The Impact of the 2018-2019 Trade War on U.S. Local Labor Markets

Felipe Benguria [*] Felipe Saffie [†]

February 19th, 2020

Abstract

We study the impact of the 2018-2019 trade war on U.S. local labor markets, distinguishing between regional exposure to foreign tariffs on U.S. exports, U.S. import tariffs, and U.S. tariffs on intermediate inputs. We find foreign retaliatory tariffs on U.S. exports have led to an increase in local unemployment rates, and this effect is magnified for regions specialized in non-manufacturing tradable goods (e.g. agriculture). U.S. import tariffs, on the other hand, have had an impact on local labor market conditions primarily through input-output linkages, leading to a decline in the employment share in the manufacturing sector and a decline in regional earnings.

Keywords: Trade war, Trade policy, Tariffs, Unemployment, Employment, Earnings, Local Labor Markets

JEL classification: F1, J2, J3

[*]Department of Economics, University of Kentucky (fbe225@uky.edu).
[†]Department of Economics, University of Maryland (fesaffie@umd.edu).

1 Introduction

In 2018 and 2019, the U.S. has been engulfed in a trade war previously unseen in the post-war era. The U.S. imposed several rounds of tariff increases on its main trading partners including China, the European Union, Canada and Mexico, leading to immediate retaliation. There is already clear evidence regarding the significant disruption of this trade war on U.S. trade flows and of its overall welfare cost [Fajgelbaum et al., 2019, Amiti et al., 2019].

Yet unknown, however, is the impact of the trade war on the U.S. labor market. In fact, there is little evidence on the impact of any similar trade policies of this magnitude on U.S. labor markets, given how unprecedented this shock has been. The magnitude of the tariffs, the size of the economies involved, and the variation across sectors targeted both by U.S. import tariffs and foreign tariffs on U.S. exports evidently provide a unique opportunity to test the response of labor markets.

In this paper we use a cross-regional approach to assess the consequences of the 2018-2019 trade war for U.S. local labor markets. This approach has already proved successful to study the consequences of trade shocks - such as rising Chinese import competition - on a set of regional labor market outcomes [Autor et al., 2013]. In the current trade war context, U.S. regions have been differentially exposed to both U.S. import tariffs and foreign retaliatory tariffs based on their initial pattern of specialization, providing an ideal context to our empirical framework.

Our analysis is based on monthly data on commuting zone labor market outcomes. We combine this with a detailed and comprehensive monthly dataset on MFN and trade war tariffs imposed by the U.S. and by all its trading partners. We thus construct regional measures of exposure to foreign tariffs on U.S. exports and U.S. import tariffs. In addition we measure input-output linkages and construct measures of regional exposure to U.S. tariffs on imported inputs.

Our first main finding is that local labor markets facing a larger degree of exposure to foreign tariffs on U.S. exports have seen an increase in unemployment rates. Comparing regions at the 25th and 75th percentiles of exposure, the latter see a 0.36 percentage point increase in the unemployment rate per year of exposure. This is about a tenth of the average unemployment rate of 3.92% during this period. In contrast, we do not find statistically significant impacts of U.S. tariffs on unemployment rates.

We extend our analysis by allowing the passthrough of tariffs to labor market outcomes

to differ based on regions' initial economic structures. We find the negative impact of foreign tariffs on unemployment rates to be heterogeneous across regions, being larger for regions with an initial specialization in non-manufacturing tradable industries (i.e. agriculture or other commodities). This is consistent with the focus of Chinese retaliatory tariffs on agricultural goods and the decline in agricultural exports observed as a consequence [Benguria and Saffie, 2019].

Our second key finding is that U.S. tariffs, acting through input-output linkages, have led to a decline in the employment share in manufacturing. Quantitatively, the effect from U.S. tariffs on intermediate inputs is such that regions at the 75th percentile of exposure see a 0.6 percentage point decline per year of exposure in the employment share in manufacturing relative to regions at the 25th percentile. In contrast, we do not find evidence that U.S. tariffs have favored manufacturing employment meaningfully by granting protection from import competition to regions' final output. We also do not find a significant impact on the manufacturing employment share from foreign tariffs.

Finally, we also examine the impact of the trade war on regional earnings.[1] We find that U.S. tariffs on intermediate inputs have had a large negative impact on earnings in relatively more exposed regions, while U.S. import tariffs have had a modest positive impact on regional earnings. The 75/25 percentile difference corresponds to a 2.9% decline in earnings per year of exposure in the case of input tariffs and a 0.5% increase in earnings due to the protection granted by import tariffs.

Our paper builds on previous work that has measured the impact of trade shocks on local labor markets in the U.S. [Autor et al., 2013, Hakobyan and McLaren, 2016] and other countries [Topalova, 2010, Dix-Carneiro and Kovak, 2017]. In the U.S. and other developed countries, the rise in Chinese import competition has been the largest development in recent decades, consequently receiving much attention in the literature, while there have not been major changes in trade policy. In developing countries, the focus has also been put in unilateral trade liberalization episodes in the 1980s and 1990s.

Our paper also contributes to recent work that has examined the consequences of the 2018-2019 trade war on the U.S. economy. Fajgelbaum et al. [2019], Amiti et al. [2019], Flaaen

[1] The earnings data, obtained from the BLS Quarterly Census of Employment and Wages (QCEW) is quarterly rather than monthly as in the rest of our analysis. In addition, it excludes part of the agricultural sector, which is a limitation given that this sector has been targeted by retaliatory tariffs. This is, however, the only source of data on earnings at this level of regional detail.

et al. [2019], Cavallo et al. [2019], and Benguria and Saffie [2019] document the impact on trade flows. In addition, Fajgelbaum et al. [2019] and Amiti et al. [2019] infer welfare impacts. Waugh [2019] uses a cross-regional approach to study the impact of the trade war on consumption across U.S. counties, based on data on automobile spending and focusing on the effect of retaliatory Chinese tariffs.[2] Flaaen and Pierce [2019] study the effects of the trade war on the manufacturing sector based on cross-industry variation in tariffs. They find that the positive effect on employment due to protection from U.S. import tariffs is offset by retaliatory tariffs and rising input costs.

Given that one of our main findings is that retaliatory tariffs raise regional unemployment rates, our paper complements a theoretical literature studying the link between globalization and unemployment [Helpman et al., 2010, Helpman and Itskhoki, 2010] and adds to the short list of empirical evidence in this regard [Autor et al., 2013, Hasan et al., 2012]. Our results also complement the vast literature on the link between globalization and wages, with the new angle in this regard being the role of input-output linkages. The transmission of trade shocks through product market linkages has been underexplored and, in our context, this is the only channel through which tariffs significantly impact earnings. Acemoglu et al. [2016] study the role of input-output linkages in spreading the impact of industry exposure to import competition, while Wang et al. [2018] extend the regional analysis in Autor et al. [2013] including imports of intermediate inputs.

The importance of input-output linkages in our results further connects our paper to a growing set of work analyzing the consequences of trade shocks from that prism. From a theoretical perspective, barriers on importing inputs (offshoring) can lead to a decline in productivity, reducing the demand for labor, or to an increase in the demand for local labor to replace imported inputs (which could alternatively be also sourced from other regions or countries) [Grossman and Rossi-Hansberg, 2008].

The rest of the paper is organized as follows. In Section 2 we describe the various data sources on labor market outcomes and tariffs. In Section 3 we document the impact of tariffs on local labor market outcomes.

[2]Exploring the mechanisms underlying the consumption effects, Waugh [2019] reports an impact of Chinese tariffs on employment in exposed U.S. counties.

2 Data Sources and Context

To assess the impact of the trade war on U.S. local labor markets, we use two different data sources. The Local Area Unemployment Statistics (LAUS) allows us to measure employment, unemployment, unemployment rates, and the size of the labor force by commuting zone at a monthly frequency. From the Quarterly Census of Employment and Wages (QCEW) we measure the share of manufacturing employment at a monthly frequency and earnings by commuting zone at a quarterly frequency.[3] We also construct a comprehensive dataset with all U.S. most-favored-nation (MFN) and trade war import tariffs, and foreign MFN and retaliatory tariffs on U.S. exports. In addition we construct input tariffs corresponding to each industry combining U.S. import tariffs and the total requirements input-output table for the U.S. economy. We then construct regional tariff measures as employment-weighted averages of these industry-level tariffs, with data for employment weights obtained from the BLS County Business Patterns (CBP) dataset supplemented with BEA data for agricultural employment. Finally, we obtain a set of commuting zone characteristics measured prior to the trade war from the American Community Survey (ACS) and the CBP and BEA employment data. We describe each of these datasets in detail below.

2.1 Labor Market Data

■ **Definition of Local Labor Markets** Following Autor et al. [2013] and subsequent work on the impact of international trade on local labor markets, our definition of local labor market is a commuting zone. These areas were originally constructed by Tolbert and Sizer [1996] based on commuting patterns and dividing the mainland U.S. into 722 regions.[4] These areas are defined to maximize commuting ties within them and minimize these ties across them.

■ **Local Area Unemployment Statistics (LAUS)** The LAUS program publishes estimates made by the Bureau of Labor Statistics (BLS) of unemployment, employment and labor force figures by county, which we aggregate to the commuting zone level. County-level estimates in LAUS

[3] Despite its name, QCEW reports monthly employment figures.

