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Empirical Studies in International Trade

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Sanjana Goswami

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2020

DEDICATION

To Somnath and Kuntala, my parents,
and Shreyasi, my sister,
for their unwavering support and encouragement.

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ABSTRACT OF THE DISSERTATION

Empirical Studies in International Trade

By

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Doctor of Philosophy in Economics

University of California, Irvine, 2020

Associate Professor Antonio Rodriguez-Lopez, Chair

This dissertation contains essays that study questions regarding how international trade shocks affect labor market outcomes and how exchange rate fluctuations affect firm-level markups.

The first chapter provides evidence on the short-run and long-run distributional effects of tariff shocks on employment in the United States. Using monthly data on tariffs and employment, I find that in the period of January 2017 to March 2019, commuting zones more exposed to Chinese retaliatory tariffs experienced a decline in employment growth, whereas U.S. import tariffs had no immediate effect on employment growth. I also study the employment effects of a hypothetical trade war between the United States and China by calculating counterfactual employment changes under three different retaliation scenarios and find that had the U.S. imposed tariffs in the 1991-2007 period on all products, the large job-destroying effect of the 'China shock' would not have occurred, irrespective of the retaliation strategy pursued by China. However in the post-recession period of 2010-2016, the 'China shock' no longer exists and therefore U.S. import tariffs would not have had a job-creating effect. This result corroborates the findings of the short-run analysis.

The second chapter is co-authored with Antonio Rodriguez-Lopez and Marco Del Angel, and published in the book World Trade Evolution: Growth, Productivity and Employment.

It studies the heterogenous impacts of import competition across occupations. Using data on occupational employment from 2002 to 2014, we find that Chinese import competition reduces employment in low wage, low education and highly routine occupations. At the local level, the employment reduction in the lowest tertile of occupations occurs in Chinese-trade exposed and as well unexposed sectors, which suggests the existence of local labor market effects in the presence of a strong regional concentration of lower-indexed occupations.

The third chapter uses firm-level data for U.S. manufacturing firms from 1964-2011 to test important empirical predictions from international trade models linking trade behavior and firms' markups. I find that firms of higher productivity have lower rates of exchange rate pass-through to export prices, i.e., they adjust their markups by a higher magnitude. However, firms of higher productivity also have less volatile markups, i.e, they adjust their markups less frequently than do firms of lower productivity. This result provides an insight to the "Exchange rate disconnect puzzle", i.e., the lack of response of aggregate prices to exchange rate movements.

Chapter 1

Employment Consequences of U.S. Trade Wars

Tariffs on imports reduce import competition for domestic firms and in turn encourages more firms to enter the market or expand, therefore generating new jobs. On the other hand, retaliatory tariffs on exports hurt domestic firms and they may shrink or even exit and may therefore displace workers. Moreover, tariffs on imports of intermediate products make inputs more expensive and also hurt domestic firms and may displace workers. A trade war imposes tariffs or quotas on imports and foreign countries retaliate with similar forms of trade protectionism. As it escalates, a trade war reduces international trade, and in turn has distributional effects on the labor market. The recent trade escalation prompted by the U.S. administration under President Donald Trump since January 2018 is an unprecedented move, incomparable to any previous episodes of trade disputes since the Great Depression. In this paper, I explore these distributional impacts by studying both the short-term and potential long-run consequences of the U.S-China trade war.

Since January 2018, the U.S. administration under President Trump has started trade wars along several fronts against most of U.S. trading partners, starting with "global safeguard tariffs" on imports of solar panels and washing machines, moving then to tariffs on steel and aluminum under national security grounds, and following with a full-blown trade war with China with the average tariff on Chinese imports above 24 percent, compared to an average of only 3 percent at the onset of the trade war[1]. In March 2018, he famously tweeted that "Trade wars are good, and easy to win".

So far, the U.S. has imposed tariffs on \$250 billion in Chinese imports out of \$539 billion of Chinese goods that were imported into the U.S. in 2018. China has retaliated with tariffs on \$110 billion of U.S. exports out of \$120 billion of U.S. goods imported into China in 2018. Further increases and tariffs are expected in October and December 2019, amounting to levies on nearly everything that comes to the United States from China. China is also expected to retaliate in kind. They have already included a 5 percent tariff on U.S. crude oil, the first time fuel has been hit in this trade battle.

Although the legal justifications for these trade wars range from national security (in the case of steel) to protection of intellectual property (in the case of China), the justification that President Trump puts forward when talking to his political base is the protection of the American worker and American jobs. I present evidence that such a claim may have been credible prior to the events of the global financial crisis, but it does not hold in today's environment.

The short-term approach estimates the effects of changes in U.S. import tariffs, U.S. import tariffs that propagate downstream to buyers of intermediate inputs, and Chinese retaliatory tariffs on commuting zone-level employment growth. Following Waugh (2019), I use monthly data on employment, U.S-China trade and tariffs from January 2017 to March 2019, and find that Chinese retaliatory tariffs have had a statistically significant and negative effect on commuting zone-level employment growth, whereas U.S. import tariffs have had no effect.

[1]Source: Peterson Institute for International Economics

This suggests that commuting zones that are relatively more exposed to the export tariffs are disproportionately hurt, whereas commuting zones that are relatively more exposed to the import tariffs are not growing any differently than they were before the trade war.

The long-run approach imposes a hypothetical trade war on a well-studied phenomenon in the empirical international trade literature: the large job-reducing effects of surging imports from China, or the 'China shock', on the U.S. labor market (Autor, Dorn, and Hanson (2013), Acemoglu, Autor, Dorn, Hanson, and Price (2016), etc) in addition to the job-creating effect of exports, which are also substantially large enough to almost offset the losses created by Chinese imports (Feenstra, Ma, and Xu, 2019).

Using an industry-level specification that estimates the effect of the change in Chinese import competition, non-Chinese import competition, and U.S. export expansion on the change in manufacturing employment, I then calculate counterfactual employment levels under three different scenarios of retaliation by China: (i) simple retaliation, which imposes identical restrictions on U.S. exports across all industries, (ii) political retaliation, which targets in particular those industries that have a large proportion of Trump supporters, and (iii) responsible retaliation, which minimizes the impact of retaliation on global supply chains. I do this exercise for two time periods: 1991-2007, where the China shock had a large negative impact on manufacturing employment, and the post-recession period of 2010-2016, where the China shock no longer has an effect on manufacturing employment. A trade war in this empirical model simultaneously reduces both import and export exposure, based on the type of retaliation, thereby bringing back some jobs lost due to Chinese imports while killing some jobs gained due to U.S. export expansion.

To guide this empirical exercise I closely follow Acemoglu, Autor, Dorn, Hanson, and Price (2016) and Feenstra, Ma, and Xu (2019). Using an instrumental variables approach, the former estimates the effects of Chinese import penetration on U.S. employment at both the industry and commuting-zone levels, while the latter expands the approach to consider also the employment effects of U.S. exports. While both papers find that Chinese import exposure is associated with employment losses in the U.S., Feenstra, Ma, and Xu (2019) find that "export exposure" has a countervailing effect that makes up for the Chinese-induced job losses during the 1991-2007 period.

First, I conduct the counterfactual exercise for the 1991-2007 period, where I find that a uniform tariff by the U.S. along with no retaliation by China would bring back enough manufacturing jobs to almost reverse the effects of the China shock. I also find that no matter the type of retaliation strategy by China, had the U.S. taken a protectionist approach during this period by imposing import tariffs, manufacturing employment would have increased.

However, these results would no longer be true if I focus on only the post-recession period of 2010-2016. In this case, I find that the job-reducing effect of the China shock no longer exists. In fact, Chinese import penetration has a positive and insignificant effect on U.S. manufacturing employment. The counterfactual analysis for this period indicates that the trade war would lead to a net destruction of jobs.

While recent research suggests that the trade war of 2018 has reduced real income in the U.S., increased prices of intermediate and final goods, reduced the availability of imported varieties (Amiti, Redding, and Weinstein (2019)) as well as led to aggregate welfare loss (Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019)), not much is known about the potential effects of trade wars on employment outcomes. This paper provides both a short-term and long-term view of these effects.

1.1 Background

International trade has important distributional impacts on the labor market. Pavcnik (2017) surveys the empirical evidence on the distributional effects of trade in both developed and

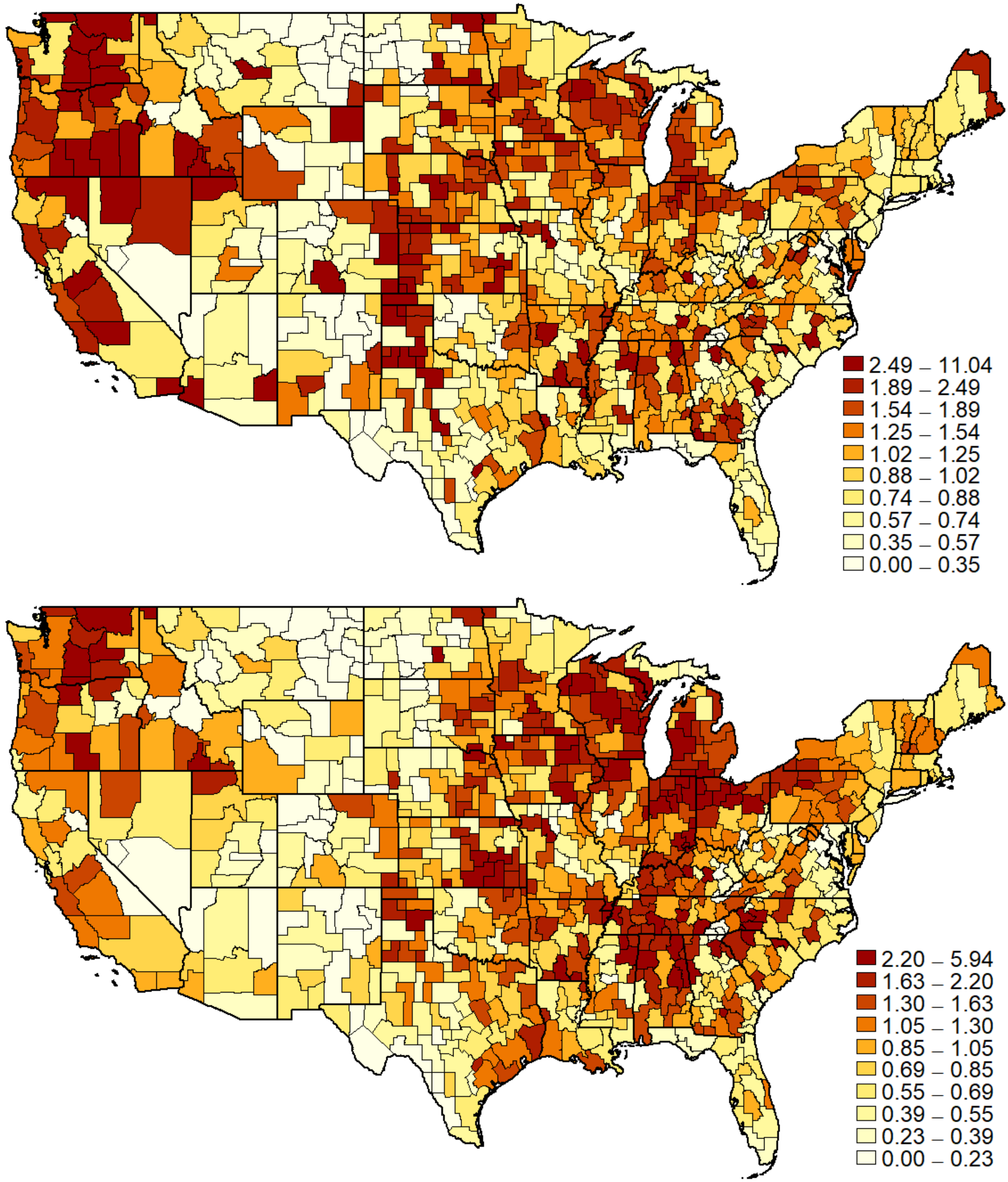


Figure 1.1: Chinese retaliatory export tariff exposure (top) and U.S. import tariff exposure (bottom) by commuting zone

developing countries. Economists have long recognized that free trade has the potential to raise living standards and that both the importing and exporting countries gain by engaging in trade. The growing body of empirical evidence supports the view of most theoretical trade models that trade reallocates resources within a country, and both destroys and creates jobs, with implications for income distribution. Evidence suggests that while the countries benefit overall, there are some losers as well. Trade's adverse effects appear to be highly geographically concentrated and long-lasting in developing and developed countries alike. The harmful effects of trade are permanent for some workers that lose their jobs to import competition. The "China shock" literature of Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016a) have established that import competition from China contributed to substantial job losses (by around 1.5 million jobs) in U.S. manufacturing in the 1990s and 2000s.

The 2018 trade war between the U.S. and its trading partners will also likely have distributional consequences across industries, and across regions with different patterns of comparative advantage. The kind of retaliation executed by partner countries will determine the extent of the distributional impacts of the trade war. Figure 1.3 shows the exposure to Chinese import and export tariffs in December by region. The regions in the map are commuting zones, which are geographic units of analysis intended to more closely reflect the local economy where people live and work. County boundaries are not always adequate confines for a local economy and often reflect political boundaries rather than an area's local economy. Exposure here is defined as the change in a commuting zone's tariff between December 2017 and December 2018[2]. Import tariffs seem to be more concentrated in the Rust Belt around the Great Lakes region, whereas retaliatory tariffs seems to be concentrated in the Corn Belt of the Mid-West, which is dominated by farming and agriculture and the North-West part of the country.

[2]The construction of the commuting-zone level tariffs are described more in detail in Section 1.3.1.1

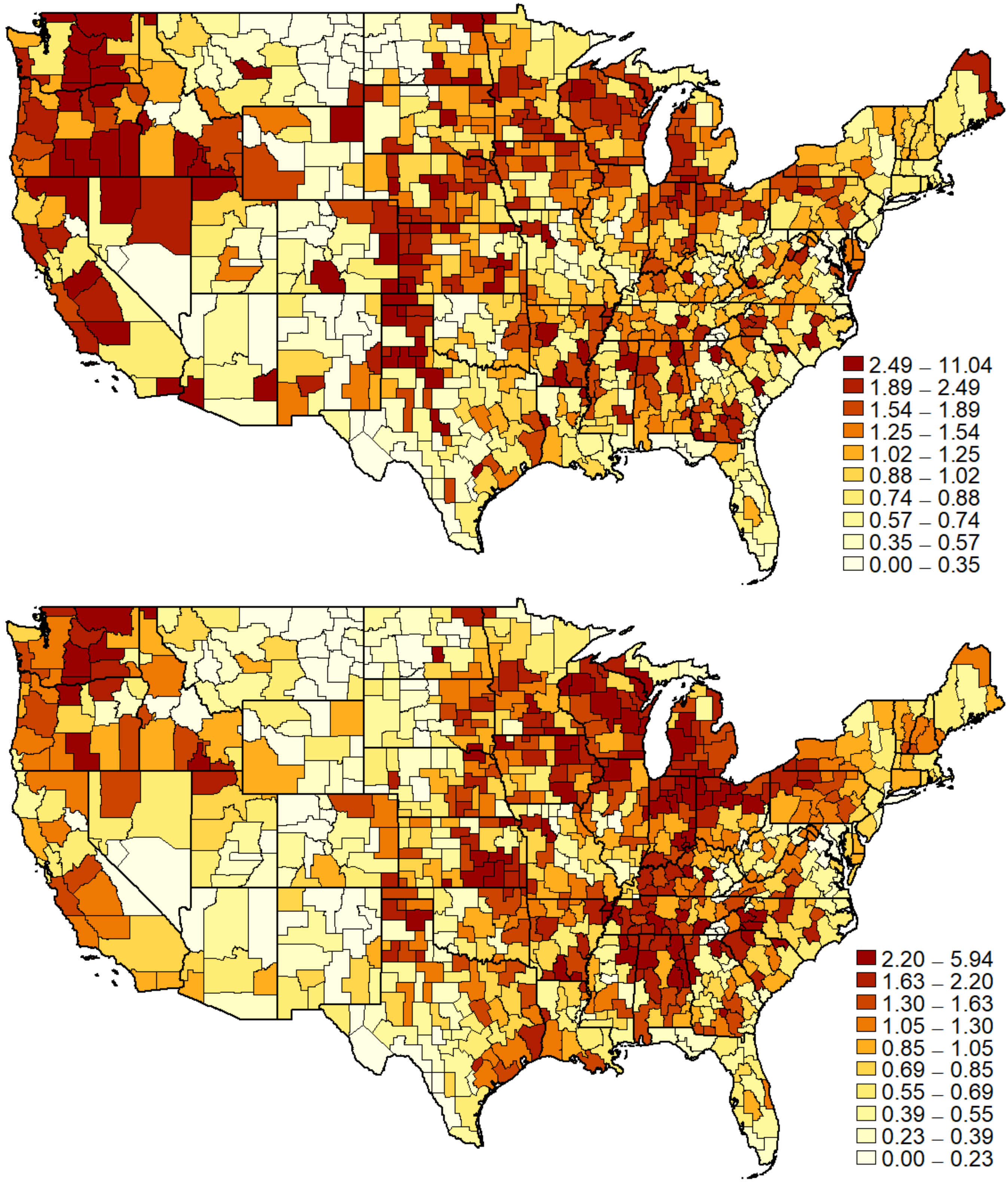


Figure 1.3: Chinese retaliatory export tariff exposure (top) and U.S. import tariff exposure (bottom) by commuting zone

