Employment Consequences of U.S. Trade Wars

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Abstract

This paper 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.

JEL Classification: F13, F14, F16, F6

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1 Introduction

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

[1]Source: Peterson Institute for International Economics

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. 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.

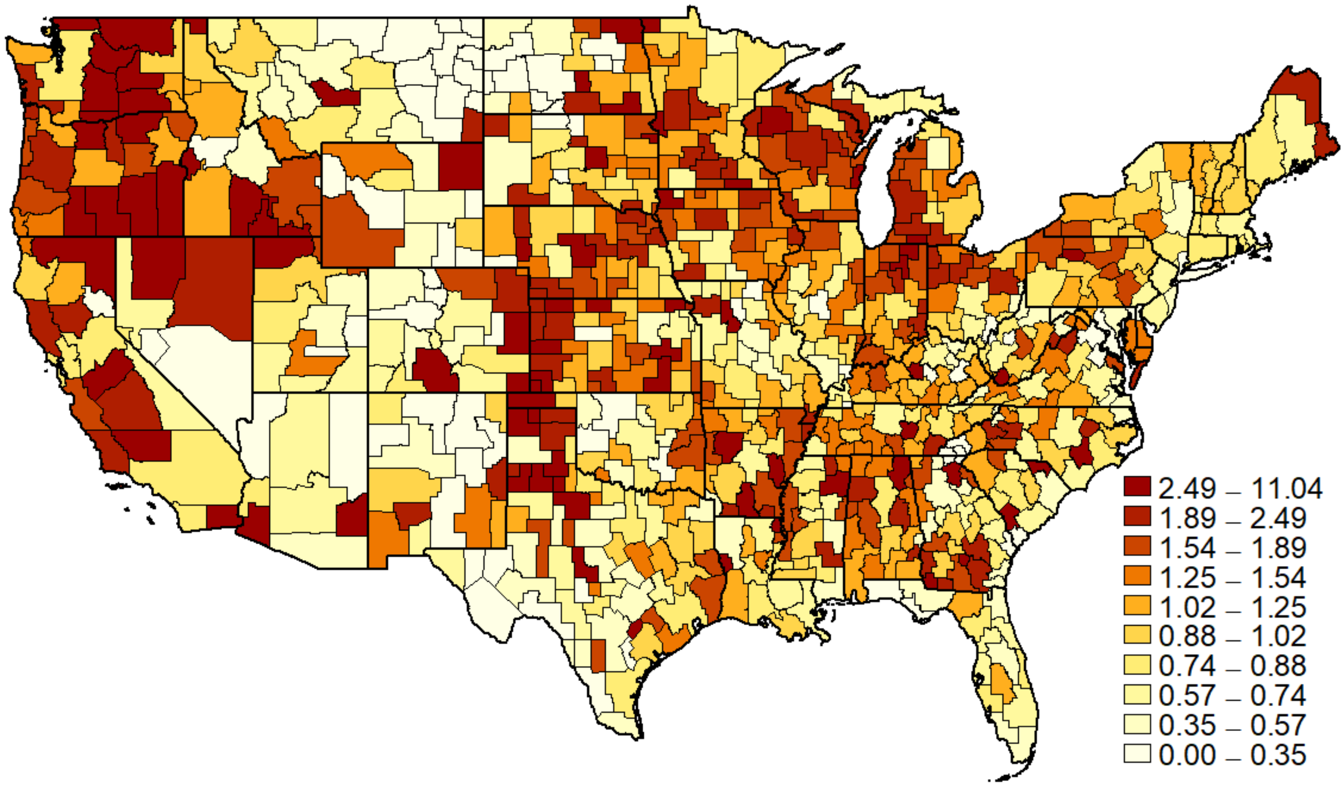
However, these results would no longer be true if I focus on only the post-recession period of 2010-2016. In this case, I find that the job-reducing effect of the China shock no longer exists. In fact, Chinese import penetration has a positive and insignificant effect on U.S. manufacturing employment. 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.