[4] Our analysis will exclude two commuting zones. The first one consists of Nantucket County (in Nantucket island) in Massachussets. The second one consists of Cook County, Minnesota, along the border with Canada. Neither reports employment in tradable sectors in the data used for constructing weights for regional tariff measures discussed below. This leaves 720 commuting zones in our sample. Note that our regressions will be weighted by population and these two commuting zones have minimal population.

are based primarily on administrative data. For employment, the main source is the Quarterly Census of Employment and Wages (discussed below). The BLS complements this using other sources to account for employment not covered by QCEW. For the purpose of this paper, the most important omission from QCEW is part of agricultural employment, because the agricultural sector has faced significant retaliatory tariffs during the trade war. The BLS also adjusts the QCEW data from a place of work to a place of residence concept. In the case of unemployment, the main source of data is state unemployment insurance (UI) programs. The BLS complements this with other sources to account for unemployment not covered by UI records, including that of individuals entering the labor market for the first time. Further details on the LAUS data are reported in Appendix A.1.[5]

■ **Quarterly Census of Employment and Wages (QCEW)** The QCEW reports employment by county, industry and month and earnings by county, industry and quarter based on reports by employers. These data cover private and public sector workers covered by state unemployment insurance laws or unemployment compensation for federal employees. The data is reported at various level of industry or sectoral aggregation. Disclosure restrictions on reported data apply at disaggregate industry level data, but in this paper we use data by region or region and sector, in which case disclosure restrictions are not an issue. The data excludes unincorporated self-employed workers, part of agricultural employment, and certain domestic workers. In most states, earnings consist of all forms of compensation, including bonuses. We define earnings per worker as total earnings over employment.

■ **County Business Patterns** To construct regional measures of tariff exposure as described below, we construct weights using data on employment by region and industry prior to the start of the trade war (in 2017). Following Fajgelbaum et al. [2019] these weights are constructed from the BLS County Business Patterns (CBP). Because CBP does not include agricultural employment (corresponding to NAICS industries 111 and 112) we supplement it with data for these industries obtained from the BEA's Regional Accounts (again following Fajgelbaum et al.

[5] LAUS data has been recently used by at the commuting zone level by Yagan [2019] and Rinz et al. [2019]. It has also been used at the county level [Hagedorn et al., 2015, Şahin et al., 2014] the MSA level [Aghion et al., 2016, Hershbein and Kahn, 2018, Chan, 2013] and state level [Chodorow-Reich et al., 2018, Bobonis and Shatz, 2007, Dao et al., 2017, Sun and Yannelis, 2016, Garthwaite et al., 2014, Bratsberg et al., 2006, Fortin, 2006, Shoag, 2013].

[2019]). We start from county × industry employment based on NAICS codes at the 3-digit level of disaggregation.[6] We then aggregate the data to the commuting zone × region level.

■ **Initial Commuting Zone Characteristics** We obtain total population and mean income by county from the 5-year 2017 American Community Survey (ACS) and aggregate them to the commuting zone level. To capture the initial economic structure of each commuting zone, we use CBP (augmented with BEA data for farm employment as described earlier) to compute the employment shares in manufacturing and in non-manufacturing tradable industries in 2017 (prior to the start of the trade war).

2.2 Tariff Data

Here we outline our dataset of foreign tariffs on U.S. exports, U.S. import tariffs, and U.S. import tariffs on intermediate inputs. We follow Fajgelbaum et al. [2019] closely but extend the data forward in time, as their sample does not include 2019. Appendix A.3 and Appendix Table 6 provide a detailed timeline of the trade war policies

In the case of both U.S. import tariffs and foreign tariffs on U.S. exports, these are almost always defined at the HS 8-digit level. At this level of disaggregation, the HS system is not standardized across countries. For this reason and following Fajgelbaum et al. [2019] we work at the HS 6-digit level assuming a tariff applies to an HS6 code if any HS 8-digit code is targeted.[7].

■ **U.S. MFN and Trade War Tariffs** Our dataset on U.S. trade war tariffs is compiled from i) communications by the U.S. Trade Representative, ii) Fajgelbaum et al. [2019] and iii) the Li [2018] trade war tariff dataset, and verified against each other. U.S. MFN tariffs at an annual frequency are obtained from the WTO (World Trade Organization) *Tariff Download Facility* database.[8] Trade war tariff rates are additional to MFN tariffs. Our data includes all the tariff rounds listed in Appendix Table 6.

[6] Defining industries at the NAICS 3-digit level reduces the issue of data supression for confidentiality reasons. In the case of suppressed data (which occurs in 9% of observations) CBP assigns ranges, and we assign the midpoint of this range.

[7] We have verified that tariffs vary almost entirely across but not within HS 6-digit codes. For example, in the case of the U.S. $200 billion round imposed on China, in more than 98.5% of HS 6-digit codes, either all or none of the underlying HS 8-digit codes are targeted by tariffs

[8] We consider non-MFN tariffs granted by the U.S. to Canada and Mexico under NAFTA.

■**Foreign Tariffs on U.S. Exports** Retaliatory foreign tariffs on U.S. exports have been imposed by China, the European Union, Canada, Mexico, Turkey, and Russia. The sources for these data are i) official documents from foreign governments, ii) Fajgelbaum et al. [2019], iii) the Li [2018] trade war tariff dataset, and iv) Bown et al. [2019], which we check against each other.[9] Our data includes all the tariff rounds listed in Appendix Table 6.

MFN tariffs for all U.S. trading partners come from the WTO *Tariff Download Facility* database at an annual frequency (except for more frequent adjustments for China).[10] In the relatively few cases of countries not reporting tariffs in the most recent years, we use the latest value reported (following Fajgelbaum et al. [2019]), which is reasonable given that changes in MFN tariffs are usually very small relative to retaliatory tariff increases during the trade war period.

Importantly, China has made several recent changes lowering its MFN tariffs. We obtain these data from Bown et al. [2019] who compiles them from official documents, as some of these are not captured by the WTO database. Chinese MFN tariff changes took place in January, May, July and November 2018 and January 2019.

■**U.S. Tariffs on Imported Intermediate Inputs** U.S. tariffs on imported intermediate inputs are constructed using the 2012 total requirements input-output table for the U.S. economy.[11] We start by defining import tariffs on each input j at time t as a weighted average of U.S. import tariffs across source countries c as follows:

$$\text{U.S. Tariff}_{jt} = \sum_{c} w_{jc} \cdot \text{U.S. Tariff}_{jct} \ , \tag{1}$$

with weights w_{jc} equal to imports in industry j from country c in 2017. Input tariffs for each industry i at time t are a weighted average of U.S. import tariffs on the intermediate inputs used by that industry:

$$\text{U.S. Input Tariff}_{it} = \sum_{j} w_{ij}^{IO} \cdot \text{U.S. Tariff}_{jt} \ . \tag{2}$$

[9] Official documents with trade war tariff schedules are obtained from China's Ministry of Finance, Canada's Department of Finance, the European Comission, Mexico's "Diario Oficial", the Russia's Government resolution No. 788 of July 6, 2018 and the World Trade Organization.

[10] We consider non-MFN tariffs granted to the U.S. by Canada and Mexico under NAFTA.

[11] Our procedure resembles Pierce and Schott [2016] who use the total requirements input-output table to construct measures of upstream or downstream exposure to their "NTR gap" variable capturing the difference between "normal trade relations" tariff rates granted by the U.S. to China and non-NTR tariffs.

The weights w_{ij}^{IO} are input requirements obtained from the input-output table.[12]

2.3 Regional Tariff Exposure

We construct regional tariffs as employment-weighted averages of industry level tariffs. Specifically, for region r at time t, the regional measure of foreign tariffs on U.S. exports $\tau_{rt}^{\text{FOREIGN}}$ is:

$$\tau_{rt}^{\text{FOREIGN}} = \sum_i \frac{L_{ri}}{L_r} \tau_{it}^{\text{FOREIGN}} \ . \tag{3}$$

In this expression, $\tau_{it}^{\text{FOREIGN}}$ is the average foreign tariff on U.S. exports in industry i. Industries are the 3-digit level of the NAICS classification and average industry tariffs are weighted averages of tariffs at the HS 6-digit level, with weights equal to U.S. export values in 2017.[13,14] The term L_{ri} denotes region r's employment in industry i and L_r is total regional employment. The employment measures used as weights are computed in year 2017, prior to the start of the trade war. Analogous measures of regional tariffs are computed for U.S. import tariffs:

$$\tau_{rt}^{\text{U.S.}} = \sum_i \frac{L_{ri}}{L_r} \tau_{it}^{\text{U.S.}} , \tag{5}$$

and for U.S. tariffs on imported inputs.[15]

$$\tau_{rt}^{\text{U.S. INPUT}} = \sum_i \frac{L_{ri}}{L_r} \tau_{it}^{\text{U.S. INPUT}} . \tag{6}$$

■ **Variation in Regional Tariffs** To illustrate the variation in regional exposure to foreign tariffs on U.S. exports, panel (a) in Figure 1 maps the change in $\tau_{rt}^{\text{FOREIGN}}$ during the trade war (between January 2018 and June 2019). The commuting zones facing the largest tariff increases

[12] We construct these measures using a concordance between BEA IO codes and NAICS codes included in the input-output table.

[13] Constructing regional measures of tariff exposure based on industries at the 3-digit NAICS level of disaggregation diminishes the issue of data supression discussed when introducing the CBP employment data.

[14] Specifically, the industry-level foreign tariff on U.S. exports is defined as:

$$\tau_{it}^{\text{FOREIGN}} = \frac{\sum_{p \epsilon i} v_p \cdot \tau_{pt}^{\text{FOREIGN}}}{\sum_{p \epsilon i} v_p} \ , \tag{4}$$

in which p refers to HS 6-digit products and i refers to NAICS 3-digit industries.