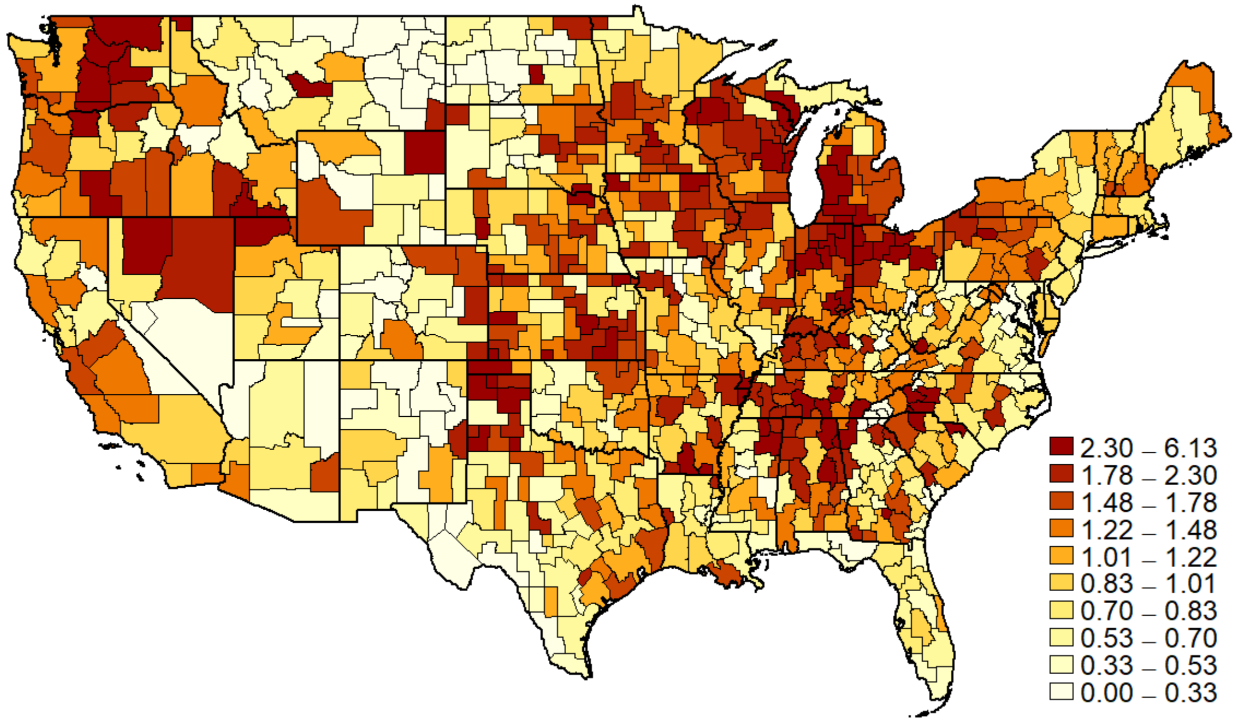


Figure 1.2: Downstream U.S. import tariff exposure by commuting zone

Figure 1.2 shows the regional distribution of U.S. import tariffs that propagate downstream to industries that purchase the products as inputs. These downstream import tariffs can be thought of as a proxy for tariffs on intermediate inputs. The regional distribution of these tariffs are similar to the import tariffs with slight variation in the degree of exposure to some regions. In Section 1.3, I will be exploiting the variation in these three measures of commuting-zone level tariffs to estimate the effect of the U.S.-China trade war on regional employment growth.

In Section 1.4, I compare three different hypothetical retaliation strategies — simple, political, and responsible — which have varying degrees of decline in manufacturing employment due to falling Chinese export exposure. Figure 1.4 shows the distribution of commuting zones according to the 2016 presidential election vote shares to the Republican party. There are commuting zones in the middle of the country that are affected more by actual Chinese retaliation, similar to the higher political concentration in this figure but the rest of

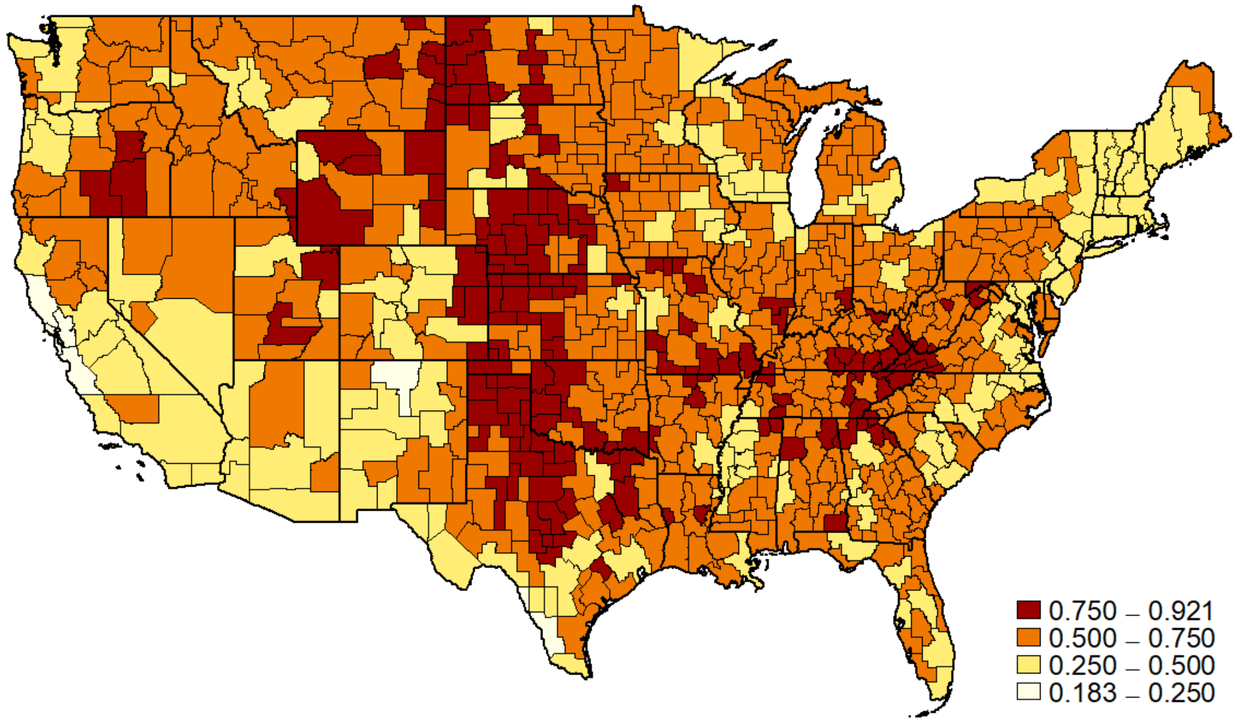


Figure 1.4: Share of votes towards the Republican party in the 2016 presidential election by commuting zone

the export tariff map looks different for many other parts of the country, which suggests that China is not just following a pure political retaliation strategy. Fetzer and Schwarz (2019) present evidence that Chinese retaliation was directly targeted to areas that swung to Donald Trump in 2016 but also suggest that the retaliation strategy was sub-optimal.

Figure 1.5 shows the distribution of commuting zones according to degree of intra-industry trade between U.S. and China in 2016. Values closer to zero denote higher level of intra-industry trade, values closer to one are for industries where the U.S. is a net exporter and values closer to negative one are for industries where the U.S. is a net importer. The commuting zone level of this index is then constructed as an employment weighted-average measure of the industry level index. If China would like to minimize the impact of their retaliation on global supply chains, it would target industries for which the U.S. is a net exporter and there is little intra-industry trade, i.e., a subset of the darkest shaded commuting-zones. There is some resemblance to the export tariff map in Figure 1.3 but the darker shaded regions in

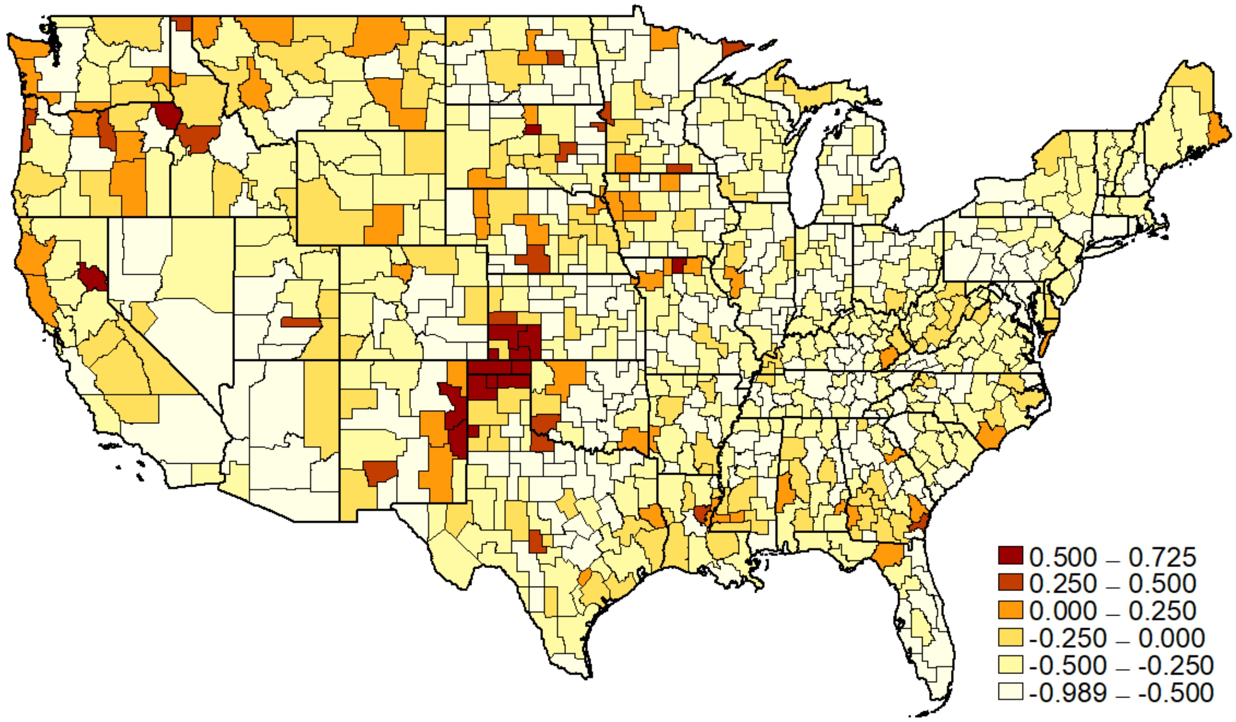


Figure 1.5: Distribution of a measure of U.S.-China intra-industry trade by commuting zone

the figure are more geographically dispersed.

In order to understand better the implications of a simple, political or responsible retaliation strategy that China could adopt, I impose a hypothetical trade war with these different retaliation strategies on past episodes of import competition and export expansion in the United States.

1.2 Overview of the Sino-American Trade War

Following is a brief overview of the trade war timeline. Wong and Koty (2018) and Bown and Kolb (2018) are two excellent resources which track the timeline of events for the trade war that started in January 2018.

First wave: In October 2017, the United States International Trade Commission found that imports of solar panels and washing machines have caused injury to the U.S. solar panel and washing machine industries and recommended that President Trump impose "global safeguard" tariffs. These tariffs of 30 percent on all solar panel imports, except for those from Canada, (worth US$8.5 billion) and 20 percent on washing machine imports (worth US$1.8 billion) went into effect in February 2018.

Second wave: In April 2017, the office of the United States Trade Representative (USTR) was authorized to investigate whether steel and aluminium imports pose a threat to national security and in March 2018, the U.S. imposed a 25 percent tariff on all steel imports (except from Argentina, Australia, Brazil, and South Korea) and a 10 percent tariff on all aluminium imports (except from Argentina and Australia). Along with some other countries, China retaliated with tariffs on U.S. aluminum waste and scrap, pork, fruits and nuts, and other US products, worth $2.4 billion in export value to match the U.S. steel and aluminum tariffs covering Chinese exports worth $2.8 billion. Subsidies for American farmers were then announced to provide relief from falling U.S. agricultural exports.

Third wave: In August 2017, the USTR initiated an investigation into certain acts, policies and practices of the Chinese government relating to technology transfer, intellectual property and innovation. In March 2018, after finding China guilty of unfair trade practices, the U.S. announces its China-specific import tariffs, which get implemented in three stages: (i) In June 2018, U.S. tariffs on $34 billion of Chinese imports go into effect, which targets mostly intermediate inputs and capital equipment in sectors like machinery, mechanical appliances, and electrical equipment. In parallel with U.S. import tariffs, China's tariffs on $34 billion of US imports also go into effect, which mostly target U.S. transportation (vehicles, aircraft, and vessels) and vegetable products (largely soybeans). (ii) In August 2018, the U.S. imposed tariffs on another $16 billion of imports from China. China immediately responded with its own revised tariffs on $16 billion of US exports. (iii) In September 2018, the largest wave of the U.S.-China trade war went into effect. U.S. tariffs on $200 billion of Chinese imports take effect, along with retaliatory tariffs by China on \$60 billion of U.S. imports. These are tariffs on intermediate goods, capital goods, and also consumer goods.

1.3 Short-term effects on Employment

1.3.1 Data and Empirical Strategy

1.3.1.1 Tariff Data

U.S. import tariffs for the events described in Section 2.2 come from Bown and Zhang (2019), and Chinese retaliatory tariffs come from Bown, Jung, and Zhang (2019). Following Waugh (2019)[3], I first convert the tariffs from Harmonized System (HS) 6-digit product level to the 3-digit North American Industry Classification System (NAICS) level by taking a trade-weighted average of the tariffs in the following manner:

$$\tau^z_{jt} = \sum_{p \in P} \frac{F_{p,j,2017}}{F_{j,2017}} \tau^z_{pt}, \tag{1.1}$$

where τ^z_{jt} is the monthly 3-digit NAICS industry level tariff measure and τ^z_{pt} is the monthly HS6 product level tariff measure. $z \in \{m, x\}$, where τ^m stands for import tariff and τ^x stands for export tariff. $F_{p,j,2017}$ is the amount of trade in 2017 at the product level, whereas $F_{j,2017}$ is theamount of trade in 2017 at the industry level. For import tariffs, I use 2017 import values as weights, whereas for retaliatory tariffs, I use 2017 export values. Monthly trade data for total U.S. imports, U.S. exports and China-specific imports and exports come from U.S. International Trade Data of the Census Bureau. I then create monthly commuting

[3] A recent working paper by Waugh (2019) studies the effect of Chinese retaliatory tariffs on county-level consumption, proxied by new auto sales and finds a decline in consumption growth. He also finds a decline in employment growth.

Table 1.1: Commuting zone level summary statistics

	Median	Mean
Change in Export tariff	0.33	1.32
Change in Import tariff	0.49	1.06
Change in Downstream import tariff	0.59	1.21
Total employment in 2017 (in thousands)	32	164
Goods employment in 2017 (in thousands)	9	29

Notes: Tariff changes are between December 2017 and December 2018.

zone-level measures of import tariff exposure and Chinese retaliatory tariff exposure measures from January 2017 to March 2019 in the following manner:

$$\tau^z_{ct} = \sum_{j \in J} \frac{L_{c,j,2017}}{L_{c,2017}} \tau^z_{jt}, \tag{1.2}$$

where τ^z_{ct} is the monthly commuting zone-level tariff measure and τ^z_{jt} is the monthly industry-level tariff measure. $L_{c,j,2017}$ is the employment level in 2017 at the commuting zone-industry level, whereas $L_{c,2017}$ is the employment level in 2017 at the commuting zone level. τ^z_{ct} captures region-specific tariffs such that if a commuting zone mostly employs workers for a certain industry which has a high tariff, then the commuting zone-level tariff will reflect the high tariff.

