Employment Consequences of U.S. Trade Wars

Sanjana Goswami*
University of California, Irvine

Click here for the most recent draft.

November 2019

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 increased manufacturing jobs. This result corroborates the findings of the short-run analysis.

JEL Classification: F14, F16

Keywords: import penetration, export expansion, tariffs, retaliation, trade war, job creation, job destruction

*Contact: sanjana.goswami@uci.edu

1 Introduction

Tariffs on imports reduce import competition for domestic firms and in turns 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 therefore 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, 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 a similar fashion. 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 both U.S. import tariffs and Chinese retaliatory tariffs on county-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

[1] Source: Peterson Institute for International Economics

Chinese retaliatory tariffs have had a statistically significant and negative effect on county-level employment growth, whereas U.S. import tariffs have had no effect. This suggests that counties that are relatively more exposed to the export tariffs are disproportionately hurt, whereas counties 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 from U.S. trading partners: (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: 1991-2016, 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 1991-2011 period.

First, I conduct the counterfactual exercise for the 1991-2016 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 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, with U.S. exports playing almost no role in the net employment change.

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. 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. 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 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. Exposure here is defined as the change in a county's average tariff between December 2017 and December 2018. Import tariffs seem to be more concentrated in the Rust Belt

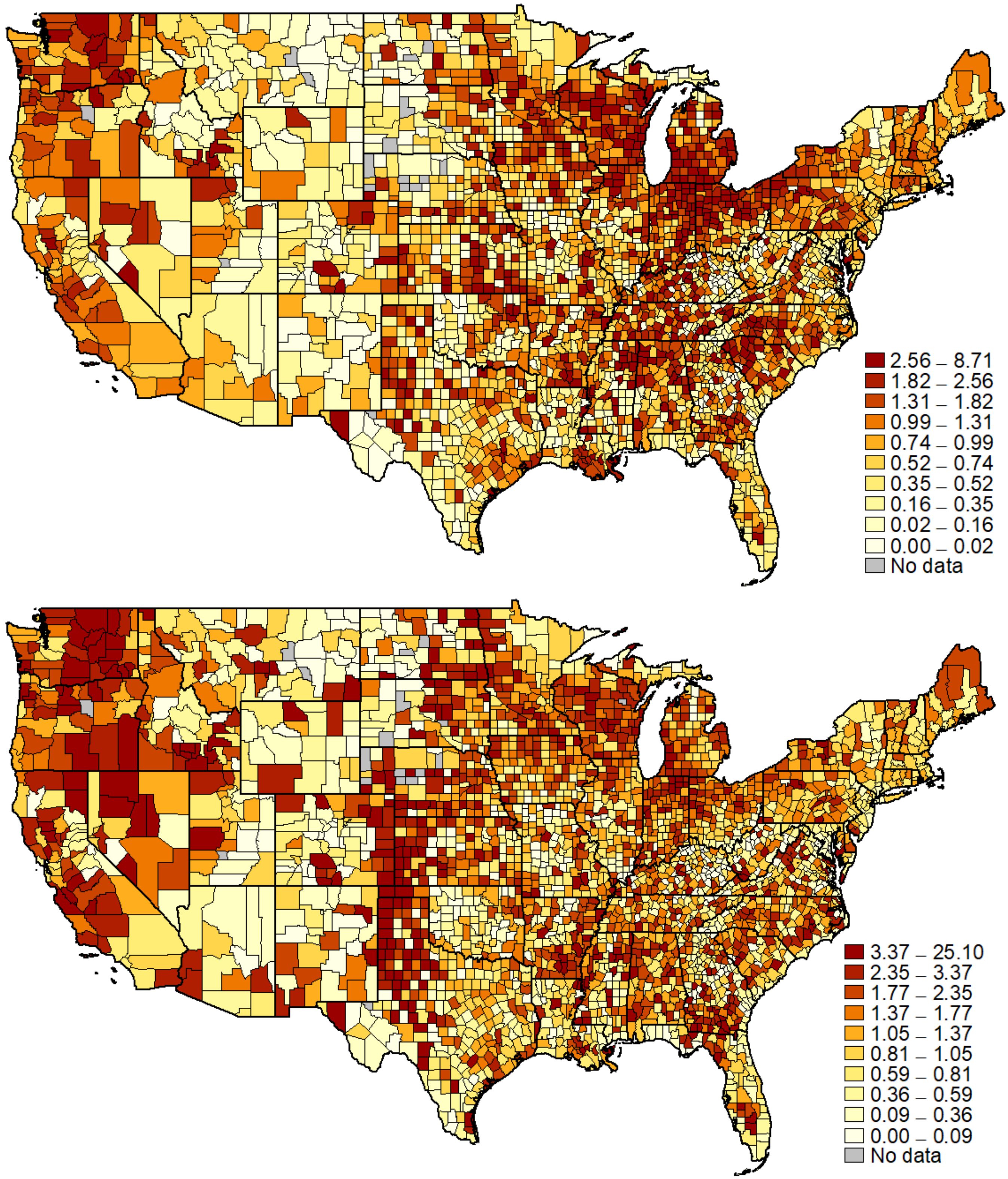

Figure 1: U.S. imports tariff exposure (top) and Chinese retaliatory export tariff exposure (bottom) by county