[15] In the case of U.S. import tariffs, industry-level tariffs are computed as weighted averages of tariffs at the HS 6-digit level, with weights equal to U.S. import values in 2017.

(in percentage points) are in parts of the Midwest and Central regions. Panel (b) illustrates the change in U.S. import tariffs over the same period. In this case the most exposed regions are the Midwest and parts of the Northeast and Southeast. Finally, panel (c) shows regional variation in exposure to U.S. tariffs on imported inputs, in which case the largest increases are also in the Midwest, Northeast and Southeast regions. In addition, Table 7 reports summary statistics for the change in regional exposure to each tariff measure.

Figure 2 further illustrates the evolution of regional tariff exposure over time. It graphs the mean and various percentiles of the distribution of each regional tariff exposure measure by month. For instance, panel (a) shows large increases in regional tariffs at the 90th and 75th percentiles of exposure following foreign tariff rounds on US exports. Panel (b) indicates that increases in U.S. import tariffs have also led, to a lesser extent, to disproportionate increases among the top percentiles. Finally, panel (c) illustrates that U.S. tariffs on imported inputs have led to large increases in regional exposure shifting all percentiles similarly.

Finally, in Appendix A.5 we document the correlation between tariff increases and regions' initial characteristics. Foreign tariffs on U.S. exports increased by larger amounts in regions with lower income and higher employment shares in the tradable sector. U.S. import tariffs also increased more in regions with larger employment shares in tradables. U.S. input tariffs saw larger increments in regions with a larger share of manufacturing employment and a smaller share of non-manufacturing tradable employment.

3 The Trade War and Local Labor Markets

To quantify the impact of tariffs on U.S. local labor markets we estimate regressions of the following form, where the dependent variable is the 12-month change between months t and $t-12$ in the labor market outcome of interest in region r.

$$\Delta Y_{rt} = \beta_1 \cdot \Delta\log(\tau_{rt}^{\text{FOREIGN}}) + \beta_2 \cdot \Delta\log(\tau_{rt}^{\text{U.S.}}) + \beta_3 \cdot \Delta\log(\tau_{rt}^{\text{U.S. INPUT}}) + \gamma_r + \delta_t + \epsilon_{rt} \tag{7}$$

The explanatory variables are the 12-month changes in the regional measures of foreign tariffs on U.S. exports, U.S. import tariffs, and U.S. tariffs on intermediate inputs, defined in equations (3), (5) and (6).[16] Each observation corresponds to a commuting zone r in a month t be-

[16] Appendix Table 5 reports the mean and standard deviation of all variables.

tween January 2018 and June 2019. The estimation is in stacked differences, with observations weighted by population in 2017 and standard errors clustered at the state level.[17] Given the concern of pre-existing trends we include regional fixed effects to control for region-specific trends.[18]

■ **Unemployment** Table 1 reports our baseline results for regional unemployment rates, defined as the ratio of the number of unemployed individuals over the labor force. We find a positive and statistically significant impact of foreign tariffs.[19] Specifically, the difference in exposure between the 25th and 75th percentiles is associated to a 0.036 percentage point increase in the unemployment rate per year of exposure. How large is this effect? This is about a tenth of the average unemployment rate (weighted by commuting zone population) in the U.S. during this period, which is 3.92%. We also find that U.S. import tariffs and U.S. tariffs on intermediate inputs do not have a statistically significant impact on unemployment rates.

The impact that foreign tariffs on US exports have on unemployment rates could be a result of changes in the total number of unemployed individuals or changes in the labor force. In Appendix Table 10 we examine these outcomes. First, panel A reports results with the regional unemployment count as the dependent variable, finding that foreign tariffs have led to an increase in regional unemployment. While not statistically significant at conventional levels (the p-value is 0.105), this coefficient reflects an economically large effect such that moving from the 25th to 75th percentiles of regional exposure to foreign tariffs is associated to a 5.8% increase in the regional unemployment count. Again, the effect of U.S. import tariffs and U.S. tariffs on intermediate inputs is not statistically significant. In contrast, panel B shows that trade war tariffs have not led to any statistically significant change in the size of the labor force. Finally, in panel C we document the impact of tariffs on regional employment. We find a negative but not statistically significant impact of foreign tariffs on the total regional employment count.[20] Similarly, we do not find statistically significant impacts on employment

[17] Commuting zones sometimes cross state boundaries. To assign a state to each commuting zone (for clustering) we choose the state in which the commuting zone has the largest share of initial (2017) population.

[18] An alternative approach to address the issue of possible pre-existing trends we have explored is to detrend the dependent variables removing regional trends using data prior to the trade war (in 2017). The results are almost identical to those described below.

[19] We have also computed standard errors accounting for a potential correlation of regression residuals across regions with similar sectoral shares as in Adao et al. [2019]. In that case we obtain smaller standard errors. Conservatively, in Table 1 we report standard errors without the Adao et al. [2019] correction.

[20] Note however that the negative impact of foreign tariffs on regional employment becomes larger and closer

from U.S. import tariffs and U.S. tariffs on intermediate inputs.

Table 1: Tariffs and Unemployment Rates

	(1)	(2)	(3)	(4)
$\Delta log(\tau^{\text{FOREIGN}})$	0.829**			0.756**
	(0.335)			(0.308)
$\Delta log(\tau^{\text{US}})$		-0.178		-0.163
		(0.130)		(0.137)
$\Delta log(\tau^{\text{US INPUT}})$			-0.190	0.061
			(0.497)	(0.597)
Observations	12960	12960	12960	12960

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of equation (7). The dependent variable is 100 × the 12-month change in the unemployment rate. Each observation corresponds to a commuting zone and period (there are 720 commuting zones and 18 periods). Standard errors are clustered by state and observations are weighted by 2017 population in each commuting zone.

We also explore the possibility that tariffs have had differential impacts across space based on the economic structure of each commuting zone. For this purpose, we interact the regional tariff measures with time-invariant regional characteristics measured in 2017, prior to the beginning of the trade war. Because foreign and U.S. tariffs impact most directly the tradable sector, we interact the regional tariff measures with the employment share of the tradable sector. Because both manufacturing and non-manufacturing industries have been targeted by tariffs, we split the employment share in tradable industries across this dimension. We estimate an augmented version of equation (7) including interaction terms between tariff measures and dummy variables for above or below median employment shares.

These results are shown in Appendix Table 11. We find (see column 1) that the effect of foreign tariffs on unemployment rates is larger among regions with larger initial employment shares in non-manufacturing tradable industries (i.e. agriculture and other commodities). The coefficients imply that the total elasticity of unemployment rates to foreign tariffs is 1.8 times larger among regions in the 75th percentile of specialization in non-manufacturing tradable industries relative to regions at the 25th percentile. In the case of the unemployment count

to statistical significance when focusing on the period of larger trade war tariffs from July 2018 to June 2019.

(column 2), the coefficients point in the same direction than for the unemployment rate, but are not statistically significant. We do find a differential positive impact of foreign tariffs on the labor force among regions specialized in non-manufacturing tradable industries (column 3). Finally, we reported earlier no statistically significant impact of tariffs on employment and we find no exception for regions with different specializations (column 4).

■ **Manufacturing Employment** Next, we examine whether the trade war has caused a reallocation of labor across sectors within regions. Using the QCEW data we examine the impact of tariffs on the share of manufacturing employment. We construct the share of manufacturing employment as the ratio of manufacturing employment divided by either total regional employment reported in LAUS (our preferred specification) or reported in QCEW (with the limitations discussed earlier in Section 2). The results are reported in Table 2. We find a negative impact of tariffs on imported inputs on the regional share of manufacturing employment, while the other two tariff measures do not have a statistically significant or economically meaningful impact.[21] The magnitude of the coefficient on input tariffs implies that moving from the 25th to 75th percentiles of exposure leads to a 0.6 percentage point lower share of manufacturing employment per year of exposure.[22] This finding evidently highlights the importance of taking into account input-output linkages in the assessment of the consequences of trade policy.

■ **Earnings** Finally, we analyze the effects of trade war tariffs on earnings per worker. We again use data from QCEW, which reports a region's total payroll at a quarterly frequency. As we mentioned earlier, QCEW does not include a part of agricultural employment. While the omission is evidently a limitation, there are no other data sources of earnings at this frequency and at this level of regional disaggregation available. We define earnings per worker as the ratio of total earnings to total employment.

Table 3 reports these results. The estimation is identical than that for employment outcomes, with the only difference being the quarterly instead of monthly frequency. These results indicate that U.S. input tariffs have had a large negative impact on earnings in relatively more

[21] Again, we have also computed standard errors using the Adao et al. [2019] procedure and obtain smaller standard errors. Conservatively, in Table 2 we report standard errors without this correction.

[22] The average share of manufacturing employment (weighted by population) is 0.09 as shown in Appendix Table 5, which reports summary statistics.