Table 1.1 reports summary statistics for the commuting zone-level change in tariffs from December 2017 to December 2018. Across 722 commuting zones, the average import tariff increased by 1.06 percent, whereas the average export tariff increased by about 1.32 percent.

While import tariffs may reduce foreign competition for import-competing firms thereby increasing domestic employment, if these import tariffs are on intermediate inputs then domestic employment may not increase. In order to study the effect of tariffs on intermediate inputs, I allow for downstream linkages across industries. Downstream linkages refer to effects flowing downward from a selling industry to a purchasing industry: if an industry expands due to import tariffs on competing products, purchasing industries have more access to domestic inputs, which may cause them to expand too; however, these domestic inputs may replace cheaper Chinese inputs, which has a countervailing impact on purchasing industries. Thus, an increase in downstream import tariff exposure may decrease or increase an industry's employment.

To calculate downstream import tariff exposure, which is a weighted average of the industries' import tariff exposure measure, I use the 2018 input-output table from the Bureau of Labor Statistics (BLS) as follows. If μ_{jg} denotes industry g's purchases from industry j, the share of industry g in total purchases of industry j is $\omega_{jg}^{D} = \mu_{jg} / \sum_{g'} \mu_{jg'}$. The downstream import tariff measure for industry j during subperiod τ is

$$D\tau_{jt} = \sum_{g} \omega_{jg}^{D} \tau_{gt}, \tag{1.3}$$

where τ_{gt} is the import tariff in industry g at time t described in equation (1.1). The commuting-zone level of downstream import tariff is then constructed in the way described in equation (1.2).

1.3.1.2 Employment Data

Monthly county and industry level data on employment comes from the Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labor Statistics (BLS), which covers about 97 percent of all employment in the U.S. The source data for the QCEW comes from the Unemployment Insurance (UI) program of the U.S. I use two different measures of employment: total private employment, which excludes government employment, and total private, goods-producing employment but mostly use the latter because it is more likely to capture employment in the tradable goods sector. I aggregate county level employment to the commuting-zone level using concordances provided by Autor and Dorn (2013). Table 1.1 shows that the average private sector employment in 2017 was 164,000 and the average private sector goods producing employment was 29,000.

1.3.2 Estimation

I closely follow Waugh (2019) to study the effect of import and export tariffs on employment growth using the following specification:

$$\Delta \ln L_{ct} = \beta_c + \beta_t + \beta_m \Delta \ln(1 + \tau_{ct}^m) + \beta_d \Delta \ln(1 + D\tau_{ct}^m) + \beta_x \Delta \ln(1 + \tau_{ct}^x) + \varepsilon_{ct}, \quad (1.4)$$

where $\Delta \ln L_{ct}$ is the 12-month log difference in employment in commuting zone c, $\Delta \ln(1 + \tau_{ct}^m)$ is the 12-month log differenced import tariff rate, $\Delta \ln(1 + D\tau_{ct}^m)$ is the 12-month log differenced downstream import tariff rate and $\Delta \ln(1 + \tau_{ct}^x)$ is the 12-month log differenced export tariff rate. β_m measures the effect of a commuting zone's exposure to U.S. import tariffs on its employment, β_d measures the effect of a commuting zone's exposure to U.S. downstream import tariffs on its employment whereas β_x measures the effect of a commuting zone's exposure to Chinese retaliatory tariffs on its employment. This specification includes commuting zone fixed effects, which control for commuting zone specific growth and time fixed effects. Standard errors are clustered at the commuting zone level and regressions are weighted by the commuting zone employment in 2017.

Table 1.2 reports results from the specification in (1.4). The coefficients on imports tariffs are statistically insignificant across all specifications, implying that import tariffs haven't yet had an impact on employment growth in the short-run. The coefficients on downstream imports tariffs are also statistically insignificant. The coefficient on export tariffs is negative across all specifications, implying that relatively more export tariff exposed commuting zones experienced reductions in employment growth.

Table 1.3 shows that commuting zones most exposed to export tariffs experienced a small

Table 1.2: Effect of Tariffs on Short-term Employment Growth

	Total Employment		*Goods Employment*	
	(1)	(2)	(3)	(4)
Δ Export Tariffs	-0.19**	-0.37**	-0.43*	-0.88**
	(0.07)	(0.14)	(0.19)	(0.29)
Δ Import Tariffs	0.07	0.27	0.13	0.40
	(0.06)	(0.24)	(0.19)	(0.60)
Δ Downstream Import Tariffs		0.002		-0.06
		(0.31)		(0.72)

Notes: The time period is January 2017 to March 2019. Regressions are weighted by commuting zone's population in 2017 (Source: U.S. Census Bureau). Standard errors are clustered at the commuting zone level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

Table 1.3: Average Employment Growth pre and post the U.S.-China trade war by Tariff Quartile

	Export Tariffs		Import Tariffs		Downstream Tariffs	
	Pre	Post	Pre	Post	Pre	Post
Most exposed	0.0089	0.0088	0.0076	0.0093	0.0086	0.0094
Least exposed	0.0147	0.0170	0.0086	0.0113	0.0109	0.0137
Difference	-0.0058	-0.0081	-0.0010	-0.0020	-0.0023	-0.0044

Notes: Employment growth, calculated as the 12-month log difference, is averaged across commuting zones and time periods. Pre-trade war period is January 2018 to June 2018 and the post-trade war period is July 2018 to January 2019. Most exposed and least exposed commuting zones are those belonging to top and bottom quartiles of the corresponding tariff distribution.

decline in employment growth, whereas commuting zones least exposed to export tariffs experienced an increase in employment growth after the onset of the trade war. Most exposed and least exposed commuting zones are those belonging to top and bottom quartiles of the corresponding tariff distribution. In the case of import tariffs and downstream import tariffs, both most and least exposed commuting zones perform better after the trade war started. However, the gap in employment growth between most and least exposed commuting is increasing for all three types of tariffs, with the highest deviation observed for the export tariff distribution.

The result that export tariffs led to a decline in employment growth in the short-run is robust across all specifications. These retaliatory tariffs affected domestic firms and displaced workers in the local labor markets where these tariffs were the largest. On the other hand, import tariffs did not encourage domestic firms to increase hiring. Moreover, import tariffs on intermediate goods, also did not lead to any increased hiring or firing by domestic firms that use these tariffed products as their inputs. Therefore, the net employment consequences of the current U.S.-China trade wars is negative so far.

1.4 Long-run effects on Employment

1.4.1 Specification and Counterfactual Formula

Now, I examine how a hypothetical trade war would have changed manufacturing employment in the past. I closely follow the specification used by Feenstra, Ma, and Xu (2019) (henceforth, FMX) to study the effect of import and export exposure on net employment changes in U.S. manufacturing, which is given by:

$$\Delta \ln L_{j\tau} = \beta_\tau + \beta_{m1}\Delta IP^{C}_{j\tau} + \beta_{m2}\Delta IP^{ROW}_{j\tau} + \beta_x \Delta EP_{j\tau} + \eta Z_j + \varepsilon_{j\tau}, \tag{1.5}$$

where for industry j during subperiod τ, $\Delta \ln L_{j\tau}$ is the annual change in log employment, and $\Delta IP^{C}_{j\tau}$, $\Delta IP^{ROW}_{j\tau}$, and $\Delta EP_{j\tau}$ are the changes in Chinese import penetration, non-Chinese import exposure from the rest of the world (ROW), and U.S. export exposure respectively. The term β_τ denotes a subperiod fixed effect, and $\varepsilon_{j\tau}$ is the error term. Z_j is a vector of time-invariant industry-level controls, which includes the share of production and non-production workers in each industry, the log of average industry wage, the ratio of capital to value-added, computer and high-tech equipment investment (all measured in the initial year of 1991), and 10 one-digit sectoral dummies which allows for differential trends in these broad manufacturing categories. Z_j also includes pretrend variables measures over

1976-1991, which are change in industry's share of total employment, and the change in log average wage. I fit this equation for stacked first differences covering two subperiods: 1991-1999, and 1999-2007. As in Acemoglu, Autor, Dorn, Hanson, and Price (2016) (henceforth, AADHP), for any variable X, I define its annual change during subperiod τ, ΔX_τ, as

$$\Delta X_\tau = 100 * \frac{\left(X_{t_{\tau,\text{end}}} - X_{t_{\tau,\text{start}}}\right)}{t_{\tau,\text{end}} - t_{\tau,\text{start}}},$$

where $t_{\tau,\text{end}}$ is the end-year of subperiod τ, and $t_{\tau,\text{start}}$ is the start-year of subperiod τ. It is always the case that $\tau \in \{1,2\}$, where subperiod 1 corresponds to 1991-1999, and subperiod 2 corresponds to 1999-2007. The employment data used in all specifications is from the County Business Patterns (CBP) database of the U.S. Census Bureau, which has data on number of employees, establishments, and payroll for the universe of all businesses at the detailed industry level.

To quantify the employment effects of import and export exposure measures, I follow FMX and calculate the predicted employment changes from specification (1.5) as:

$$\Delta L_{j\tau} = \sum_j \left[1 - e^{-\left(\Delta \tilde{IP}_{j\tau} + \Delta \tilde{EP}_{j\tau}\right)}\right] L_{j,end}, \tag{1.6}$$

where $\Delta \tilde{IP}_{j\tau} = \hat{\beta}_{m1} \Delta IP^C_{j\tau} + \hat{\beta}_{m2} \Delta IP^{ROW}_{j\tau}$, and $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^C_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$. $L_{j,end}$ is the employment level in the end year of τ. Moreover, using a second-order approximation $e^x - 1 \approx x + x^2/2$, the effects of imports and exports can be calculated separately as follows:

$$\sum_j \left[1 - e^{-\left(\Delta \tilde{IP}_{j\tau} + \Delta \tilde{EP}_{j\tau}\right)}\right] \approx \sum_j \left[\left(1 - e^{-\Delta \tilde{IP}_{j\tau}}\right) + \left(1 - e^{-\Delta \tilde{EP}_{j\tau}}\right) - C_{j\tau}\right], \tag{1.7}$$

where $C_{j\tau} = \Delta \tilde{IP}_{j\tau} \Delta \tilde{EP}_{j\tau}$ is a combined effect that is generally small.

1.4.2 Types of retaliation

A "trade war" in this empirical model is captured by simultaneous reductions in import exposure (which reflects the U.S. protectionist policy) and export exposure (which reflects retaliation responses of U.S. trading partners). It is reasonable to expect both imports and exports to decline due to tariff increases. Using a monthly panel dataset of tariffs and trade data up to November 2018, Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) estimate the immediate effects of the trade war and find that imports from targeted countries declined 31.5 percent within products, while targeted U.S. exports fell 11.0 percent.

I consider three different scenarios of retaliation from China: *(i) simple retaliation*, which imposes identical restrictions on U.S. exports to China across all industries, *(ii) political retaliation*, which targets in particular those industries that have a large proportion of people that voted for Donald Trump in the 2016 presidential election, and *(iii) responsible retaliation*, which minimizes the impact of retaliation on global supply chains.

1.4.2.1 Simple Retaliation

I modify the formula in (2.8) so that a 10 percent uniform import tariff increase is met by a 10 percent uniform export tariff increase across all industries. Since the effect of a change in tariff on trade volumes would be different for different industries, I use trade cost elasticities (θ_j) from Caliendo and Parro (2015)[4]. A ten percent increase in tariffs would therefore lead to $10 \times \theta$ percent decline in both import and export exposure. For instance, the trade cost elasticity in the Food sector is 2.62. A 10 percent increase in trade costs (which includes tariffs) in this sector would decrease both import and export exposure by 26.2 percent.

[4]Appendix Table A.1 contains the different values of θ_j used.

The formula used to calculate the effect of this simple retaliation is given by (2.8), where

$$\Delta \tilde{IP}_{j\tau} = [(1 - 0.1\theta_j) \times \hat{\beta}_{m1}\Delta IP^{C}_{j\tau}] + \hat{\beta}_{m2}\Delta IP^{ROW}_{j\tau},$$

and

$$\Delta \tilde{EP}_{j\tau} = [(1 - 0.1\theta_j) \times \hat{\beta}_{x}\Delta EP^{C}_{j\tau}] + \hat{\beta}_{x}\Delta EP^{ROW}_{j\tau}$$

The U.S. imports a lot more from China than it exports to China. In order to see the effect of balanced trade war, I restrict the effect of U.S. import tariffs such that the U.S. targets the same volume of trade as China. The average across 1991 to 2007 for U.S. exports to China is \$27 billion in 2007 dollars. The average for U.S. imports from China in the same period is \$131 billion. I therefore allow U.S. import tariffs on only 20 percent ($\approx 27/131$) of each industry's U.S. imports from China.

The formula used to calculate the effect of a balanced trade war under simple retaliation is given by (2.8), where

$$\Delta \tilde{IP}_{j\tau} = [(1 - 0.1\theta_j) \times 0.20 \times \hat{\beta}_{m1}\Delta IP^{C}_{j\tau} + 0.80 \times \hat{\beta}_{m1}\Delta IP^{C}_{j\tau}] + \hat{\beta}_{m2}\Delta IP^{ROW}_{j\tau},$$

and

$$\Delta \tilde{EP}_{j\tau} = [(1 - 0.1\theta_j) \times \hat{\beta}_{x}\Delta EP^{C}_{j\tau}] + \hat{\beta}_{x}\Delta EP^{ROW}_{j\tau}$$

1.4.2.2 Political Retaliation

Under political retaliation, a partner country tries to maximize political damage by targeting those industries with large proportions of Trump supporters. Using 2016 presidential election data[5], I approximate the share of Trump supporters in each industry as

$$T_j = \frac{\sum_c L_{jc} \times \mathbb{1}_c\{R\}}{L_j} \in (0, 1),$$

where L_{jc} is total employment in industry j in commuting zone c in 2016, $\mathbb{1}_c\{R\}$ is an indicator function taking the value of 1 if the Republican party won the majority vote (greater than 50 percent) in commuting zone c in the 2016 Presidential election. Based on this measure of political alignment, I calculate predicted employment changes when China targets U.S. export value for those industries in which $T_j > 0.5$.

The formula used to calculate the effect of this political retaliation is given by (2.8), where

$$\Delta \tilde{IP}_{j\tau} = [(1 - 0.1\theta_j) \times \hat{\beta}_{m1} \Delta IP^{C}_{j\tau}] + \hat{\beta}_{m2} \Delta IP^{ROW}_{j\tau},$$

and

$$\Delta \tilde{EP}_{j\tau} = [(1 - 0.1\theta_j) \times \hat{\beta}_{x} \Delta EP^{C}_{s\tau}] + \hat{\beta}_{x} \Delta EP^{C}_{p\tau} + \hat{\beta}_{x} \Delta EP^{ROW}_{j\tau},$$

where s denotes the subset of industries for which $T_j > 0.5$ and p denotes the subset of industries for which $T_j \leq 0.5$.

For a balanced trade war, I again restrict the effect of U.S. import tariffs such that the U.S. targets the same volume of trade as China. The average across 1991 to 2007 for U.S. exports to China in Trump-majority industries is \$10 billion in 2007 dollars. I therefore allow U.S. import tariffs on only 8 percent ($\approx 10/131$) of each industry's U.S. imports from China. The formula used to calculate the effect of a balanced trade war under political retaliation is given by (2.8), where

$$\Delta \tilde{IP}_{j\tau} = [(1 - 0.1\theta_j) \times 0.08 \times \hat{\beta}_{m1} \Delta IP^{C}_{j\tau} + 0.92 \times \hat{\beta}_{m1} \Delta IP^{C}_{j\tau}] + \hat{\beta}_{m2} \Delta IP^{ROW}_{j\tau},$$

[5]Compiled by Tony McGovern from The Guardian and townhall.com.

and

$$\Delta\tilde{EP}_{j\tau} = [(1-0.1\theta_j) \times \hat{\beta}_x \Delta EP^{C}_{s\tau}] + \hat{\beta}_x \Delta EP^{C}_{p\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}.$$

1.4.2.3 Responsible Retaliation

Under responsible retaliation, partner countries protect themselves by not targeting U.S. exports from industries that are heavily involved in global supply chains, as disruptions in global value chains are more likely to have negative spillover effects in their economies. Letting X_{ij} and M_{ij} denote respectively U.S. exports and imports to/from country i in industry j, I construct a modified version of the Grubel-Lloyd index of intraindustry trade as

$$GL_{ij} = \frac{X_{ij} - M_{ij}}{X_{ij} + M_{ij}} \in [-1, 1],$$

which is close to zero for high levels of intraindustry trade, which I interpret as an indication of integrated supply chains. Based on that index, under the responsible-retaliation scenario China will target U.S. export value for higher indexed industries, for which the U.S. is a net exporter and there is little intraindustry trade, i.e., $GL_{US,C} > 0.5$.