2 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 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 (2016) 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



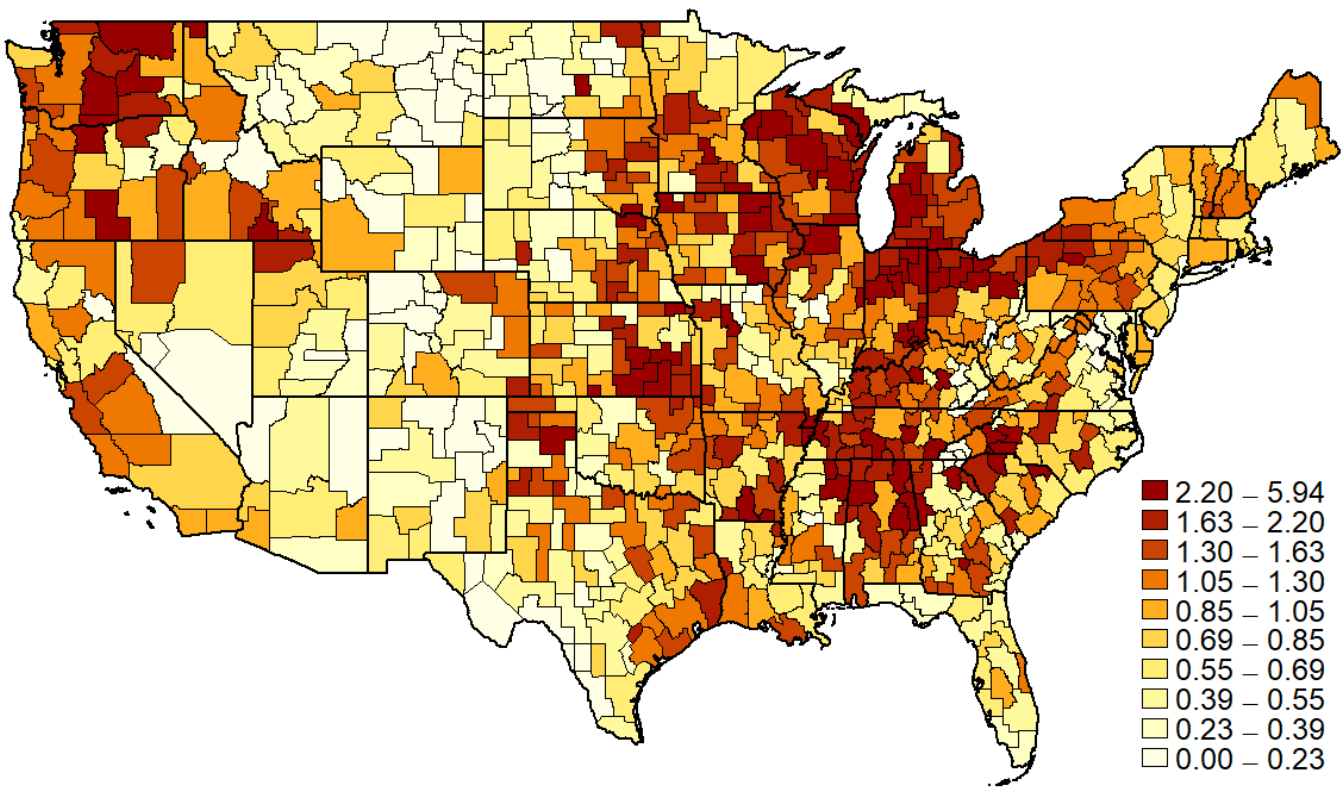


Figure 1: Chinese retaliatory export tariff exposure (top) and U.S. import tariff exposure (bottom) by commuting zone

