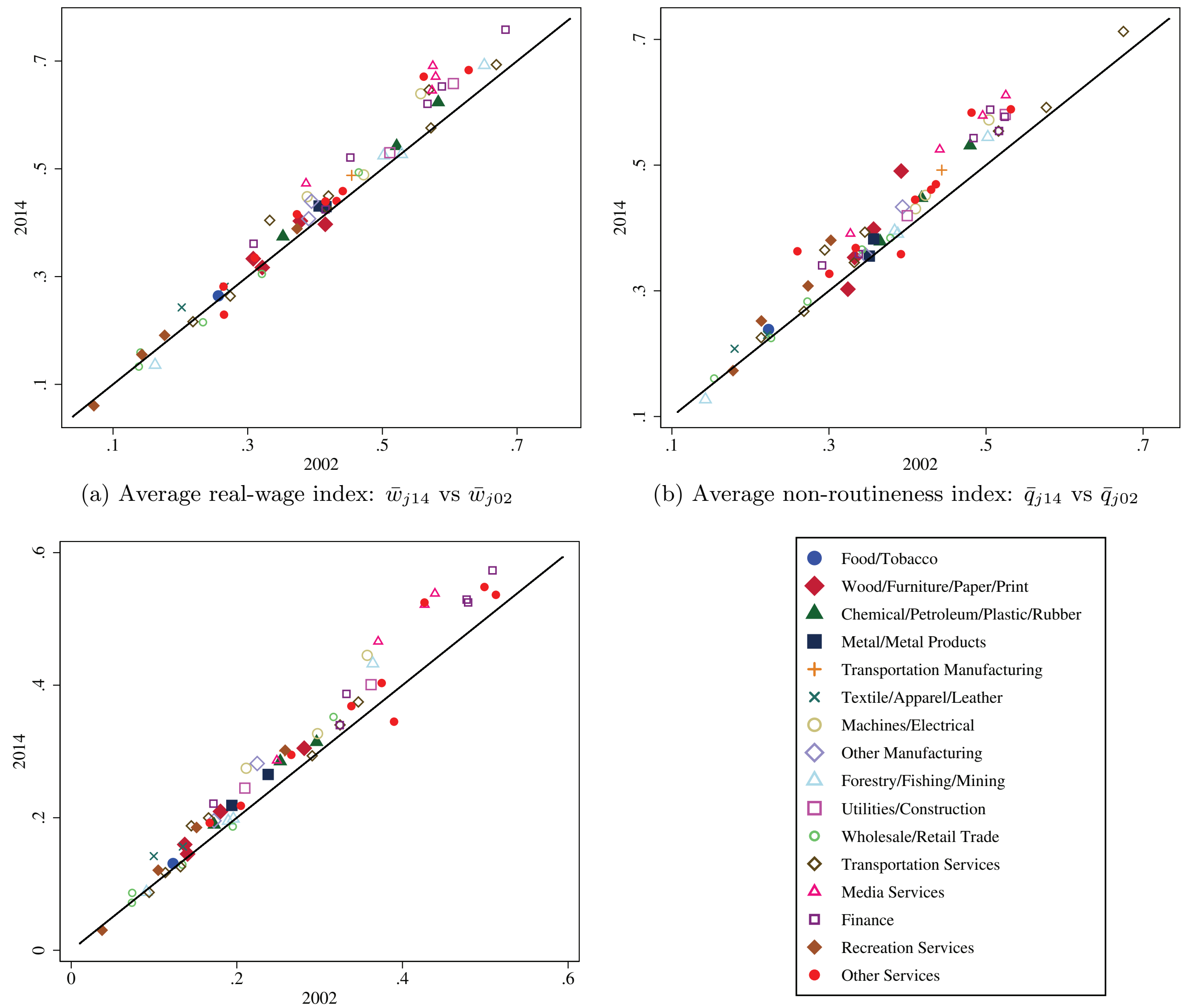
Using our three sorting criteria, we can now look at changes in the composition of U.S. occupational employment during our period of study. Let $\bar{w}_{jt} \in (0,1)$ denote the *average real-wage index* of industry j in year t, defined as

$$\bar{w}_{jt} = \sum_i \left(\frac{L_{ijt}}{L_{jt}} \right) w_i,$$

where L_{ijt} is the total employment in occupation i in industry j at year t, and $L_{jt} \equiv \sum_i L_{ijt}$ is total employment in industry j at year t (L_{ijt}/L_{jt} is the employment share of occupation i in industry j at year t). Note that an increase in $\bar{w}_{jt}$ indicates a higher employment share of high-wage occupations in that industry, while the opposite is true for a reduction in $\bar{w}_{jt}$. With analogous definitions for $\bar{q}_{jt}$ and $\bar{e}_{jt}$—the *average non-routineness index* and the *average education index* of industry j in year t—Figure 1 plots the 2014 values of our three average indexes against their 2002 values for our 60 industries. Most 2014 values are above the 45 degree line for each sorting criteria, showing a generalized change in the composition of U.S. employment toward higher-indexed (higher wage, more non-routine, higher education) occupations. These findings are consistent with previous evidence by Berman, Bound, and Griliches (1994), who similarly reported a shift in employment towards skilled labor in manufacturing during the 1980s.

In addition, Figure 1 classifies our 60 industries into 16 categories. This allows us to identify which industries are more intensive in lower-indexed or higher-indexed occupations, and also to pinpoint similarities and differences across the three indexes. Along the three dimensions, the industries that are intensive in lower-indexed occupations are Recreation Services, Wholesale/Retail Trade, Textile/Apparel/Leather, and Food/Tobacco; the industries that are intensive in higher-indexed occupations are Finance and Media Services; and the industries that are in the middle of the pack are in general manufacturing industries such as Wood/Furniture/Paper/Print, Metal Products, Chemical/Petrolatum/Plastic/Rubber, and Machines/Electrical. On the other hand, Transportation Services is the most non-routine category, and while industries in this category have in general mid-to-high average real wages, they have low average education indexes.

Reinforcing the point of a generalized change in the composition of U.S. employment toward higher-indexed occupations, Figure 2 shows the kernel distributions of occupational employment in 2002 and 2014 under our three sorting criteria. Figure 2a shows that the decline in the employment share of lower-wage occupations occurs up to the 60th percentile, while Figure 2b shows that the



(a) Average real-wage index: $\bar{w}_{j14}$ vs $\bar{w}_{j02}$

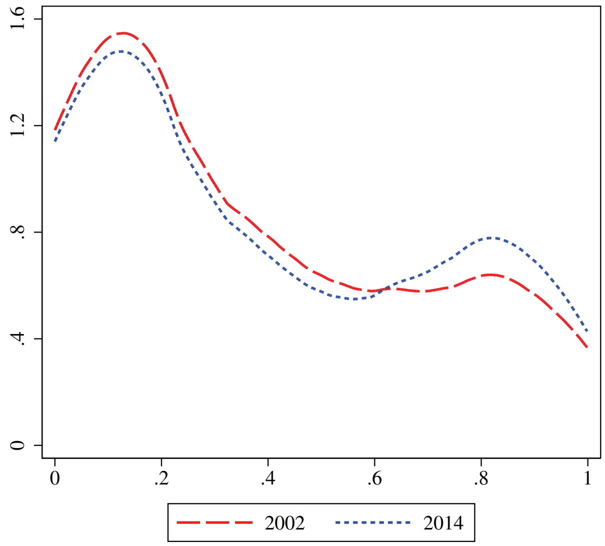
(b) Average non-routineness index: $\bar{q}_{j14}$ vs $\bar{q}_{j02}$