The formula used to calculate the effect of this responsible retaliation is given by (2.8), where

$$\Delta\tilde{IP}_{j\tau} = [(1-0.1\theta_j) \times \hat{\beta}_{m1} \Delta IP^{C}_{j\tau}] + \hat{\beta}_{m2} \Delta IP^{ROW}_{j\tau},$$

and

$$\Delta\tilde{EP}_{j\tau} = [(1-0.1\theta_j) \times \hat{\beta}_x \Delta EP^{C}_{s\tau}] + \hat{\beta}_x \Delta EP^{C}_{p\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau},$$

where s denotes the subset of industries for which $GL_{US,C} > 0.5$ and p denotes the subset of industries for which $GL_{US,C} \leq 0.5$.

The average across 1991 to 2007 for U.S. exports to China in $GL_{US,C} > 0.5$ industries is \$3.4 billion in 2007 dollars. I therefore allow U.S. import tariffs on only 3 percent ($\approx 3.4/131$) of each industry's U.S. imports from China. The formula used to calculate the effect of a balanced trade war under responsible retaliation is given by (2.8), where

$$\Delta\tilde{IP}_{j\tau} = [(1-0.1\theta_j)\times 0.03 \times \hat{\beta}_{m1}\Delta IP^{C}_{j\tau} + 0.97 \times \hat{\beta}_{m1}\Delta IP^{C}_{j\tau}] + \hat{\beta}_{m2}\Delta IP^{ROW}_{j\tau},$$

and

$$\Delta\tilde{EP}_{j\tau} = [(1-0.1\theta_j)\times \hat{\beta}_{x}\Delta EP^{C}_{s\tau}] + \hat{\beta}_{x}\Delta EP^{C}_{p\tau} + \hat{\beta}_{x}\Delta EP^{ROW}_{j\tau}.$$

1.4.3 Measures of Trade Exposure

I closely follow AADHP to construct their measure of Chinese import penetration, which is defined as

$$IP^{C}_{jt} = \frac{\mathbb{M}^{C}_{jt}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}},$$

where $\mathbb{M}^{C}_{jt}$ represents real U.S. imports from China of goods from industry j at year t, and $\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}$ is real domestic absorption of U.S. industry j (the industry's real output, plus real imports, less real exports) in 1991. An increase in IP^{C}_{jt} over time indicates tougher competition from China, and thus, larger changes in IP^{C}_{jt} are related to higher Chinese import exposure. Nominal imports and exports data is gathered from the United Nations Comtrade database, and nominal output is given by the value of shipments from the NBER productivity database. To calculate real values, I follow AADHP and use as deflator the Personal Consumption Expenditure Price Index (PCEPI) of the Bureau of Economic Analysis (BEA). I use AADHP's 392 manufacturing industries at the 4-digit SIC (Standard Industrial Classification) level to extend their analysis to include 2016.

The measure of Chinese import exposure in industry j during subperiod τ is then given by the annual change in import penetration, $\Delta IP_{j\tau}^{C}$ as:

$$\Delta IP_{j\tau}^{C} = \frac{\Delta \mathbb{M}_{j\tau}^{C}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \tag{1.8}$$

Similarly, the measure of import exposure from the rest of the world (ROW), not including China, in industry j is given by,

$$\Delta IP_{j\tau}^{ROW} = \frac{\Delta \mathbb{M}_{j\tau}^{ROW}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \tag{1.9}$$

For export exposure, I follow FMX. They use an analogous measure to (1.8) as

$$\Delta EP_{j\tau} = \frac{\Delta \mathbb{X}_{j\tau}}{\mathbb{Y}_{j91}}, \tag{1.10}$$

where $\Delta EP_{j\tau}$ measures the change in export exposure of industry j during subperiod τ, defined as changes in U.S. industry exports $\Delta \mathbb{X}_{j\tau}$, divided by initial industry shipments $\mathbb{Y}_{j91}$. Thus, $\Delta EP_{j\tau}$ is a measure of export intensity, capturing the share of export value out of total industrial output.

1.4.4 Intrumental Variables

Both import and export exposure measures in (1.5) suffer from endogeneity problems. Other than a Chinese supply shock, $\Delta IP_{j\tau}^{C}$ could be capturing U.S. domestic shocks that increase U.S. demand for Chinese imports. Therefore, AADHP use as an instrumental variable the sum of Chinese exports to eight other high-income countries. This should reflect China's supply shock to the world and falling trade costs that are common for high-income importing countries. At the same time, the industry import demand shocks are assumed to be uncorrelated between the U.S. and these high-income countries. [6] In particular, the instrument is defined as $\Delta IP^{*C}_{j\tau}$, with

$$IP^{C*}_{jt} = \frac{\mathbb{M}^{C*}_{jt}}{\mathbb{Y}_{j88} + \mathbb{M}_{j88} - \mathbb{X}_{j88}},$$

where $\mathbb{M}^{C*}_{jt}$ is the sum of eight high-income countries' real imports from China of goods from industry j at year t, and the denominator is real domestic absorption of U.S. industry j in 1988. Similarly, IP^{ROW*}_{jt} should capture supply shocks from the rest of the world that affect U.S. imports and are not driven exclusively by U.S. demand shocks.

The effects of export expansion coming from foreign demand shocks on U.S. employment are also difficult to identify. In order to deal with this problem, FMX create two types of instruments. The first type of instrument, which they call OTH, is analogous to the AADHP import instrument:

$$\Delta EP^{*}_{j\tau} = \frac{\Delta \mathbb{X}^{OTH}_{jt}}{\mathbb{Y}_{j91}},$$

where the numerator captures the change in export expansion of eight other high-income economies to the world (except for the United States). This is based on the assumption that these high-income countries face similar import demand shocks in foreign countries as does the United States in its exports to those countries. The world's rising demand for goods could be due to income growth in emerging economies since the 1980s, which drives demand for high-quality consumption goods from high-income countries (Costa, Garred, and Pessoa (2016)), and also due to the involvement of emerging economies in global supply chains, which drives up their demand for capital goods that are supplied by high-income countries (Eaton and Kortum (2001)). FMX provide evidence that these foreign demand shocks are not substantially correlated with U.S. domestic demand shocks, which supports the validity

[6] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Table 1.4: Estimation of U.S. Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)
Δ Chinese imports	-0.51***	-0.77***	-0.74***	-0.71***	1.81
	(0.10)	(0.15)	(0.15)	(0.17)	(0.97)
Δ Non-Chinese imports	0.23**	0.11	0.08	0.04	-0.18
	(0.09)	(0.12)	(0.10)	(0.16)	(0.51)
Δ Exports	0.23	0.59***	0.61***	0.61*	0.13
	(0.15)	(0.19)	(0.18)	(0.26)	(0.13)
Estimation method	OLS	2SLS	2SLS	2SLS	2SLS
FMX instruments		Both	OTH	OTH	OTH
Time period	1991-2007	1991-2007	1991-2007	1991-2011	2010-2016

Notes: Robust standard errors in parentheses, clustered on three-digit SIC industries. The estimations comes from specification 1.5. OTH denotes the first type of instrument from FMX described in Section 1.4.4. The sample includes 784 observations: 392 manufacturing industries during two periods (1991-1999 and 1999-2007, or 2010-2013 and 2013-2016). All regressions are weighted by start-of-period employment share of the industry and include period dummies, industry dummies, trend and control variables capturing initial industry conditions. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

of this instrument. This is the instrument I use in my analysis.[7]

1.4.5 Estimation

Table 1.4 presents the industry-level results for the manufacturing sector. All regressions in columns (1)-(4) include 392 manufacturing industries, subperiod fixed effects, and are weighted by 1991 employment. The first three rows show $\hat{\beta}_{m1}$, $\hat{\beta}_{m2}$, and $\hat{\beta}_x$ from the estimation of (1.5).

Column (1) starts with an OLS regression, where import exposure from China has a significantly negative impact on the industrial employment growth, while import exposure from the rest of the world has a positive and significant effect and export expansion has a positive but insignificant effect on employment. More specifically, a one percentage point rise

[7]The second type of instrument also corrects for domestic supply shocks and is based on a constant-elasticity, monopolistic competition framework. However, the estimation using either type of instrument yield similar results and therefore, I use only the first instrument as the second instrument requires data on tariffs that is unavailable for more recent years.

in industry Chinese import penetration reduces domestic industry employment by 0.51 percentage points, while a one percentage point rise in import penetration from ROW increases industrial employment by 0.23 percentage points.

As noted in Section 1.4.4, estimates for the import exposure and export exposure could be biased due to simultaneous changes in domestic demand. Thus, starting from column (2), I present results that use two-stage least squares (2SLS). Based on the results in column (2), using both types of FMX instruments, a one percentage point rise in industry Chinese import penetration reduces domestic industry employment by 0.77 percentage points, while a one percentage point rise in export expansion increases industrial employment by 0.59 percentage points. Both of these effects are larger in absolute terms with 2SLS than with OLS. For a positive domestic demand shock that increases domestic employment, the OLS coefficient on imports is biased up since both imports and employment are increasing, and the OLS coefficient on exports is biased down since exports are decreasing while employment is increasing.

The effect of import penetration from ROW is till positive but insignificant. Column (3) uses only the first type of instrument as described by $\Delta IP^*_{j\tau}$ and $\Delta EP^*_{j\tau}$, where I find that a one percentage point rise in industry import penetration reduces domestic industry employment by 0.74 percentage points and a one percentage point rise in export expansion increases industrial employment by 0.61 percentage points. As noted earlier, the results from using only the first instrument is similar to using both instruments of FMX. Column (4) include 2 stacked periods, with the final period ending in 2011. This is the time period most commonly used in the "China shock" literature. The general result that Chinese import exposure reduces jobs while export expansion creates them holds across columns (1)-(4).

I estimate the specification in (1.5) again for only the post-recession period of 2010-2016 using two stacked periods (2010-2013 and 2013-2016) and using the level of employment in 2010 as weights, 2010 start-of-period controls, and trade exposure measures with industry shipments

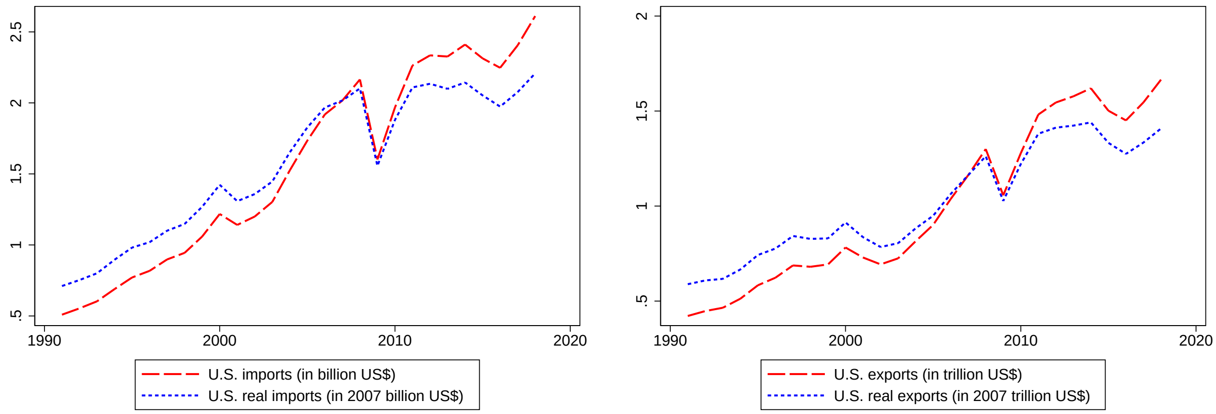


Figure 1.6: U.S. imports and exports over time

from 2010 in the denominator. I find that the effect of the "China Shock" disappears in this period (column (5)). Using U.S. Census micro data, Bloom, Handley, Kurman, and Luck (2019) also find strong employment impacts of Chinese imports from 2000 to 2007, but nothing from 2008 to 2015. In particular, they find that rising Chinese imports were historically responsible for manufacturing job losses and services job gains in the U.S., but exposure to the China shock has not been a major factor for the last decade.

I also find the coefficient on export exposure to be insignificant. There has been some evidence of a decline in U.S. export value in recent years, which may be responsible for this result. The International Trade Administration, which keeps a database of jobs supported by the export sector, has calculated that approximately 500,000 jobs supported by goods exports were lost between 2014 and 2016 and this decline was due to the fall in the value of exports. Figure 1.6 shows a decline in both imports and exports around the year 2015.

Table 1.5: Predicted changes in manufacturing employment (in thousands) due to an unbalanced trade war between U.S. and China (1991-2007)

	No Trade War	**No Retaliation**	**Simple Retaliation**	**Political Retaliation**	**Responsible Retaliation**
	(1)	(4)	(3)	(4)	(5)
1991-1999					
Imports	-124	103	103	103	103
Exports	735	735	710	730	734
Net	613	823	799	818	822
1999-2007					
Imports	-547	-104	-104	-104	-104
Exports	463	463	418	455	458
Net	-71	368	323	360	364
1991-2007					
Total Imports	-671	-1	-1	-1	-1
Total Exports	1,198	1,198	1,128	1,185	1193
Total Net	**542**	**1191**	**1,122**	**1,178**	**1186**

Notes: These calculations come from the coefficients in Table 1.4 column (3). The formula used to calculate the effect of no retaliation on the full volume of U.S. imports from China is given by (2.8), where $\Delta \tilde{IP}_{j\tau} = [(1-0.1\theta_j) \times \hat{\beta_{m1}} \Delta IP^{C}_{j\tau}] + \hat{\beta_{m2}} \Delta IP^{ROW}_{j\tau}$, and $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^{C}_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$.

1.4.6 Employment Impact of a Hypothetical Trade War, 1991-2007

Column (1) of Table 1.5 shows predicted net employment changes from the specification in column (3) of Table 1.4, where $\hat{\beta}_{m1}$, $\hat{\beta}_{m2}$, and $\hat{\beta}_x$ are the coefficients from the regression, and $L_{j,end}$ is the employment in industry j in the end year of the period (i.e., 1999 or 2007). U.S. export expansion net of import penetration led to a net gain of 542,000 jobs in the U.S. manufacturing sector during 1991-2007. 671,000 jobs were lost due to import penetration and 1,198,000 jobs were also gained due to export expansion. Export expansion created enough jobs to offset job losses due to Chinese import penetration.[8]

Column (2) reports the calculations of predicted employment changes for 1991-2007 under the scenario where the U.S. imposed 10 percent uniform tariffs on all Chinese imports and there is no retaliation by China. The number of jobs gained due to reduction in import

[8] This is the key result of FMX

competition is around 670,000 jobs, which is about the same amount that were lost due to Chinese import competition during this time period. This implies that had the U.S. imposed uniform import tariffs during this time, the "China shock" would not have occurred. The tariffs would not have allowed Chinese imports to rapidly increase the way they did in the 2000s.

Columns (3)-(5) report calculations for three different retaliation scenarios described in Section 1.4.2. Here I find that all scenarios of retaliation make the U.S. better off and that the net outcomes are not that much worse compared to the scenario with no retaliation. The number of jobs gained due to the import tariffs is very large and the number of jobs lost due to retaliatory tariffs is very little. The U.S. is able to take advantage of the huge trade deficit with China.

Table 1.6 shows calculations for a balanced trade war between U.S. and China under three different retaliation scenarios. Columns (1) and (5) report the actual predicted employment changes from the specification in (1.5) for total U.S. trade and U.S.-China trade respectively. Column (5) shows that the employment decrease due to import competition is mostly driven by Chinese import competition, whereas the employment increase due to export expansion is mostly driven by exports to countries other than China. The net effect on employment from Chinese trade alone is negative and quite large ($\approx$ 800,000 jobs).