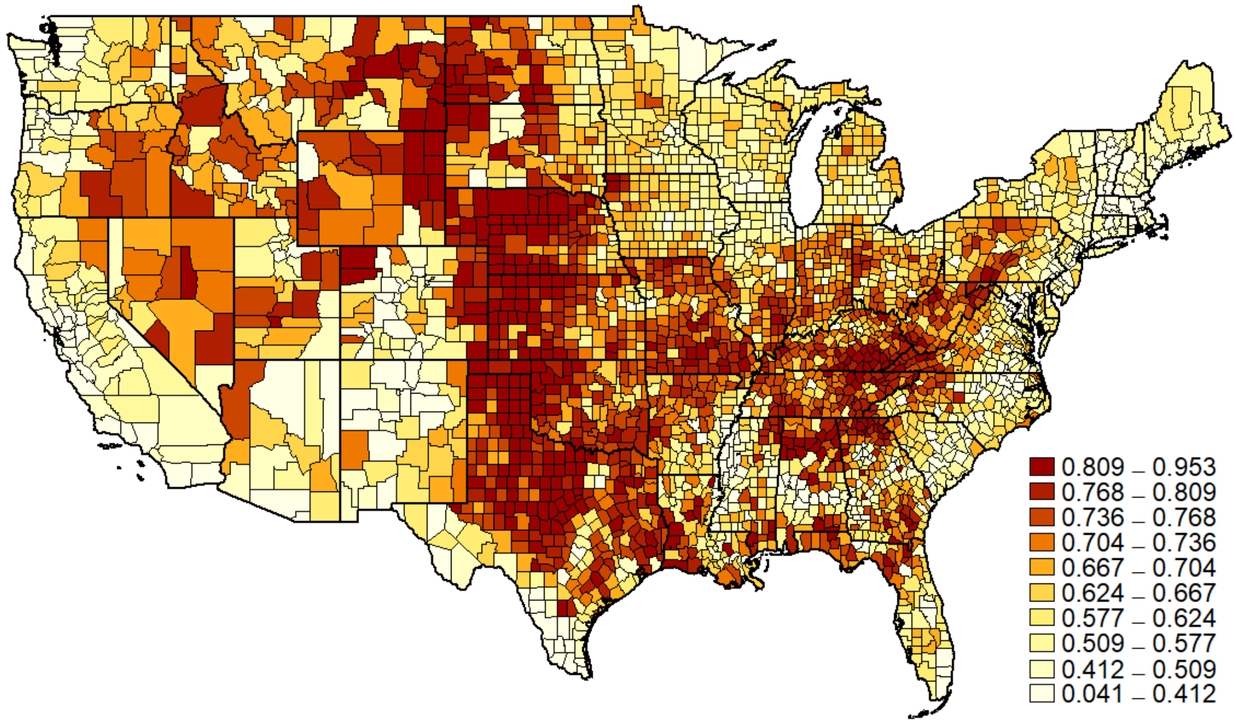

Figure 2: Share of votes towards the Republican party in the 2016 presidential election by county

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.

In this paper, I compare three different retaliation strategies — simple, political, and responsible — which have varying degrees of decline in manufacturing employment due to falling Chinese export exposure. Figure 2 shows the distribution of counties according to the 2016 presidential election vote shares to the Republican party. The counties affected by actual Chinese retaliation is similar in the middle of the country but still different in 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. In order to understand better the implications of a simple, political or responsible retaliation strategy that China could adopt, I impose a trade war with these different retaliation strategies on past data.

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

4.1.1 Tariff and Trade 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) [2], 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. 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 county-level measures of import tariff exposure and Chinese retaliatory tariff exposure measures from January 2017 to March 2019 in the following manner:

$$\tau_{ct}^{z} = \sum_{j \in J} \frac{L_{c,j,2017}}{L_{c,2017}} \tau_{jt}^{z}, \tag{1}$$

where τ_{ct}^{z} is the monthly county-level tariff measure and τ_{jt}^{z} is the monthly industry-level tariff measure. $z \in \{m, x\}$, where τ^{m} stands for import tariff and τ^{x} stands for export tariff. $L_{c,j,2017}$ is the employment level in 2017 at the county-industry level, whereas $L_{c,2017}$ is the employment level in 2017 at the county level. τ_{ct}^{z} captures region-specific tariffs such that if a county mostly employs workers for a certain industry which has a high tariff, then the county-level tariff will reflect the high tariff.

Table 1 reports summary statistics for the county-level change in import and export tariffs from December 2017 to December 2018 in the first column. Across 3,123 counties, the average import tariff increased by 1.08 percent, whereas the average export tariff increased by about 1.6 percent.

Table 1 also reports the average per worker value of Chinese imports and exports to the U.S. in 2017 at the county-level, which are calculated as:

$$F_{ct}^{z} = \frac{1}{L_{c,2017}} \sum_{j \in J} \frac{L_{c,j,2017}}{L_{j,2017}} F_{jt}^{z},$$

where $z \in \{m, x\}$, such that F^{m} stands for U.S. imports from China and F^{x} stands for U.S. exports to China, $L_{c,j,2017}$ is the employment level in 2017 at the county-industry level, $L_{j,2017}$ is the national employment level in 2017 in industry j, and $L_{c,2017}$ is the employment level in 2017 at the county level.

