Appendix

This online appendix provides additional background information and robustness checks related to Flaaen, Aaron B. and Justin R. Pierce, "Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector." *Review of Economics and Statistics*, forthcoming.

A Theory

In this appendix, we appeal to an existing model to discuss how the empirical measures of tariff effects we consider in this paper relate to theoretically-derived analogues. While there are a range of international trade models with input-output linkages that could rationalize our measures, a recent well-suited example comes from Adão et al. (2020), which examines the effect of international trade shocks on spatially connected markets. Most relevantly for our purposes, Adão et al. (2020) derives relationships between the shift share measures commonly used in empirical research and the partial and general equilibrium effects of trade shocks. Moreover, given our focus on several channels through which tariffs can affect outcomes, the extension of the model in Appendix C.5 that includes input-output linkages, as in Caliendo and Parro (2015), is of particular importance.

Because the theoretical framework we present here is taken directly from Adão et al. (2020), we do not replicate the derivations of the model, and instead refer the interested reader to that paper (and online Appendix C.5 in particular) for more details. In the discussion that follows, we discuss how the model in Adão et al. (2020) provides a theoretical backing for the empirical measures constructed in Section 2.3 in the main text.

We focus attention on the equations describing comparative statics in the model, a key emphasis of Adão et al. (2020). Specifically, Adão et al. (2020) highlight how exogenous changes in bilateral trade costs, $\hat{\tau}_{ij,s}$, from country i to country j in sector s affect other outcomes in both partial equilibrium and general equilibrium. In comparative static exercises applied to the version of the model including intermediate inputs, there are three channels of partial equilibrium shifts from the shock to trade costs $\eta_j(\eta_j^R, \eta_j^C, \eta_j^M)$.

The first of these partial equilibrium shifts from Adão et al. (2020) details how changes in bilateral trade costs affecting sector k output impact revenues in country j. It is given by

$$\hat{\eta}_{j,k}^R = -\,\varepsilon_k \sum_i y_{ji,k} \left(\hat{\tau}_{ji,k} + \sum_o x_{oi,k} \hat{\tau}_{oi,k} \right) \tag{A1}$$

where $y_{ji,k}$ is the share of sector k revenue of country j that comes from country i, and x is defined similarly in terms of spending. In the application to the tariff escalation highlighted in this paper, we focus on the first term only as the second term ends up being second order in magnitude.[25] Focusing on this first term:

[25] To see this, consider the example of Chinese retaliatory tariffs on the U.S., with $\hat{\tau}_{ji,k} > 0$ for $j = \{U.S.\}$ and $i = \{China\}$ only, and hence $\hat{\tau}_{oi,k} = 0\ \forall o \neq \{U.S.\}$. Thus, the second term results in only being the two shares $y_{ji,k}$ and $x_{ji,k}$ multiplied together combined with the $\hat{\tau}_{ji,k}$, which amounts to second-order in magnitude relative to the first term.

$$\hat{\eta}^{R}_{j,k} = -\,\varepsilon_k \sum_i y_{ji,k}\hat{\tau}_{ji,k}, \tag{A2}$$

where $\varepsilon_k > 0$ is the trade elasticity. In words, this measure weights the country i tariff changes on country j output by the share of j sales to i, and (given the negative sign) indicates that increases in tariffs affecting domestic output lead to revenue losses. In this sense, equation (A2) is similar to the empirical measure for export retaliation in equation (2) in the main text.

The second shift described in the expanded model of Adão et al. (2020), with intermediate inputs, is ($\hat{\eta}^{C}_{i}$). This measure is defined at the overall market level as

$$\hat{\eta}^{C}_{i} = \sum_{o,k} \xi_{i,k} x_{oi,k}\hat{\tau}_{oi,k},$$

where $\xi_{i,k}$ is the spending share of i on goods from sector k. Our industry-level measure, which we denote as $\hat{\eta}^{C}_{i,k}$, is the second term in the equation below:

$$= \sum_k \xi_{i,k} \underbrace{\sum_o x_{oi,k}\hat{\tau}_{oi,k}}_{\hat{\eta}^{C}_{i,k}}$$

After substituting in the definition of $x_{oi,k}$

$$x_{oi,k} = \frac{\left(\frac{\tau_{oi,k}p_{o,k}}{\Psi_o(\mathbf{L})}\right)^{-\varepsilon_k}}{\sum_j \left(\frac{\tau_{ji,k}p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k}}, \tag{A3}$$

which describes the spending share in country i, we can re-organize the industry-level component $\hat{\eta}^{C}_{i,k}$ as follows:

$$\begin{aligned}\hat{\eta}^{C}_{i,k} &= \sum_o \left(\frac{\left(\frac{\tau_{oi,k}p_{o,k}}{\Psi_o(\mathbf{L})}\right)^{-\varepsilon_k}}{\sum_j \left(\frac{\tau_{ji,k}p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k}} \hat{\tau}_{oi,k} \right) \\ &= \frac{\sum_o \left(\frac{\tau_{oi,k}p_{o,k}}{\Psi_o(\mathbf{L})}\right)^{-\varepsilon_k} \hat{\tau}_{oi,k}}{\sum_j \left(\frac{\tau_{ji,k}p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k}} \end{aligned} \tag{A4}$$

Once again, this equation simply weights the changes in bilateral trade costs by the respective country shares within a given sector. In the context of our focus on the manufacturing sector, the change in bilateral trade costs owing to a rise in own-country tariffs ($\hat{\tau}_{oi,k}$ above) implies the higher prices paid by domestic firms that forms the basis of import protection. Equation (A4), therefore, is similar to our empirical measure for import protection in equation (1) in the main text.