Columns (2) and (6) report the calculations of predicted employment changes based on the scenario of simple retaliation described in section 1.4.2.1. Both U.S. and China target similar trade volumes in this case ($27 billion in 2007 dollars). The simple trade war leads to a net increase in employment relative to the no-trade-war scenario. This is because the jobs gains due to falling import exposure is more than the jobs lost due to falling export exposure, which is driven by the larger negative effect of Chinese import competition relative to the positive effect of U.S. export expansion.

Table 1.6: Predicted changes in manufacturing employment (in thousands) due to a balanced trade war between U.S. and China (1991-2007)

	All U.S. trade				*U.S.-China trade*			
	No Trade War	Simple Retaliation	Political Retaliation	Responsible Retaliation	No Trade War	Simple Retaliation	Political Retaliation	Responsible Retaliation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1991-1999								
Imports	-124	-76	-106	-118	-281	-231	-262	-274
Exports	735	710	730	734	39	9	34	38
Net	613	633	625	618	-240	-222	-227	-236
1999-2007								
Imports	-547	-450	-509	-534	-631	-534	-593	-619
Exports	463	418	455	458	75	31	66	70
Net	-71	-21	-42	-63	-553	-502	-525	-545
1991-2007								
Total imports	-671	-526	-615	-653	-912	-764	-855	-893
Total exports	1,198	1128	1,185	1,193	114	39	99	108
Total Net	**542**	**612**	**583**	**555**	**-794**	**-724**	**-752**	**-781**

Notes: These calculations come from the coefficients in Table 1.4 column (3).

Table 1.7: Characteristics of Trump manufacturing industries (1991-2007)

Number of industries	165
Average trade cost elasticity	5.97
Share of employment in 1991	0.37
Share of employment in 2007	0.40
Share of Chinese imports in 1991	0.16
Share of Chinese imports in 2007	0.28
Share of non-Chinese imports in 1991	0.44
Share of non-Chinese imports in 2007	0.48
Share of exports in 1991	0.42
Share of exports in 2007	0.44

A balanced trade war with political retaliation by China as described in Section 1.4.2.2 also gives a net gain of manufacturing jobs compared to the no-trade-war scenario. The net effect is slightly worse than the simple retaliation case, since the retaliation by China is on a subset of industries. Table A.2 lists the top ten Trump industries and some characteristics of Trump industries are highlighted in Table 1.7. Industries with a higher share of Trump supporters are fewer in number (165 out of 392), have a lower average trade cost elasticity (5.97 versus 7.71 for non-Trump industries), and a lower share of total manufacturing employment (39 percent on average). Trump industries also export more globally than they import from China.

Responsible retaliation as described in Section 1.4.2.3 focuses only on those industries where U.S. is a net exporter and there is little intra-industry trade between the U.S. and China. Responsible retaliation by China also gives a net increase in employment compared to the no-trade-war scenario. Table 1.8 presents a summary of some characteristics of these industries. There is a very low share of employment in these industries to begin with.

Overall, it appears that the U.S. seems to gain in net employment no matter how the partner countries retaliate. This is also driven by the fact that the negative effect of Chinese import exposure is much larger than the positive effect of U.S. export exposure, which in turns makes the job creating effect of import tariffs larger.

Table 1.8: Characteristics of industries where the U.S. is a net exporter and there is very little intra-industry trade with China (1991-2007)

Number of industries	38
Average trade cost elasticity	6.65
Share of employment in 1991	0.08
Share of employment in 2007	0.09
Share of imports from China in 1991	0.01
Share of imports from China in 2007	0.004
Share of exports to China in 1991	0.10
Share of exports to China in 2007	0.34

1.4.7 Employment Impact of a Hypothetical Trade War, 2010-2016

The China shock of the 2000s may not be relevant in 2018 as a motivation for protectionism. Import tariffs now are unlikely to bring back manufacturing jobs that were labor-intensive in the 1990s and 2000s but are now replaced by automation and offshoring. Using U.S. Census micro data, Bloom, Handley, Kurman, and Luck (2019) find strong manufacturing employment impacts of Chinese imports from 2000 to 2007, but nothing from 2008 to 2015. Moreover, they find that find almost all of the manufacturing job losses were in large, multinational firms that were offshoring manufacturing jobs while simultaneously expanding in services and that there is no evidence that Chinese import competition generated net job losses.

Given this insight, I now focus on only the post-recession period of 2010-2016 to see how the long-run employment consequences of the trade war might actually turn out. Note from figure 1.7 that although manufacturing employment has been unable to return to pre-China shock levels, there has been a steady increase in these jobs in the past decade.

As discussed in Section 1.4.5, Table 1.4 column (5) shows that neither Chinese import penetration nor U.S. export expansion have any significant effect on manufacturing employment. In fact, even the sign for the coefficient on Chinese import exposure changes. This supports

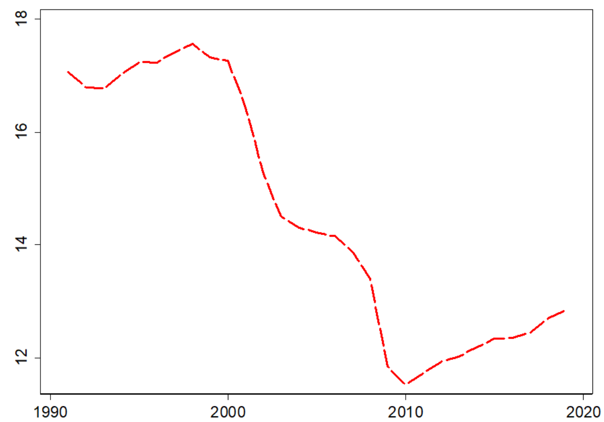


Figure 1.7: Average U.S. manufacturing employment over time (in millions)

previous evidence that the China shock is no longer prevalent since the Great Recession of 2008.

Using the coefficients from column (5), I find that the actual predicted net change in employment due to import and export exposure during 2010-2016 is positive (Table 1.9). Because Chinese imports no longer have a negative effect on employment, any kind of retaliation scenario would lead a reduction in jobs compared to the no-trade-war scenario. Had there been protectionism during this post-recession period even with no retaliation by China, the U.S. would have lost more manufacturing jobs. This is completely opposite to the result in Section 1.4.6.

1.5 Discussion

The result that U.S. import tariffs would have reversed the loss of manufacturing jobs due to Chinese import competition between 1991-2007 is what one would expect. Much of the U.S. political debate focuses on the huge number of manufacturing jobs lost due to trade with China and other factors, such as technological advancement. However, trade with China has led to many positive outcomes. Not only do cheaper Chinese products make American

Table 1.9: Predicted changes in manufacturing employment (in thousands) due to an unbalanced trade war between U.S. and China (2010-2016)

	No Trade War	**No Retaliation**	**Simple Retaliation**	**Political Retaliation**	**Responsible Retaliation**
	(1)	(4)	(3)	(4)	(5)
2010-2013					
Imports	103	6	6	6	6
Exports	44	44	42	43	43
Net	145	50	48	49	49
2013-2016					
Imports	71	6	6	6	6
Exports	-31	-31	-30	-31	-31
Net	40	-25	-24	-24	-25
2013-2016					
Total Imports	174	12	12	12	12
Total Exports	13	13	12	12	12
Total Net	**185**	**25**	**24**	**24**	**24**

Notes: These calculations come from the coefficients in Table 1.4 column (5). The formula used to calculate the effect of no retaliation on the full volume of U.S. imports from China is given by (2.8), where $\Delta \tilde{IP}_{j\tau} = [(1-0.1\theta_j)\times \hat{\beta_{m1}} \Delta IP^{C}_{j\tau}] + \hat{\beta_{m2}} \Delta IP^{ROW}_{j\tau}$, and $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^{C}_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$.

consumers better off, American producers also benefit a lot from access to the Chinese consumer market. Companies like KFC and General Motors sell more of their products in China than they do in the U.S. Moreover, although the number of manufacturing jobs plummeted, manufacturing output continued to grow, except during the 2008 recession. The result that after the Great Recession, there was no effect of Chinese import competition on manufacturing jobs combined with the fact that manufacturing output has continued to grow, suggests that production patterns have shifted already during this time towards more automation and offshoring and import tariffs might bring back some jobs but is unlikely to reopen factories and cause a reversal of the manufacturing decline. The jobs that were lost were more labor-intensive and using older technology, and are unlikely to be revived.

The ongoing trade war also creates a lot of uncertainty, which may slow down or delay major business investment decisions both for exporting and importing firms. With no end to the trade war in sight, companies may be already looking to shift production to other countries, such as Vietnam. The short-term effects of the ongoing trade war on employment suggest that import tariffs are not yet causing a change in the employment growth but export tariffs are already having a negative impact. China is already able to hurt U.S. employment but the tariffs imposed by the U.S. itself is not having any immediate impact.

There have been studies on other short-run outcomes, which all estimate mostly negative effects. Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) estimate annual consumer and producer losses from higher cost of imports to be $68.8 billion, which is 0.37 percent of GDP. The aggregate welfare loss was found to be $7.8 billion (0.04 percent of GDP). They also find that tradable-sector workers in heavily Republican counties were the most negatively affected by the trade war. Amiti, Redding, and Weinstein (2019) find that the burden of U.S. import tariffs fall on domestic consumers, with a reduction in U.S. real income of $1.4 billion per month in 2018.

1.6 Concluding Remarks

While Chinese import competition reduced a large number of U.S. manufacturing jobs, export expansion has also been very large for the U.S., thereby creating enough jobs to offset the job losses due to Chinese imports between 1991-2007. The reverse would have happened if there was a trade war during this period since U.S. import tariffs would limit the job reducing effect of Chinese import competition, while retaliatory tariffs on U.S. exports would reduce the job creating effect of U.S. export expansion. I calculate the effect of a hypothetical trade war on employment under three different retaliation scenarios and find that the United States would have experienced a net gain in jobs relative to the actual no-trade-war scenario between 1991-2007 irrespective of the kind of retaliation imposed by China. This is because the job creating effect of import tariffs turn out to be much larger than the job destroying effect of retaliatory tariffs. However, the opposite is true when I consider the post-recession period of 2010-2016, which is more representative of the manufacturing industry composition in the United States today.

I also find that the immediate effects of the Chinese retaliatory tariffs from the ongoing U.S.-China trade war on commuting zone-level employment growth is negative and statistically significant, whereas there is no significant effect of U.S. import tariffs. These results combined together suggest that the employment consequences of the U.S-China trade wars are negative in the short-run and are unlikely to be largely positive in the long-run either because of the shift in the nature of manufacturing production towards automation and offshoring in the past decade.

Chapter 2

Chinese Import Exposure and U.S. Occupational Employment

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 (2016b) 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

[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.

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 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 (2003a), 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 2.1 briefly describes the relevant literature. In section 2.2 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 2.3 presents our empirical analysis for the impact of Chinese import exposure on U.S. occupational employment. Lastly, section 2.4 concludes.

2.1 Literature Review

As mentioned above, this paper builds on the recent contributions of Autor, Dorn, and Hanson (2013), AADHP, and Pierce and Schott (2016b), 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

[2]While Pierce and Schott (2016b) 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.

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 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.

2.2 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).

2.2.1 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 B.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]

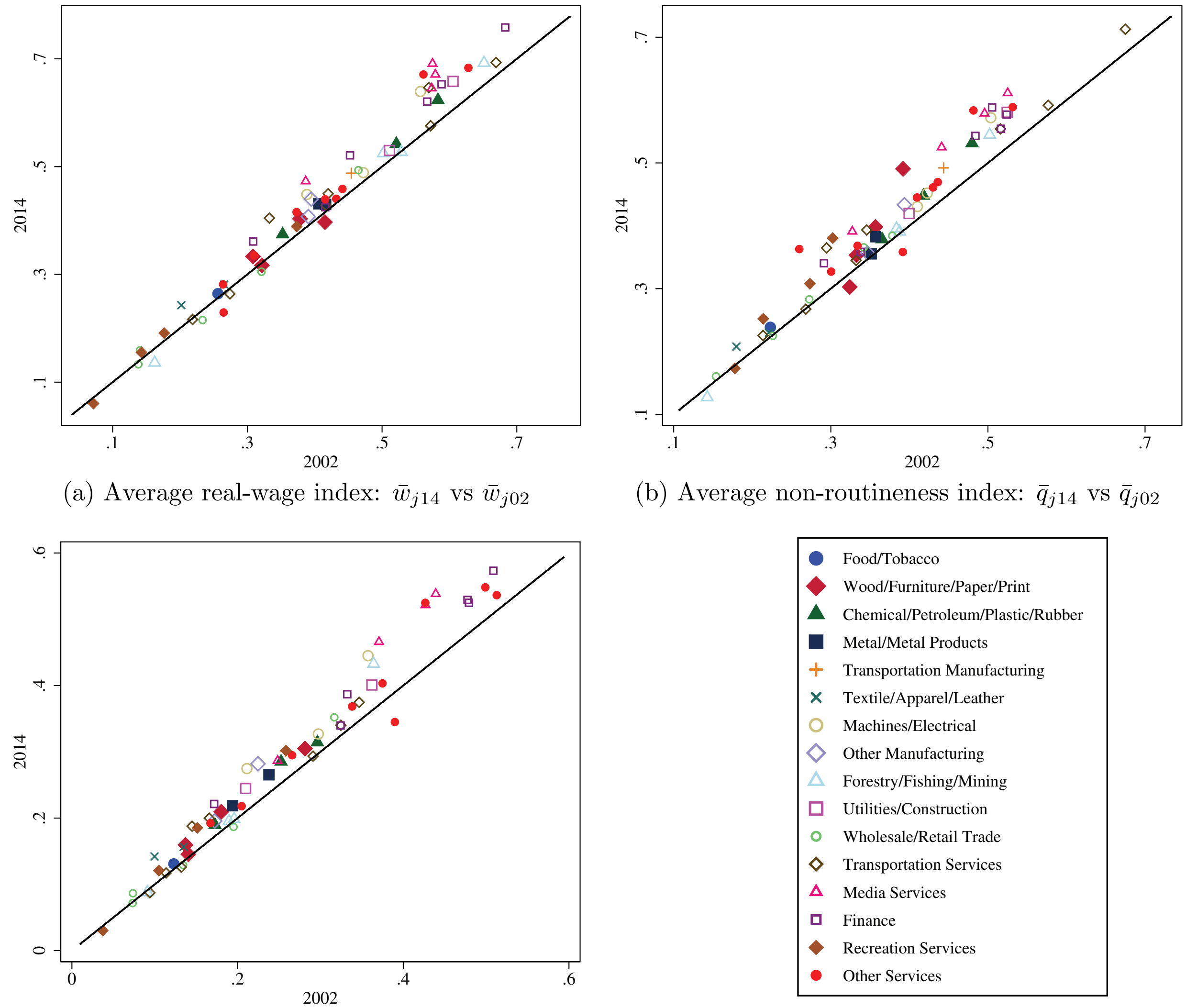
[3] According to the O*NET's website (https://www.onetonline.org/help/online/zones), occupations in job zone 1 need little or no preparation (some may require high school), occupations in job zone 2 need some preparation (usually require high school), occupations in job zone 3 need medium preparation (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).

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 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 2.1 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.



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

In addition, Figure 2.1 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

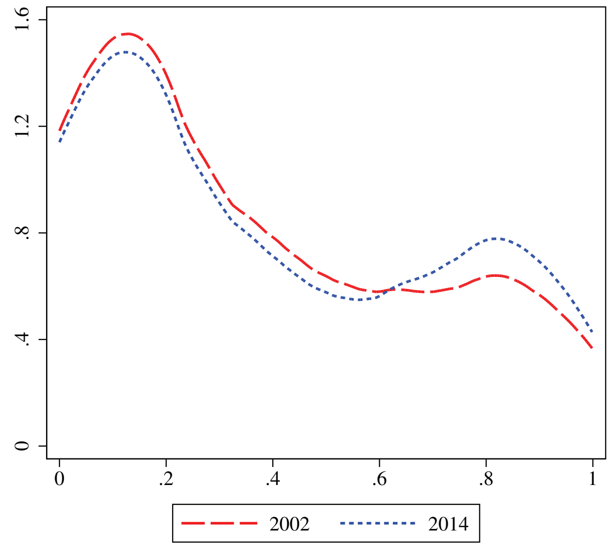
Wood/Furniture/Paper/Print, Metal Products, Chemical/Petrolatum/Plastic/Rubber, and Machines/Electrical. On the other hand, Transportation Services is the most non-routine category, and while industries in this category have in general mid-to-high average real wages, they have low average education indexes.