(c) Average education index: $\bar{e}_{j14}$ vs $\bar{e}_{j02}$

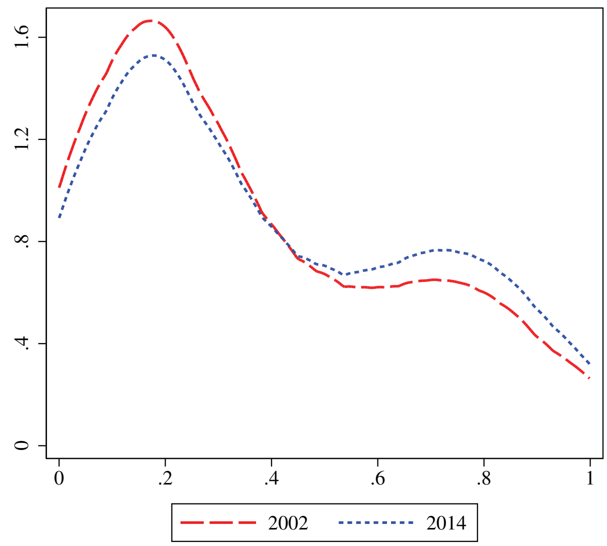
Figure 1: Average Industry-Level Composition of U.S. Occupational Employment in 2002 and 2014

decline in the employment share of routine occupations occurs up to the 40th percentile. An interesting fact from the distributions in Figures 2a and 2b is that they evolved from slightly bimodal in 2002 to distinctly bimodal in 2014. This shows that polarization in the U.S. labor market during the 2002-2014 period is mostly the result of an increase in relative employment in occupations on the right side of the distribution, rather than in occupations on the left side.

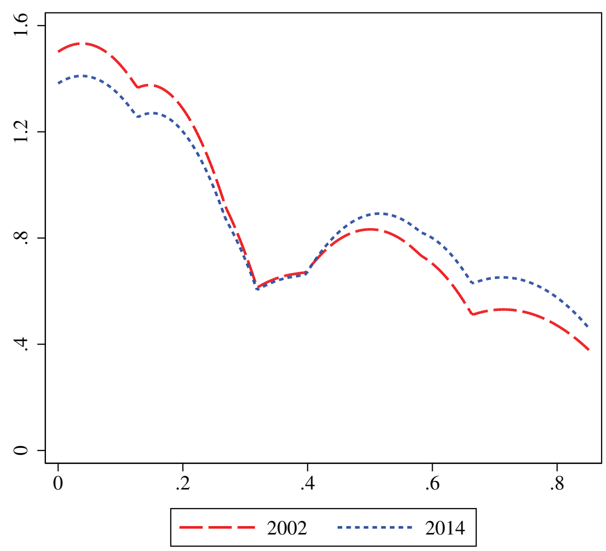
From Figure 2c we see that the kernel distribution of occupational employment based on the education ranking is not as smooth as the distributions based on the wage and non-routineness rankings. This is simply a consequence of the O*NET "job zone" rating, which clusters in integer values from 1 to 5 (corresponding to values 0, 0.05, 0.39, 0.66, and 0.85 in the percentile education



(a) From low to high wage



(b) From routine to non-routine



(c) From low to high education

Figure 2: Distribution of U.S. Occupational Employment in 2002 and 2014 (by Sorting Criterion)

rank, e). Nevertheless, the same story emerges: from 2002 to 2014 there has been a change in the composition of employment in favor of occupations that need a higher level of education.

3.2 Chinese Import Penetration

This section describes our measures of U.S. exposure to Chinese imports. First we discuss the construction of the industry-level measures, and then show how to construct from them the occupation-specific measures of Chinese import penetration.

3.2.1 Industry-Level Chinese Import Penetration

We use the industry-level Chinese import penetration variables of AADHP. The differences are our industry classification, which is based on 60 BEA industries, and our period of study.

AADHP define Chinese import penetration in industry j in year t as the ratio of U.S. industry j's real imports from China in year t to industry j's real domestic absorption in a base year. Taking 2000 as our base year, the Chinese import penetration ratio in industry j in year t is given by

$$IP_{jt} = \frac{\mathbb{M}_{jt}^{C}}{\mathbb{Y}_{j00} + \mathbb{M}_{j00} - \mathbb{X}_{j00}}, \tag{1}$$

where $\mathbb{M}_{jt}^{C}$ are U.S. industry j's real imports from China in year t, $\mathbb{Y}_{j00}$ is industry j's real gross output in 2000, $\mathbb{M}_{j00}$ are industry j's real total imports in 2000, and $\mathbb{X}_{j00}$ are industry j's real total exports in 2000. Nominal U.S. imports from China come from the United Nations Comtrade Database, while U.S. industry-level gross output, total exports, and total imports come from the BEA's Industry and International Economic Accounts. All nominal values are converted to real terms using the BEA's PCE price index.[4]

AADHP are concerned about U.S. demand shocks possibly driving the increase in U.S. imports from China. To isolate the supply-driven component of the rise of China's exports to the U.S., AADHP follow Autor, Dorn, and Hanson (2013) and instrument Chinese import penetration in the U.S. with Chinese exports to other developed economies. Hence, and in line with AADHP, the instrument for our variable in equation (1) is

$$IP_{jt}^{*} = \frac{\mathbb{M}_{jt}^{C*}}{\mathbb{Y}_{j00} + \mathbb{M}_{j00} - \mathbb{X}_{j00}}, \tag{2}$$

where $\mathbb{M}_{jt}^{C*}$ is the sum of Chinese exports to Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland in industry j at year t. The data on Chinese exports to these countries is obtained from Comtrade (in nominal U.S. dollars) and is deflated using the PCE price index.

Chinese import exposure may also affect an industry's employment indirectly through input-output linkages. Inspired by Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), AADHP define *upstream* import penetration as the import effects flowing from directly-impacted buying industries to their domestic supplying industries, and *downstream* import penetration as the effects

[4]The Comtrade annual trade data from 2000 to 2014 is at the ten-digit Harmonized System (HS) product level. We then use the HS-NAICS crosswalk of Pierce and Schott (2012), available up to 2009, to convert the trade data to six-digit NAICS industries. For 2010 to 2014, we use the Foreign Trade Reference Codes from the U.S. Census Bureau (available since 2006): we aggregate up to the level of six-digit HS codes and then use a unique mapping from six-digit HS codes to six-digit NAICS codes. Lastly, we aggregate to the BEA three-digit NAICS classification described in Table A.1.

flowing from directly-impacted supplying industries to their domestic buying industries. While the impact of upstream import exposure on employment is expected to be negative (if buying industries shrink due to foreign competition, then their domestic providers will sell less and will shrink too), the impact of downstream import exposure on employment may be positive or negative (if domestic providers shrink due to foreign competition, then industries may contract due to less access to domestic inputs, but may also expand due to access to cheaper inputs from abroad). In this paper we also take into account employment responses to Chinese import exposure due to first-order upstream and downstream linkages.[5]

The upstream and downstream import penetration variables are weighted averages of the direct import penetration variable in equation (1), with weights obtained from the BEA's 2000 input-output table.[6] Let μ_{gj} denote the value of industry j's output purchased by industry g. Then, upstream weights are computed as $\omega^U_{gj} = \mu_{gj} / \sum_{g'} \mu_{g'j}$ for every g, where $\sum_{g'} \mu_{g'j}$ is industry j's total output value. Therefore, the upstream import penetration from China for industry j is given by

$$UIP_{jt} = \sum_g \omega^U_{gj} IP_{gt}. \tag{3}$$

Likewise, downstream weights for industry j are calculated as $\omega^D_{jg} = \mu_{jg} / \sum_{g'} \mu_{jg'}$ for every g, where $\sum_{g'} \mu_{jg'}$ is the value of industry j's total purchases; hence, downstream import penetration from China for industry j is

$$DIP_{jt} = \sum_g \omega^D_{jg} IP_{gt}. \tag{4}$$

Using (2), we construct the instruments for UIP_{jt} and DIP_{jt} as $UIP^*_{jt} = \sum_g \omega^U_{gj} IP^*_{gt}$ and $DIP^*_{jt} = \sum_g \omega^D_{jg} IP^*_{gt}$.

3.2.2 Occupation-Specific Chinese Import Penetration

Occupations vary in their degree of exposure to Chinese imports. For example, an occupation that is mainly employed in the computer and electronics industry is more exposed to Chinese imports than an occupation mainly employed in the real estate industry. To account for this, we construct occupation-specific measures of Chinese import exposure using the industry-level import penetration variables from the previous section.