Table 2: Tariffs and Manufacturing Employment Share

	(1)	(2)	(3)	(4)	(5)
$\Delta log(\tau^{\text{FOREIGN}})$	0.172			0.287	0.316
	(0.225)			(0.277)	(0.318)
$\Delta log(\tau^{\text{US}})$		-0.126		0.077	0.079
		(0.098)		(0.140)	(0.161)
$\Delta log(\tau^{\text{US INPUT}})$			-0.712**	-0.877**	-0.981**
			(0.284)	(0.390)	(0.366)
Observations	12960	12960	12960	12960	12960

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of equation (7). The dependent variable is 100 × the 12-month change in the employment share in manufacturing. In columns 1 through 4, the employment share in manufacturing is constructed using total regional employment from LAUS in the denominator. In column 5, the employment share in manufacturing is constructed using total regional employment from QCEW in the denominator (i.e. the denominator excludes some agricultural employment). Each observation corresponds to a commuting zone and period (there are 720 commuting zones and 6 periods). Standard errors are clustered by state and observations are weighted by 2017 population in each commuting zone.

exposed regions. We also find U.S. import tariffs have had a more modest positive impact on regional earnings.[23] For input tariffs, the difference between the 25th and 75th percentile of exposure is a 2.9% decline in earnings per year of exposure, while in the case of import tariffs, this difference amounts to a 0.5% increase in earnings. In other words, the overall impact of U.S. tariffs is negative because the negative effect on earnings through input-output linkages largely dominates the positive effect through tariffs on output granting protection from import competition.

■ **Discussion** Overall, our results indicate that regions facing a larger degree of exposure to foreign tariffs on U.S. exports during the trade war have seen an increase in unemployment rates. Regions more exposed to U.S. tariffs have experienced a decline in the share of manu-

[23] In this case, the Adao et al. [2019] procedure to account for a potential correlation of regression residuals across regions with similar sectoral shares leads to somewhat larger standard errors. For input tariffs in column 4, the standard error increases from 1.507 to 1.850 and the t-statistic changes from -2.74 to -2.23, mantaining statistical significance. For US import tariffs in column 4, the standard error increases from 0.541 to 0.837 and the t-statistic changes from 1.92 to 1.24, losing statistical significance.

Table 3: Tariffs and Earnings per Worker

	(1)	(2)	(3)	(4)
$\Delta log(\tau^{\text{FOREIGN}})$	1.195			2.218
	(1.459)			(1.562)
$\Delta log(\tau^{\text{US}})$		0.010		1.039*
		(0.491)		(0.541)
$\Delta log(\tau^{\text{US INPUT}})$			-2.066	-4.129***
			(1.297)	(1.507)
Observations	4320	4320	4320	4320

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of equation (7) with quarterly data. The dependent variable is 100 × the yearly change in (log) earnings per worker. Each observation corresponds to a commuting zone and period (there are 720 commuting zones and 6 periods). Standard errors are clustered by state and observations are weighted by 2017 population in each commuting zone.

facturing employment and regional earnings per worker due to the action of tariffs through input-output linkages. These results, however, do not necessarily imply that the *full* impact of tariffs on the U.S. economy is negative, given that our cross-regional analysis abstracts from general equilibrium effects and from medium or long-run dynamic effects.[24]

Our results point to the importance of considering input-output linkages (supply chains) when assessing the role of trade policy. U.S. tariffs appear to act mostly through this channel both regarding their negative impact on the share of manufacturing employment and on earnings per worker. In the context of the current trade war, Benguria and Saffie [2019] and Handley et al. [2020] document that tariffs on intermediate inputs hurt U.S. exports, so it is not surprising to find a similar message regarding employment. In fact, Flaaen and Pierce [2019] document a similar effect for employment in the manufacturing sector based on cross-industry variation. In the context of Chinese import competition during the 1990s and 2000s, Acemoglu et al. [2016] and Wang et al. [2018] extend Autor et al. [2013] considering the effect from import competition to upstream industries, finding an effect not statistically different from zero

[24]Note however that Acemoglu et al. [2016] estimate general equilibrium effects of the increase in Chinese competition faced by the U.S. labor market finding that it magnifies rather than offsets the partial equilibrium effect obtained from an approach equivalent to the one used in this paper.

in the first case and positive in the latter.

We have explored the heterogeneous passthrough of tariffs to regional outcomes, depending on regions' initial economic structure, focusing on the share of manufacturing and non-manufacturing tradable employment. Trade war tariffs (and particularly foreign tariffs on U.S. exports) have significantly targeted agricultural goods. This stands in contrast to the analysis of previous trade shocks to U.S. local labor markets, in which the main focus has been the manufacturing sector. In the current context, both manufacturing and agriculture have been impacted, and regions with a large share of agricultural (or more in general commodities) employment have seen larger increases in unemployment rates. Generally, there is little evidence in the literature showing which regional characteristics shape regional trade adjustment.

These results can be contrasted to the regional effects of the rise in Chinese import competition during the 1990s and 2000s documented by Autor et al. [2013]. Evidently, there are constrasts between the shocks in each case. The 'China shock' is an ongoing shock driven by China's increased productivity and openness to world markets that spans decades, while the trade war tariffs have appeared suddenly, are a direct policy instrument, and in this paper we focus on a much shorter horizon than Autor et al. [2013]. Autor et al. [2013] establish that rising import competition from China leads to higher unemployment, a decline in the labor force, lower wages and a lower manufacturing employment share. Our findings show that U.S. tariffs, granting protection from import competition and applied mostly to China, are not effective in reversing the effects found by Autor et al. [2013]. In the case of earnings, which U.S. tariffs do raise to some extent through their direct effect, the negative impact through input-output linkages more than offsets this effect.

4 Conclusions

We have a documented the impact of the set of policies jointly labelled the 2018-2019 trade war on U.S. local labor market outcomes. Tariff increases between the U.S. and several of its main trading partners have given shape to the largest shock to U.S. trade policy in the post-war era.

We analyze the response of local labor markets to foreign tariffs on U.S. exports, U.S. import tariffs, and U.S. tariffs on imported inputs. We highlight three main findings. First, foreign re-

taliatory tariffs have led to an increase in unemployment rates in more exposed regions, such that the difference between regions at the 75th and 25th percentiles of exposure is associated to a 0.36 percentage point increase in the unemployment rate. This effect is magnified among regions specialized in non-manufacturing tradable industries (i.e. agriculture and other commodities). Second, U.S. import tariffs have led to a contraction in manufacturing employment through input-output linkages. Finally, while U.S. import tariffs have had a modest positive impact on regional earnings directly by impact granting protection from import competition, their overall effect on earnings is negative because tariffs on intermediate inputs more than offset the direct effect.

Future work could later estimate long-run effects of these policies on local labor market outcomes, further study the transmission of the impact of tariffs across industries through general equilibrium effects (as in Acemoglu et al. [2016]), or focus on the heterogeneous impact of these policies across individual workers.

Table 4: Tariffs and U.S. Local Labor Market Outcomes Based on Initial Commuting Zone Characteristics

	(1) Unemp. Rate	(2) Unemp.	(3) Labor Force	(4) Employment
$\Delta log(\tau^{\text{FOREIGN}})$	0.746**	16.280*	0.151	-0.633
	(0.350)	(9.326)	(0.845)	(1.014)
$\Delta log(\tau^{\text{FOREIGN}}) \times$ High Tradable Emp. Share (Non-Mftg.)	0.431**	6.100	0.858**	0.392
	(0.207)	(5.458)	(0.401)	(0.465)
$\Delta log(\tau^{\text{FOREIGN}}) \times$ High Tradable Emp. Share (Mftg.)	-0.323	-9.202	-0.307	0.029
	(0.235)	(6.428)	(0.401)	(0.420)
$\Delta log(\tau^{\text{US}})$	-0.037	-1.195	-0.283	-0.241
	(0.179)	(4.753)	(0.443)	(0.510)
$\Delta log(\tau^{\text{US}}) \times$ High Tradable Emp. Share (Non-Mftg.)	0.038	0.663	-1.687	-1.714
	(0.284)	(6.537)	(1.126)	(1.270)
$\Delta log(\tau^{\text{US}}) \times$ High Tradable Emp. Share (Mftg.)	0.258	7.396	0.895	0.619
	(0.187)	(4.841)	(0.661)	(0.711)
$\Delta log(\tau^{\text{US INPUT}})$	-0.529	-10.625	-0.045	0.525
	(0.397)	(7.669)	(0.946)	(1.166)
$\Delta log(\tau^{\text{US INPUT}}) \times$ High Tradable Emp. Share (Non-Mftg.)	0.057	0.540	0.870	0.794
	(0.252)	(6.230)	(0.781)	(0.888)
$\Delta log(\tau^{\text{US INPUT}}) \times$ High Tradable Emp. Share (Mftg.)	0.040	0.963	-0.576	-0.611
	(0.199)	(5.152)	(0.669)	(0.700)
Observations	12960	12960	12960	12960

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of an extended version of equation (7) including interaction terms between regional tariff measures and dummy variables indicating above-median 2017 employment shares in manufacturing and in non-manufacturing tradable industries (agriculture and other commodities). The dependent variable is 100 × the 12-month change in the unemployment rate (column 1), (log) unemployment (column 2), the (log) labor force (column 3) or (log) employment (column 4). Each observation corresponds to a commuting zone and period (there are 720 commuting zones and 18 periods). Standard errors are clustered by state and observations are weighted by 2017 population in each commuting zone.

5 References

D. Acemoglu, D. Autor, D. Dorn, G. H. Hanson, and B. Price. Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198, 2016.

R. Adao, M. Kolesár, and E. Morales. Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, 134(4):1949–2010, 2019.

P. Aghion, U. Akcigit, A. Deaton, and A. Roulet. Creative destruction and subjective well-being. *American Economic Review*, 106(12):3869–97, 2016.

M. Amiti, S. J. Redding, and D. Weinstein. The Impact of the 2018 Trade War on US Prices and Welfare. *NBER Working Paper #25672*, 2019.