Finally, the third shift ($\hat{\eta}^M_{i,s}$) described in the appendix to Adão et al. (2020) identifies the impact of increased input costs for each sector-market:

$$\hat{\eta}^M_{i,s} = \sum_{o,k} \theta_{ik,s} x_{oi,k} \hat{\tau}_{oi,k}, \tag{A5}$$

where, importantly, $\theta_{ik,s}$ governs the input shares of sector k in the production of sector s in country i. Expanding out equation (A5) as above and rearranging yields:

$$\begin{aligned}
&= \sum_k \theta_{ik,s} \sum_o x_{oi,k} \hat{\tau}_{oi,k} \\
&= \sum_k \theta_{ik,s} \sum_o \left(\frac{\left(\frac{\tau_{ji,k} p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k}}{\sum_j \left(\frac{\tau_{ji,k} p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k}} \hat{\tau}_{oi,k} \right) \\
&= \sum_k \theta_{ik,s} \frac{\sum_o \left(\frac{\tau_{ji,k} p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k} \hat{\tau}_{oi,k}}{\sum_j \left(\frac{\tau_{ji,k} p_{j,k}}{\Psi_j(\mathbf{L})}\right)^{-\varepsilon_k}}.
\end{aligned} \tag{A6}$$

This equation says that the shocks to bilateral trade costs ($\hat{\tau}_{oi,k}$) for a given country o and product k are weighted by the corresponding shares of country-origin (which include domestic origin), and then further weighted by their use by sector s according to the input shares $\theta_{ik,s}$. Thus, equation (A6) provides an analogue to our empirical measure for rising input costs in equation (5) in the main text.

B Expanded Detail on Implemented Tariffs

Tables B1 and B2 provide additional information regarding the data on products covered by tariffs. Specifically, the tables report the value of trade–based on 2017 annual data from the U.S. Census Bureau–that we calculate was subject to new tariffs, along with comparisons to values of trade publicly announced by governments and those calculated by other researchers. In addition, we provide links to sources of the lists of HS codes covered by new tariffs.

We map the Harmonized System (HS) codes covered by tariffs to the North American Industry Classification System (NAICS) using the concordance developed by Pierce and Schott (2012). For U.S. import tariffs, this requires a simple application of the concordance. For tariffs imposed by U.S. trade partners, this process is complicated by the fact that the import product codes published by foreign governments cannot be matched to the Schedule B system used for U.S. exports below the six-digit HS level. Therefore, for foreign retaliatory tariffs, we treat an entire six-digit HS code as being covered by tariffs if any product with that six-digit HS prefix is covered by a tariff, as in Blanchard et al. (2019), Waugh (2019) and Bown et al. (2019a). A reasonable concern is that this assumption may lead to the inclusion of HS8 codes that were not subject to retaliatory tariffs, but happen to fall within an HS6 that includes some tariff-affected products. We confirm the validity of the assumption and provide further discussion immediately below.

B.1 Assumptions for Retaliatory Tariffs

In this sub-section, we focus on evaluating the assumption that a six-digit HS code can be treated as being subject to retaliatory tariffs if any foreign eight-digit code with an HS6 prefix is listed by foreign governments as being subject to new tariffs on U.S. exports. While this assumption has been employed in other research examining retaliatory tariffs (Blanchard et al., 2019; Bown et al., 2019a; Waugh, 2019), a reasonable concern is that it may include HS8 codes that were not actually subject to retaliatory tariffs, but happen to fall within an HS6 that includes some tariff-affected products.

To evaluate the assumption, Table B2 compares the value of 2017 U.S. exports that our approach treats as being subject to new retaliatory tariffs (the column labeled "2017 Export Volume") to the value of 2017 U.S. exports that foreign governments announced would be subject to those tariffs (the column labeled "Reported by Foreign Government"). If our approach was inadvertently including HS8s not subject to retaliatory tariffs, the values in the "2017 Export Volume" would be systematically higher than those in the "Reported by Foreign Government" column. Not only is this not case, but the values in the two columns end up being remarkably close to one another: As shown in the final row of the table, totaling over the various rounds of retaliatory tariffs, we identify USD 185.9 billion of 2017 U.S. exports as being subject to tariffs, essentially identical to the USD 185.7 billion announced by foreign governments. The value of trade that we identify as being subject to retaliatory tariffs is also very close to the values that have been identified in other research (the column labeled "Other Estimates"; sources for the other research are in the final column of the table). Given these findings, we conclude that it's acceptable to treat an HS6 as being covered by retaliatory tariffs if any HS8 within it is covered.

An option to relax this assumption would be to weight the export retaliation measure by the share of HS8 codes or foreign imports covered by tariffs, within an HS6. Because these detailed codes do not match to US export product codes below the six-digit level, however, doing so would require use of detailed tariff schedules for all countries imposing retaliatory tariffs (China, Russia, India, the EU, Canada, etc.) for multiple years. Unfortunately, these schedules are not readily available, publicly, particularly for non-OECD countries. Nonetheless, given the close match between the value of trade we identify as being subject to retaliatory tariffs and the values announced by foreign governments, it appears that this type of weighting would not meaningfully change the calculated export retaliation measures.

B.2 Characteristics of Products and Industries Subject to U.S. Tariffs

The effect of U.S. tariffs on the domestic manufacturing sector depends, at least in part, on the products that are affected and how those products fit into global trade linkages and supply chains. U.S. manufacturers competing with Chinese imports in the U.S. market, for example, would likely fare differently than manufacturers that rely on Chinese inputs for their U.S. production. As a rough guide of how these tariffs are split along these dimensions, we apply the United Nations Broad Economic Categories (BEC) classification to these tariffs

Table B1: New U.S. Import Tariffs by Trade Action and Wave

Import Tariff	Reference for Affected Products	2017 Import Volume	Reported by Foreign Government	Other Estimates	Source for Other Estimates
		Billions of U.S. Dollars			
Sec. 201: Solar Panels		7	8.5		
Sec. 201: Washing Machines		1.85	1.8		
Sec. 232: Steel	Link	27.7	10.2	29	Source
Sec. 232: Aluminum	Link	17.4	7.7	17	Source
Sec. 301 Part 1	Link	32.3	34		
Sec. 301 Part 2	Link	13.7	16		
Sec. 301 Part 1+2		46.0	50	45.7	Source
Section 301 Part 3	Link	189	200	177	Source