[5] AADHP also consider higher-order input-output linkages. We abstract from these higher-order effects in this paper.

[6] First we obtain the BEA's Use-of-Commodities-by-Industries input-output table (in producer's prices) for 71 industries in the year 2000, and then we aggregate it to our 60 industries in Table A.1.

Similar to Ebenstein, Harrison, and McMillan (2015), the occupation-specific trade variables are weighted averages of the industry-level trade variables, with weights determined by each industry's share in the occupation's total employment. Using weights from 2002, which is the first year in our occupational employment data, we define the Chinese import penetration for occupation i as

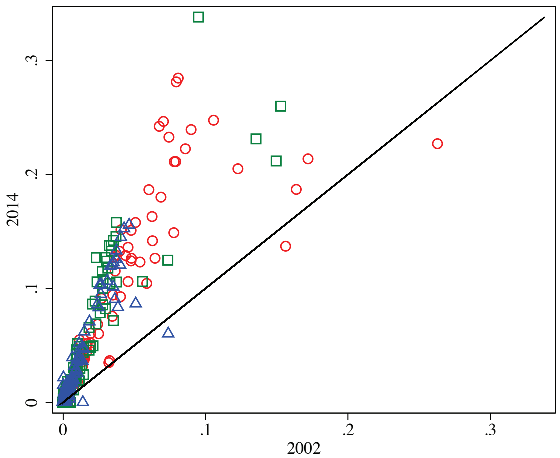
$$IP_{it} = \sum_j \left(\frac{L_{ij02}}{L_{i02}} \right) IP_{jt}, \tag{5}$$

where L_{ij02} is the employment of occupation i in industry j in 2002, $L_{i02} \equiv \sum_j L_{ij02}$ is the total employment in occupation i in 2002, and IP_{jt} is the Chinese import penetration in industry j in year t as described in (1). As weights may respond endogenously to changes in Chinese import penetration—which may lead to selection bias in a measure with changing weights—the best approach in the construction of occupation-specific variables is to use the same weights throughout our period of study.[7] We follow the same formula (and weights) from (5) to construct occupation-specific upstream and downstream Chinese import penetration variables, UIP_{it} and DIP_{it}, as well as occupation-specific import penetration instruments, IP^*_{it}, UIP^*_{it}, and DIP^*_{it}.

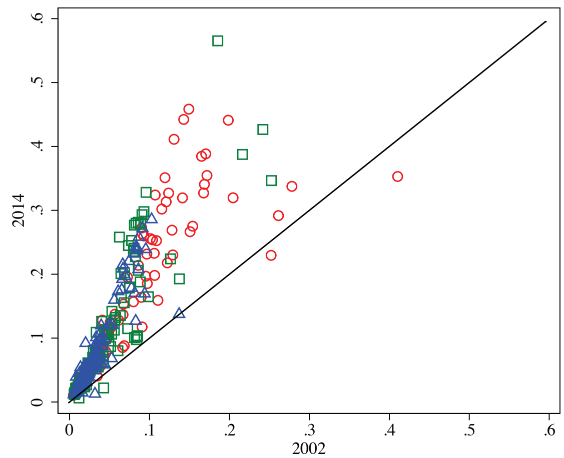
We can now look at the evolution of occupation-specific variables during our period of study. For the 671 occupations that report employment in every year, Figure 3 shows the values in 2002 of the direct import penetration, IP_{it}, and the combined import penetration, $IP_{it} + UIP_{it} + DIP_{it}$, against their values in 2014. Two of our econometric specifications in section 4 classify occupations into tertiles (low, middle, high) for each of our sorting criteria (wage, non-routineness, and education). In line with this, the graphics in the left side of Figure 3 show the same plot of direct import penetration, but differ in their sorting criteria, while the graphics on the right side do the same for the combined measure of import exposure. Occupations marked with a circle denote the lowest-tertile occupations (low wage, routine, low-education), those marked with a square denote the middle-tertile occupations (mid wage, mid-routine, mid-education), and those marked with a triangle denote the highest-tertile occupations (high wage, non-routine, high-education).

First, note that the vast majority of occupations are well above the 45 degree line for both types of Chinese import penetration (direct and combined), indicating extensive occupational exposure to Chinese imports during the period. For the combined import penetration measure, for example,

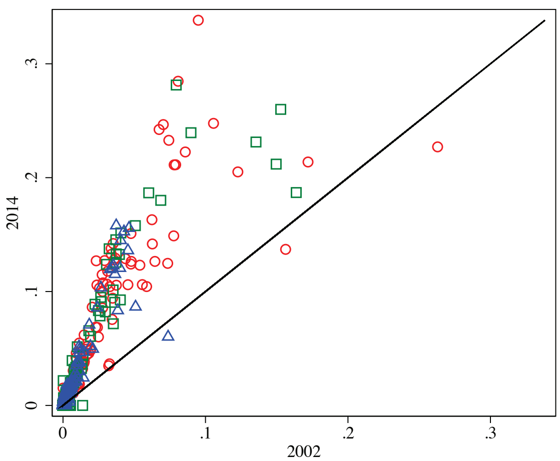
[7] If we allow weights to change, IP_{it} may become irrelevant as a measure of occupation-specific import penetration due to selection bias. For example, suppose that 95 percent of employment of an occupation is in the computer industry, and the remaining 5 percent is in the food services industry. If Chinese import exposure depletes that occupation's employment in the computer industry but does not affect its employment in the food services industry, with weights changing to 10 percent in the computer industry and 90 percent in the other industry, the new import penetration measure for that occupation will likely decline, misleadingly indicating a reduction in that occupation's exposure.



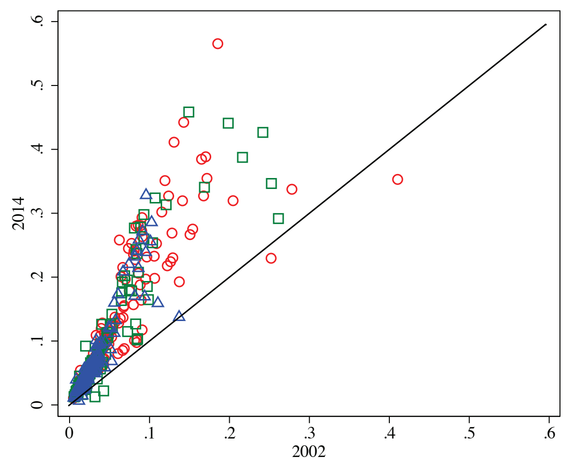
(a) Direct import penetration – Wage



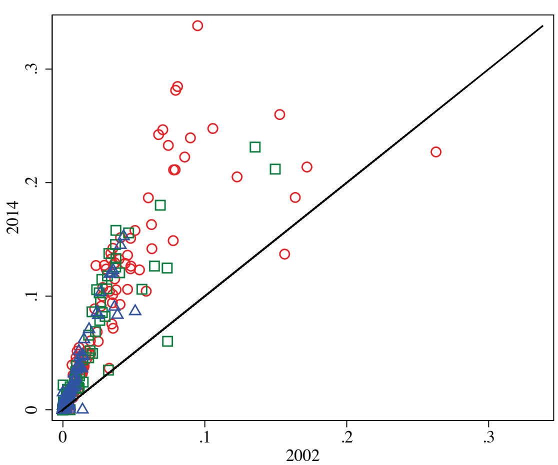
(b) Combined import penetration – Wage



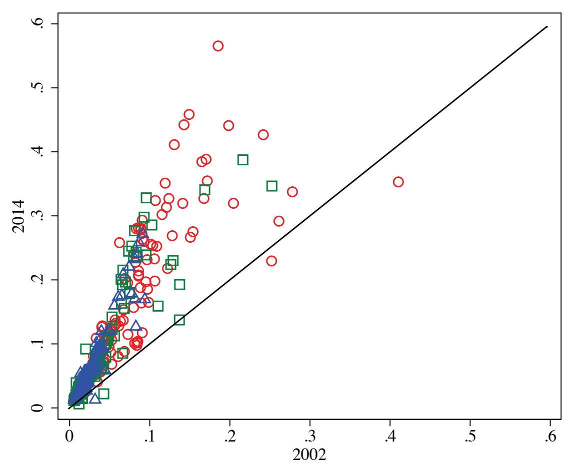
(c) Direct import penetration – Non-routineness



(d) Combined import penetration – Non-routineness



(e) Direct import penetration – Education



(f) Combined import penetration – Education

Figure 3: Occupation-Specific Import Penetration Measures in 2002 and 2014 under Three Sorting Criteria (Wage, Non-routineness, Education): ○ Lowest tertile, □ Middle tertile, △ Highest tertile

only six occupations (out of 671) had a decline in Chinese import exposure from 2002 to 2014. Second, note that across the three sorting criteria and for both measures of import penetration, lowest-indexed occupations are the most exposed to Chinese import competition, while the highest-indexed occupations are the least exposed. This highlights the strong heterogeneity in the exposure of different occupations to Chinese import competition.