D. Autor, D. Dorn, and G. H. Hanson. The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68, 2013.

F. Benguria and F. Saffie. Dissecting the Impact of the 2018-2019 Trade War on US Exports. *SSRN Working Paper*, 2019.

G. J. Bobonis and H. J. Shatz. Agglomeration, adjustment, and state policies in the location of foreign direct investment in the united states. *The Review of Economics and Statistics*, 89(1): 30–43, 2007.

C. Bown, E. Jung, and E. Zhang. Trump Has Gotten China to Lower Its Tariffs. Just Toward Everyone Else. 2019.

B. Bratsberg, E. Barth, and O. Raaum. Local unemployment and the relative wages of immigrants: Evidence from the current population surveys. *The Review of Economics and Statistics*, 88(2):243–263, 2006.

A. Cavallo, G. Gopinath, B. Neiman, and J. Tang. Tariff passthrough at the border and at the store: Evidence from us trade policy. *NBER Working Paper #26396*, 2019.

M. K. Chan. A dynamic model of welfare reform. *Econometrica*, 81(3):941–1001, 2013.

R. Chetty, N. Hendren, P. Kline, and E. Saez. Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics*, 129 (4):1553–1623, 2014.

G. Chodorow-Reich, J. Coglianese, and L. Karabarbounis. The macro effects of unemployment benefit extensions: a measurement error approach. *The Quarterly Journal of Economics*, 134 (1):227–279, 2018.

M. Dao, D. Furceri, and P. Loungani. Regional labor market adjustment in the united states: trend and cycle. *Review of Economics and Statistics*, 99(2):243–257, 2017.

R. Dix-Carneiro and B. K. Kovak. Trade Liberalization and Regional Dynamics. *American Economic Review*, 107(10):2908–46, 2017.

P. D. Fajgelbaum, P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal. The Return to Protectionism. *NBER Working Paper #25638*, 2019.

A. Flaaen and J. Pierce. Disentangling the effects of the 2018-2019 tariffs on a globally connected us manufacturing sector. *Working Paper*, 2019.

A. B. Flaaen, A. Hortaçsu, and F. Tintelnot. The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines. *NBER Working Paper #25767*, 2019.

N. M. Fortin. Higher-education policies and the college wage premium: Cross-state evidence from the 1990s. *American Economic Review*, 96(4):959–987, 2006.

C. Garthwaite, T. Gross, and M. J. Notowidigdo. Public health insurance, labor supply, and employment lock. *The Quarterly Journal of Economics*, 129(2):653–696, 2014.

G. M. Grossman and E. Rossi-Hansberg. Trading tasks: A simple theory of offshoring. *American Economic Review*, 98(5):1978–97, 2008.

M. Hagedorn, I. Manovskii, and K. Mitman. The impact of unemployment benefit extensions on employment: The 2014 employment miracle? Technical report, National Bureau of Economic Research, 2015.

S. Hakobyan and J. McLaren. Looking for local labor market effects of nafta. *Review of Economics and Statistics*, 98(4):728–741, 2016.

K. Handley, F. Kamal, and R. Monarch. Rising import tariffs, falling export growth: When modern supply chains meet old-style protectionism. 2020.

R. Hasan, D. Mitra, P. Ranjan, and R. N. Ahsan. Trade liberalization and unemployment: Theory and evidence from india. *Journal of Development Economics*, 97(2):269–280, 2012.

E. Helpman and O. Itskhoki. Labour market rigidities, trade and unemployment. *The Review of Economic Studies*, 77(3):1100–1137, 2010.

E. Helpman, O. Itskhoki, and S. Redding. Inequality and unemployment in a global economy. *Econometrica*, 78(4):1239–1283, 2010.

B. Hershbein and L. B. Kahn. Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1737–72, 2018.

M. Li. CARD Trade War Tariffs Database. 2018.

J. R. Pierce and P. K. Schott. The surprisingly swift decline of us manufacturing employment. *American Economic Review*, 106(7):1632–62, 2016.

K. Rinz et al. Did timing matter? life cycle differences in effects of exposure to the great recession. Technical report, 2019.

A. Şahin, J. Song, G. Topa, and G. L. Violante. Mismatch unemployment. *American Economic Review*, 104(11):3529–64, 2014.

D. Shoag. Using state pension shocks to estimate fiscal multipliers since the great recession. *American Economic Review*, 103(3):121–24, 2013.

S. T. Sun and C. Yannelis. Credit constraints and demand for higher education: Evidence from financial deregulation. *Review of Economics and Statistics*, 98(1):12–24, 2016.

C. M. Tolbert and M. Sizer. Us commuting zones and labor market areas: A 1990 update. 1996.

P. Topalova. Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics*, 2(4):1–41, 2010.

Z. Wang, S.-J. Wei, X. Yu, and K. Zhu. Re-examining the effects of trading with china on local labor markets: A supply chain perspective. 2018.

M. E. Waugh. The consumption response to trade shocks: Evidence from the us-china trade war. 2019.

D. Yagan. Employment hysteresis from the great recession. *Journal of Political Economy*, 127 (5):2505–2558, 2019.

A Appendix

A.1 Description of the BLS' Local Area Unemployment Statistics

- The BLS uses two different methods to construct LAUS figures of employment and unemployment. At the state level (or more aggregate units) estimates are model-based and the Current Population Survey is the primary input.

- Estimates at the county level are based primarily on administrative data. In the case of employment, the primary source is the Quarterly Census of Employment and Wages (QCEW) (which despite its name does report *monthly* employment data). This is complemented with other sources to account for workers not covered by QCEW (such as farm employment and unincorporated self-employed individuals). For unemployment, the main source is data from state unemployment insurance programs. This is complemented with other sources to account for unemployment of individuals entering the labor market.

- To construct commuting zone level estimates we follow exactly the same procedure used by the BLS to construct MSA level data: we aggregate county level estimates of employment, unemployment and the labor force.[25] We then compute the unemployment rate at the commuting zone level using the same definition used by the BLS (the ratio of those unemployed over the total labor force).

- Details of the construction of LAUS data are found in the BLS Handbook of Methods:

  https://www.bls.gov/opub/hom/lau/pdf/lau.pdf

- The BLS homgepage for the LAUS data is:

  https://www.bls.gov/lau/

[25] The BLS reports that estimates at the MSA level reported by LAUS are constructed by simply by aggregating the county level data.

A.2 Descriptive Statistics

Table 5: Means and Standard Deviations

	Mean	St. Dev.
Tradable Emp. Share (Non-Mftg.)	0.031	0.048
Tradable Emp. Share (Mftg.)	0.090	0.054
(log) Foreign Tariff on U.S. Exports (12-month change)	0.265	0.199
(log) U.S. Import Tariff (12-month change)	0.481	0.389
(log) U.S. Input Tariff (12-month change)	0.502	0.360
(log) Employment (12-month change)	0.013	0.013
(log) Unemployment (12-month change)	-0.088	0.099
(log) Labor Force (12-month change)	0.009	0.013
Unemployment Rate (12-month change)	-0.004	0.004
Share of Mftg. Employment (12-month change)	0.0005	0.0035
(log) Earnings per Worker (12-month change)	0.031	0.018

Notes: This table reports means and standard deviations of all the variables used in the analysis across commuting zones. These summary statistics are weighted by 2017 population.

A.3 Timeline of the 2018-2019 Trade War

In this section we provide a brief outline of the policies that constitute the 2018-2019 trade war. Overall, between January 2018 and June 2019 U.S. trade war tariffs have targeted a list of products representing 12% of U.S. imports, and 52% of imports from China.[26] At the same time, foreign retaliatory tariffs cover a list of products representing 6% of U.S. exports, and 67% of exports to China. The main events are the following:[27]

■ **January 2018: U.S. imposes global safeguard tariffs on washing machines and solar panels.** These tariffs apply to imports from all sources (excluding Canada) and cover $1.8 billion in imports of washing machines and $8.5 billion in imports of solar panels. They were imposed under Section 201 of the Trade Act of 1974 based on an argument of material injury to these industries following U.S. ITC recommendations announced in October and November 2017. South Korea and China file WTO disputes in response.

■ **March 2018: the U.S. imposes tariffs on steel and aluminum.** These tariffs impose a 25% rate on steel and a 10% rate on aluminum. They are imposed based on Section 232 of the Trade Expansion Act of 1962 following a a national security threat justification. They apply to all trading partners but several (including Canada, Mexico and the European Union) are temporarily exempt.

■ **April 2018: China retaliates following U.S. steel and aluminum tariffs with a tariff round targeting about $2.4 billion in U.S. exports.** This tariff round applies 15% and 25% ad-valorem rates targeting 91 HS 6-digit products. These are mostly final goods (83% weighted by 2017 U.S. exports).

■ **June/July/August 2018: Retaliatory tariffs in response to U.S. tariffs on steel and aluminum** The exemption regarding steel and aluminum tariffs for Canada, Mexico and the European Union ends in June 2018 and these countries enact retaliatory tariffs covering $17.8, $4.5 and $8.2 billion of U.S. exports respectively. Turkey and Russia also retaliate.

[26] The amount of trade targeted by tariffs is based on 2017 U.S. imports (in the case of U.S. tariffs) or exports (in the case of foreign tariffs).

[27] Table 6 provides exact dates for each tariff round.