[2] 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: Summary Statistics

Import Tariff Quartile	Δ Import Tariff	Imports from China	Employment
Upper quartile	2.7	5,693	6,764
25th-75th quartiles	0.78	2,220	9,079
Bottom quartile	0.08	363	1,861
Average	1.08	2,829	6,657
Export Tariff Quartile	**Δ Export Tariff**	**Exports to China**	**Employment**
Upper quartile	3.9	4,113	3,901
25th-75th quartiles	1.12	1,314	9,501
Bottom quartile	0.18	307	3,880
Average	1.58	1,894	6,657

Notes: Average imports, exports and employment data are for the United States in 2017. Tariff change is between December 2017 and December 2018 Imports and Exports are on a per worker basis. Employment reported here is total private, goods-producing employment.

The second column shows that high-tariff counties have disproportionately more trade with China. On a per worker basis, a high import tariff county has more than twice the level of imports from China relative to the average county and the same is true for a high export tariff county.

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.

The last column of table 1 shows that on average, high import tariff counties employ a similar number of goods-producing workers as the average county, whereas, high export tariff counties employ only about 60 percent of good-producing workers as the average county. Also, low import tariff counties employ much less people than low export tariff counties.

4.2 Estimation

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

$$\Delta \ln L_{ct} = \beta_c + \beta_t + \beta_m \Delta \ln(1 + \tau^m_{ct}) + \beta_x \Delta \ln(1 + \tau^x_{ct}) + \varepsilon_{ct}, \tag{2}$$

Table 2: Employment Growth

Import Tariff Quartile	Pre-Trade War	Post-Trade War
Upper quartile	0.0102	0.0113
	[0.001]	[0.001]
Bottom quartile	0.0073	0.0089
	[0.001]	[0.001]
Export Tariff Quartile	**Pre-Trade War**	**Post-Trade War**
Upper quartile	0.0098	0.0092
	[0.001]	[0.001]
Bottom quartile	0.0108	0.0113
	[0.001]	[0.001]

Notes: Employment growth, calculated as the 12-month log difference, is averaged across counties 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. Standard deviations are reported in brackets.

where $\Delta \ln L_{ct}$ is the 12-month log difference in employment in county c, $\Delta \ln(1+\tau^m_{ct})$ is the 12-month log differenced import tariff rate, and $\Delta \ln(1+\tau^x_{ct})$ is the 12-month log differenced export tariff rate. β_m measures the effect of a county's exposure to U.S. import tariffs on its employment, whereas β_x measures the effect of a county's exposure to Chinese retaliatory tariffs on its employment. Standard errors are clustered at the county level and regressions are weighted by the county employment in 2017.

Table 2 shows that prior to the trade war, employment growth in high and low export tariff counties were relatively similar but after the U.S.-China trade war began, the least exposed counties had an increase in employment growth, whereas most exposed counties did relatively poorly. In contrast, employment growth in high and low import tariff counties were different before the trade war and they both did better after beginning of the trade war.

Figure 3 shows that the difference in employment growth between high and low export tariff counties became larger as the U.S.-China trade war started, whereas for import tariffs, the difference became smaller.

Table 3 reports results from the specification in (2). The coefficients on imports tariffs are statistically insignificant across all specifications, implying that import tariffs haven't had an impact on employment growth in the short-run. The coefficients on export tariffs is negative across all specifications, implying that relatively more export tariff exposed counties experienced reductions in employment growth. For goods employment, the average point estimate on export tariffs is -0.42. Therefore, moving from the 25th to the 75th quartile of the export tariff distribution implies a 1.56 (.42 $\times$ (3.9-0.18)) percentage point decline in employment growth. For total employment, it would

Table 3: Effect of Tariffs on Short-term Employment Growth

	Goods Employment			Total Employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Import Tariffs	0.05	-0.10	0.13	-0.06	-0.12	0.07
	(0.10)	(0.13)	(0.19)	(0.05)	(0.07)	(0.06)
Δ Export Tariffs	-0.39***	-0.44***	-0.43*	-0.15**	-0.15*	-0.19**
	(0.10)	(0.11)	(0.19)	(0.05)	(0.06)	(0.07)
Time effects	No	Yes	Yes	No	Yes	Yes
County fixed effects	No	No	Yes	No	No	Yes