Table B2: New Retaliatory Tariffs on U.S. Exports by Trade Action and Wave

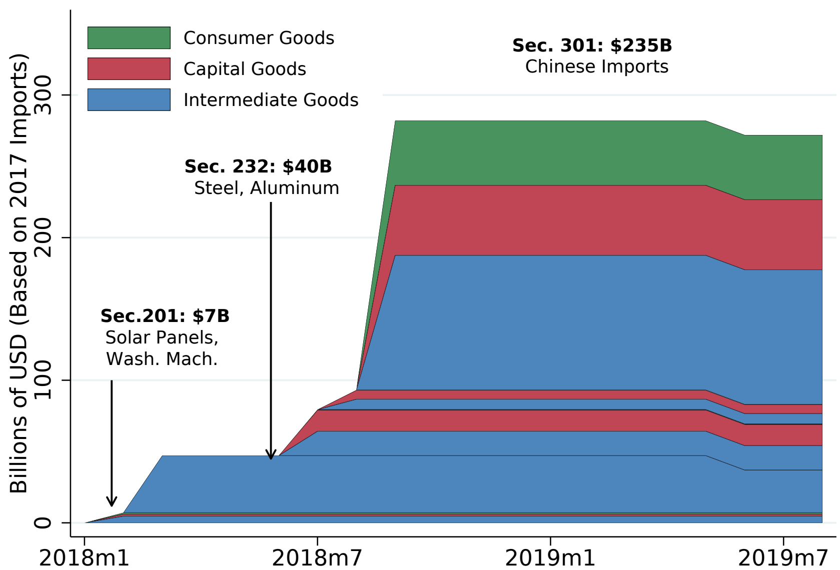
Retaliatory Tariff	Reference for Affected Products	2017 Export Volume	Reported by Government	Other Estimates	Source for Other Estimates
		Billions of U.S. Dollars			
China on US – Apr. 2018	Link	2.44	2.4	2.39	Source
EU on US – Jun. 2018	Link	4.23	3.2	3.24	Source
Canada on US – Jul. 2018	Link	17.8	12.8	12.76	Source
China on US – Jul. 2018	Link	29.2	34		
China on US – Aug. 2018	Link	21.9	16		
China on US – Jul.+Aug.		51.1	50	49.8	Source
China on US – Sep. 2018	Link	52	60	53.4	Source
Mexico on US – Jun. 2018	Link	4.51	3.8		
India on US – Jan. 2019	Link	0.89	1.3	1.3	Source
Turkey on US – Jun. 2018	Link	1.56	1.8		
Russia on US – Aug. 2018	Link	0.27	0.43		
Total		185.9	185.7		

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.

Notes: The column headed "2017 Export Volume" displays the value of 2017 U.S. exports subject to retaliatory tariffs according to our estimates, which—as discussed in Section 2.2—treat an HS6 as being covered by retaliatory tariffs if any product with that HS6 prefix is listed by a foreign government as being subject to tariffs on U.S. exports. The column headed "Reported by Government" reports the value of 2017 U.S. exports subject to retaliatory tariffs according to announcements from the foreign governments imposing the tariffs on U.S. exports. The column headed "Other Estimates" provides estimates of the value of 2017 U.S. exports subject to retaliatory tariffs from other researchers (Bown and Kolb, 2019; Bown et al., 2019a,b).

(see also Bown et al. (2019b) for a similar breakdown). As shown in Figure B1, the early U.S. tariffs predominantly covered intermediate goods, represented by the blue areas of the section 232 and initial section 301 phases of U.S. tariffs, as well as capital goods, shown in red. Media reports suggested that this focus on intermediate goods over consumer goods was a purposeful effort on the part of the United States to shield U.S. consumers from some of the most salient effects of tariffs on prices (Lawder and Schneider, 2018). The prominence of imported inputs among the set of goods subject to tariffs is helpful when considering the effects of the three channels of tariffs in Section 3.

Figure B1: Composition of New U.S. Import Tariffs: 2018-2019



Source: USITC for 2017 import values.
Notes: See Table B1 for details on the set of relevant products and trade values. Classification comes from the Broad Economic Categories from the United Nations (further details are available here).

B.3 Statutory vs Effective Rates

While we use statutory tariff rates in this analysis, an alternative approach would use the *effective* tariff rates paid by importers and exporters. Such effective tariff rates would reflect tariff rate exclusions and other endogenous responses to the tariffs such as tariff evasion. Unfortunately, although it is possible to calculate measures of effective tariff rate changes facing U.S. imports, it is not currently feasible to calculate corresponding effective tariff rates facing U.S. exports. Applying effective tariff rates for one channel with statutory rates for another would be inconsistent and likely confusing. Moreover, we believe using statutory rates provides the relevant tariff rate shock for a variety of reasons.

First, the salient shock facing firms is the change in the statutory rate, and any decisions by firms resulting in differing effective tariff rates would be introducing a certain endogeneity in our measures.

Second, although it is true that U.S. firms were allowed to file petition requests to the U.S. Trade Representative (USTR) for tariff exemptions for the Section 301 tariffs against China, these exemptions are unlikely to materially affect our results due to the timing of the exemption process. The number of industries affected by tariffs, combined with the extensive detail required for these petitions, led to long delays in decision notices on tariff exemptions by the USTR. For Phase 1 of the Section 301 tariffs, these decisions were announced on a rolling basis between December 2018 and October 2019; decisions on Phase 2 and Phase 3 didn't begin until July 2019 and August 2019, respectively, at the very end of our sample period. Hence, the vast majority of tariffs were not affected by exemptions during the period we study in this paper. See Flaaen et al. (2021) for further technical details of the exemption process.

Finally, an attempt to introduce monthly variation (what little may exist) from the effective tariff rate into our specification would likely add confusion without yielding further insight. In such a fully saturated model, one would need to interact effective tariff measures with month fixed effects that are then instrumented by statutory tariff measures interacted with month dummies. With the three tariff channels we study, this would be an enormous amount of instruments and endogenous regressors.

B.4 "Phase One" Trade Deal

We note two features of the "Phase One" trade deal adopted by the U.S. and China in January 2020 that are relevant to our study, and particularly our sample period, which extends from January 2017 to September 2019. First, the Phase One trade deal left all tariffs examined in this paper in place, underscoring their continued importance. Second, while the deal did decrease rates on a fourth round of U.S. tariffs imposed in September 2019, we are unable to examine that additional round of tariffs given the short amount of time between its imposition and the massive disruption of international trade—particularly trade with China—that began with the outbreak of Covid-19 in China in December 2019.

C Additional Information on Variables

This section provides summary statistics and other background information on the independent and dependent variables we use in the analysis.