■ **July/August 2018: the U.S. imposes a $50 billion tariff round on China, and China retaliates.** Following an investigation on China's treatment of U.S. intellectual property rights and based on Section 301 of the Trade Act of 1974, the U.S. imposes a first round of tariffs covering $50 billion. These tariffs had been announced in April 2018. This round is imposed in two waves, in July and August 2018. These two waves apply 25% ad-valorem rates to lists of 560 and 199 HS-6 products respectively. These products are exclusively intermediate inputs, capital goods and fuels.

China retaliates with a tariff round on an equivalent amount in U.S. goods, also in two waves. China's two waves target lists of 382 and 180 HS-6 products with a 25% retaliatory rate. Targeted products include capital goods (31%), intermediate fuels (30%), inputs (26%) and final goods (13%), where shares are weighted by 2017 U.S. exports.

■ **September 2018: the U.S. imposes a $200 billion tariff round on China, and China retaliates** This U.S. round applies a 10% rate to 3194 HS 6-digit products. The announcement includes a further increase of the ad-valorem rate to 25% to be implemented in January 2019 (which will be later postponed until May 2019). Weighted by value, only 11% of the products targeted are final goods.

China retaliates immediately with a $52 billion round imposing additional 5% and 10% ad-valorem rates on 3734 HS 8-digit level products.[28] This round targets capital goods (48%), inputs (38%), and final goods (13%).

■ **December/January 2019:** The U.S. and Chinese presidents meet at a G-20 summit and agree to a truce that postpones the increase in the rates on the products targeted by the U.S. $200 billion round and China's retaliatory $52 billion round. In January, China eliminates some retaliatory tariffs on cars and car parts. In addition, China reduces MFN tariffs.

■ **May 2019: the U.S. raises the ad-valorem rate on products in the $ 200 billion round** The 10% rate imposed in September increases to 25%. In addition, the U.S. removes tariffs on steel and aluminum for Canada and Mexico and these countries remove their retaliatory tariffs.

[28] China's $52 billion tariff round in September 2018 was first labeled as a $60 billion round given the approximate amount of trade targeted.

■ **June 2019: China retaliates** China raises the ad-valorem rates on $36 billion among the goods targeted by the earlier September 2018 round.

A.4 Summary of Trade War Tariffs

Table 6: List of Tariff Rounds

Panel A: Foreign Tariffs on U.S. Exports

Tariff Round	Date of implementation	Month rounded to	HS-6 product count
China $2.4 billion	April 2, 2018	April 2018	91
European Union $8.2 billion	June 22, 2018	July 2018	146
Canada $17.8 billion	July 1, 2018	July 2018	208
Mexico $4.5 billion	June 5, 2018	June 2018	51
Russia $0.26 billion	Aug 6, 2018	Aug. 2018	37
Turkey $1.6 billion	June 21, 2018	June 2018	102
China $50 billion - wave 1	July 6, 2018	July 2018	382
China $50 billion - wave 2	Aug. 23, 2018	Sept. 2018	180
China $52 billion - increase 1	Sept. 24, 2018	Oct. 2018	3734
China suspension of tariffs on cars and car parts	Jan 1, 2019	Jan. 2019	37
China $52 billion - increase 2	June 1, 2019	June 2019	3404

Panel B: U.S. Import Tariffs

Tariff Round	Date implemented	Month rounded to	HS-6 product count
Washing machines and solar panels	Jan. 22, 2018	Feb. 2018	4
Steel and Aluminum	March 23, 2018	April 2018	180
Aluminum (KOR)	April 30, 2018	May 2018	20
Steel and Aluminum (EU, CAN, MEX)	June 1,2018	June 2018	180
China $50 billion - wave 1	July 6, 2018	July 2018	560
China $50 billion - wave 2	Aug 23, 2018	Sept. 2018	199
China $200 billion - increase 1	Sept. 24, 2018	Oct. 2018	3194
China $200 billion - increase 2	May 10, 2018	May 2018	3194

Notes: This table describes each trade war tariff round implemented between Jan. 2018 and June 2019. Panel A refers to foreign tariffs on U.S. exports and panel B refers to U.S. import tariffs.

■ **Additional notes regarding tariff rounds in Table 6:**

1. The table does not include changes to Chinese MFN tariffs that have taken place during this period, which are included in the dataset.
2. Retaliatory tariffs by Canada and Mexico were lifted in May 20, 2018 in response to the end of steel and aluminum tariffs on these countries.
3. Retaliatory tariffs by Mexico include a further rate increase for a small number of products in July 5, 2018.

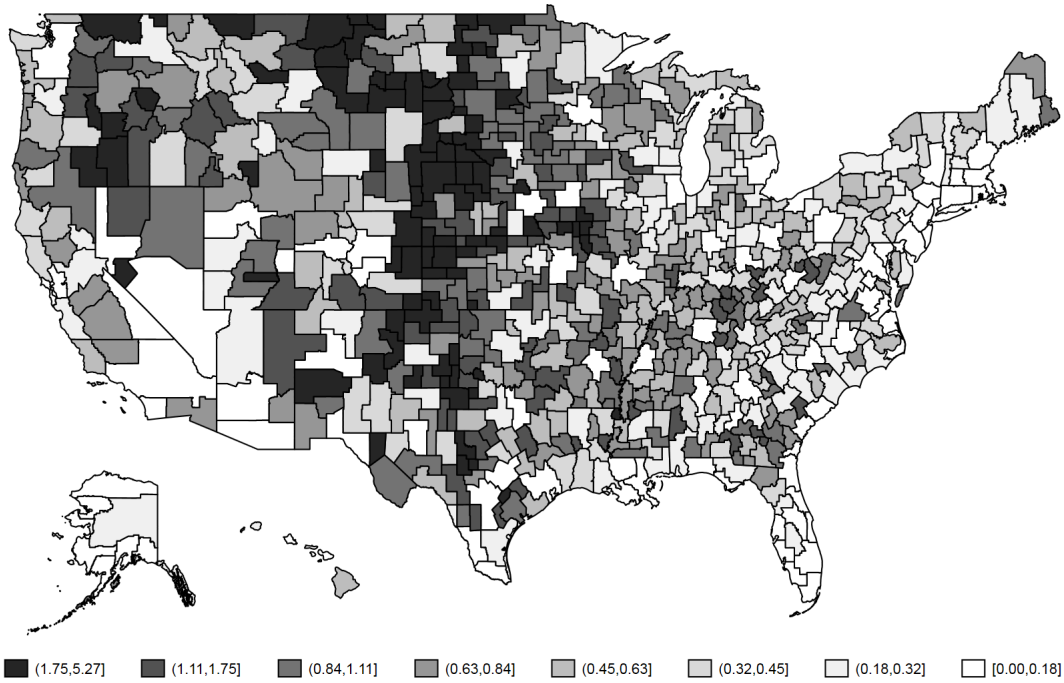
4. Retaliatory tariffs by Turkey include a further increase in rates in August 15, 2018.

5. U.S. tariffs on solar panels and washing machines exclude Canada.

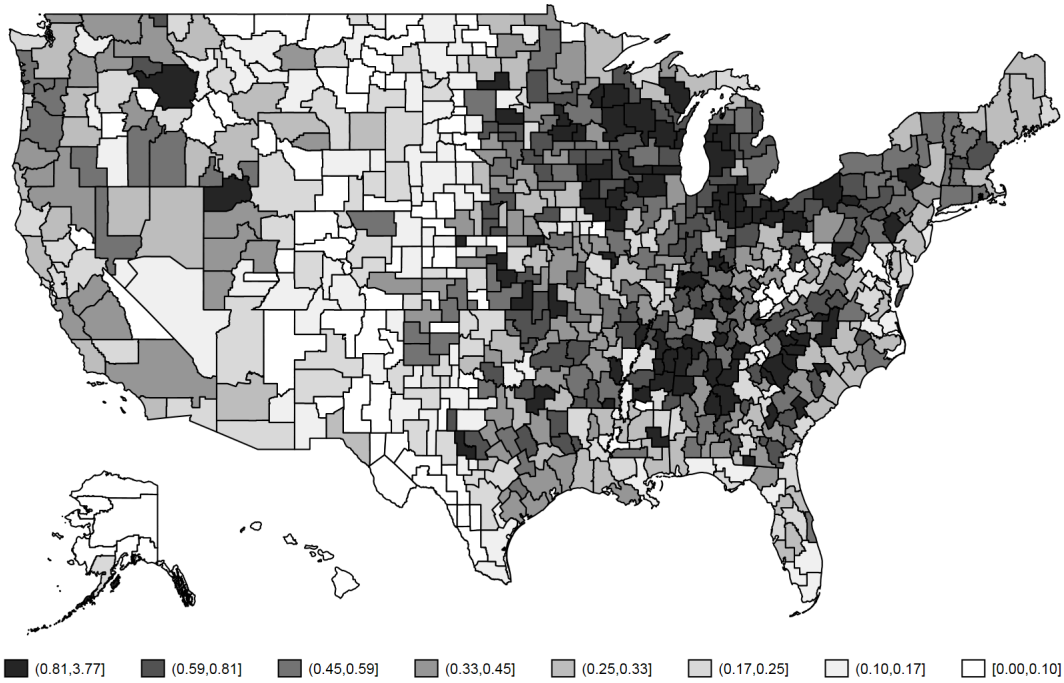
6. U.S. steel and aluminum tariffs in March 23, 2018 included exemptions to the EU, Canada, Mexico. This exemption ended in June 1, 2018. Steel and aluminum tariffs on Canda and Mexico were finally eliminated on May 21, 2019. Korea was exempt from tariffs on steel (permanently) and aluminum (until April 30, 2018). Argentina, Brazil and Australia were also exempt.