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

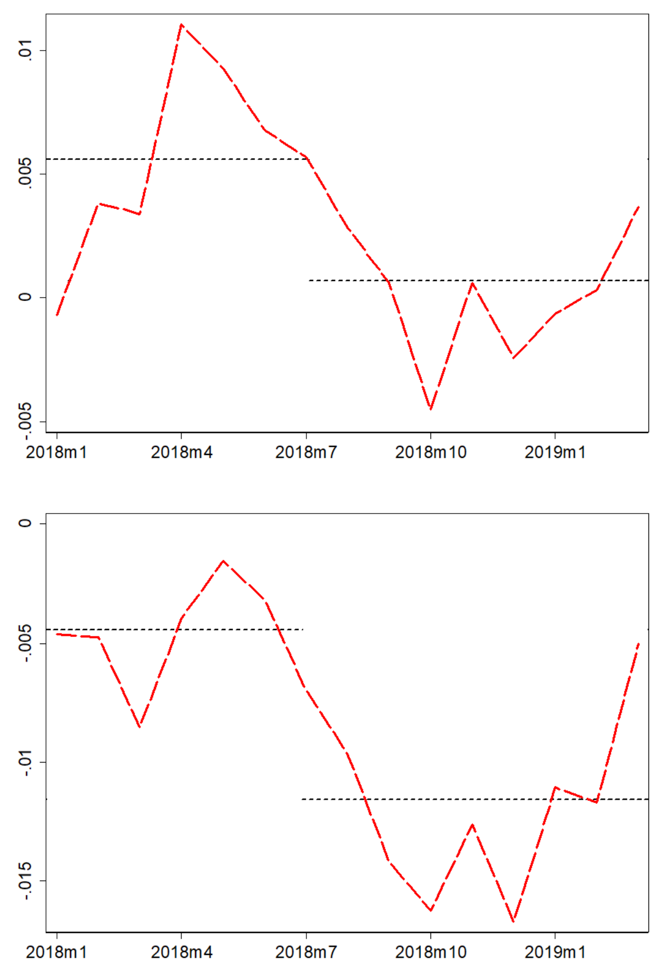

Figure 3: Difference between top and bottom quartile of county-level import tariff change (top) and Chinese retaliatory export tariff change (bottom)

be about a 0.6 percentage point decline in employment growth.

5 Long-run effects on Employment

5.1 Specification and Counterfactual Formula

Now, I examine how a hypothetical trade war would have changed 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:

$$\Delta \ln L_{j\tau} = \beta_\tau + \beta_{m1}\Delta IP^{C}_{j\tau} + \beta_{m2}\Delta IP^{ROW}_{j\tau} + \beta_x \Delta EP_{j\tau} + \eta Z_j + \varepsilon_{j\tau}, \tag{3}$$

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, Z_j is a vector of time-invariant industry-level controls, and $\varepsilon_{j\tau}$ is the error term. I fit this equation for stacked first differences covering three subperiods: 1991-1999, 1999-2007, and 2007-2016. As in 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 $\tau \in \{1, 2, 3\}$, where subperiod 1 corresponds to 1991-1999, subperiod 2 corresponds to 1999-2007, and subperiod 3 corresponds to 2007-2016. 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 industry-county level. I extend their data and analysis to 2016, the latest year for which County Business Patterns employment data is currently available.

To quantify the employment effects of import and export exposure measures, I follow FMX and calculate the predicted employment changes from specification (3) as:

$$\Delta L_{j\tau} = \sum_j \left[1 - e^{-\left(\Delta \tilde{IP}_{j\tau} + \Delta \tilde{EP}_{j\tau}\right)}\right] L_{j,end}, \tag{4}$$

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:

$$\sum_j \left[1 - e^{-\left(\Delta \tilde{IP}_{j\tau} + \Delta \tilde{EP}_{j\tau}\right)}\right] \approx \sum_j \left[\left(1 - e^{-\Delta \tilde{IP}_{j\tau}}\right) + \left(1 - e^{-\Delta \tilde{EP}_{j\tau}}\right) - C_{j\tau}\right], \tag{5}$$

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 Trump supporters, and *(iii) responsible retaliation*, which minimizes the impact of retaliation on global supply chains.

5.2.1 Simple Retaliation

I modify the formula in (4) 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)[3]. A ten percent increase in tariffs would therefore lead to $10 \times \theta$ percent decline in 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. However, the U.S. imports a lot more from China than it exports to China. In order to see the effect of a uniform 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 2016 for U.S. exports to China is \$40 billion in 2007 dollars. The average for U.S. imports from China in the same period is \$197 billion. I therefore allow U.S. import tariffs on only 20 percent ($\approx 40/197$) of each industry's U.S. imports from China.

The formula used to calculate the effect of this simple retaliation is given by (4), where

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

and

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

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

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[4], 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 $T_j > 0.5$.

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 2016 for U.S. exports to China in Trump-majority industries is \$17 billion in 2007 dollars. I therefore allow U.S. import tariffs on only 9 percent ($\approx$ 17/197) of each industry's U.S. imports from China.

The formula used to calculate the effect of this political retaliation is given by (4), where

$$\Delta \tilde{IP}_{j\tau} = [(1 - 0.1\theta_j) \times 0.09 \times \hat{\beta}_{m1} \Delta IP^C_{j\tau}] + \hat{\beta}_{m2} \Delta IP^{ROW}_{j\tau},$$

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 $T_j \leq 0.5$.

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 they know that 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

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

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

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 average across 1991 to 2016 for U.S. exports to China in $GL_{US,C} > 0.5$ industries is \$8 billion in 2007 dollars. I therefore allow U.S. import tariffs on only 4 percent ($\approx 8/197$) of each industry's U.S. imports from China.

The formula used to calculate the effect of this political retaliation is given by (4), where

$$\Delta \tilde{IP}_{j\tau} = [(1 - 0.1\theta_j) \times 0.04 \times \hat{\beta}_{m1} \Delta IP^C_{j\tau}] + \hat{\beta}_{m2} \Delta IP^{ROW}_{j\tau},$$

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 $GL_{US,C} \leq 0.5$.