Reinforcing the point of a generalized change in the composition of U.S. employment toward higher-indexed occupations, Figure 2.2 shows the kernel distributions of occupational employment in 2002 and 2014 under our three sorting criteria. Figure 2.2a shows that the decline in the employment share of lower-wage occupations occurs up to the 60th percentile, while Figure 2.2b shows that the decline in the employment share of routine occupations occurs up to the 40th percentile. An interesting fact from the distributions in Figures 2.2a and 2.2b 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.

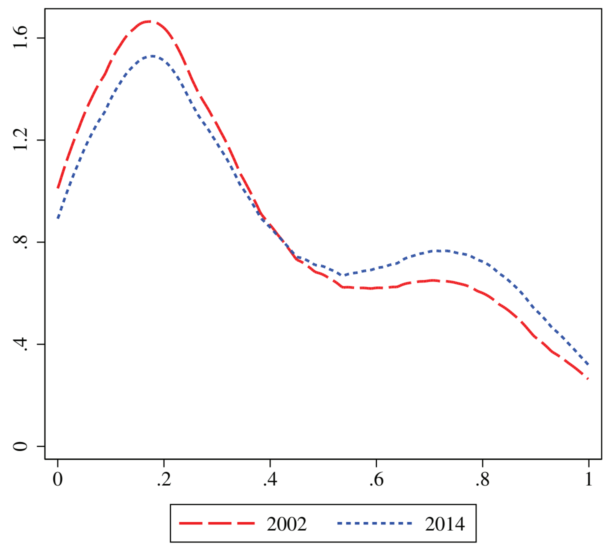
From Figure 2.2c we see that the kernel distribution of occupational employment based on the education ranking is not as smooth as the distributions based on the wage and non-routineness rankings. This is simply a consequence of the O*NET "job zone" rating, which clusters in integer values from 1 to 5 (corresponding to values 0, 0.05, 0.39, 0.66, and 0.85 in the percentile education 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.

2.2.2 Chinese Import Penetration

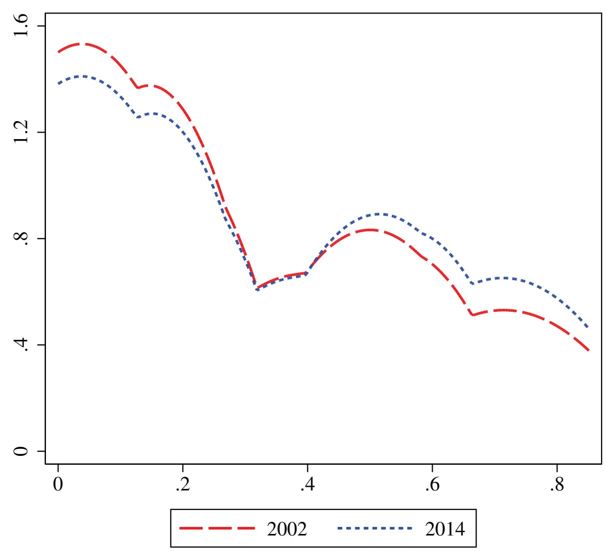
This section describes our measures of U.S. exposure to Chinese imports. First we discuss the construction of the industry-level measures, and then show how to construct from them



(a) From low to high wage



(b) From routine to non-routine



(c) From low to high education

Figure 2.2: Distribution of U.S. Occupational Employment in 2002 and 2014 (by Sorting Criterion)

the occupation-specific measures of Chinese import penetration.

2.2.2.1 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

$$IP_{jt} = \frac{\mathbb{M}^C_{jt}}{\mathbb{Y}_{j00} + \mathbb{M}_{j00} - \mathbb{X}_{j00}}, \tag{2.1}$$

where $\mathbb{M}^C_{jt}$ 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

[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 B.1.

line with AADHP, the instrument for our variable in equation (2.1) is

$$IP^*_{jt} = \frac{\mathbb{M}^{C*}_{jt}}{\mathbb{Y}_{j00} + \mathbb{M}_{j00} - \mathbb{X}_{j00}}, \tag{2.2}$$

where $\mathbb{M}^{C*}_{jt}$ 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 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 (2.1), 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

[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 B.1.

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

$$UIP_{jt} = \sum_g \omega^U_{gj} IP_{gt}. \tag{2.3}$$

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

$$DIP_{jt} = \sum_g \omega^D_{jg} IP_{gt}. \tag{2.4}$$

Using (2.2), we construct the instruments for UIP_{jt} and DIP_{jt} as $UIP^*_{jt} = \sum_g \omega^U_{gj} IP^*_{gt}$ and $DIP^*_{jt} = \sum_g \omega^D_{jg} IP^*_{gt}$.

2.2.2.2 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.

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

$$IP_{it} = \sum_{j} \left(\frac{L_{ij02}}{L_{i02}} \right) IP_{jt}, \tag{2.5}$$

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 (2.1). 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 (2.5) 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 2.3 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 2.3 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 2.3 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,

[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.

mid-routine, mid-education), and those marked with a triangle denote the highest-tertile occupations (high wage, non-routine, high-education).

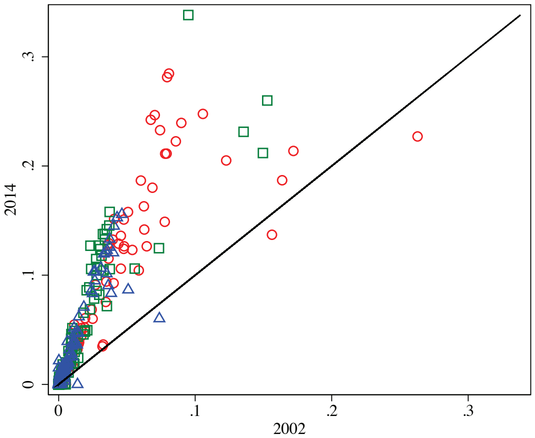
First, note that the vast majority of occupations are well above the 45 degree line for both types of Chinese import penetration (direct and combined), indicating extensive occupational exposure to Chinese imports during the period. For the combined import penetration measure, for example, only six occupations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

2.2.3 Occupation-Specific Capital Exposure Controls

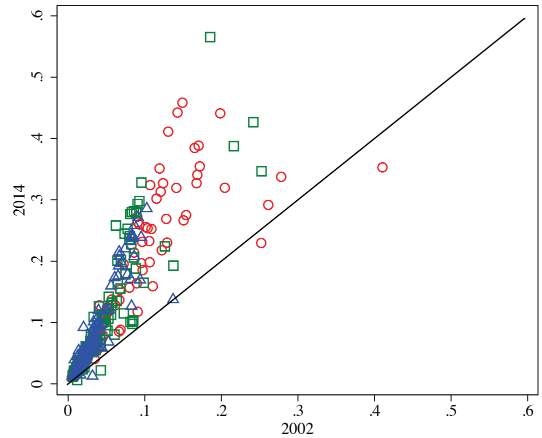
To control for automation forces, which may substitute workers of some occupations but may complement workers in other occupations, in our specifications below we include occupation-specific measures of capital exposure as regressors. Given that changes in capital stock throughout the period are likely 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,

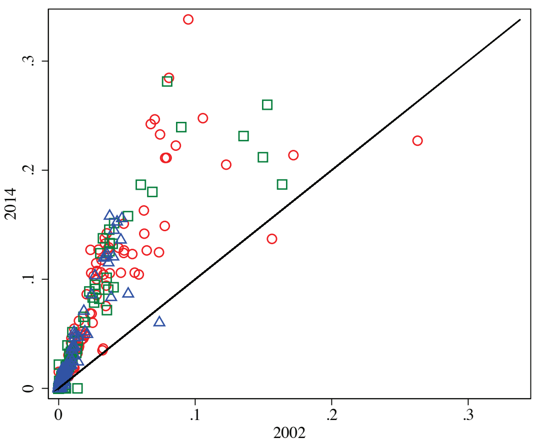
[8]The BEA report 96 types of fixed private assets. Following Eden and Gaggl (2015), 23 of them are



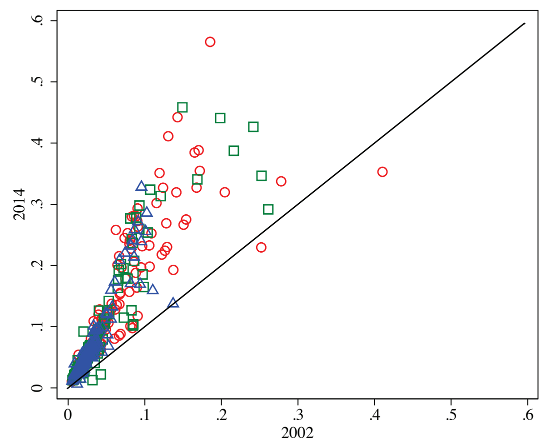
(a) Direct import penetration – Wage



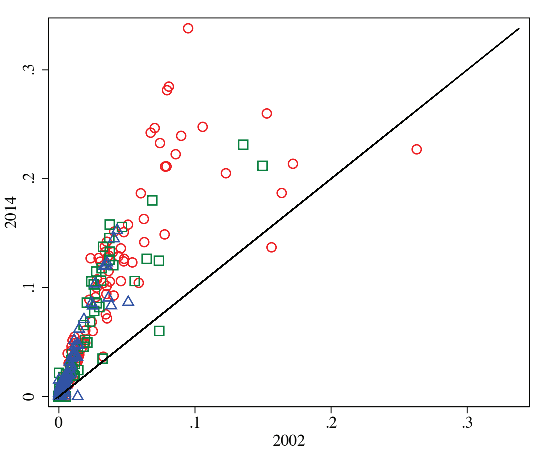
(b) Combined import penetration – Wage



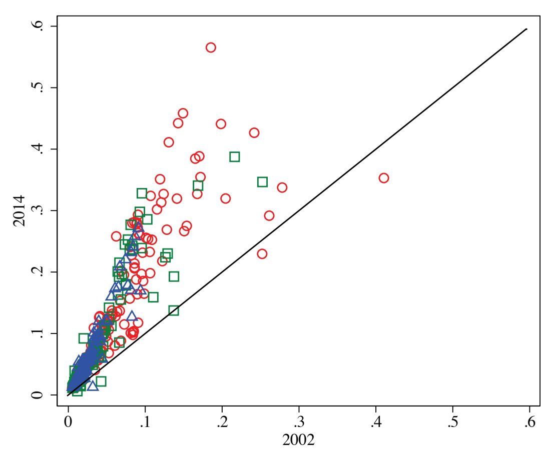
(c) Direct import penetration – Non-routineness



(d) Combined import penetration – Non-routineness



(e) Direct import penetration – Education



(f) Combined import penetration – Education

Figure 2.3: Occupation-Specific Import Penetration Measures in 2002 and 2014 under Three Sorting Criteria (Wage, Non-routineness, Education): Lowest tertile in red circle, Middle tertile in green square, Highest tertile in blue triangle

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 (2.5), the index of ICT capital exposure for occupation i is given by

$$K^I_i = \sum_j \left(\frac{L_{ij02}}{L_{i02}} \right) K^I_{j02}, \tag{2.6}$$

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

2.3 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

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

classified as ICT capital, and 73 as non-ICT capital.

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

2.3.1 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

$$\Delta \ln L_{it} = \alpha_t + \beta \Delta IP_{it} + \gamma Z_i + \varepsilon_{it}, \tag{2.7}$$

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 2.1 presents the results of the estimation of the specification in (2.7). All regressions in Table 2.1, 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 (2.5), 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 2.1 are negative and statistically significant

Table 2.1: 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.

at least at the 5 percent level, showing that—as found by Autor, Dorn, and Hanson (2013) at the 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

$$Predicted\ employment\ change = \sum_i \left[1 - e^{-\hat{\beta}\rho(IP_{i14} - IP_{i02})}\right] L_{i14}, \tag{2.8}$$

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]

2.3.2 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-

[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).

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 2.2.1. Thus, the econometric specification with occupational sorting is

$$\Delta \ln L_{it} = \sum_{k=1}^{3} \left[\alpha_{kt}^{\ell} + \beta_k^{\ell} \Delta IP_{it} + \gamma_k^{\ell} Z_i \right] \mathbb{1}_i \{T_k^{\ell}\} + \varepsilon_{it}, \tag{2.9}$$

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 2.2 shows our estimation of (2.9) 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 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-

Table 2.2: 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.

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 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

[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.

workers.[11] The most plausible mechanism for the results in column 6 is a combination of the second and third scenarios.

Table 2.3 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 2.1, 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 (2.8).

Table 2.4 presents the predicted employment changes from Chinese import exposure based on the regressions with production controls (in the even columns) of Tables 2.2 and 2.3, as well as for other specifications described below. For our three sorting criteria, the first three rows of Table 2.4 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 2.2 shows a strong positive effect of direct import exposure on high-education occupations, with the first row of Table 2.4 showing that the 1.2 million predicted

[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 2.3: 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 in high-education occupations more than make up for the 0.8 million job losses in low-education occupations. However, column 6 of Table 2.3 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 2.4 show predicted job gains in high-education occupations that continue to be larger than job losses in low-education occupations, these 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 2.2, 2.3, and the first three rows of Table 2.4 suggest, not surpris-

Table 2.4: 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 2.2									
Direct import exposure	**-731**	205	606	**-602**	**-497**	876	**-794**	-9	**1,227**
Table 2.3, panel A									
Direct + upstream	**-1,292**	266	813	**-1,101**	**-609**	1,352	**-1,216**	-56	1,580
Table 2.3, panel B									
Direct + upstream+downstream	**-1,751**	112	811	**-1,429**	**-907**	1,526	**-1,662**	-66	2,097
Table 2.5									
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 2.6, 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 2.6, 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 2.2-2.5 with wage and capital controls. Negative values indicate that import exposure reduces employment. Equation (2.8) shows the general formula to calculate predicted employment changes. The numbers in bold denote predicted changes corresponding to statistically significant coefficients in Tables 2.2-2.5. The predicted employment changes changes from Table 2.1 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.

ingly, 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.

2.3.3 Employment Responses by Sector Exposure

The last part of our empirical analysis expands the specification in equation (2.9) 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

[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.

written as

$$\Delta \ln L_{ist} = \sum_{k=1}^{3} \Big[\alpha^{\ell}_{kst} + \beta^{\ell}_{k1}\Delta IP_{it} \times \mathbb{1}_s\{1\} + \beta^{\ell}_{k2}\Delta IP_{it} \times \mathbb{1}_s\{2\} + \beta^{\ell}_{k3}\Delta IP_{it} \times \mathbb{1}_s\{3\}$$
$$+\gamma^{\ell}_{ks} Z_{is}\Big] \mathbb{1}_i\{T^{\ell}_k\} + \varepsilon_{ist}, \tag{2.10}$$

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 2.5 shows the results from the estimation of equation (2.10) 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.

For the exposed sector, Table 2.5 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

[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 2.5: 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.

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 2.5 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 2.6 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 2.5, 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

[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 2.6: 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.

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.

To gauge the importance of the effects obtained in our occupational-sectoral estimation, the last nine rows of Table 2.4 present the 2002-2014 implied employment changes from Tables 2.5 and 2.6 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]

2.4 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

[17] Note, however, that the statistically significant creation of 1.2 million jobs in high-education occupations reported in the first row of Table 2.4 (corresponding to the results from Table 2.2) present indirect evidence of an active job reallocation channel toward better 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 (2019) 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 (2003a), by which low-productivity firms exposed to Chinese 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.

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

Chapter 3

Markups and Productivity of Heterogeneous Producers

One of the chief puzzles in international macroeconomics is why large movements in nominal and real exchange rates have little impact on the prices of internationally traded goods. Exchange rate pass-through[1], which is a measure of how responsive international prices are to changes in exchange rates, have been estimated by various studies and have been found to be quite low or incomplete (e.g.,Goldberg and Knetter (1996), Campa and Goldberg (2005))[2]. The causes of incomplete pass-through have been attributed to the presence of local costs (Corsetti and Dedola (2005)), price rigidity (Devereux and Engel (2002)), and product differentiation in quality (Yu et al. (2013)).

With respect to the response of markups to exchange rate movements, Goldberg and Knetter (1996) show that destination-specific changes in markups due to third-degree price discrim-

[1]Exchange rate pass-through to import (export) price = percentage change in import (export) price / percentage change in exchange rate. An exchange rate pass-through that is equal to one implies complete pass-through. As the importer's currency depreciates, as a result of incomplete pass-through, the markup decreases to accommodate for the less than full increase in import price.