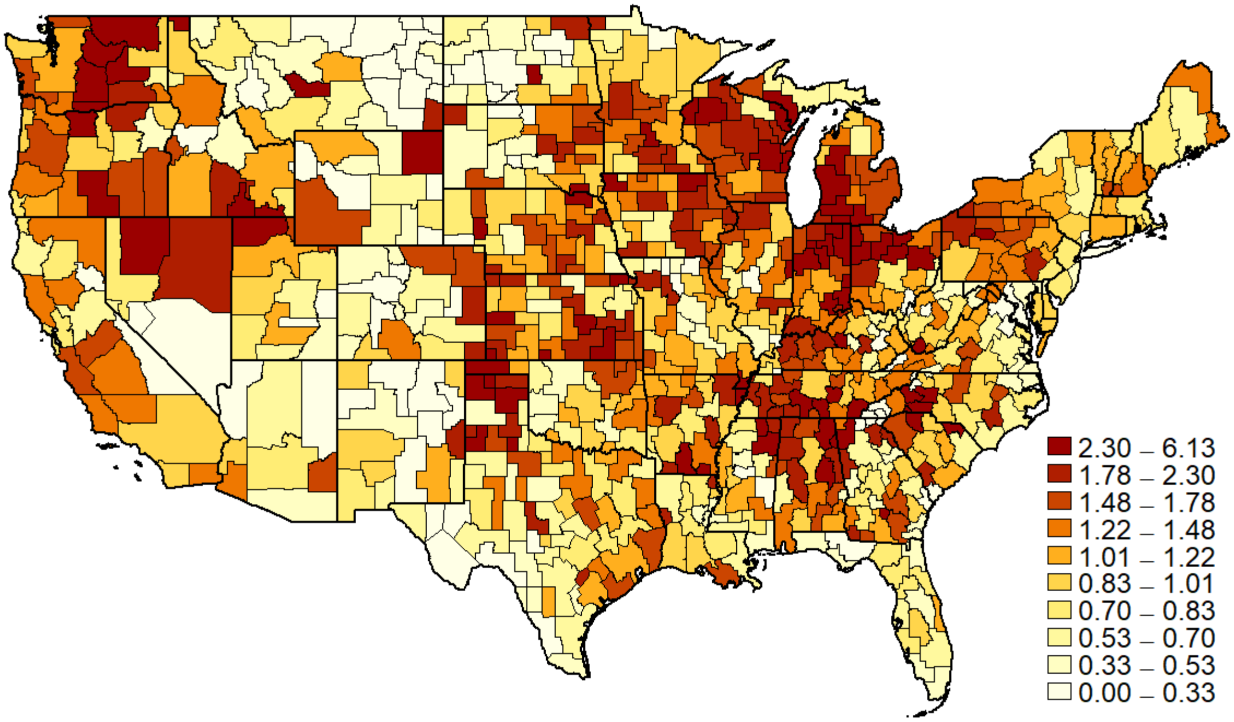


Figure 2: Downstream U.S. import tariff exposure by commuting zone

advantage. The kind of retaliation executed by partner countries will determine the extent of the distributional impacts of the trade war. Figure 1 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.

Figure 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 4, 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.

[2]The construction of the commuting-zone level tariffs are described more in detail in Section 4.1.1