C.1 Level of Aggregation

We conduct the analysis largely at the four-digit NAICS industry level, which is the most detailed level at which comprehensive data for industrial production, producer prices, employment, and input-output relationships are typically available at a consistent level of aggregation. There are minor differences in availability of data at the four-digit industry level across the different outcome variables—the BLS employment data sometimes combine small four-digit industries—and data are only available at the three-digit NAICS level for Apparel Manufacturing (NAICS 315) and Leather and Allied Product Manufacturing (NAICS 316).[26] Ultimately, our baseline samples, which each cover the entire manufacturing sector at slightly different levels of aggregation, contain 76 industries for employment, 84 industries for industrial production, and 82 industries for producer prices.[27] While there is almost certainly heterogeneity in the extent of exposure to each of the three tariff channels for the finer industries, firms, and plants, within our four-digit NAICS industries, our baseline estimates provide the net effect of these heterogeneous responses. Furthermore, the presence of heterogeneous responses within four-digit NAICS industries likely biases us away from finding any statistically significant relationships between tariffs and industry-level outcomes.

C.2 Summary Statistics

This section reports summary statistics for the three industry-level tariff exposure measures: import protection, rising input costs, and export retaliation. We report summary statistics both unweighted and weighted by industry employment as of December 2017.

Table C3: Summary Statistics (Unweighted) for Three Tariff Exposure Measures

Variable	**Mean**	**Std. Dev.**	**25 pctl**	**50 pctl**	**75 pctl**
Import Protection	0.013	0.016	0.0015	0.0064	0.018
Export Retaliation	0.003	0.003	0.001	0.002	0.004
Rising Input Costs	0.0063	0.0047	0.0029	0.0048	0.0095

Notes: Table displays unweighted summary statistics for the three industry-level tariff exposure measures explored in the text. Summary statistics are mean, standard deviation, 25th percentile, 50th percentile, and 75th percentile.

For further detail on the distribution of exposure to the three tariff channels considered in this paper, Figure C2 shows density estimates across the 76 manufacturing industries for which manufacturing employment data are available.

[26] Results are qualitatively identical if NAICS 315 and 316 are excluded, given their small size.

[27] Industrial production has the largest number of industries because detail is available to separate aluminum manufacturing (NAICS 3313) into three sub-industries that are relevant given the set of tariffs we study: Primary aluminum production (NAICS 331313), secondary smelting and alloying of aluminum (NAICS 331314), and aluminum product (sheet, plate, foil, etc.) production. This split takes into account that while all three of these groups stand to benefit from tariffs on their output, the latter two are also subject to tariffs on their inputs, implying different overall effects of tariffs. We note, however, that use of this additional detail does not have substantive effects on our estimates—we find little relationship between tariffs and industrial production whether the additional detail is used or not.

Table C4: Summary Statistics (Employment Weighted) for Three Tariff Exposure Measures

Variable	**Mean**	**Std. Dev.**	**25 pctl**	**50 pctl**	**75 pctl**
Import Protection	0.011	0.015	0.0012	0.0050	0.013
Export Retaliation	0.0024	0.0025	0.001	0.002	0.003
Rising Input Costs	0.0060	0.0043	0.0029	0.0047	0.0094

Notes: Table displays employment weighted summary statistics for the three industry-level tariff exposure measures explored in the text. Summary statistics are mean, standard deviation, 25th percentile, 50th percentile, and 75th percentile.

Table C5 displays the top ten industries by exposure to import protection. The list includes industries protected by the China-specific Section 301 tariffs, such as electric lighting equipment (NAICS 3351), household and institutional furniture and kitchen cabinets (NAICS 3371), and other electrical equipment and component (NAICS 3359). Also prominent in the list are industries affected by the global tariffs—Section 232 tariffs on steel and aluminum and the Section 201 tariffs on washing machines. As an example of the calculation of the import protection measure, for the Iron and Steel Mills and Ferroalloy Manufacturing Industry (NAICS 3311), the value of 2016 imports subject to new tariffs is USD 19.3 billion, the value of domestic absorption is USD 92.9 billion, and an increase in tariffs of 25 percentage points yields an import protection measure of 0.052.

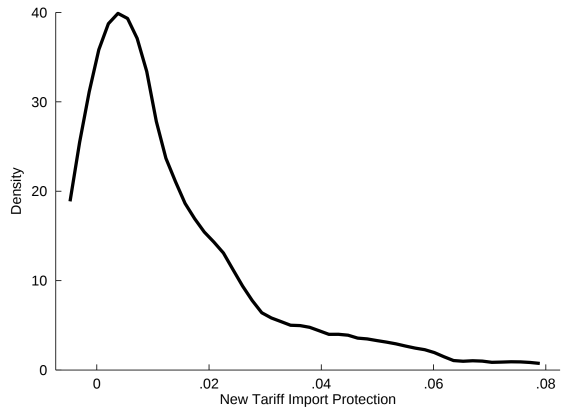
Table C5: Top Ten Industries by Exposure to New Import Protection

Rank	**NAICS**	**Industry Description**	**Import Protection Measure**
1	3351	Electric Lighting Equipment	7.4%
2	331313	Primary Aluminum Production	6.7%
3	3371	Household and Institutional Furniture and Kitchen Cabinet	6.0%
4	3344	Semiconductor and Other Electronic Component	5.4%
5	3311	Iron and Steel Mills and Ferroalloy Mfg	5.2%
6	3352	Household Appliance Manufacturing	4.3%
7	3359	Other Electrical Equipment & Component	4.1%
8	3160	Leather and Allied Product	3.7%
9	3332	Industrial Machinery	3.6%
10	3322	Cutlery and Handtool Manufacturing	3.6%

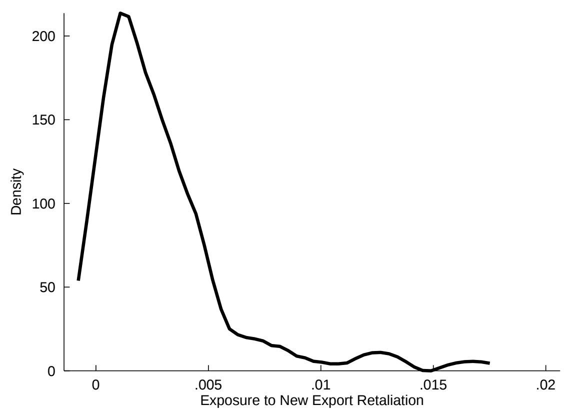
Sources: Authors' calculations based on equation (1) in the text.
Notes: This measure corresponds to the cumulative coverage of all three 2018-2019 tariff actions.