Figure 1: Regional Exposure to Tariffs

a) Change in Foreign Tariffs on U.S. Exports, 2018m1-2019m6



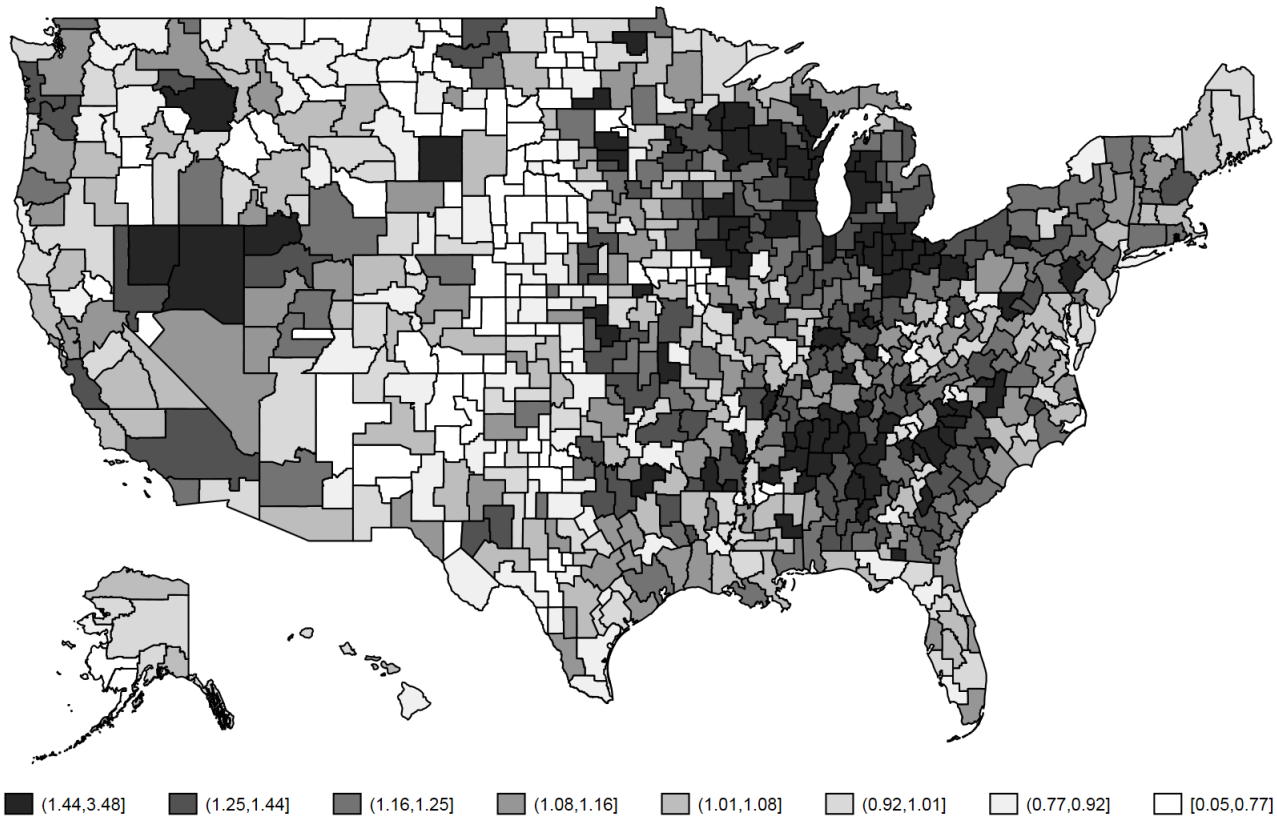
b) Change in U.S. Import Tariffs, 2018m1-2019m6



See notes in next page

Figure 1: Regional Exposure to Tariffs (*Continued*)

c) Change in U.S. Input Tariffs, 2018m1-2019m6



Notes: This figure illustrates differences across commuting zones in exposure to foreign tariffs on U.S. exports (panel (a)), U.S. import tariffs (panel (b)), and U.S. tariffs on inputs (panel (c)). Commuting zones are shaded according to the change in $\tau_r^{FOREIGN}$, τ_r^{US} or $\tau_r^{USInput}$ (defined in equations (3), (5) and (6) respectively) between 2018m1 and 2019m6. Darker shades represent larger increases in these regional tariff measures. Note that only commuting zones in the mainland US are included in the analysis.

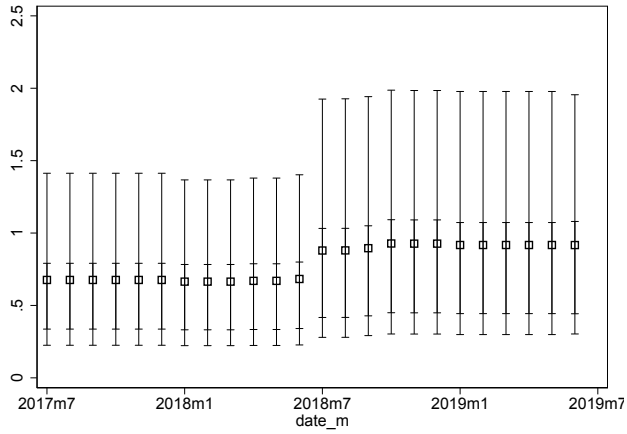
Table 7: Summary Statistics for Changes Regional Tariffs

	Mean	St. Dev.	p10	p25	p50	p75	p90
$\Delta(\tau^{\text{FOREIGN}})$	0.88	0.82	0.16	0.32	0.62	1.11	1.93
$\Delta(\tau^{\text{US}})$	0.44	0.38	0.09	0.17	0.33	0.59	0.88
$\Delta(\tau^{\text{US INPUT}})$	1.11	0.35	0.72	0.93	1.09	1.26	1.48

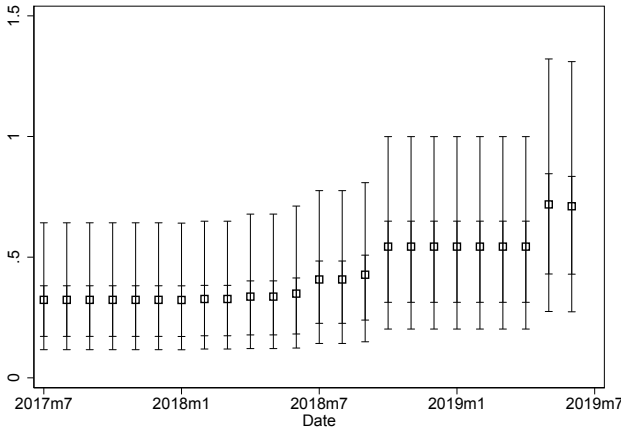
Notes: This table reports summary statistics of the distribution of changes the regional measures of tariff exposure ($\tau_r^{FOREIGN}$, τ_r^{US} or $\tau_r^{USInput}$) between 2018m1 and 2019m6.

Figure 2: Regional Exposure to Tariffs

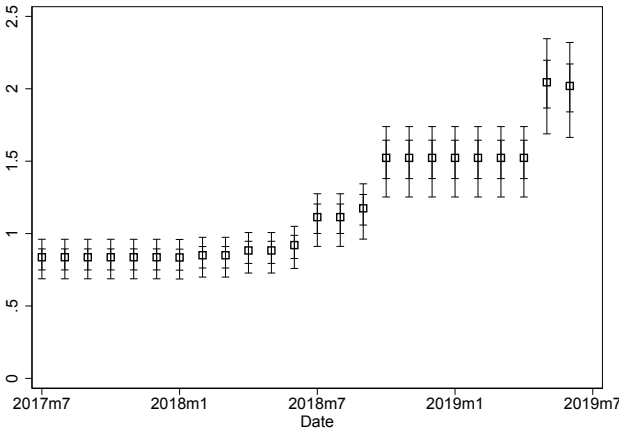
a) Foreign Tariffs on U.S. Exports, 2017m7-2019m6



b) U.S. Import Tariffs, 2017m7-2019m6



c) U.S. Input Tariffs, 2017m7-2019m6



Notes: This figure illustrates the evolution of the mean and the 10th, 25th, 75th, and 90th percentiles of the distribution of the regional tariff measures defined in equations (3), (5) and (6). These summary statistics are weighted by commuting zone 2017 population.

Table 8: Largest and Smallest Foreign Tariff Increase Among 40 Largest CZs.