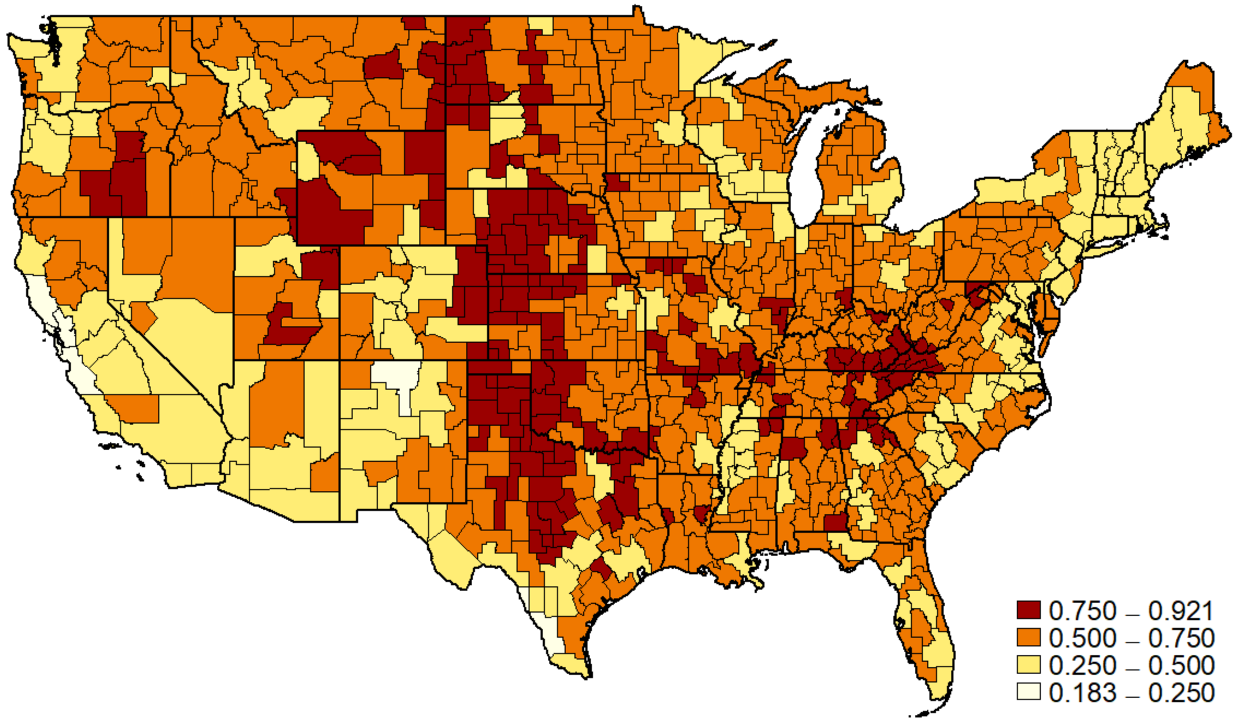


Figure 3: Share of votes towards the Republican party in the 2016 presidential election by commuting zone

In Section 5, 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 3 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 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 4 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

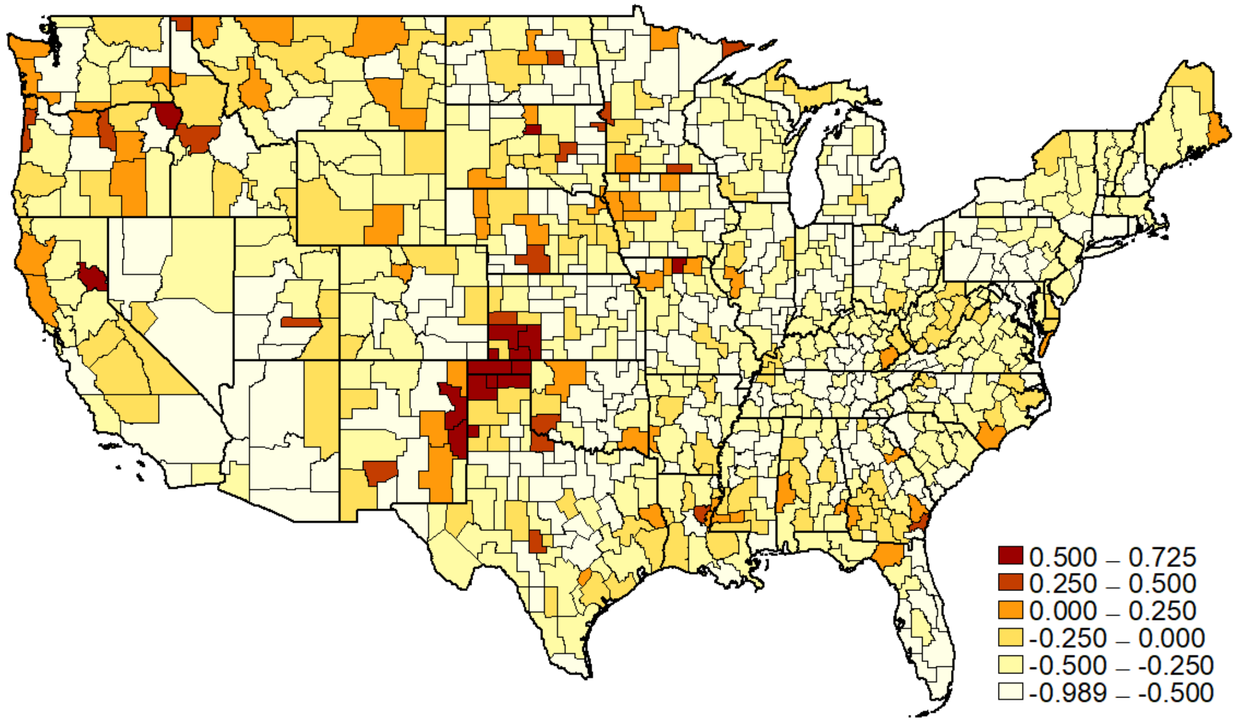


Figure 4: Distribution of a measure of U.S.-China intra-industry trade by commuting zone

of the darkest shaded commuting-zones. There is some resemblance to the export tariff map in Figure 1 but the darker shaded regions in 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.