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:

$$\Delta IP^C_{j\tau} = \frac{\Delta \mathbb{M}^C_{j\tau}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \tag{6}$$

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

$$\Delta IP_{j\tau}^{ROW} = \frac{\Delta \mathbb{M}_{j\tau}^{ROW}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \quad (7)$$

For export exposure, I follow FMX. They use an analogous measure to (6) as

$$\Delta EP_{j\tau} = \frac{\Delta \mathbb{X}_{j\tau}}{\mathbb{Y}_{j91}}, \quad (8)$$

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 (3) 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 other high-income countries. This should reflect China's supply shock to the world, which should be common for high-income importing countries.[5] In particular, the instrument is defined as $\Delta IP_{j\tau}^{*C}$, with

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

where $\mathbb{M}_{jt}^{C*}$ 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_{jt}^{ROW*} 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 are also difficult to identify. Access to new markets would drive up demand for employment but domestic supply shocks, such as new technology, would also reduce employment. Domestic demand shocks also may affect exports and employment simultaneously. 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:

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

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

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

Table 4: Estimation of US Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)
Δ Chinese imports	-0.51***	-0.81***	-0.71***	-0.69***	1.81
	(0.10)	(0.18)	(0.17)	(0.16)	(0.97)
Δ Non-Chinese imports	0.31**	0.11	0.04	0.08	-0.18
	(0.10)	(0.18)	(0.16)	(0.10)	(0.51)
Δ Exports	0.10	0.49*	0.61*	0.37	0.13
	(0.12)	(0.26)	(0.26)	(0.19)	(0.13)
Estimation method	OLS	2SLS	2SLS	2SLS	2SLS
FMX instruments		Both	OTH	OTH	OTH
Time period	1991-2011	1991-2011	1991-2011	1991-2016	2010-2016

Notes: Robust standard errors in parentheses, clustered on commuting zones. The estimation comes from column 3 of Table 6 of Feenstra, Ma, and Xu (2019), which is their preferred specification with two types of instruments for the import and export exposure variables, named OTH and TAR. The sample includes 1,444 observations: 722 commuting zones stacked for two periods (1991-1999 and 1999-2011). The regression is weighted by start-of-period employment share of the commuting zone. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

in its exports to those countries. FMX provide evidence that these foreign demand shocks are not substantially correlated with U.S. domestic demand shocks. I use this instrument to extend their analysis to include more recent years

5.5 Estimation

Table 4 presents the industry-level results for the manufacturing sector. All regressions include 392 manufacturing industries, subperiod fixed effects, and are weighted by 1991 employment. The first two rows show $\hat{\beta}_{m1}$, $\hat{\beta}_{m2}$, and $\hat{\beta}_x$ from the estimation of (3).

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 creates a positive but insignificant effect on employment. More specifically, a one percentage point rise in industry 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 0.31 percentage points.

As noted above, both estimates for the import exposure and export exposure could be biased due to simultaneous changes in domestic demand and supply. 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.[6], a one percentage point rise in industry import penetration reduces domestic industry employment by 0.81 percentage points, while a one percentage point rise in

[6] The second instrument of FMX relies on a CES framework, and includes information regarding tariffs faced by the United States and all other countries selling in that market.

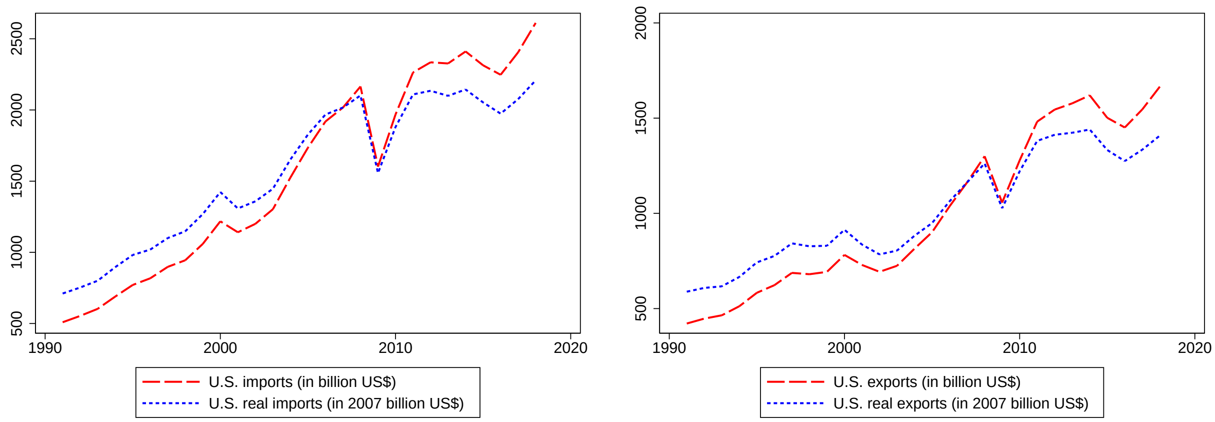

Figure 4: U.S. imports and exports over time

export expansion increases industrial employment by 0.49 percentage points. Both of these effects are larger with 2SLS than with OLS. 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 0.71 percentage points and a one percentage point rise in export expansion increases industrial employment by 0.61 percentage points. The general result that Chinese import exposure reduces jobs while export expansion creates them holds across all specifications.