3.3 Occupation-Specific Capital Exposure Controls

To control for automation forces, which may substitute workers of some occupations but may complement workers in other occupations, in our specifications below we include occupation-specific measures of capital exposure as regressors. Given that changes in capital stock throughout the period are likely to be endogenous, our time-invariant capital-exposure measures are based on 2002 data, which is the first year in our sample.

From the BEA's Fixed Assets accounts, we obtain the quantity index for net capital stock by asset type for each of our industries in 2002. Eden and Gaggl (2015) argue that information and communication technology (ICT) capital—which is related to software and computer equipment—is a closer to substitute to routine occupations than non-ICT capital (equipment, structures, and intellectual property) and suggest to distinguish between them. Following their classification, each asset is labeled as either ICT capital or non-ICT capital.[8] Then, an industry's ICT capital stock index is the weighted average of the industry's ICT-assets quantity indexes, with the weight of each asset determined by the ratio of the asset's current-cost value to the total current-cost of ICT assets in the industry. We follow an analogous procedure to calculate the non-ICT capital stock index.

Let K^I_{j02} denote the ICT capital stock index for industry j in 2002, and let K^N_{j02} denote the non-ICT capital stock index for industry j in 2002. Hence, similar to the construction of the occupation-specific import penetration variables in (5), the index of ICT capital exposure for occupation i is given by

$$K^I_i = \sum_j \left(\frac{L_{ij02}}{L_{i02}}\right) K^I_{j02}, \tag{6}$$

with a similar definition for K^N_i, which is occupation i's index of non-ICT capital exposure based on 2002 data.

[8] The BEA report 96 types of fixed private assets. Following Eden and Gaggl (2015), 23 of them are classified as ICT capital, and 73 as non-ICT capital.

4 Responses of U.S. Occupational Employment to Chinese Import Exposure

This section estimates the effects of Chinese import exposure on U.S. occupational employment. Given that the effects of import exposure may take some time before they are reflected in employment, we focus our analysis on a panel with three-year changes. Thus, we use periods 2002-2005, 2005-2008, 2008-2011, and 2011-2014. Following AADHP, we use the operator "Δ" to denote annualized changes times 100 so that for any variable X_{it}, we define ΔX_{it} as

$$\Delta X_{it} \equiv \frac{100}{3}\left[X_{it} - X_{it-3}\right].$$

We refer to ΔX_{it} as the "annualized change" in X between $t-3$ and t.

4.1 Employment Responses without Occupational Sorting

We start by ignoring occupational sorting. Hence, our specification to estimate the average impact of Chinese import exposure on occupational employment is

$$\Delta \ln L_{it} = \alpha_t + \beta \Delta IP_{it} + \gamma Z_i + \varepsilon_{it}, \tag{7}$$

where for occupation i and between $t-3$ and t, $\Delta \ln L_{it}$ is the annualized change in log employment, ΔIP_{it} is the annualized change in Chinese import exposure, α_t is a time fixed effect, and ε_{it} is an error term. For each occupation i, the term Z_i is a vector of time-invariant *production controls* that includes the 2002 values of the log average real wage, and the log of the ICT and non-ICT capital-stock indexes (K_i^I and K_i^N). Our coefficient of interest is β, which represents the semi-elasticity of occupational employment to Chinese import exposure.

Table 1 presents the results of the estimation of the specification in (7). All regressions in Table 1, as well as all the following regressions, are weighted by 2002 employment and show standard errors clustered at the occupation level. Columns 1-3 use as main regressor the annualized change in direct import penetration as defined in (5), while columns 4 and 5 use instead annualized changes of combined import penetration measures. The first combined measure adds the direct and upstream measures ($IP_{it} + UIP_{it}$), while the second combined measure adds the direct, upstream, and downstream measures ($IP_{it} + UIP_{it} + DIP_{it}$). Consequently, in the instrumental variables (IV) regressions, the instrument in columns 2-3 is ΔIP_{it}^{*}, the instrument in column 4 is $\Delta(IP_{it}^{*} + UIP_{it}^{*})$, and the instrument in column 5 is $\Delta(IP_{it}^{*} + UIP_{it}^{*} + DIP_{it}^{*})$.

All the estimates for β in the six columns of Table 1 are negative and statistically significant at least at the 5 percent level, showing that—as found by Autor, Dorn, and Hanson (2013) at the

Table 1: Estimation of U.S. Occupational Employment Responses to Chinese Import Exposure

	OLS	**IV Estimation**			
	(1)	(2)	(3)	(4)	(5)
Direct import exposure	-0.97***	-1.91***	-1.16***		
	(0.34)	(0.37)	(0.40)		
Combined import exposure I				-0.83**	
(direct + upstream)				(0.38)	
Combined import exposure II					-0.69**
(direct + upstream + downstream)					(0.30)
Production controls	No	No	Yes	Yes	Yes
Observations	2,672	2,672	2,444	2,444	2,444

Notes: All regressions include time fixed effects (not reported) and are weighted by 2002 employment. Standard errors (in parentheses) are clustered at the occupation level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

commuting-zone level and by AADHP at the industry level—Chinese import exposure is associated with job losses in the United States. Column 1 presents the OLS estimation without production controls, and column 2 presents the analogous IV estimation. Note that the estimate for β in column 2 is almost twice as large as the coefficient in column 1, which highlights the importance of the IV approach to take care of a strong endogeneity bias. Columns 3-5 include production controls. Comparing columns 2 and 3, notice that the magnitude of the estimate for β declines by almost 40 percent (the coefficient changes from -1.91 to -1.16), which indicates that the exclusion of production controls leads to an overestimation of the negative impact of Chinese imports on U.S. employment.

From column 4, note that the coefficient on import exposure declines in magnitude if we use instead the combined measure of direct plus upstream import penetration (the coefficient changes from -1.16 to -0.83). This, however, does not imply that the negative effects of Chinese import exposure on U.S. occupational employment are smaller when we consider upstream input-output linkages. To know this, we need to separately calculate the 2002-2014 predicted employment losses from columns 3 and 4. Following Autor, Dorn, and Hanson (2013) and AADHP, the formula to calculate column 4's predicted employment changes from Chinese import exposure from 2002 to 2014 is

$$\textit{Predicted employment change} = \sum_i \left[1 - e^{-\hat{\beta}\rho(IP_{i14} - IP_{i02})}\right] L_{i14}, \tag{8}$$

where $\rho = 0.78$ is the partial $R-$squared from the first-stage regression of ΔIP_{it} on ΔIP^*_{it} from the specification in column 2. We derive a similar expression to calculate column 4's predicted losses, with the value of ρ kept constant at 0.78.