Figure C2: Density Estimates of Tariff Exposure Channels Across Manufacturing

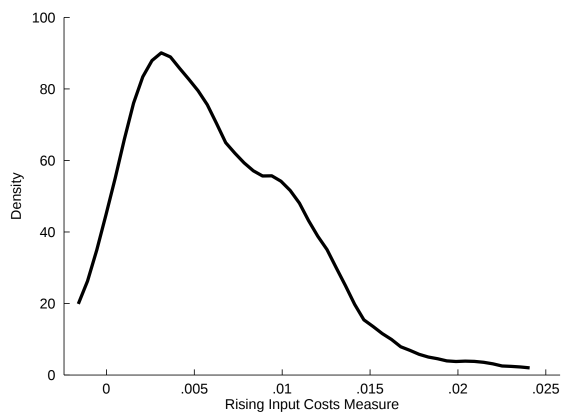
(a) Import Protection



(b) Export Retaliation



(c) Rising Input Costs



Sources: Figures display densities of industry-level measures of exposure to each tariff channel.

Table C6 displays the top ten industries by exposure to export retaliation. This list also includes a mixture of products subject to retaliatory tariffs by China, as well as metals-producing industries subject to tariffs by a broader set of retaliating trade partners.[28] Using again the example of the Iron and Steel Mills and Ferroalloy Manufacturing Industry, the value of 2016 exports subject to retaliatory tariffs is USD 5.5 billion, the value of output is USD 79.6 billion, and the increase in retaliatory tariffs is 24 percentage points, yielding an export retaliation measure of 0.017.

Table C6: Top Ten Industries by Exposure to New Export Retaliation

Rank	**NAICS**	**Industry Description**	**Foreign Retaliation Measure**
1	3346	Manufacturing and Reproducing Magnetic & Optical Media	1.71%
2	3311	Iron and Steel Mills and Ferroalloy Mfg	1.67%
3	3361	Motor Vehicle Manufacturing	1.23%
4	3160	Leather and Allied Product	1.06%
5	33131B	Aluminum Sheet/Plate/Foil & Rolling/Drawing/Extruding	0.96%
6	3211	Sawmills and Wood Preservation	0.95%
7	3343	Audio and Video Equipment	0.84%
8	3341	Computer and Peripheral Equipment	0.79%
9	3369	Other Transportation Equipment	0.74%
10	3352	Household Appliance Manufacturing	0.71%

Sources: Authors' calculations based on equation (2) in the text.
Notes: This measure corresponds to the cumulative coverage of all three 2018-2019 tariff actions.

Table C7 displays the top ten industries in terms of exposure to rising input costs. As is apparent in the table, all of these industries are heavily dependent on various metals for domestic production. In addition, the above tables highlight the value in jointly analyzing these channels. For the case of household appliance manufacturing (NAICS 3352), our measures indicate that the industry was highly exposed to all three channels. For the example of the Iron and Steel Mills and Ferroalloy Manufacturing industry, the share of industry costs covered by new tariffs is 12.9 percent, and applying the input-specific tariff rates increases to this share yields an exposure to the rising input cost channel of 0.009.[29]

C.3 Visualization and Discussion of County-Level Tariff Exposure Measures

This section displays and discusses variation in county-level exposure to the three tariff measures. The distribution of tariff exposure across counties is displayed in Figure C3. The

[28] This measure of retaliatory tariffs includes retaliatory tariffs by China on U.S. exports of motor vehicles (NAICS 3361), which were imposed in July of 2018, but then suspended in January of 2019.

[29] The Section 201 tariffs on solar panels are excluded from the rising input cost channel because the level of aggregation in the input-output tables does not allow them to be separated from semiconductors.

Table C7: Top Ten Industries by Exposure to Rising Input Costs

Rank	NAICS	Industry Description	Rising Input Cost Measure
1	3312	Steel Product Mfg from Purchased Steel	2.23%
2	33131B	Aluminum Sheet/Plate/Foil & Rolling/Drawing/Extruding	1.94%
3	3321	Forging and Stamping	1.86%
4	3324	Boiler, Tank, and Shipping Container	1.53%
5	3323	Architectural and Structural Metals	1.39%
6	3332	Industrial Machinery Manufacturing	1.29%
7	3339	Other General Purpose Machinery Manufacturing	1.29%
8	3352	Household Appliance Manufacturing	1.26%
9	3369	Other Transportation Equipment	1.26%
10	3363	Motor Vehicle Parts Manufacturing	1.16%

Sources: Authors' calculations based on equation (5) in the text.
Notes: This measure corresponds to the cumulative coverage of all three 2018-2019 tariff actions.

maps highlight once again the importance of simultaneously considering the multiple effects of tariffs. For example, as shown in panel (a), clusters of counties in the industrial Midwest and Southeast are apparent as being the most highly protected by import protection, which might benefit industries in those areas. However, as shown in panels (b) and (c), these areas are also among those that are most subject to exposure to both export retaliation and rising input costs. More precisely, the correlations between the import protection channel and the rising input cost and export retaliation channels are 0.73 and 0.52, respectively.

These correlations are higher than their industry-level analogues because each county-level measure of tariff exposure is related, in part, to the extent of manufacturing activity in a county. Therefore to ensure that we accurately estimate the relationship between exposure to *tariffs* and movements in the labor force and unemployment rate, the regressions in section 4.1 include controls for each county's manufacturing share of employment. As a result, coefficients on the tariff channel variables capture the effects of variation in tariff exposure holding constant the extent of a county's manufacturing activity.

C.4 Local Area Unemployment Statistics

The BLS derives the county-level data in the LAUS from several sources, including the Current Employment Statistics, the Quarterly Census on Employment and Wages, the Current Population Survey, the American Community Survey, and local unemployment insurance agencies. We scale measures of the labor force by a county's population in 2017 and seasonally adjust these data using the standard Census Bureau X-13 seasonal adjustment program available at https://www.census.gov/srd/www/x13as/.