Column (4) extends the specification in column (3) to include 3 stacked periods, with the final period ending in 2016. I find that the job reducing effect of Chinese imports is similar when compared to column (3) but the job creating effect of exports is no longer significant after extending the analysis to 2016. 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 4 shows a decline in both imports and exports around 2015.

Column (1) of Table 5 shows predicted net employment changes from the specification in column (4) 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, 2007, or 2016). U.S. export expansion net of import penetration led to a net gain of 37,000 jobs in the U.S. manufacturing sector during 1991-2016. 716,000 jobs were lost due to import penetration and 748,000 jobs were also gained due to export expansion. Export expansion created enough jobs to offset job losses due to Chinese import penetration. This is the main result of FMX.[7]

[7]Table **??** shows the calculations using the specification in column (2) of Table 4, which is their preferred speci-

I estimate (3) 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" also 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 regional differences in exposure to the China shock have not been a major factor for the last decade.

5.6 Employment Impact of a Hypothetical Trade War, 1991-2016

Table 5 reports the calculations of predicted employment changes for 1991-2016 based on two scenarios. Columns (1) and (3) report the predicted employment changes from the specification in (3). The actual predicted net change in employment due to import and export exposure during 1991-2016 is positive, which supports the results from FMX that U.S. export exposure also increased in the same period as the China shock and it offset the manufacturing job losses due to the China shock. This is mainly due to the exports to countries other than China because the net effect from Chinese trade alone is negative and quite large (900,000 jobs). Columns (2) and (4) compare the actual changes to a scenario where the U.S. imposes 10 percent import tariffs on all Chinese manufacturing imports but China does not retaliate in return. The effect of total imports in this period becomes positive, leading to an increase of around 720,000 jobs. The effect of Chinese imports also reduces by around 730,000 jobs, implying that had there been protectionism during this period with no retaliation by China, the China shock would not have occurred.

Columns (3) and (6) of Table 6 reports the calculations of predicted employment changes for 1991-2016 based on the scenario of simple retaliation described in section 5.2.1. Since both U.S. and China target similar trade volumes in this case, I also report the calculations of actual employment changes and the no retaliation case based on the restricted volume of trade ($40 billion in 2007 dollars). In this case, The actual predicted net change in employment due to import and export exposure during 1991-2016 is largely positive, with an increase in employment from total imports as well (column (1)). The effect of total Chinese imports, as well as total net Chinese imports are still negative (column (4)). A scenario where a uniform 10 percent tariff by the U.S. is met with a uniform 10 percent tariff by China leads to a net increase in employment relative to the no-trade-war scenario. This is because while the increase in employment due to falling Chinese

fication. The net job gain in this case is 379,000 jobs between 1991-2011.

Table 5: Predicted changes in manufacturing employment (in thousands) due to no retaliation by China (1991-2016)

	All U.S. trade		*U.S.-China trade*	
	No Trade War	No Retaliation	No Trade War	No Retaliation
	(1)	(2)	(3)	(4)
1991-1999				
Imports	-106	108	-263	-45
Exports	462	462	9	9
Net	357	560	-254	-36
1999-2007				
Imports	-506	-92	-590	-174
Exports	297	297	31	31
Net	-202	209	-557	-142
2007-2016				
Imports	-104	-11	-136	-43
Exports	-11	-11	18	18
Net	-118	-28	-118	-25
1991-2016				
Total imports	-716	5	-990	-262
Total exports	748	748	58	58
Total Net	**37**	**741**	**-929**	**-203**

Notes: These calculations come from the coefficients in Table 4 specification (4). The formula used to calculate the effect of no retaliation on the full volume of U.S. imports from China is given by (4), 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 $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^{C}_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$.

import exposure is by about 75 percent, the decrease in employment due to falling Chinese export exposure is only by about 64 percent (column (6)). Therefore, a trade war with uniform retaliation by China in the period 1991-2016 would have also led to a net increase in jobs in the industries targeted by China.

Political retaliation by China as described in Section 5.2.2 also gives a net gain of manufacturing jobs. Table 7 reports these calculations. The restricted volume of trade such that both U.S. and China target similar trade volumes is \$17 billion in 2007 dollars. Again, The actual predicted net change in employment due to import and export exposure during 1991-2016 is positive, although there is a decrease in employment from total imports (column (1)). The effect of total Chinese imports, as well as total net Chinese imports are largely negative (column (4)). A scenario where a uniform 10 percent tariff by the U.S. is met with a 10 percent tariff by China on industries where the Republican Party had a majority, also leads to a net increase in employment relative to the no-trade-war scenario. The increase in employment due to falling Chinese import exposure is by about 73 percent, while the decrease in employment due to falling Chinese export exposure is only by about 19 percent (column (6)). There is still a decrease in employment due to net Chinese trade

Table 6: Predicted changes in manufacturing employment (in thousands) due to simple retaliation by China (1991-2016)