Predicted employment losses from 2002 to 2014 are 1.05 million from direct exposure (column 3) and 1.51 million from the combined direct and upstream exposure (column 4). Therefore, upstream input-output links further reduce U.S. employment by about 0.46 million jobs. Column 5 adds downstream exposure to the combined measure and reports a smaller estimate for β (-0.69), but again, we need to calculate predicted employment losses because changes in the combined exposure measure are likely to be larger. Indeed, column 5's predicted employment losses from Chinese exposure are 2.12 million, so that about 0.61 million jobs (2.12 million minus 1.51 million) are lost due to downstream input-output linkages.[9]

4.2 Employment Responses with Occupational Sorting

The main contribution of this paper is that we can analyze the effects of Chinese import exposure on different types of occupations classified by either wage level, degree of non-routineness, or required education. For each of these criteria, we sort occupations into tertiles (low, middle, and high) using the percentile ranks described in section 3.1. Thus, the econometric specification with occupational sorting is

$$\Delta \ln L_{it} = \sum_{k=1}^{3} \left[\alpha_{kt}^{\ell} + \beta_k^{\ell} \Delta IP_{it} + \gamma_k^{\ell} Z_i \right] \mathbb{1}_i\{T_k^{\ell}\} + \varepsilon_{it}, \tag{9}$$

where $\ell \in \{w, q, e\}$ denotes the sorting criteria (wage, non-routineness, or education), $k \in \{1, 2, 3\}$ indicates the tertile (from low to high), $\mathbb{1}_i\{T_k^{\ell}\}$ is a dummy variable taking the value of 1 if occupation i belongs to tertile k under criteria ℓ, and α_{kt}^{ℓ} accounts for tertile-time fixed effects. This specification is estimated separately for each sorting criteria. Hence, for each $\ell \in \{w, q, e\}$, the coefficients of interest are β_1^{ℓ}, β_2^{ℓ}, and β_3^{ℓ}, which indicate the employment semi-elasticity to Chinese import exposure for each occupational tertile.

Table 2 shows our estimation of (9) for the impact of direct import exposure. Production controls are included in even columns and excluded in odd columns. All six columns show strong and highly-significant negative effects of direct Chinese import exposure on the lowest occupational tertiles (low-wage, routine, low-education occupations). Therefore, Chinese import exposure is

[9] These predicted losses are well in line with the industry-level numbers reported by AADHP for the period from 1999 to 2011. They calculate direct losses of 0.56 million jobs, and combined direct and upstream losses of 1.58 million jobs. Considering higher-order upstream linkages—which we do not do—the losses increase to 1.98 million. AADHP do not report losses from downstream linkages because their downstream import exposure coefficients are not statistically significant. We only use combined measures of import exposure—instead of separately including them in the regressions as AADHP do—because the correlation between them is very high, which would highly reduce the precision of our estimation (the correlation is 0.63 between direct and upstream exposures, 0.61 between direct and downstream exposures, and 0.59 between upstream and downstream exposures).

Table 2: Estimation of U.S. Occupational Employment Responses to Chinese Direct Import Exposure: By Tertiles based on Three Occupation-Sorting Criteria

	Wage		**Non-routineness**		**Education**	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct import exposure						
Lowest tertile	-2.42***	-1.81***	-2.07***	-1.46***	-2.19***	-1.63***
	(0.60)	(0.55)	(0.52)	(0.43)	(0.52)	(0.50)
Middle tertile	0.14	0.91	-2.73***	-2.25***	-0.78	-0.04
	(0.75)	(1.01)	(0.46)	(0.71)	(0.87)	(1.12)
Highest tertile	-0.21	2.35	0.63	3.42	3.40	7.08*
	(2.16)	(2.64)	(1.80)	(2.47)	(2.85)	(4.21)
Production controls	No	Yes	No	Yes	No	Yes
Observations	2,460	2,444	2,660	2,436	2,660	2,436

Notes: All regressions include tertile-time fixed effects (not reported). Standard errors (in parentheses) are clustered at the occupation level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

related to job losses in all kinds of lower-indexed occupations, suggesting that a high content of these types of occupations is embodied in U.S. imports from China. As well, columns 3-4 show statistically-significant evidence of Chinese-induced job losses in mid-routine occupations.

Under the education-sorting criterion with production controls, column 6 shows a positive and mildly significant coefficient for the impact of direct import exposure on high-education occupations. The predicted employment expansion in high-education occupations—while employment declines in occupations in the lowest tertiles—can be the result of *(i)* reallocation of workers from low- to high-education occupations, *(ii)* strong productivity effects in the presence of complementarities between low- and high-education occupations, or *(iii)* Melitz-type reallocation of markets shares from low-productivity firms to high-productivity firms.

The first scenario is, however, unlikely, as released low-educated workers would have to retool themselves with college degrees, or a large number of highly-educated workers would have to be employed in low-education occupations in the first place. Regarding the second scenario, and as discussed by Grossman and Rossi-Hansberg (2008) and Groizard, Ranjan, and Rodriguez-Lopez (2014), the offshoring of lower-indexed occupations allows firms to reduce marginal costs (so that productivity increases), which allows them to set lower prices and capture larger market shares; this translates to higher employment in occupations that remain inside the firm, with larger employment gains if there is complementarity across occupations.[10] Lastly, the third scenario requires that

[10] Groizard, Ranjan, and Rodriguez-Lopez (2014) show that the productivity effect is a source of job creation in offshoring firms even if tasks are substitutable (as long as the elasticity of substitution across tasks is smaller than the elasticity of substitution across goods), but the effect is stronger if tasks are complementary.

contracting or dying firms have a disproportionately large share of low-educated workers, while expanding high-productivity firms either upgrade their labor force or have a disproportionately large share of highly-educated workers.[11] The most plausible mechanism for the results in column 6 is a combination of the second and third scenarios.

Table 3 considers the occupational employment effects of combined import exposure. For both combined measures, the implications described from direct import exposure on lower-indexed occupations remain robust: there is Chinese-induced job destruction in low-wage, routine and mid-routine, and low-education occupations when we consider input-output linkages across industries. Similar to what we observed in Table 1, the import-exposure estimates decline in magnitude when we use the combined measures. However, this does not imply smaller employment effects because changes in the combined import-exposure measures are likely to be larger. To shed light on this, we need to calculate predicted employment changes for each occupational tertile (under each sorting criteria) using formulas that are analogous to equation (8).

Table 4 presents the predicted employment changes from Chinese import exposure based on the regressions with production controls (in the even columns) of Tables 2 and 3, as well as for other specifications described below. For our three sorting criteria, the first three rows of Table 4 show that predicted employment losses for occupations in the lowest tertile are between 0.6 and 0.8 million due to direct exposure, are between 1.1 and 1.3 million when we consider upstream links, and further increase to between 1.43 and 1.75 million if we also consider downstream links. These losses are the main component of the average employment losses reported in the previous section. In addition, the statistically-significant predicted job losses in mid-routine occupations range between 0.5 million from direct exposure to about 0.9 million when considering upstream and downstream linkages.

Column 6 in Table 2 shows a strong positive effect of direct import exposure on high-education occupations, with the first row of Table 4 showing that the 1.2 million predicted job gains in high-education occupations more than make up for the 0.8 million job losses in low-education occupations. However, column 6 of Table 3 shows that the high-education import exposure coefficient loses its statistical significance once we consider input-output linkages (for both combined measures). Hence, although the second and third row of Table 4 show predicted job gains in high-education occupations that continue to be larger than job losses in low-education occupations, these

[11] As mentioned below, Abowd, McKinney, and Vilhuber (2009) show that U.S. firms are more likely to die if they hire a disproportionately large share of workers from the lowest quartile of the human capital distribution, and are less likely to die if they disproportionately hire workers from the highest quartile.