3 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.

4 Short-term effects on Employment

4.1 Data and Empirical Strategy

4.1.1 Tariff Data

U.S. import tariffs for the events described in Section 3 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

[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: Commuting zone level summary statistics

	Median	Mean
Δ Export tariff	0.33	1.32
Δ Import tariff	0.49	1.06
Δ 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.

tariffs in the following manner:

$$\tau_{jt}^{z} = \sum_{p \in P} \frac{F_{p,j,2017}}{F_{j,2017}} \tau_{pt}^{z}, \tag{1}$$

where τ_{jt}^{z} is the monthly 3-digit NAICS industry level tariff measure and τ_{pt}^{z} 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 zone-level measures of import tariff exposure and Chinese retaliatory tariff exposure measures from January 2017 to March 2019 in the following manner:

$$\tau_{ct}^{z} = \sum_{j \in J} \frac{L_{c,j,2017}}{L_{c,2017}} \tau_{jt}^{z}, \tag{2}$$

where τ_{ct}^{z} is the monthly commuting zone-level tariff measure and τ_{jt}^{z} 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_{ct}^{z} 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 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

$$D\tau_{jt} = \sum_{g} \omega_{jg}^{D} \tau_{gt}, \tag{3}$$

where τ_{gt} is the import tariff in industry g at time t described in equation (1). The commuting-zone level of downstream import tariff is then constructed in the way described in equation (2).

4.1.2 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 shows that the average private sector employment in 2017 was 164,000 and the average private sector goods producing employment was 29,000.

4.2 Estimation

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

$$\Delta \ln L_{ct} = \beta_c + \beta_t + \beta_m \Delta \ln(1 + \tau_{ct}^{m}) + \beta_d \Delta \ln(1 + D\tau_{ct}^{m}) + \beta_x \Delta \ln(1 + \tau_{ct}^{x}) + \varepsilon_{ct}, \tag{4}$$

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,

Table 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.

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 2 reports results from the specification in (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 3 shows that commuting zones most exposed to export tariffs experienced a small 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,

Table 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.

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.

5 Long-run effects on Employment

5.1 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:

$$\Delta \ln L_{j\tau} = \beta_\tau + \beta_{m1}\Delta IP^{C}_{j\tau} + \beta_{m2}\Delta IP^{ROW}_{j\tau} + \beta_x \Delta EP_{j\tau} + \eta Z_j + \varepsilon_{j\tau}, \tag{5}$$

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

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

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 (5) as:

$$\Delta L_{j\tau} = \sum_j \left[1 - e^{-\left(\Delta \tilde{IP}_{j\tau} + \Delta \tilde{EP}_{j\tau}\right)}\right] L_{j,end}, \tag{6}$$

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:

$$\sum_j \left[1 - e^{-\left(\Delta \tilde{IP}_{j\tau} + \Delta \tilde{EP}_{j\tau}\right)}\right] \approx \sum_j \left[\left(1 - e^{-\Delta \tilde{IP}_{j\tau}}\right) + \left(1 - e^{-\Delta \tilde{EP}_{j\tau}}\right) - C_{j\tau}\right], \tag{7}$$

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

5.2 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.

5.2.1 Simple Retaliation

I modify the formula in (6) 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.

The formula used to calculate the effect of this simple retaliation is given by (6), 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 (6), 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

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

5.2.2 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

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

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

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

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 (6), 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 (6), where

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

and

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

5.2.3 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 (6), 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 (6), 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

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

5.3 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, $\Delta IP^C_{j\tau}$ as:

$$\Delta IP^C_{j\tau} = \frac{\Delta \mathbb{M}^C_{j\tau}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \tag{8}$$

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

$$\Delta IP^{ROW}_{j\tau} = \frac{\Delta \mathbb{M}^{ROW}_{j\tau}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \tag{9}$$

For export exposure, I follow FMX. They use an analogous measure to (8) as

$$\Delta EP_{j\tau} = \frac{\Delta \mathbb{X}_{j\tau}}{\mathbb{Y}_{j91}}, \tag{10}$$

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.