	All U.S. trade			*U.S.-China trade*		
	No Trade War	No Retaliation	Simple Retaliation	No Trade War	No Retaliation	Simple Retaliation
	(1)	(2)	(3)	(4)	(5)	(6)
1991-1999						
Imports	103	145	145	-51	-9	-9
Exports	462	462	456	9	9	1
Net	557	596	590	-42		-7
1999-2007						
Imports	-35	43	43	-109	-32	-32
Exports	297	297	282	31	31	16
Net	255	332	317	-77		-15
2007-2016						
Imports	4	22	22	-26	-8	-8
Exports	-11	-11	-24	18	18	4
Net	-17	0	-12	-8	10	-4
1991-2016						
Total imports	72	209	209	-186	-48	-48
Total exports	748	748	714	58	58	21
Total Net	**795**	**928**	**895**	**-128**	**10**	**-27**

Notes: These calculations come from the coefficients in Table 4 specification (4). The formula used to calculate the effect of simple retaliation is given by (5.2.1).

but the decrease is much smaller compared to the actual no-trade-war decrease. Therefore, a trade war with political retaliation by China in the period 1991-2016 would have also led to a net increase in jobs in the industries targeted by China.

Table A.2 lists the top ten Trump industries and some characteristics of Trump industries are highlighted in Table 8. 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. The net increase in employment due to political retaliation is likely due to a combination of these factors.

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 for $8 billion of exports and imports between the U.S. and China. The increase in employment due to falling Chinese import exposure is by about 73 percent, while the decrease in employment due to falling Chinese export exposure is only by about 10 percent (column (6)). There is still a decrease in employment due to net Chinese trade but the decrease is much smaller compared to the

Table 7: Predicted changes in manufacturing employment (in thousands) due to political retaliation by China (1991-2016)

	All U.S. trade			*U.S.-China trade*		
	No Trade War	No Retaliation	Political Retaliation	No Trade War	No Retaliation	Political Retaliation
	(1)	(2)	(3)	(4)	(5)	(6)
1991-1999						
Imports	-50	118	118	-207	-35	-35
Exports	462	462	461	9	9	8
Net	412	570	569	-197	-26	-27
1999-2007						
Imports	-328	-52	-52	-411	-134	-134
Exports	297	297	292	31	31	26
Net	-28	247	244	-379	-102	-108
2007-2016						
Imports	-57	9	9	-89	-22	-22
Exports	-11	-11	-15	18	18	14
Net	-71	-7	-10	-71	-4	-8
1991-2016						
Total imports	-435	75	75	-707	-191	-191
Total exports	748	748	737	58	58	47
Total Net	**312**	**810**	**799**	**-647**	**-132**	**-143**

Notes: These calculations come from the coefficients in Table 4 specification (4). The formula used to calculate the effect of political retaliation is given by (5.2.2).

Table 8: Characteristics of Trump manufacturing industries

Number of industries	165
Average trade cost elasticity	5.97
Share of employment in 1991	0.37
Share of employment in 2016	0.40
Share of Chinese imports in 1991	0.16
Share of Chinese imports in 2016	0.30
Share of non-Chinese imports in 1991	0.44
Share of non-Chinese imports in 2016	0.50
Share of exports in 1991	0.42
Share of exports in 2016	0.47

Table 9: Predicted changes in manufacturing employment (in thousands) due to responsible retaliation by China (1991-2016)

	All U.S. trade			*U.S.-China trade*		
	No Trade War	No Retaliation	Responsible Retaliation	No Trade War	No Retaliation	Responsible Retaliation
	(1)	(2)	(3)	(4)	(5)	(6)
1991-1999						
Imports	-105	108	108	-262	-45	-45
Exports	462	462	462	9	9	9
Net	358	560	560	-253	-36	-36
1999-2007						
Imports	-502	-92	-92	-585	-175	-175
Exports	297	297	295	31	31	30
Net	-197	209	207	-553	-143	-144
2007-2016						
Imports	-102	-10	-10	-134	-41	-41
Exports	-11	-11	-15	18	18	13
Net	-117	-27	-30	-116	-23	-28
1991-2016						
Total imports	-709	5	5	-982	-261	-261
Total exports	748	748	742	58	58	52
Total Net	**44**	**742**	**736**	**-921**	**-202**	**-209**

Notes: These calculations come from the coefficients in Table 4 specification (4). The formula used to calculate the effect of responsible retaliation is given by (5.2.3).

actual no-trade-war decrease. Therefore, a trade war with responsible retaliation by China in the period 1991-2016 would have also led to a net increase in jobs in the industries targeted by China. Table 10 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 a lot 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 much larger.

Table 10: Characteristics of industries where the U.S. is a net exporter and there is very little intra-industry trade China (1991-2016)

Number of industries	38
Average trade cost elasticity	6.65
Share of employment in 1991	0.08
Share of employment in 2016	0.10
Share of imports from China in 1991	0.01
Share of imports from China in 2016	0.01
Share of exports to China in 1991	0.10
Share of exports to China in 2016	0.34

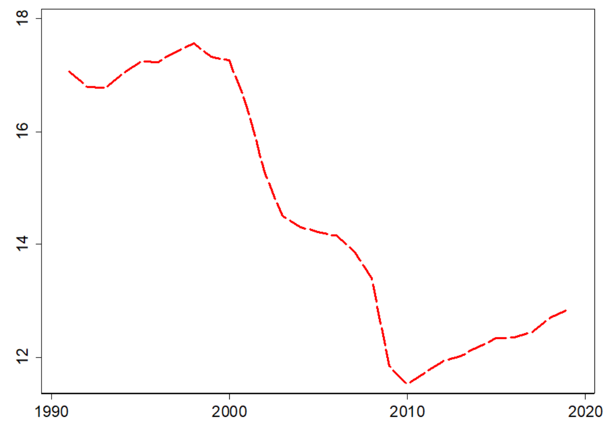

Figure 5: Average U.S. manufacturing employment over time (in millions)

Table A.3 reports calculations based on retaliation scenarios where the U.S. targets all Chinese imports and China retaliates. 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 a 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.