Table 3: Estimation of U.S. Occupational Employment Responses to Chinese Combined Import Exposure: By Tertiles based on Three Occupation-Sorting Criteria

	Wage		**Non-routineness**		**Education**	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Combined import exposure I *(direct + upstream)*						
Lowest tertile	-2.00***	-1.47***	-1.69***	-1.16***	-1.72***	-1.19***
	(0.46)	(0.42)	(0.41)	(0.35)	(0.38)	(0.36)
Middle tertile	0.06	0.62	-1.86***	-1.55**	-0.24	-0.13
	(0.55)	(0.77)	(0.48)	(0.64)	(0.78)	(0.86)
Highest tertile	-0.37	1.76	0.60	3.08	1.64	4.83
	(1.62)	(2.12)	(1.45)	(2.08)	(2.03)	(3.25)
B. Combined import exposure II *(direct + upstream + downstream)*						
Lowest tertile	-1.55***	-1.12***	-1.30***	-0.87***	-1.40***	-0.99***
	(0.37)	(0.34)	(0.31)	(0.27)	(0.32)	(0.31)
Middle tertile	-0.13	0.17	-1.51**	-1.42***	0.29	-0.09
	(0.45)	(0.60)	(0.59)	(0.52)	(0.97)	(0.65)
Highest tertile	-0.36	1.08	0.44	2.17	1.52	3.78
	(1.41)	(1.70)	(1.35)	(1.82)	(1.83)	(2.69)
Production controls	No	Yes	No	Yes	No	Yes
Observations	2,460	2,444	2,660	2,436	2,660	2,436

Notes: All regressions include tertile-time fixed effects (not reported). Standard errors (in parentheses) are clustered at the occupation level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

job gains are no longer statistically significant. Thus, the Chinese-induced positive productivity effects on U.S. firms occur through direct exposure, and not through input-output linkages.

The results of Tables 2, 3, and the first three rows of Table 4 suggest, not surprisingly, substantial overlap in the employment losses of low-wage, routine, and low-education occupations. They also suggest an overlap between mid-routine occupations and low-wage, low-education occupations. Moreover, although there are always predicted job gains in the highest-tertile occupations along the three criteria, they are only significant for direct exposure in high-education occupations. This indicates either that *(i)* high-education occupations that benefit from Chinese exposure are not necessarily concentrated in non-routine, high-wage occupations, or that *(ii)* there is a large fraction of Chinese-impacted low-education occupations that are non-routine or high-wage, which average out employment gains in other higher wage and non-routine occupations, or *(iii)* a combination of both.

Table 4: Predicted Employment Changes (in Thousands) from Chinese Import Exposure (2002-2014)

	Wage			Non-routineness			Education		
	Lowest tertile	*Middle tertile*	*Highest tertile*	*Lowest tertile*	*Middle tertile*	*Highest tertile*	*Lowest tertile*	*Middle tertile*	*Highest tertile*
Table 2									
Direct import exposure	**-731**	205	606	**-602**	**-497**	876	**-794**	-9	**1,227**
Table 3, panel A									
Direct + upstream	**-1,292**	266	813	**-1,101**	**-609**	1,352	**-1,216**	-56	1,580
Table 3, panel B									
Direct + upstream+downstream	**-1,751**	112	811	**-1,429**	**-907**	1,526	**-1,662**	-66	2,097
Table 5									
Direct import exposure									
Exposed	**-380**	122	2,187	**-243**	**-257**	1,954	**-401**	42	2,248
Non-exposed tradable	**-23**	**25**	5	**-22**	**-17**	**17**	**-32**	**16**	10
Non-exposed non-tradable	**-289**	117	-126	-119	**-247**	249	-216	-27	117
Table 6, panel A									
Direct + upstream									
Exposed	**-530**	199	3,083	**-293**	-290	2,464	**-508**	98	2,991
Non-exposed tradable	**-36**	**38**	13	**-32**	-18	**23**	**-46**	**20**	17
Non-exposed non-tradable	-448	81	-453	-448	-323	565	-148	-201	-122
Table 6, panel B									
Direct + upstream + downstream									
Exposed	**-720**	181	3,311	**-421**	**-381**	2,627	**-705**	67	3,277
Non-exposed tradable	**-40**	**45**	19	**-36**	-20	**29**	**-51**	**23**	19
Non-exposed non-tradable	209	-28	**-871**	-253	-801	1,070	94	-161	-282

Notes: Reported quantities represent the change in employment attributed to instrumented changes in import exposure in all specifications reported in Tables 2-5 with wage and capital controls. Negative values indicate that import exposure reduces employment. Equation (8) shows the general formula to calculate predicted employment changes. The numbers in bold denote predicted changes corresponding to statistically significant coefficients in Tables 2-5. The predicted employment changes changes from Table 1 are -1,051,651 for the direct effect, -1,512,415 for the direct and upstream combined effect and -2,122,630 for the direct, upstream and downstream combined effect of import exposure.

4.3 Employment Responses by Sector Exposure

The last part of our empirical analysis expands the specification in equation (9) to account for different impacts of Chinese import exposure across occupational employment in different sectors. This exercise is motivated by AADHP, who classify industries into three sectors—exposed, non-exposed tradable, and non-exposed non-tradable—according to industry-level measures of (direct and upstream) Chinese import exposure, to investigate different sectoral employment responses within a local-labor-market analysis, as well as to look for evidence of employment reallocation across sectors.[12]

As in AADHP, we begin by dividing our 60 industries into three sectors, $s \in \{1, 2, 3\}$, with '1' denoting the exposed sector, '2' denoting the non-exposed tradable sector, and '3' denoting the non-exposed non-tradable sector.[13] The sectoral econometric specification can then be written as

$$\Delta \ln L_{ist} = \sum_{k=1}^{3} \Big[\alpha^{\ell}_{kst} + \beta^{\ell}_{k1} \Delta IP_{it} \times \mathbb{1}_s\{1\} + \beta^{\ell}_{k2} \Delta IP_{it} \times \mathbb{1}_s\{2\} + \beta^{\ell}_{k3} \Delta IP_{it} \times \mathbb{1}_s\{3\} + \gamma^{\ell}_{ks} Z_{is} \Big] \mathbb{1}_i\{T^{\ell}_k\} + \varepsilon_{ist}, \tag{10}$$

where, between $t-3$ and t, $\Delta \ln L_{ist}$ is the annualized change in log employment of occupation i in sector s, ΔIP_{it} is the annualized change in Chinese import exposure of occupation i, and Z_{is} is a vector of time-invariant production controls of occupation i in sector s.[14] Also, $\mathbb{1}_s\{S\}$ is a dummy variable taking the value of 1 if $s \equiv S$, for $S \in \{1, 2, 3\}$, and $\mathbb{1}_i\{T^{\ell}_k\}$ is a dummy variable taking the value of 1 if occupation i belongs to tertile k under sorting criterion $\ell \in \{w, q, e\}$. The term α_{kst} denotes a tertile-sector-time fixed effect, and ε_{ist} is the error term.

Table 5 shows the results from the estimation of equation (10) for the impact of Chinese direct import exposure on U.S. occupational-sectoral employment. Columns 1 and 2 use the occupation-sorting criterion based on wage, columns 3 and 4 use the non-routineness criterion, and columns 5 and 6 use the education criterion. Regressions in even columns include production controls, and regressions in odd columns do not include them. Note that each column reports estimates for nine β-coefficients: one coefficient for each tertile (low, middle, high) in each of the three sectors.

[12] Within local labor markets, AADHP find that from 1991 to 2011, U.S. employment loses due to Chinese import exposure were concentrated in the exposed sector, and find no evidence of employment reallocation toward the other sectors.

[13] Following AADHP, we classify industries into exposed and non-exposed sectors based on industry-level direct and upstream import penetration measures. First we calculate the change in each type of import penetration from 2002 to 2014, and then we classify as exposed those industries whose import penetration changes are equal or above the mean for at least one of the measures. Similar to AADHP, tradable industries are those in agriculture, forestry, fishing, mining, and manufacturing.

[14] Note that production controls are at the occupation-sectoral level, so that we allow for an occupation i to be subject to different wages and capital exposures across sectors.