[2]For example, Campa and Goldberg (2005) find that in the U.S., pass-through rate is 25 percent in the short run and 40 percent in the long run.

ination are significant in explaining the lack of response of prices to exchange rate changes, and Hellerstein (2008) finds that in the beer industry, markup adjustments explain roughly half of the incomplete transmission of exchange rate changes into prices. However, there have been very few empirical studies using firm-level heterogeneity in markup adjustments as an explanation for the lack of response of aggregate prices to exchange rate movements.

Firms are heterogeneous with respect to their levels of productivity. This has been documented empirically. Bernard and Jensen (1999) find that U.S. exporters are more productive than non-exporters in the same industry. Firms of higher productivity have lower marginal cost of production and hence set lower prices and are also able to set higher markups. The question of interest here is whether the markup of a very productive firm or that of a low-productivity firm will be more responsive when faced with an exogenous exchange rate shock. The answer to this question has broad implications for the effects of exchange rate changes on prices and trade flows, and for theoretical modeling choices.

This paper links firm-level heterogeneity to responses to exchange rate changes. I find that firms of higher productivity have lower rates of exchange rate pass-through to export prices, i.e., they adjust their markups by a higher magnitude. However, firms of higher productivity also have less volatile markups, i.e, they adjust their markups less frequently than do firms of lower productivity. I document these results using Compustat firm-level unbalanced panel data for around 4000 U.S. manufacturing firms from 1964 to 2011.

Recent theoretical models of international trade have introduced firm heterogeneity at the core of the analysis (e.g. Melitz (2003b), Bernard, Eaton, Jensen, and Kortum (2003)). Newer theoretical models of heterogeneous firms assume preferences that imply endogenous markups. Bernard, Eaton, Jensen, and Kortum (2003) assume Bertrand oligopolistic price competition, Atkeson and Burstein (2008) assume Cournot oligopolistic quantity competition, Melitz and Ottaviano (2008) assume a quasilinear-quadratic utility function that generates a linear demand system with endogenous markups and Rodriguez-Lopez (2011) assumes a translog expenditure function that generates a demand system with endogenous markups. Although these models agree on the positive relationship between productivity and markups, different assumptions in preferences can have opposite implications regarding the responsiveness of heterogeneous firms' markups to exogenous shocks. For example, in response to exchange rate shocks, a model with the quasilinear-quadratic preferences of Melitz and Ottaviano (2008) predicts that markups of more productive firms are more responsive, while a model with the translog preferences of Bergin and Feenstra (2000) predicts the opposite (see Rodriguez-Lopez (2011)).

Using French firm-level data, Berman, Martin, and Mayer (2012) find that high-productivity firms have lower pass-through rates of exchange rate changes to prices, which they suggest is evidence that more productive firms have more responsive markups (i.e., they prefer to absorb a shock in their markups rather than changing prices), thus supporting the theoretical model of Melitz and Ottaviano (2008). I explore this question empirically following a different approach.

Instead of simply looking at whether higher productivity firms have higher or lower pass-through rates, I also compute the volatility of markup adjustments and investigate whether firms of higher productivity have more volatile markups or not. Empirically, I find that smaller and less productive firms adjust their markups more frequently in response to exchange rate movements in order to remain competitive. In other words, even though less productive firms have a lower markup elasticity, they have more volatile markups in order to save their market share from more productive firms.

This suggests that the price adjustment costs (or menu costs) of more productive firms are smaller since they adjust their prices more frequently and by smaller amounts. Therefore, it appears that the lump-sum component of menu costs that all firms have to pay irrespective of their size, is important for explaining the heterogeneous markup adjustment behavior of firms and consequently the aggregate pricing behavior. Larger and more productive firms account for a higher share of aggregate exports and also absorb more of the exchange rate changes in their markups. Therefore, aggregate prices do not change very much. At the same time, smaller and less productive firms, which are more in number, adjust their markups much more frequently, another reason why exchange rate movements do not show up much in aggregate prices in the short-run. This paper is complementary to existing studies on incomplete exchange rate pass-through and heterogeneous firm behavior.

The rest of the paper is organized as follows. Section 3.1 presents related literature. Section 3.2 introduces the empirical strategy, presents the data and empirical findings, and also discusses the implications of the findings. Section 3.3 concludes.

3.1 Related Literature

Empirical studies on the magnitude of price adjustments find that price changes are quite large but many small price changes also occur. Nakamura and Steinsson (2008) use U.S. microdata from the Bureau of Labor Statistics to find that the median magnitude of finished-goods producer prices is 7.7 percent, while Klenow and Kryvtsov (2005) find that the median of regular consumer price changes is 10 percent , which can be considered as pretty large. However, Klenow and Kryvtsov (2005) also find that there are many small price changes that occur. Since large firms are the ones making small price changes, as reported using Compustat data, this finding is not surprising.

The theoretical literature has also tried to accommodate the fact that small price changes do exist. Midrigan (2011) models both large and small price changes by assuming economies of scope in price adjustment, while Caballero and Engel (1999) assume that the cost of changing prices is stochastic, such that when the cost is low, firms might make frequent price changes. These firms would be the more productive firms, as suggested by this paper.

As far as the frequency of price adjustments is concerned, Nakamura and Steinsson (2008) document that the median duration of regular price changes is 8-11 months. Klenow and Malin (2010) survey various studies and data sources to conclude that price changes occur at least once a year but the degree of price stickiness differs across countries. More specifically, producer prices have a median duration of 12 months in the Euro area, 6-8 months in the U.S., and are even less stickier in high-inflation developing countries like Brazil, Chile and Mexico.

Gopinath and Itskhoki (2008) using BLS microdata run cost pass-through regressions and find evidence that firms that adjust prices infrequently also pass-through a lower amount even after several periods and multiple rounds of price adjustment, as compared to high frequency adjusters. They take this evidence to imply that firms that infrequently adjust prices are typically not as far from their desired price, while firms that have high pass-through drift farther away from their optimal price and, therefore make more frequent adjustments.

In this paper, more productive firms are high frequency adjusters, not because they drift away from their optimal price, but because the menu costs they face are lower and therefore, it is easier for them to adjust their prices more frequently. However, despite being high frequency adjusters, they do not pass-through a higher amount, as observed by Gopinath and Itskhoki (2008). The fact that more productive firms have lower rates of pass-through has also been observed by Berman, Martin, and Mayer (2012).

Using New Zealand survey data, Buckle and Carlson (2000) show that large firms change prices more frequently than small firms. In fact, they report a perfect rank-order correlation between firm size and the average frequency of price changes. In their paper, size is defined by the number of employees. Since firm size and productivity are positively related, this can be taken as evidence that more productive firms do change prices more frequently.

On the subject of the significance of menu costs, theoretically, menu costs of price adjustment are a popular explanation for price stickiness in markets characterized by monopolistic competition. Ball, Mankiw, Romer, Akerlof, Rose, Yellen, and Sims (1988) find that menu costs cause prices to adjust infrequently. So the higher the menu cost, the higher is the infrequency of price adjustment. This supports the claim that more productive firm have lower menu costs, since they are the ones to adjust prices more frequently.

Levy, Bergen, Dutta, and Venable (1997) provide direct empirical evidence on menu costs using store-level data. They find that the magnitude of menu costs found is large enough to be capable of having macroeconomic significance. They also suggest that managerial menu costs are very important. This includes the time and attention required by managers to gather relevant information to implement a price change. This is lump-sum and independent of firm size. Slade et al. (1998) also find that the estimated magnitude of fixed costs of price adjustment is substantially larger than that of variable costs. This evidence helps emphasize the importance of lump-sum menu costs in explaining price adjustment behavior by heterogeneous firms.

3.2 Empirical Analysis

3.2.1 Empirical Specification

First, to verify that firms of higher productivity do set higher markups and to determine whether firms of higher or lower productivity have higher pass-through rates to export prices, I run the following regression:

$$ln(\mu_{it}) = \alpha ln(TFP_{it}) + \beta ln(REER_t) + \gamma ln(REER_t) * \Phi_i + \Psi_i + u_{it}, \tag{3.1}$$

where, μ_{it} is the markup of firm i at time t, TFP_{it} is the firm-level total factor productivity at time t, and $REER_t$ is the real effective exchange rate between the U.S. and its major trading partners at time t. An increase in this index means appreciation. Φ_i is the relative TFP of each firm compared to its 4-digit SIC industry peers. I first rank the firms within each industry based on their average lifetime TFP and then map this ranking to the [0,2] range such that zero corresponds to the firm with lowest productivity, 1 corresponds to the firm with median productivity within each industry, and 2 corresponds to the firm with the highest productivity. This is done for ease of interpretation when distinguishing the effects of an exchange rate movement between a firm of lower productivity versus a firm of higher productivity. Firm fixed-effects are included in the regression. The effect of an exchange rate movement will be seen by $\beta + \gamma\Phi$ for firms of different productivity levels.

I expect α to be positive, since firms of higher productivity are expected to set higher markups. If there is incomplete exchange rate pass-through to export prices along with an appreciation of the exporter's currency, prices in the importer's currency will increase but less than the complete pass-through price, and exporters will achieve this by absorbing a part of the exchange rate movement in their markups. I expect β to be negative since an appreciation will cause markups to decrease. Now the question of interest is whether firms of higher or lower productivity will lower their markups more following an appreciation. In the theoretical framework of Rodriguez-Lopez (2011), more productive firms have higher pass-through in the exact translog expenditure case and lower pass-through in the quasilinear-quadratic utility case.

The empirical specification for the relationship between the volatility of markups and exchange rate movements is:

$$ln(Volatility_{it}^{\mu}) = \alpha ln(sale_{it}) + \beta ln(REER_t) + \gamma ln(REER_t) * \Phi_t + \Psi_i + u_{it}, \qquad (3.2)$$

where $Volatility^{\mu}_{it}$ is the standard deviation of five-year rolling windows of firm-level markup adjustments computed as $\sigma(\triangle\mu_{it}) = \sqrt{\frac{1}{5}\sum_{\tau=t-2}^{t+2}(\mu_{i\tau} - \bar{\mu}_{it})^2}$, where $\bar{\mu}_{it}$ is the average from $t-2$ to $t+2$. $\triangle\mu_{it}$ is the percentage change in μ_{it} from period $t-1$ to t. The use of rolling standard deviations to compute volatility of micro-level variables such as sales growth and earnings can be found in Comin and Philippon (2006) and Cournède, Garda, and Ziemann (2015). Again, $\beta + \gamma\Phi$ will be able to tell us whether firms of higher or lower productivity have more volatile markups.

I also use another measure of volatility that is used in Cournède, Garda, and Ziemann (2015). I count the incidences of large adjustment in markups by every firm. I define a large change as being greater than the 75th percentile of the distribution of absolute percentage change in firm-level markups from one year to the next. Using this measure of markup volatility, I run a Poisson regression, where the log of the response variable $count_i$ follows a Poisson distribution and is modeled as a function of the predictor variable, which is Φ_i, the relative productivity of each firm.

$$P(count|\Phi, \beta) = \frac{\lambda^y e^{-\lambda}}{y!}, ln(E(count|\Phi)) = \alpha + \beta\Phi = \lambda. \tag{3.3}$$

I expect the coefficient on Φ_i to have the same sign as α in estimation (3.2).

3.2.2 Data

I use three different sources of data. First, I use the CRSP/Compustat Merged (CCM) - Fundamentals Annual database for our firm-level analysis. Compustat is compiled by Standard and Poor from annual corporate reports of publicly traded companies. Compustat data contains annual and quarterly income statement, balance sheet, cash flow, pension, supplemental, and descriptive data items for active and inactive companies, whereas the CRSP (The Center for Research in Security Prices) contains security-level historical descriptive information and market data on stocks. The CSRP data was used only to procure information on start and end date of firms in the Compustat database, in order to calculate age and exit variables for the analysis. All other firm-level information on sales, capital expenditures, capital stock, material cost, payroll, etc came from the Compustat database. A detailed description of the construction of firm-level variables for the estimation can be found in the Data Appendix. I keep only U.S manufacturing firms and use annual data from 1962 to 2011. This gives an unbalanced panel with 3917 distinct firms and the total number of firm-year observations is around 45,890.

Table 3.1 gives an overview of the type of firms in the Compustat sample. The most number of manufacturing firms are from the different Equipments sectors, while there are little to no firms in Apparel, Leather and Tobacco Products. Table 3.2 shows the composition of firms by age. The median age of firms is 9, in the sample as reported later in Table 3.4. We see that there are very few firms that were followed for entire duration of the sample. I use the entry and exit dates of the firms in the Compustat sample to proxy for the actual entry and exit of firms from the industry.

In the absence of export-related information, a valid concern might be about the representativeness of Compustat firms as firms engaging in international trade. Table 3.3 shows what fraction of total manufacturing employment is made by Compustat firms. The data on the total number of manufacturing firms and total employments come from the U.S. Census. As the evidence suggests, our sample represents very large firms, which are very likely to engage in some sort of international trade, such that exchange rate movements would affect them.

In order to deflate the nominal values from the Compustat database, I use the NBER-CES Manufacturing Industry Database, which has 4-digit SIC level deflators for capital stock, investment, materials and sales and proceed with instructions in the technical notes by Becker, Gray, and Marvakov (2013).

Table 3.1: Industry Composition of Compustat firms, 1962-2011

2 digit SIC code	Industry name	Number of firms
20	Food and Kindred Products	141
21	Tobacco Products	5
22	Textile Mill Products	72
23	Apparel and Other Textile Products	0
24	Lumber and Wood Products	50
25	Furniture and Fixtures	35
26	Paper and Allied Products	52
27	Printing and Publishing	97
28	Chemical and Allied Products	453
29	Petroleum and Coal Products	46
30	Rubber and Misc. Plastic Products	136
31	Leather and Leather Products	0
32	Stone, Clay and Glass Products	44
33	Primary Metal Products	111
34	Fabricated Metal Products	113
35	Industrial Machinery and Equipment	636
36	Electronic Equipment	772
37	Transportation Equipment	252
38	Instruments	797
39	Misc. Manufacturing Industries	105
Total	Manufacturing Industry	3,917

Since export destination-level information is unavailable, I cannot use bilateral exchange rates. Hence, I use the Real Narrow CPI-based Effective Exchange Rate database (Index: 2010 = 100) from the Bank of International Settlements, which is available from 1964. An increase in the real effective exchange rate (REER) means an appreciation. It is the trade-weighted effective exchange rate between U.S and 26 other economies, which include the major trading partners.[3] Figure 3.1 shows the evolution of the real effective exchange rate. There are two major periods of appreciation and three periods of depreciation within the duration of the sample.

Table 3.4 shows descriptive statistics of the key estimation variables. Markup is defined as the price-cost margin. In other words, an average markup of 1.43 implies that, on an average, firms in the Compustat sample charge a markup of 43 percent.

[3] However, it doesn't include China, Brazil and India, which are also major trading partners of the U.S.