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 5 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 A.4). 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 5.6.

6 Discussion

The result that U.S. import tariffs would have reversed the loss of jobs due to Chinese import competition between 1991-2016 is what one would expect. Much of the U.S. political debate focuses on the huge number of jobs lost due to trade and other factors, although trade with China accounts for only 25 percent of that loss. The rest of it is due to other reasons, such as technological advancement. 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 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. 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 1991-2016. 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. Combined with the result that the negative effect of Chinese import competition is larger than the positive effect of U.S export expansion, I calculate the effect of President Trump's trade war on employment under three different retaliation scenarios and find that the United States would have experienced a net gain in jobs between 1991-2016 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 only, 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 county-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.

References

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2016): "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34(S1), S141–S198.

Amiti, M., S. J. Redding, and D. Weinstein (2019): "The impact of the 2018 trade war on US prices and welfare," Discussion paper, National Bureau of Economic Research.

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6), 2121–2168.

BLOOM, N., K. HANDLEY, A. KURMAN, AND P. LUCK (2019): "The Impact of Chinese Trade on US Employment: The Good, The Bad, and The Debatable," Discussion paper, Working Paper.

BOWN, C., AND M. KOLB (2018): "Trumps trade war timeline: An up-to-date guide," *Peterson Institute for International Economics.*

BOWN, C., AND Y. ZHANG (2019): "Measuring Trumps 2018 Trade Protection: Five Takeaways," Discussion paper, Tech. rep., Peterson Institute for International Economics.

BOWN, C. P., E. JUNG, AND E. ZHANG (2019): "Trump Has Gotten China to Lower Its Tariffs. Just Toward Everyone Else," *Trade and Investment Policy Watch.–2019.–June*, 12.

CALIENDO, L., AND F. PARRO (2015): "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 82(1), 1–44.

FAJGELBAUM, P. D., P. K. GOLDBERG, P. J. KENNEDY, AND A. K. KHANDELWAL (2019): "The return to protectionism," Discussion paper, National Bureau of Economic Research.

FEENSTRA, R. C., H. MA, AND Y. XU (2019): "U.S. exports and employment," *Journal of International Economics.*

FETZER, T., AND C. SCHWARZ (2019): "Tariffs and politics: evidence from Trump's trade wars," *CEPR Discussion Paper No. DP13579.*

PAVCNIK, N. (2017): "The impact of trade on inequality in developing countries," Discussion paper, National Bureau of Economic Research.

PIERCE, J. R., AND P. K. SCHOTT (2016): "The surprisingly swift decline of US manufacturing employment," *American Economic Review*, 106(7), 1632–62.

WAUGH, M. E. (2019): "The Consumption Response to Trade Shocks: Evidence from the US-China Trade War," Discussion paper, National Bureau of Economic Research.

WONG, D., AND A. C. KOTY (2018): "The US-China Trade War: A Timeline," *China Briefing.*

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

Table A.3: Predicted changes in manufacturing employment (in thousands) due to an unbalanced trade war between the U.S. and China

	No Trade War	**No Retaliation**	**Simple Retaliation**	**Political Retaliation**	**Responsible Retaliation**
	(1)	(4)	(3)	(4)	(5)
1991-1999					
Imports	-106	108	108	108	108
Exports	462	462	456	461	462
Net	357	560	554	559	560
1999-2007					
Imports	-506	-92	-92	-92	-92
Exports	297	297	282	292	295
Net	-202	209	195	204	208
2007-2016					
Imports	-104	-11	-11	-11	-11
Exports	-11	-11	-24	-15	-15
Net	-118	-28	-41	-32	-32
1991-2016					
Total Imports	-716	5	5	5	5
Total Exports	748	748	714	737	742
Total Net	**37**	**741**	**708**	**731**	**736**

Notes: These calculations come from Table 4 specification (4).

Table A.4: Predicted changes in manufacturing employment (in thousands) due to no retaliation by China (2010-2016)

	All U.S. trade		*U.S.-China trade*	
	No Trade War	No Retaliation	No Trade War	No Retaliation
	(1)	(2)	(3)	(4)
2010-2013				
Imports	103	6	169	74
Exports	44	44	4	4
Net	145	50	173	78
2013-2016				
Imports	71	6	97	32
Exports	-31	-31	-2	-2
Net	40	-25	95	30
2010-2016				
Total Imports	174	12	266	106
Total Exports	13	13	2	2
Total Net	**185**	**25**	**268**	**108**

Notes: These calculations come from the coefficients in Table 4 specification (5). The formula used to calculate the effect of no retaliation on the full volume of U.S. imports from China is given by (4), 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 $\Delta \tilde{EP}_{j\tau} = \hat{\beta}_x \Delta EP^{C}_{j\tau} + \hat{\beta}_x \Delta EP^{ROW}_{j\tau}$.