Table 5: Estimation of U.S. Occupational Employment Responses to Chinese Direct Import Exposure: By Sector Exposure under Three Occupation-Sorting Criteria

	Wage		**Non-routineness**		**Education**	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct import exposure						
Exposed						
Lowest tertile	-2.33***	-1.47***	-1.77***	-1.07**	-2.21***	-1.21***
	(0.67)	(0.57)	(0.62)	(0.46)	(0.58)	(0.45)
Middle tertile	0.01	0.87	-2.66***	-1.54**	0.01	0.38
	(1.06)	(0.98)	(0.57)	(0.75)	(1.22)	(1.27)
Highest tertile	15.13	24.50	11.72	21.90	30.00	41.69
	(15.94)	(22.57)	(13.30)	(19.75)	(25.57)	(32.86)
Non-exposed tradable						
Lowest tertile	-1.42***	-1.00***	-1.28***	-0.88***	-1.41***	-1.00***
	(0.26)	(0.23)	(0.24)	(0.24)	(0.24)	(0.21)
Middle tertile	1.15	2.55*	-1.96***	-1.55***	2.31*	2.35*
	(1.08)	(1.35)	(0.63)	(0.58)	(1.34)	(1.30)
Highest tertile	0.94	0.60	2.17**	2.47*	2.60	2.40
	(1.31)	(1.52)	(1.09)	(1.31)	(2.51)	(2.38)
Non-exposed non-tradable						
Lowest tertile	-2.55*	-2.50*	-2.13**	-0.95	-2.42*	-1.81
	(1.33)	(1.31)	(1.04)	(0.99)	(1.26)	(1.16)
Middle tertile	2.08	1.67	-4.22***	-3.46***	-0.63	-0.31
	(1.51)	(1.39)	(1.29)	(1.14)	(1.40)	(1.30)
Highest tertile	-2.08	-0.98	1.73	2.18	-1.11	1.13
	(1.66)	(1.50)	(2.08)	(1.93)	(1.97)	(1.67)
Production controls	No	Yes	No	Yes	No	Yes
Observations	5,372	5,273	5,581	5,253	5,581	5,253

Notes: All regressions include tertile-sector-time fixed effects (not reported). Standard errors (in parentheses) are clustered at the occupation level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

For the exposed sector, Table 5 shows that direct import exposure has negative and statistically significant effects in lower-indexed occupations under the three criteria, as well as on mid-routine occupations. Indeed, the job destruction effect on mid-routine occupations is larger in magnitude than the impact on the highly-routine (lowest tertile) occupations, which suggests that an important fraction of mid-routine occupations are low wage and low education. In contrast, although there are large and positive coefficients for the higher-indexed occupations, none of them is statistically significant.

The non-exposed tradable sector also has statistically significant job destruction in lower-indexed (under the three criteria) and mid-routine occupations, but also shows mildly significant evidence of job creation in mid-wage, mid-education, and highly non-routine occupations. The implied job destruction in a non-exposed sector is likely a consequence of local labor market effects, as described by Autor, Dorn, and Hanson (2013). The result that these job destruction effects of direct exposure happen in the same types of occupations as in the exposed sector, indicates a heavy regional concentration of lower-indexed occupations.[15] On the other hand, the implied job creation in mid-wage, mid-education, highly non-routine occupations is evidence of job reallocation from negatively affected lower-indexed occupations; that is, some released workers are able to find better jobs in more sophisticated occupations.

The coefficients for the non-exposed non-tradable sector in Table 5 also show evidence of job destruction in lower-indexed and mid-routine occupations, which also points out toward the existence of local labor market effects under heavy regional concentration of lower-indexed occupations. Note, however, that the coefficients for the lower-indexed occupations under the non-routineness and education criteria lose their statistical significance once production controls are added to the regressions. Moreover, and in contrast to the findings for the non-exposed tradable sector, there is no evidence of job reallocation from occupations with shrinking employment to occupations in the non-exposed non-tradable sector.[16]

Table 6 considers the combined measures of Chinese import exposure. Panel A shows the estimation results that use the measure that adds upstream linkages, and panel B shows the results that use the measure that adds upstream and downstream linkages. As before, the magnitudes of the coefficients are in general smaller when adding input-output linkages, but this is simply a consequence of the rescaling of the import exposure measure. The results from both panels are qualitatively similar to those discussed for direct import exposure from Table 5, though our previous findings for the non-exposed non-tradable sector become largely insignificant.

The only novelty for the non-exposed non-tradable sector comes from significant and negative import-exposure coefficients for high-wage occupations in both panels, which indicates Chinese-induced job destruction in high-wage occupations in this sector. This may be evidence of job reallocation of high-wage occupations from the non-exposed to the exposed sector, with the latter sector demanding more high-wage workers due to productivity effects. However, the evidence is not conclusive because in spite of very large and positive coefficients for high-wage occupations in the exposed sector (indicating a large expansion in these occupations' employment), they have large standard errors and are not statistically significant.

[15] Unfortunately, we cannot directly verify this explanation because our occupational employment data does not contain geographical information.

[16] Ebenstein, Harrison, and McMillan (2015) find evidence of job reallocation of high-wage workers in the manufacturing sector to lower-wage jobs in non-manufacturing. In contrast, we do not find evidence of Chinese-induced job destruction in high-wage occupations (nor in non-routine or high-education occupations) in the exposed sector, which includes most manufacturing industries.

Table 6: Estimation of U.S. Occupational Employment Responses to Chinese Combined Import Exposure: By Sector Exposure under Three Occupation-Sorting Criteria

	Wage		Non-routineness		Education	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Combined import exposure I *(direct + upstream)*						
Exposed						
Lowest tertile	-1.90***	-1.18***	-1.26***	-0.72*	-1.73***	-0.90***
	(0.51)	(0.44)	(0.46)	(0.38)	(0.43)	(0.34)
Middle tertile	0.18	0.85	-1.96***	-1.01	0.19	0.54
	(0.82)	(0.84)	(0.49)	(0.69)	(0.88)	(0.94)
Highest tertile	14.47	21.77	10.92	19.12	26.31	33.97
	(13.68)	(17.88)	(11.52)	(16.00)	(20.04)	(23.43)
Non-exposed tradable						
Lowest tertile	-1.21***	-0.86***	-1.09***	-0.75***	-1.16***	-0.82***
	(0.23)	(0.21)	(0.22)	(0.22)	(0.21)	(0.20)
Middle tertile	1.37*	2.32**	-1.26**	-0.90	1.86*	1.90*
	(0.82)	(0.95)	(0.56)	(0.55)	(1.08)	(1.06)
Highest tertile	1.12	0.89	1.93**	2.21**	2.76*	2.48
	(0.98)	(1.14)	(0.84)	(1.00)	(1.63)	(1.61)
Non-exposed non-tradable						
Lowest tertile	-1.44	-1.18	-2.22**	-1.22	-1.15	-0.38
	(1.39)	(1.37)	(1.03)	(0.98)	(1.32)	(1.28)
Middle tertile	0.64	0.49	-3.02*	-1.60	-1.30	-0.99
	(1.15)	(1.14)	(1.59)	(1.64)	(1.11)	(1.07)
Highest tertile	-2.81**	-1.78	1.65	2.52	-2.25	-0.58
	(1.35)	(1.21)	(2.02)	(2.03)	(1.69)	(1.47)
B. Combined import exposure II *(direct + upstream + downstream)*						
Exposed						
Lowest tertile	-1.70***	-1.18***	-1.14***	-0.74**	-1.54***	-0.92***
	(0.48)	(0.44)	(0.41)	(0.34)	(0.40)	(0.33)
Middle tertile	0.08	0.58	-1.70***	-0.99*	0.06	0.27
	(0.67)	(0.68)	(0.43)	(0.57)	(0.72)	(0.75)
Highest tertile	11.62	17.18	8.83	15.18	21.96	27.96
	(11.27)	(14.49)	(9.62)	(13.20)	(16.97)	(19.57)
Non-exposed tradable						
Lowest tertile	-0.93***	-0.68***	-0.82***	-0.59***	-0.89***	-0.64***
	(0.19)	(0.17)	(0.19)	(0.19)	(0.17)	(0.17)
Middle tertile	1.22*	1.93**	-0.99**	-0.72	1.56*	1.55*
	(0.71)	(0.81)	(0.44)	(0.44)	(0.86)	(0.85)
Highest tertile	1.20	1.02	1.85***	2.10***	2.25*	2.05
	(0.79)	(0.93)	(0.61)	(0.77)	(1.32)	(1.29)
Non-exposed non-tradable						
Lowest tertile	0.20	0.24	-0.82	-0.32	-0.31	0.12
	(1.39)	(1.41)	(0.72)	(0.78)	(1.25)	(1.26)
Middle tertile	-0.03	-0.09	-3.29*	-1.90	-0.55	-0.38
	(1.12)	(1.11)	(1.69)	(1.70)	(0.86)	(0.88)
Highest tertile	-2.53**	-1.80*	2.10	2.62	-1.85	-0.70
	(1.11)	(1.04)	(2.32)	(2.45)	(1.41)	(1.26)
Production controls	No	Yes	No	Yes	No	Yes
Observations	5,372	5,273	5,581	5,253	5,581	5,253

Notes: All regressions include tertile-sector-time fixed effects (not reported). Standard errors (in parentheses) are clustered at the occupation level. The coefficients are statistically significant at the *10%, **5 %, or ***1% level.