Table 3.2: Firm composition by age, 1962-2011

Age	Number of firms
60	3
50	4
40	140
30	399
20	930
10	1,988

Table 3.3: The representativeness of the Compustat sample

Year	Total number of firms	Number of Compustat firms	Percentage share of employment
1980	270,322	1,273	48.46
1990	298,052	1,536	40.87
2000	291,743	1,678	45.03
2010	241,097	1,046	56.90

3.2.3 Firm-level Variables

3.2.3.1 Firm-level Total Factor Productivity

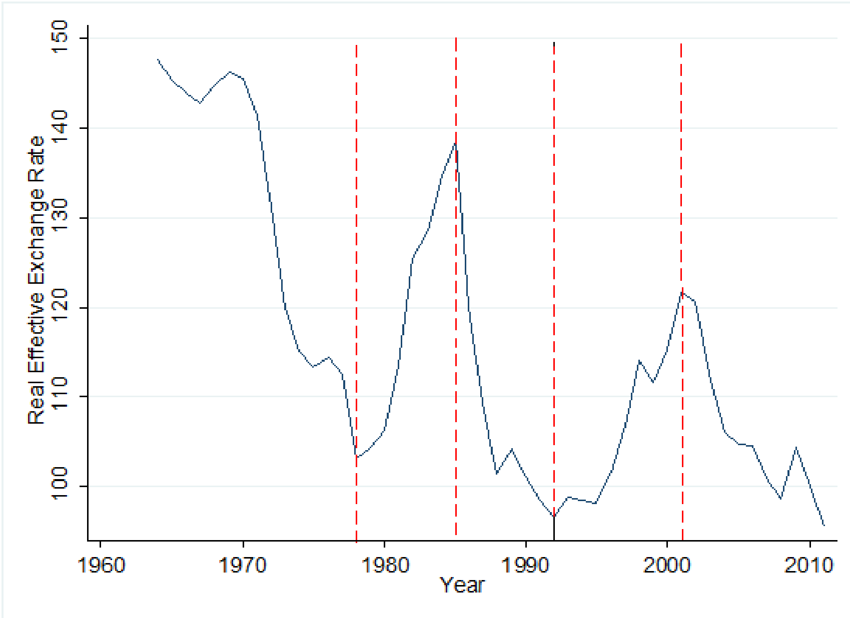
The straightforward way to compute Total Factor Productivity (TFP) is to find the residuals from estimating a Cobb-Douglas production function via Ordinary Least Squares (OLS). However, there are several more evolved ways to do this.[4] I will be using the Levinsohn and

Table 3.4: Descriptive Statistics of Compustat Firms, 1964-2011, N = 45,890

	Mean	Median	Std. dev
Markup	1.43	1.15	0.99
Log Markup	0.21	0.14	0.50
Log Total Factor Productivity	1.62	1.55	1.18
REER (Index: 2010=100)	112.19	109.21	13.48
Log REER	4.71	4.69	0.11
Sales (in millions)	1,272.14	112.07	6,825.11
Log Sales	4.85	4.72	2.03
Employees (in thousands)	7.56	1.07	29.41
Age	12.02	9.00	10.23

[4]The four most popular methods are the Olley and Pakes (1996) approach, the Levinsohn and Petrin (2003) approach, the Blundell and Bond (2000) system-GMM approach, and the apparent labor productivity.

Figure 3.1: REER between U.S. and 26 other countries, 1964-2011, Index: 2010 = 100, increase = appreciation



Petrin (2003) approach.

In estimating the parameters of a production function, there could be potential correlation between input choices and firm-specific productivity shocks that are unobserved by the econometrician but observed by the firm. This will lead to biased estimates of the input co-efficients. To solve this endogeneity problem, Levinsohn-Petrin used intermediate inputs to proxy for an unobserved time-varying productivity shock. More precisely, assuming a Cobb-Douglas specification in logarithm terms, we have:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_i i_{it} + \omega_{it} + \eta_{it}, \tag{3.4}$$

where ω_{it} is the productivity observed by firm i, which can be used to potentially make input choices, and η_{it} is the productivity unobserved by both the firm and the econometrician. Capital stock k_{it} is the state variable, labor l_{it} is a freely variable input and i_{it} is any intermediate input such as materials or energy.

In order to solve the endogeneity issue, we write the intermediate input demand as $i_{it} = i(\omega_{it}, k_{it})$. We need to assume that i_{it} is monotonic, i.e, it is increasing in productivity given the state variables. This allows us to invert i_{it} to obtain $\omega_{it} = \omega(i_{it}, k_{it})$.

Now we re-write (3.4) as

$$y_{it} = \beta_l l_{it} + \phi(i_{it}, k_{it}) + \eta_{it}, \tag{3.5}$$

where $\phi(i_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + \beta_i i_{it} + \omega(i_{it}, k_{it})$. I take ϕ as a third-order polynomial and run OLS to obtain $\hat{\beta}_l$. This is done as prescribed in Petrin, Poi, Levinsohn, et al. (2004).

3.2.3.2 Firm-level Markups

I follow the method prescribed by De Loecker and Warzynski (2012) to estimate markups at the firm-level. They rely on standard cost minimization conditions. Consider the following cost-minimization problem: $Min\ P^l_{it}L_{it} + r_{it}K_{it}$ subject to $Y_{it} = Y_{it}(L_{it}, K_{it})$, where P^l_{it} and r_{it} are the prices of labor input and capital respectively. The corresponding Lagrangean is: $\mathcal{L} = P^l_{it}L_{it} + r_{it}K_{it} + \lambda_{it}(Y_{it} - Y_{it}(L_{it}, K_{it}))$. The first-order condition with respect to labor input is $\frac{d\mathcal{L}}{dL_{it}} = P^l_{it} - \lambda_{it}\frac{dY_{it}}{L_it}$, where λ_{it} can be thought of the marginal cost as $\frac{d\mathcal{L}}{dY_{it}} = \lambda_{it}$. Re-writing the first-order condition yields

$$\frac{dY_{it}}{dL_{it}}\frac{L_{it}}{Y_{it}} = \frac{1}{\lambda_{it}}\frac{P^l_{it}L_{it}}{Y_{it}}$$

This generates the price-marginal cost fraction[5], which they define as the markup:

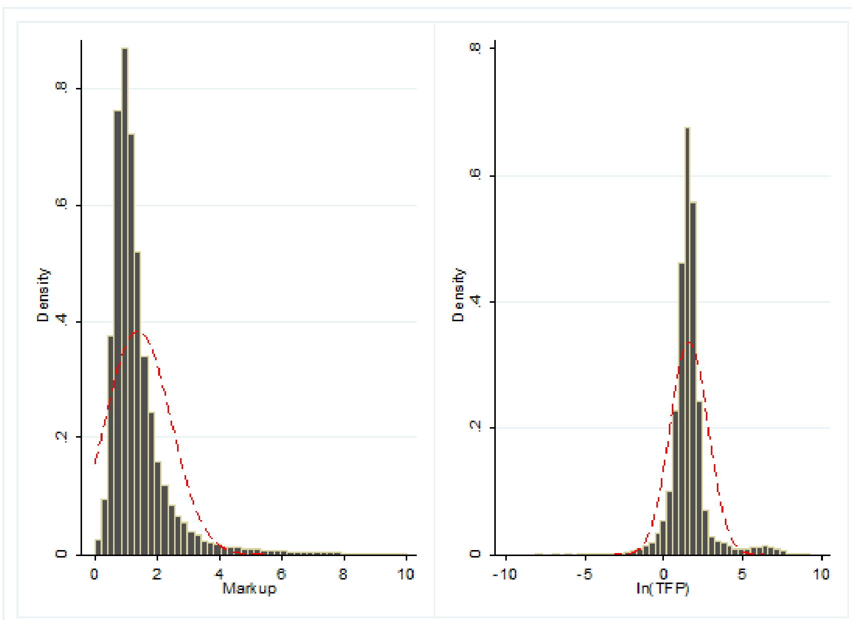
$$\mu_{it} = \theta^l_{it}/\alpha^l_{it} \tag{3.6}$$

[5]Markup is identified as the difference between a firm's variable input cost share and revenue share, where the cost share is not observed but by optimality conditions has to equal the output elasticity of the relevant input.

where θ_{it}^{l} is the output elasticity of L_{it} and α_{it}^{l} is the share of expenditures on L_{it} in total sales.

While α_{it}^{l} is observed in the data, θ_{it}^{l} is not, and therefore has to be estimated. For labor input, it is in fact equal to $\hat{\beta}_l$ from the Levinsohn-Petrin Cobb-Douglas production function estimation in Section 3.2.3.1 [6]. Note that I am only able to obtain firm-level markups since I do not have firm-product level information in the dataset. Figure 3.2 shows the distribution of firm-level markups and firm-level log TFP in the Compustat sample.

Figure 3.2: Markup and TFP distribution of Compustat firms, 1962-2011, dashed line = normal density.



3.2.4 Empirical Results

Table 3.5 reports the results for the regression in (3.1). I find that a 10 percent increase in productivity of firms leads to a 0.33 percent increase in firm markups. Following a 10

[6] Under a translog production function, it would be given by $\hat{\beta}_l + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lk} k_{it}$. Under Cobb-Douglas, the estimated output elasticity of labor is constant within each industry and markups vary across firms because of the difference in revenue share. Under translog, markup variation comes both from the variation in the estimated output elasticity and the revenue share.

percent appreciation in the exporter's currency, the firms of lowest productivity decrease their markups by 2.5 percent, firms of median productivity decrease their markups by 4.06 percent and firms of the highest productivity decrease their markups by 5.61 percent. In other words, firms of lowest productivity in the sample have an exchange rate pass-through of 75 percent, while firms of highest productivity have the lowest rates of exchange pass-through at 43.9 percent. The results are quite similar when including lagged values of $ln(TFP)$ or lagged value of $ln(REER)$ instead and can be found in columns (2) and (3).[7]

Table 3.5: Estimation of exchange rates on firm-level markups

	(1)	(2)	(3)
Log TFP	0.033***		
	(0.06)		
Log REER	-0.251***	-0.272***	
	(0.05)	(0.06)	
Log REER × Φ_i	-0.155***	-0.149**	
	(0.05)	(0.05)	
Lagged Log TFP		0.023***	0.022***
		(0.01)	(0.01)
Lagged Log REER			-0.302***
			(0.05)
Log REER × Φ_i			-0.159***
			(0.05)
Number of observations	45,890	42,958	42,697
Number of firms	3,843	3,653	3,653
Firm fixed effects	Yes	Yes	Yes

Notes: Φ_i is the relative Total Factor Productivity of each firm compared to its 4-digit SIC industry peers. Robust standard errors (clustered by firms) in parentheses. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

This result can be understood easily with the help of a hypothetical numerical example as follows. Consider two countries, where the dollar is the exporter's currency and the pound is the importer's currency. Suppose that the pound depreciates by 50 percent. With complete pass-through to import prices, the price of the good that was originally priced at £10 should increase to £15. However, as the empirical evidence suggests, pass-through is incomplete.

[7]These results are also robust to a different and less complicated measure of productivity, the apparent labor productivity (value-added per worker).

Table 3.6: Exporter = United States, Importer = United Kingdom

		low Φ		high Φ	
time	ER	price in £	price in \$	price in £	price in \$
t = 0	\$1 = £1	£10	\$10	£10	\$10
t = 1	\$1 = £1.50	£13.75	\$9.16	£12.25	\$8.16
		ERPT = 75%		ERPT = 45%	
		%△ ER = 50%		%△ ER = 50%	
		%△ price = 37.5%		%△ price = 22.5%	
		%△ markup = 12.5%		%△ markup = 27.5%	

.

Let us consider the pass-through rates of column (1) of table 3.5. Table 3.6 shows the different adjustments firms of low and high productivity levels would make in this scenario.

Table 3.7 reports the results for the regression in (3.2), I find that as firm size increases, markup volatility decreases. For the firms of lowest productivity, a 10 percent appreciation of dollar causes markup volatility to increase by 6.42 percent, for median productivity firms, markup volatility increases by 3.65 percent and for firms of highest productivity, markup volatility increases by only 0.88 percent. Therefore, firms of lower productivity have more volatile markups, i.e, they adjust their markups more frequently than do firms of higher productivity in order to remain competitive.

Table 3.7: Estimation of exchange rates on firm-level markup volatility

Log REER	0.642***
	(0.08)
Log REER × Φ_i	-0.277***
	(0.06)
Log Sales	-0.019***
	(0.00)
Number of observations	31,114
Number of firms	2,662

Notes: Firm fixed effects are included. Φ_i is the relative Total Factor Productivity of each firm compared to its 4-digit SIC industry peers. Robust standard errors (clustered by firms) in parentheses. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

Table 3.8: Estimation of exchange rates on firm-level counts of incidences of large markup changes

Φ	-0.287***
	(0.03)
Number of firms	3,318

As a robustness check to this measure of volatility, I use another measure of volatility, which is the incidence of large markup changes as defined in Section 3.2.1. As we can see in Table 3.8, a 1 unit increase in productivity leads to a decrease in the count of large markup adjustments by 28.7 percent, which reinforces the previous result that firms of higher productivity do not adjust their markups as frequently as do firms of lower productivity.

3.2.5 Discussion

I summarize the main findings from Section 3.2.4 as follows:

less productive firms	**more productive firms**
higher exchange rate pass-through	lower exchange rate pass-through
adjust markup by smaller amounts	adjust markup by greater amounts
adjust price by greater amounts	adjust price by smaller amounts
adjust markup more frequently	adjust markup less frequently
adjust price less frequently	adjust price more frequently

If firms of higher productivity are more comfortable in adjusting prices more frequently, this seems to suggest that the price adjustment cost (or menu cost) is lower for them. Menu costs can be characterized as $c = g(\phi) + f$, where the firsr component $g(\phi)$ constitutes the cost of changing catalogues and advertisement that varies with firm size or productivity, and the second component f has to be incurred by all firms irrespective of their levels of productivity. f is lump-sum and includes managerial costs of implementing a price change.

If menu costs as a whole are lower for more productive firms, then it is this fixed or lump-sum component of menu costs that is important for explaining the heterogeneous markup adjustment behavior of firms that we have observed in this paper. In the presence of such lump-sum menu costs, large firms will exhibit greater price flexibility (or lower markup flexibility) since the adjustment cost per unit of output will be lower for them. A theoretical model of heterogeneous firms such as Melitz and Ottaviano (2008), along with fixed price adjustments costs will be able to give us the cut-off productivity levels for firms that choose to incur menu costs and adjust their prices versus firms that choose to stick to their original price, following an exchange rate shock.

3.3 Conclusion

In this paper, I tested important empirical predictions from international trade models linking trade behavior and firms markups. My empirical exercise using firm-level panel data for U.S. manufacturing firms over 50 years produced the following results: firms of higher productivity have lower rates of exchange rate pass-through to export prices, however, firms of higher productivity also have less volatile markups, i.e, they adjust their markups less frequently than do firms of lower productivity. The higher magnitude of markup adjustment by more productive firms suggests that the markups of more productive firms are more responsive to exchange rate movements, however the higher frequency of markup adjustment by less productive firms suggests that the markups of less productive firms are more responsive to exchange rate movements. The former explanation supports the theoretical model of endogenous markups by Melitz and Ottaviano (2008). However, the magnitude of change is not enough to explain the lack of response of exchange movements on aggregate prices. The latter explanation suggests that the price adjustment costs faced by more productive firms are lower.

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Appendix A

Additional Tables for Chapter 1

Table A.1 lists the values for the trade cost elasticities used in the long-run analysis. These values come from the benchmark 99 percent sample of Caliendo and Parro (2015). This sample was constructed by dropping countries with the lowest 1 percent share of trade they contribute to a particular sector.

Table A.1: Trade cost elasticities

Food	2.62	Metal products	6.99
Textile	8.10	Machinery n.e.c	1.45
Wood	11.50	Office	12.95
Paper	16.52	Electrical	12.91
Petroleum	64.85	Communication	3.95
Chemicals	3.13	Medical	8.71
Plastic	1.67	Auto	1.84
Minerals	2.41	Other Transport	0.39
Basic metals	3.28	Other	3.98

Table A.2 lists the 4-digit SIC industries with the largest proportion of Donald Trump supporters.

Table A.2: Top 10 Trump industries

SIC code	Description	T_j
3633	Household laundry equipment	1.00
2273	Carpets and rugs	0.90
3792	Travel trailers and campers	0.88
2252	Hosiery, n.e.c.	0.82
3799	Transportation equipment, n.e.c.	0.82
2281	Yarn spinning mills	0.79
2611	Pulp mills	0.79
2493	Reconstituted wood products	0.78
2015	Poultry slaughtering and processing	0.77
3715	Truck trailers	0.76

Appendix B

Industry Classification for Chapter 2

Table B.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			

Appendix C

Data Appendix for Chapter 3

The main data source for firm-level productivity and markup estimation is the CSRP/Compustat merged (CCM) fundamental annual database. I use annual data from 1962 to 2011 for only U.S. manufacturing firms (Standard Industrial Classification 2000-3999).

The key variables for estimating the firm-level productivity are output, capital input, material input, labor input and age of the firm, which are calculated as follows:

- Output = Net Sales/Deflator for shipments
- Capital Input is calculated using the Perpetual Inventory Method, where $K_t = K_{t-1} + I_{t-1} - d_{t-1}K_{t-1}$, where d_t is the industry-level rate of depreciation.
  Initial Capital Stock = Property, Plant and Equipment/New investments price index
  Investment = Capital Expenditures/New investments price index
- Material input = (Cost of goods sold + Administrative and Selling Expenses - Depreciation - Wages)/Deflator for total cost of materials, where Wages = average wage at the industry level $\times$ number of workers in the firm
- Labor input = number of workers

- Value-added = Real Sales - Real Material Input

All the deflators and industry-level variables mentioned above are from the NBER-CES Manufacturing Productivity Database.