Panel A: Foreign Tariffs on U.S. Exports

Rank	CZ Name	Change in Tariff	Rank	CZ Name	Change in Tariff
1	Fort Worth, TX	0.218	31	Denver, CO	0.094
2	Portland , OR	0.212	32	Newark, NJ	0.084
3	San Jose, CA	0.211	33	Orlando, FL	0.082
4	Buffalo, NY	0.197	34	Boston, MA	0.079
5	Sacramento, CA	0.191	35	Atlanta, GA	0.075
6	San Antonio, TX	0.171	36	Baltimore, MD	0.074
7	Cincinnati, OH	0.168	37	Miami, FL	0.074
8	Cleveland, OH	0.159	38	Las Vegas, NV	0.046
9	Austin, TX	0.150	39	Washington DC	0.038
10	Pittsburgh, PA	0.149	40	New York, NY	0.033

Panel B: U.S. Import Tariffs

Rank	CZ Name	Change in Tariff	Rank	CZ Name	Change in Tariff
1	Cleveland, OH	0.645	31	Atlanta, GA	0.219
2	Portland, OR	0.547	32	Baltimore, MD	0.202
3	Minneapolis, MN	0.516	33	Denver, CO	0.195
4	Buffalo, NY	0.506	34	San Antonio, TX	0.188
5	Detroit, MI	0.491	35	Orlando, FL	0.179
6	Bridgeport, CT	0.458	36	Miami, FL	0.156
7	Cincinnati, OH	0.428	37	Port St. Lucie, FL	0.119
8	San Jose, CA	0.425	38	Las Vegas, NV	0.115
9	Pittsburgh, PA	0.404	39	New York, NY	0.102
10	Los Angeles, CA	0.398	40	Washington DC	0.065

Panel C: U.S. Input Tariffs

Rank	CZ Name	Change in Tariff	Rank	CZ Name	Change in Tariff
1	Cleveland, OH	1.352	31	Sacramento, CA	1.095
2	Detroit, MI	1.348	32	Tampa, FL	1.090
3	Charlotte, NC	1.336	33	San Antonio, TX	1.066
4	Portland , OR	1.313	34	Boston, MA	1.057
5	Dallas, TX	1.300	35	Baltimore, MD	1.043
6	Cincinnati, OH	1.295	36	Philadelphia, PA	1.042
7	Chicago , IL	1.287	37	Orlando, FL	1.024
8	San Jose, CA	1.277	38	Washington DC	1.023
9	Minneapolis, MN	1.274	39	Port St. Lucie, FL	0.939
10	Fort Worth, TX	1.270	40	New York, NY	0.923

Notes: This table reports the list of commuting zones facing the largest and smallest increases in regional tariff exposure among the largest 40 commuting zones in terms of population. Panel (a) corresponds to foreign tariffs on U.S. exports as defined in equation (3). Panel (b) corresponds to U.S. import tariffs as defined in equation (5). Panel (c) corresponds to U.S. input tariffs as defined in equation (6). Commuting zone names are obtained from Chetty et al. [2014].

A.5 Tariff Increases and Initial Commuting Zone Characteristics

Which regions were targeted by tariffs? Here we associate initial regional characteristcs measured prior to the trade war with tariff increases during the trade war period (Jan 2018 to June 2019). To do so, we estimate the following regression in which the symbol τ in the dependent variable stands alternatively for foreign tariffs on U.S. exports τ_{rt}^{WLD}, U.S. import tariffs $\tau_{rt}^{\text{U.S.}}$ or U.S. input tariffs $\tau_{rt}^{\text{U.S. input}}$. The explanatory variables are (log) population, log mean income, and the employment shares in manufacturing and in non-manufacturing tradable industries (i.e. agriculture and other commodities). Standard errors are clustered by state.[29]

$$\begin{aligned}\Delta\tau_r = \beta_0 + \beta_1 \cdot \log\,(\text{Pop.})_r^{t0} + \beta_2 \cdot \log\,(\text{Mean Income})_r^{t0} + \\ \beta_3 \cdot \text{Share Mftg. Emp.}_r^{t0} + \beta_4 \cdot \text{Share Non-Mftg. Tradable Emp.}_r^{t0} + \epsilon_r\end{aligned} \tag{8}$$

The results are reported in Table 9. Foreign tariffs on U.S. exports (in column 1) increased by larger amounts in regions with lower income and higher employment shares in manufacturing and non-manufacturing tradables. U.S. import tariffs (in column 2) also increased more in regions with larger employment shares in tradables. Finally, U.S. input tariffs (in column 3) saw larger increments in regions with a larger share of manufacturing employment and a smaller employment of non-manufacturing tradable employment.

In the case of foreign tariffs on U.S. exports, the p75/p25 percentile differences in regional income, employment share in manufacturing, and employment share in non-manufacturing tradables are associated to -0.07, 0.18 and 1.0. standard deviation differences in the increase in tariffs between January 2018 and June 2019. In the case of U.S. import tariffs, the p75/p25 percentile differences in regional employment share in manufacturing and employment share in non-manufacturing tradables are associated to 0.16 and 0.07 standard deviation differences in the increase in tariffs between January 2018 and June 2019. Finally, in the case of U.S. input tariffs, the p75/p25 percentile differences in the regional employment share in manufacturing, and in non-manufacturing tradables are associated to 0.87 and -0.29 standard deviation differences in the increase in tariffs.

[29] To cluster standard errors by state, in cases when commuting zones cross state boundaries we choose the state in which the commuting zone has the largest share of initial (2017) population.

Table 9: Tariff Increases and Commuting Zone Characteristics

	(1)	(2)	(3)
	Δ Foreign Tariff	Δ US Import Tariff	Δ US Input Tariff
log mean income (2017)	-0.283***	-0.053	0.104
	(0.077)	(0.049)	(0.071)
log population (2017)	-0.011	0.003	0.001
	(0.010)	(0.007)	(0.008)
Tradable Emp. Share (Non-Mftg.) (2017)	5.212***	0.179***	-0.634***
	(0.190)	(0.051)	(0.081)
Tradable Emp. Share (Mftg.) (2017)	1.356***	4.159***	2.875***
	(0.112)	(0.323)	(0.294)
Observations	720	720	720

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of equation (8). The dependent variable is the change in regional exposure to foreign tariffs on U.S. exports (column 1), the change in regional exposure to U.S. import tariffs (column 2), or the change in regional exposure to U.S. input tariffs (column 3) between January 2018 and June 2019. Observations are not weighted. Standard errors are clustered by state.

A.6 Additional Results

Table 10: Tariffs and U.S. Local Labor Market Outcomes

	(1)	(2)	(3)	(4)
Panel A: Unemployment				
$\Delta log(\tau^{\text{FOREIGN}})$	13.700			12.367
	(8.474)			(7.479)
$\Delta log(\tau^{\text{US}})$		-1.871		-2.301
		(2.738)		(3.821)
$\Delta log(\tau^{\text{US INPUT}})$			0.592	4.006
			(9.841)	(13.408)
Panel B: Labor Force				
$\Delta log(\tau^{\text{FOREIGN}})$	0.487			0.323
	(0.974)			(1.025)
$\Delta log(\tau^{\text{US}})$		-0.228		-0.304
		(0.263)		(0.378)
$\Delta log(\tau^{\text{US INPUT}})$			-0.145	0.400
			(0.623)	(0.967)
Panel C: Employment				
$\Delta log(\tau^{\text{FOREIGN}})$	-0.403			-0.487
	(1.048)			(1.028)
$\Delta log(\tau^{\text{US}})$		-0.029		-0.123
		(0.235)		(0.408)
$\Delta log(\tau^{\text{US INPUT}})$			0.082	0.346
			(0.694)	(1.164)
Observations	12960	12960	12960	12960

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of equation (7) introducing the regional tariff measures sequentially. The dependent variable is 100 × the 12-month change in (log) unemployment (panel a), (log) labor force (panel b), or (log) employment (panel c). Each observation corresponds to a commuting zone and period (there are 720 commuting zones and 18 periods). Standard errors are clustered by state and observations are weighted by 2017 population in each commuting zone.

Table 11: Tariffs and U.S. Local Labor Market Outcomes Based on Initial Commuting Zone Characteristics

	(1) Unemp. Rate	(2) Unemp.	(3) Labor Force	(4) Employment
$\Delta log(\tau^{\text{FOREIGN}})$	0.746**	16.280*	0.151	-0.633
	(0.350)	(9.326)	(0.845)	(1.014)
$\Delta log(\tau^{\text{FOREIGN}}) \times$ High Tradable Emp. Share (Non-Mftg.)	0.431**	6.100	0.858**	0.392
	(0.207)	(5.458)	(0.401)	(0.465)
$\Delta log(\tau^{\text{FOREIGN}}) \times$ High Tradable Emp. Share (Mftg.)	-0.323	-9.202	-0.307	0.029
	(0.235)	(6.428)	(0.401)	(0.420)
$\Delta log(\tau^{\text{US}})$	-0.037	-1.195	-0.283	-0.241
	(0.179)	(4.753)	(0.443)	(0.510)
$\Delta log(\tau^{\text{US}}) \times$ High Tradable Emp. Share (Non-Mftg.)	0.038	0.663	-1.687	-1.714
	(0.284)	(6.537)	(1.126)	(1.270)
$\Delta log(\tau^{\text{US}}) \times$ High Tradable Emp. Share (Mftg.)	0.258	7.396	0.895	0.619
	(0.187)	(4.841)	(0.661)	(0.711)
$\Delta log(\tau^{\text{US INPUT}})$	-0.529	-10.625	-0.045	0.525
	(0.397)	(7.669)	(0.946)	(1.166)
$\Delta log(\tau^{\text{US INPUT}}) \times$ High Tradable Emp. Share (Non-Mftg.)	0.057	0.540	0.870	0.794
	(0.252)	(6.230)	(0.781)	(0.888)
$\Delta log(\tau^{\text{US INPUT}}) \times$ High Tradable Emp. Share (Mftg.)	0.040	0.963	-0.576	-0.611
	(0.199)	(5.152)	(0.669)	(0.700)
Observations	12960	12960	12960	12960

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of the estimation of an extended version of equation (7) including interaction terms between regional tariff measures and dummy variables indicating above-median 2017 employment shares in manufacturing and in non-manufacturing tradable industries (agriculture and other commodities). The dependent variable is 100 × the 12-month change in the unemployment rate (column 1), (log) unemployment (column 2), the (log) labor force (column 3) or (log) employment (column 4). Each observation corresponds to a commuting zone and period (there are 720 commuting zones and 18 periods). Standard errors are clustered by state and observations are weighted by 2017 population in each commuting zone.