To gauge the importance of the effects obtained in our occupational-sectoral estimation, the last nine rows of Table 4 present the 2002-2014 implied employment changes from Tables 5 and 6 for the specifications including production controls. The predicted changes from direct import exposure show that the exposed sector accounts for the majority of the employment losses in occupations in the lowest tertile: the share of the exposed sector in lowest-tertile losses is 55 percent under the wage criterion, 63 percent under the non-routineness criterion, and 62 percent under the education criterion. Thus, between 38 and 45 percent of predicted job losses in lower-indexed occupations are likely the consequence of local-labor-market effects à la Autor, Dorn, and Hanson (2013), which indicates—given the non-significant employment responses of higher-indexed occupations—that employment in lower-indexed occupations is heavily concentrated in particular regions.

Although the non-exposed tradable sector has statistically significant employment gains in mid-wage, mid-education, and highly non-routine occupations, these are relatively small—between 16,000 jobs in mid-education occupations and 25,000 jobs in mid-wage occupations—when compared to predicted changes in the exposed and non-exposed non-tradable sectors. This is the case because the non-exposed tradable sector is very small, accounting on average for only 2.3 percent of total employment per year. Thus, although these gains are evidence of job reallocation toward better occupations, their overall impact is very small.

Across our three sorting criteria, upstream and downstream linkages in occupational exposure to Chinese imports increase the exposed sector's job losses in the lowest occupational tertile—considering both types of linkages, job losses increase 89 percent under the wage criterion, 73 percent under the non-routineness criterion, and 76 percent under the education criterion. Note that after adding downstream linkages, the significant job losses in high-wage occupations in the non-exposed non-tradable sector amount to 871,000 jobs (which is larger than the 720,000 job losses in low-wage occupations in the exposed sector). Although it is possible that this reflects job reallocation of high-wage occupations from the non-exposed to the exposed sector, the lack of significance of the large predicted gains in the latter sector does not allow us to reach a precise interpretation.[17]

[17] Note, however, that the statistically significant creation of 1.2 million jobs in high-education occupations reported in the first row of Table 4 (corresponding to the results from Table 2) present indirect evidence of an active job reallocation channel toward better occupations.

5 Conclusion

Chinese import exposure has a differential impact in employment across occupations. After sorting occupations according to their real wages, degree of non-routineness, and education requirements, we find that employment losses from occupational-level Chinese import exposure are concentrated in low-wage, routine, low-education occupations. These losses occur in both Chinese-trade exposed and non-exposed sectors. Although the result of negative employment effects in the exposed sector's lower-indexed occupations is expected—these U.S. occupations would be the most adversely affected in the influential offshoring models of Feenstra and Hanson (1996) and Grossman and Rossi-Hansberg (2008)—our finding of employment reductions in lower-indexed occupations in the non-exposed sectors is novel and does not have a straightforward interpretation.

We argue that the latter result is a consequence of local labor market effects à la Autor, Dorn, and Hanson (2013), in combination with a heavy concentration of lower-indexed occupations in particular regions. In support of this interpretation, exploratory analysis conducted by Van Dam and Ma (2016) using the Chinese import-exposure data of AADHP and Autor, Dorn, and Hanson (2013) shows that the U.S. areas most affected by the China shock were "less educated, older and poorer than most of the rest of America."[18]

In a related paper, Asquith, Goswami, Neumark, and Rodriguez-Lopez (2017) find that deaths of establishments account for most of the Chinese-induced job destruction in the United States. In conjuction with this paper's findings, this implies that establishments that die due to the China shock have a larger proportion of workers in lower-indexed occupations than surviving establishments. Although this issue requires further investigation, previous work from Abowd, McKinney, and Vilhuber (2009) shows evidence in that direction. Using Longitudinal Employer-Household Dynamics (LEHD) data, they find that firms that employ more workers from the lowest quartile of the human capital distribution are much more likely to die, while firms that employ workers from the highest quartile of the distribution are less likely to die.

We also find mild evidence that direct Chinese exposure drives an employment expansion in high-education occupations. This suggests the existence of productivity effects as in Grossman and Rossi-Hansberg (2008), by which the replacement of low-wage employment with imports from China allows U.S. firms to reduce marginal costs and expand their markets shares; consequently, this leads to higher employment in occupations that remain inside U.S. firms. Another possibility is the existence of effects à la Melitz (2003), by which low-productivity firms exposed to Chinese

[18]See http://graphics.wsj.com/china-exposure/ and http://chinashock.info/.

competition die, with market shares being reallocated toward more productive firms that use high-education occupations more intensively. Disentangling these effects is another relevant research topic spanning from our findings.

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Table A.1: Industry Classification

	Industry	Three-digit NAICS		Industry	Three-digit NAICS
1	Forestry and fishing	113, 114, 115	31	Rail transportation	482
2	Oil and gas extraction	211	32	Water transportation	483
3	Mining, except oil and gas	212	33	Truck transportation	484
4	Support activities for mining	213	34	Transit and ground passenger transportation	485
5	Utilities	221	35	Pipeline transportation	486
6	Construction	236, 237, 238	36	Other transportation and support activities	487, 488, 492
7	Food, beverage, and tobacco products	311, 312	37	Warehousing and storage	493
8	Textile mills and textile product mills	313, 314	38	Publishing industries (includes software)	511, 516
9	Apparel, leather, and allied products	315, 316	39	Motion picture and sound recording	512
10	Paper products	322	40	Broadcasting and telecommunications	515, 517
11	Printing and related support activities	323	41	Information and data processing services	518, 519
12	Petroleum and coal products	324	42	Federal Reserve banks, credit intermediation	521, 522
13	Chemical products	325	43	Securities, commodity contracts, and investments	523
14	Plastics and rubber products	326	44	Insurance carriers	524
15	Wood products	321	45	Funds, trusts, and other financial vehicles	525
16	Nonmetallic mineral products	327	46	Real estate	531
17	Primary metals	331	47	Rental and leasing services	532, 533
18	Fabricated metal products	332	48	Professional, scientific, and technical services	541
19	Machinery	333	49	Management of companies and enterprises	551
20	Computer and electronic products	334	50	Administrative and support services	561
21	Electrical equipment	335	51	Waste management and remediation services	562
22	Transportation equipment	336	52	Educational services	611
23	Furniture and related products	337	53	Ambulatory health care services	621
24	Miscellaneous manufacturing	339	54	Hospitals, nursing, and residential care	622, 623
25	Wholesale trade	423, 424, 425	55	Social assistance	624
26	Motor vehicle and part dealers	441	56	Performing arts, spectator sports, and museums	711, 712
27	Food and beverage stores	445	57	Amusements, gambling, and recreation	713
28	General merchandise stores	452	58	Accommodation	721
29	Other retail	442, 443, 444, 446, 447, 448, 451, 453, 454	59	Food services and drinking places	722
			60	Other services, except government	811, 812, 813, 814
30	Air transportation	481			