D Additional Industry-Level Results and Robustness Checks

D.1 Results for Control Variables

Here, we report coefficient estimates and 90 percent confidence intervals for the control variables used in equation (6). These variables include interactions of month dummies with industry export share of output, industry import share of domestic absorption, and industry import share of costs. These first three controls are intended to capture features of international exposure that are not directly to tariffs, such as exchange rate movements and overall foreign growth. These variables may also capture some of the potential impact from increased uncertainty on international markets. We also report estimates for interactions of month dummies with industry capital intensity (capital-labor ratio), to account for the possibility that industries with different capital intensities may respond differently to some other shock that happens to occur at the same time as tariffs are imposed. Figure D4 reports these results pertaining to employment, industrial production, and PPIs.

D.2 Alternative Measures of Tariff Exposure

Our baseline measures of exposure to tariffs described in Section 2.3 account for the magnitude of tariff increases, the value of trade flows affected, and the relevance of those trade flows to an industry's output (shipments) or domestic market (absorption, or $output + exports - imports$). In this sub-section, we consider two alternative measures of tariff exposure.

Non-Normalized Exposure: To determine the effect of tariffs on percentage changes in outcome variables, our baseline measures of tariff exposure (equations 1, 2, and 5) consider the magnitude of tariff-affected trade flows *relative to an industry's output or domestic market size*. An alternative approach is to measure tariff exposure only as the change in tariff rate multiplied by the value of trade affected, which simply eliminates normalization by output or domestic absorption from the baseline exposure measures. Column 1 of Table D8 reports results of estimating our baseline estimating equation (equation 6) for manufacturing employment using the natural log of these alternative measures of tariff exposure. As indicated in the Table, results are highly similar in sign and significance to our baseline estimates, with higher exposure to rising input costs or export retaliation associated with relative declines in manufacturing employment. The coefficient for import protection is imprecisely estimated and not statistically different from zero.

Exposure Only To Changes in Tariff Rates: Another approach to measuring exposure to tariff changes is to simply calculate industry-level average changes in ad-valorem rates on output, exports, and inputs. This approach is straightforward, but it does not account for either the value of trade flows affected or the size of those affected trade flows relative to the industry's output or domestic market. Column 2 of Table D8 provides estimates using this simple measure of exposure to tariff increases. Despite being conceptually distant from our baseline measures of tariff exposure, we continue to find that higher exposure to tariffs on inputs is associated with relative declines in employment, and this relationship is highly statistically significant. Estimates of the relationship between employment and export tariffs or import tariffs are imprecisely estimated, a finding that is unsurprising given the lack of accounting for the importance of tariff changes either to trade flows or industry size.

Table D8: Robustness Results: Alternative Exposure Measures

	Dep. Var: Log Employment	
Variable	(1)	(2)
Import Protection	-0.001	-0.003
	(0.002)	(0.070)
Export Retaliation	-0.005***	0.006
	(0.002)	(0.082)
Rising Input Costs	-0.009**	-0.692***
	(0.004)	(0.219)
Industry Fixed Effects	yes	yes
Year-Month Fixed Effects	yes	yes
Number of Industries	76	76
Observations	2,475	2,508

Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.

Notes: For import protection, rising input costs, and export retaliation, the table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Column (1) modifies our standard measures of exposures by removing the normalization (by output or domestic absorption). Column (2) modified our baseline exposure measures by only measuring the change in industry-level average ad-valorem tariff rates. Results are weighted by employment as of December 2017. $* \ p < 0.10$, $** \ p < 0.05$, $* * * \ p < 0.01$.

D.3 Removing intra-industry input usage

One concern with the way we disentangle these factors is that the import protection measure may get conflated with the input cost measure in so far as an industry is a heavy user of intra-industry inputs. Indeed, comparing equations (1) and (6) reveals that one interpretation of our rising input costs measure is as a re-weighted version of the import protection measure.

The concern may be that industries with a very high intra-industry input share may run into collinearity issues between the import protection and rising input costs measures. However, it is for precisely these reasons that we use the detailed input-output tables containing much greater detail and the ability to make this distinction empirically. Indeed, in the detailed use tables, the average intra-industry share of inputs (materials plus compensation of employees) for manufacturing industries is under 6 percent.

To explore this concern in greater detail, we re-calculate our rising input cost measures when we *exclude* the intra-industry measure of inputs (essentially exclude the diagonal in the use matrix). We then re-calculate our measures as normal, and the results are shown in Table D9. The results in the table are quite similar to the baseline estimates in Table 1, with the biggest difference being a reduced magnitude of the import protection channel. Hence, we conclude that the intra-industry share is not driving our results.

Table D9: Robustness Results: Excluding Intra-Industry Inputs

Variable	Dep. Var: Log Employment (1)
Import Protection	0.204
	(0.172)
Export Retaliation	-4.62**
	(1.703)
Rising Input Costs	-2.96***
	(0.870)
Industry Fixed Effects	yes
Year-Month Fixed Effects	yes
Number of Industries	76
Observations	2,508

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: For import protection, rising input costs, and export retaliation, the table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Column (1) modifies our standard measures of rising input costs to be calculated while excluding the diagonal of the use matrix, thereby removing intra-industry costs. Results are weighted by employment as of December 2017. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

D.4 Total Requirements Input Exposure

Another way of measuring the input cost exposure coming from additional tariffs would be to apply the Leontief inverse and calculate the full total requirements matrix which takes into account indirect costs from all upstream linkages. There are two reasons why we do not believe this is an appropriate measure as a baseline for capturing changes in input costs resulting from new tariffs.

First, because the total requirements matrix requires a symmetric input-output structure relating commodities to industries, we are forced to reduce the detail of the commodities affected by tariffs substantially, from 297 commodities (based on the detailed input-output tables on the direct requirements basis) to only 76 (based on the unit of analysis in our employment results, on a total requirements basis). Hence, the benefits of a more holistic impact of tariffs coming from a total requirements calculation are outweighed by much greater aggregation bias coming from allocating detailed trade commodities to aggregated industries. Second, the indirect effects captured from a total requirements table may take even longer to manifest themselves through the domestic production system, and hence our available window may be insufficient.

Second, the indirect effects captured from a total requirements table may take even longer to manifest themselves through the domestic production system, and hence our available window may be insufficient. Extending the window further is complicated by the fourth wave of tariffs, the initial agreement struck between the China and the Trump administration, and ultimately the onset of COVID-19.