5.4 Intrumental Variables

Both import and export exposure measures in (5) suffer from endogeneity problems. Other than a Chinese supply shock, $\Delta IP^C_{j\tau}$ 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:

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

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

Table 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 5. OTH denotes the first type of instrument from FMX described in Section 5.4. 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.

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

5.5 Estimation

Table 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 (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

[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.

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 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 5.4, 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 (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 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.

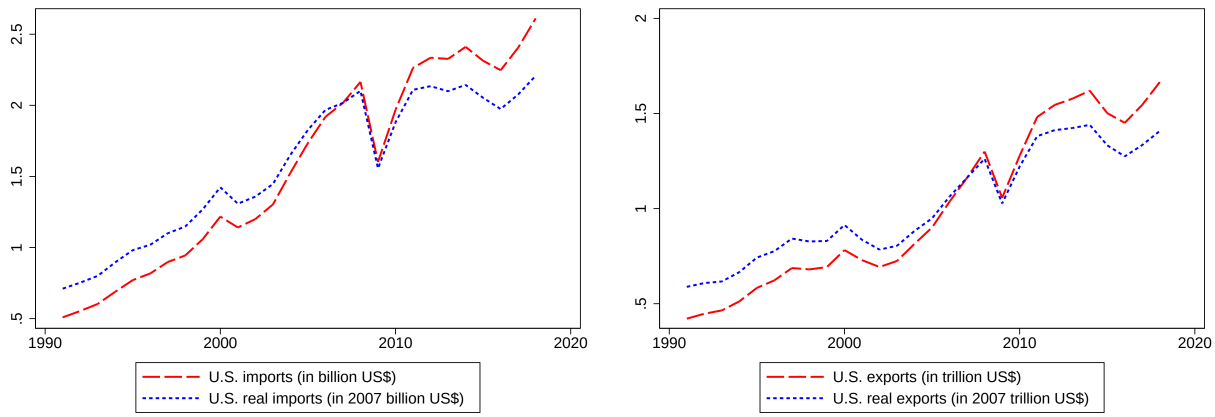


Figure 5: U.S. imports and exports over time

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 5 shows a decline in both imports and exports around the year 2015.

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

Column (1) of Table 5 shows predicted net employment changes from the specification in column (3) of Table 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 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.

[8] This is the key result of FMX

Table 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 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 (6), 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 $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^{C}_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$.

Columns (3)-(5) report calculations for three different retaliation scenarios described in Section 5.2. 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 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 (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 5.2.1. 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 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 4 column (3).

Table 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

Table 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

A balanced trade war with political retaliation by China as described in Section 5.2.2 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 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 5.2.3 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 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.

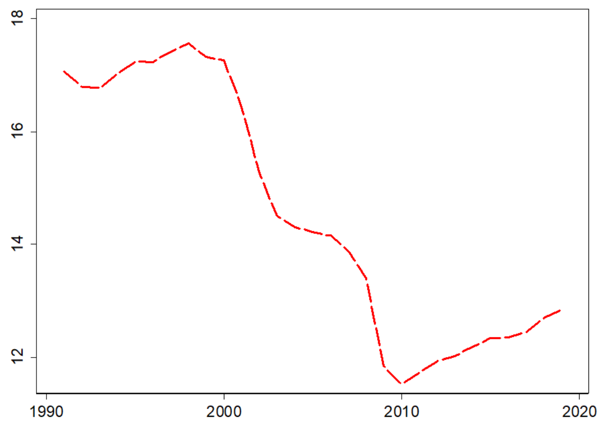


Figure 6: Average U.S. manufacturing employment over time (in millions)

5.7 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 6 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 5.5, Table 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 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 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

Table 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 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 (6), 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 $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^{C}_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$.

manufacturing jobs. This is completely opposite to the result in Section 5.6.

6 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 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.

7 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.

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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

Notes: These values come from the benchmark 99 percent sample of Caliendo and Parro. This sample was contructed by dropping countries with the lowest 1 percent share of trade they contribute to a particular sector.

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