Nevertheless, we aggregated up the commodities to construct a square I-O matrix at the most disaggregated detail possible and applied the Leontief inverse to construct total requirements for each industry. We then used this measure to calculate our rising input costs exposure measure, and the results as applied to manufacturing employment are shown below in Table D10. On the whole, these results have less precision than those in Table 1, which may reflect the higher level of aggregation at which the tariff measures were applied to industries, in particular the rising input cost measure based on total requirements. It is important to note that the magnitude for this rising input cost measure is not directly comparable to those in our baseline, since the total requirements table has a higher overall level, reflecting the full upstream indirect requirements.

Table D10: Robustness Results: Total Requirements Measure of Input Exposure

Variable	Dep. Var: Log Employment (1)
Import Protection	1.13*
	(0.624)
Export Retaliation	-4.52**
	(1.703)
Rising Input Costs	-2.27*
	(1.092)
Industry Fixed Effects	yes
Year-Month Fixed Effects	yes
Number of Industries	76
Observations	2,508

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: For import protection, rising input costs, and export retaliation, the table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Column (1) modifies our standard measures of rising input costs to be calculated based on the total requirements matrix, which comes from a 76 commodity by 76 industry table. Results are weighted by employment as of December 2017. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

D.5 First Differences Specification

An additional way to control for pre-existing trends in the dependent variable is to estimate a version of equation 6 in which the dependent variable is transformed to be in first differences. We explore this alternative specification for manufacturing employment, with results reported in Table D11, below. As shown in the Table, the relationship between manufacturing employment and the three tariff exposure measures for the first differences specification (column 2) is highly similar to our baseline approach (column 1), with the coefficient on the rising input cost channel being negative and highly statistically significant. In addition, like in the baseline, the coefficient for export retaliation is negative, and that for import protection is positive, though estimates from the first differences specification are a bit less precise (p-values of 0.13 and 0.17, respectively). We note that one drawback of this first differences specification, relative to the baseline log level specification (equation 6) is that it does not as clearly illustrate the cumulative effects of tariffs.

Table D11: First Differences Specification

Variable	Dep. Var: Δ Employment (1)	(2)
Import Protection	0.31*	0.159
	(0.171)	(0.113)
Export Retaliation	-4.479**	-1.309
	(1.679)	(0.848)
Rising Input Costs	-3.085***	-1.140***
	(0.867)	(0.265)
Intl. Exposure Controls	Yes	Yes
Cap. Intensity Controls	Yes	Yes
Clustering	N3	N3
Observations	2,508	2,508

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.

Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Column 1 reproduces the baseline results arising from a specification in which the dependent variable is the log level of manufacturing employment (6). Column 2 presents results arising from a specification in which the dependent variable is the first difference of log manufacturing employment. Both regressions include industry and month fixed effects. Results are weighted by employment as of December 2017. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

D.6 Tests for Presence of Pre-Trends

In this section, we test for the presence of pre-trends for more- versus less-exposed industries in terms of each tariff channel. To do so, we employ the approach from Finkelstein (2007) that tests for changes in coefficient estimates over the course of the pre-period, i.e. the second term in equation 7 that is subtracted in that equation to account for pre-trends:

$$\Delta y_{it}^{\gamma} = \quad \kappa(\overline{\gamma}_{\text{Dec17-Feb18}} - \overline{\gamma}_{\text{Feb17-Apr17}}). \tag{D7}$$

A statistically significant test statistic estimated from equation D7 indicates the presence of pre-existing trends, with results reported in Table D12. As shown in columns 1 and 3 of the Table, for employment and producer prices, we find evidence of pre-trends for industries that are more exposed to both the rising input cost and export retaliation tariff channels. For industrial production, we do not find evidence of pre-trends for any of the tariff channels.

As discussed in Section 3.2, it is the movement away from these trends that can be plausibly attributed to the policy change, which requires the use of a technique to control for pre-trends, such as the linear detrending of Figure 4 or the Finkelstein (2007) adjustment of Table 1. Note that not all tariff channels show the presence of statistically significant pre-trends in Table D12. However, even in instances where we apply a pre-trend adjustment where none exists, the effect is innocuous, as the pre-trend being netted out is inconsequential. This can be seen by comparing non-detrended and detrended results for industrial production, for which Table D12 indicates a lack of pre-trends. As can be seen by comparing results for IP in panel (b) of Figures 3 and 4, the estimates are highly similar, as the linear detrending has little effect.

Table D12: Point Estimates of Cumulative Effect by Channel

Variable	Employment	Industrial Production	Producer Prices
Import Protection	-0.109	0.070	0.421
	(0.187)	(0.487)	(0.370)
Export Retaliation	2.927*	-0.416	-2.251*
	(1.538)	(0.896)	(1.243)
Rising Input Costs	1.818***	0.995	-1.687**
	(0.420)	(1.184)	(0.654)
Industry Fixed Effects	yes	yes	yes
Month Fixed Effects	yes	yes	yes
Number of Industries	76	84	82
Observations	2,508	2,772	2,706

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach estimated over the period January 2017 - February 2018. Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

D.7 Selection of Pre-Tariff Period, Placebo Test, Extended Pre-Period

In this section, we discuss the selection of the pre-tariff period used in our analysis, consider a placebo test that treats 2014 as a "pre" period and 2015-2016 as a "post" period, and report results of a regression that begins the sample in January 2012—versus January 2017 in the baseline—detrending over the period from January 2012 to February 2018.

D.7.1 Selection of Pre-Tariff Period

Our baseline sample period includes 13 months before the imposition of tariffs (January 2017 - January 2018) and 20 months after tariffs have been imposed (February 2018 - September 2019). The baseline pre-tariff period was chosen to reflect the prevailing trends in the manufacturing sector in the *immediate* lead-up to the tariffs. As shown in Figure D5, from January 2017 to January 2018, before the first tariffs studied in this paper were imposed, U.S. manufacturing employment increased by nearly 200,000 jobs. In the two years prior, the trend is noticeably different, with employment following a flatter trajectory. Because the purpose of this paper is to examine *short-term* effects of tariffs on U.S. manufacturing activity, and how they relate to the post-tariff manufacturing slowdown, our approaches to detrending account for the observable trend in place from January 2017 to January 2018. In the following two sub-sections, we examine a placebo test over an earlier sample period and consider a longer detrending period.

D.7.2 Placebo Test

In this section, we consider a placebo test conducted over a pre-tariff period to get a sense of the extent to which more-exposed versus less-exposed industries were on different trajectories for a period in the run-up to the 2016 election. Then-candidate Donald Trump, who would ultimately win the 2016 Presidential election, was threatening to impose tariffs throughout his campaign, and this placebo test helps examine whether products might have been selected to be subject to tariffs based on their pre-election performance. To be precise, the test treats 2014 as the "pre" period and 2015-2016 as the "post" period in a straightforward differences-in-differences specification:

$$\begin{aligned} ln(y_{it}) = \quad & \alpha + \gamma_t(\text{Import Protection}_i \times \text{Post}_t) + \ \ldots \\ & \lambda_t(\text{Export Retaliation}_i \times \text{Post}_t) + \theta_t(\text{Input Cost}_i \times \text{Post}_t) + \delta_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{D8}$$

As indicated in equation D8, each tariff exposure measure used in our baseline estimation is interacted with a *Post* indicator that takes the value one for months in 2015 and 2016 and zero for months in 2014. Results of this regression are reported in Table D13. As shown in the Table, none of the coefficient estimates on the DID terms in this placebo test are statistically significant.

Table D13: Placebo test: 2014 Pre-Period vs. 2015-2016 Post-Period

Variable	Employment (1)
Import Protection$_i$ × Post$_t$	0.284
	(0.368)
Export Retaliation$_i$ × Post$_t$	1.717
	(1.208)
Input Cost$_i$ × Post$_t$	-1.781
	(1.774)
Industry Fixed Effects	yes
Year-Month Fixed Effects	yes
Number of Industries	76
Observations	2,812

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table reports results of a placebo differences-in-differences exercise that treats 2014 as the "Pre" period and 2015-2016" as the post period. Regressors are each of the three tariff exposure measures used in the baseline estimates interacted with a *Post* indicator that takes the value one for months in 2015 or 2016 and takes the value zero otherwise. Results are weighted by employment as of December 2017. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

D.7.3 Beginning Sample in January 2012

The goal of this paper is to examine the role of tariffs in the manufacturing slowdown observed after they are put in place, and there are not yet sufficient data available to examine how they might alter longer-term trends in the sector. As such, the results in this paper should be interpreted as providing short-term estimates of the effects of tariffs, both in terms of the duration of post-tariff effects, and in terms of their comparison with the pre-tariff period.

To illustrate this point, in this section, we consider an alternative sample period that begins the pre-tariff period in January 2012, well before the run-up to the 2016 election. We perform the same Finkelstein (2007) approach to net out pre-existing trends, with pre-trends now defined from January 2012 to January 2018, as opposed to January 2017 to January 2018 in the baseline.

Results for this longer sample period are presented in Table D14. As shown in the Table, coefficient estimates are not statistically significant. These results are a reminder that while we find that tariffs are associated with the manufacturing sector's slowdown and break from prevailing trend after their imposition, their longer-term effects remain an important topic for future study.

Table D14: Sample Period Beginning in January 2012

Variable	Employment (1)
Import Protection	0.119
	(0.347)
Export Retaliation	-1.992
	(1.739)
Input Cost	-0.272
	(1.967)
Industry Fixed Effects	yes
Year-Month Fixed Effects	yes
Number of Industries	76
Observations	7,068

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: For import protection, rising input costs, and export retaliation, the table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text, applied over a sample period beginning in 2012.Results are weighted by employment as of December 2017. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

D.8 Staggered Treatment and Long Differences Specification

As discussed in Section 2.1, both U.S. and foreign retaliatory tariffs were imposed in stages throughout 2018 and 2019. This timing implies a staggered treatment, which Goodman-Bacon (2021) and Callaway and Sant'Anna (2021) argue can lead to biased estimates and even flipped signs in standard differences-in-differences approaches. One of the key problems highlighted in these papers is that some industries in the control groups in early portions of the sample are about to join the treatment group at later portions of the sample.

We note that a key feature of our approach sidesteps some of the concerns of staggered treatment. In particular, each of the three tariff exposure measures in Equations 1, 2, and 5 are based on the *cumulative* set of tariffs imposed by the U.S. and its trading partners. Thus, when they enter Equation 6, each industry's ultimate exposure to tariffs is captured, so that industries that are initially untreated (or less treated) are not effectively serving as a "control group."

Another way to assess the potential relevance of staggered treatment is to step away from the monthly panel framework and simply estimate a specification in long differences. To do so, we define a long difference covering the period from the beginning of the sample to just prior to the imposition of tariffs. Then, we define a second long difference from the period just prior to the imposition of tariffs to the end of the sample. The difference between these two long differences becomes our dependent variable. In this setup, none of the industries are treated in the earlier period and all are treated in the second period (granted, their *duration* of treatment varies in the second period). Results are reported in Table D15. As shown in the Table, estimates are nearly identical to our baseline results in terms of sign and significance (the only difference being that the p-value for the import protection channel in the employment regression edges up to 0.106). This is unsurprising given that our cumulative tariff exposure measures combined with the Finkelstein (2007) hypothesis are conceptually very similar to the long differences specification.

Table D15: Long Differences Specification

Variable	Employment	Industrial Production	Producer Prices
Import Protection	0.238	-0.336	-1.154
	(0.140)	(0.948)	(0.707)
Export Retaliation	-3.423**	3.301	1.165
	(1.388)	(2.677)	(3.756)
Rising Input Costs	-2.413***	-1.126	5.730***
	(0.927)	(3.103)	(1.662)
Observations	76	84	82

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of a differences in differences specification in which the dependent variable is the difference of two long differences: one covering Jan.- Mar. 2017 (averaged) to Nov. 2017 - Jan. 2018 (averaged); the second covering Nov. 2017 - Jan. 2018 (averaged) to Jul. 2019 - Sep. 2019 (averaged). The first period is scaled to match the duration of the second. Results for employment are weighted by employment as of December 2017 and results for IP and PPI are weighted value added as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

D.9 Standardized Coefficient Estimates

In this section, we report standardized versions of Table 1's estimates as an alternative approach to considering the economic significance of our baseline results. Here, each coefficient estimate indicates the change in the relevant dependent variable (in terms of its standard deviation) associated with a one standard deviation change in the relevant independent variable. As indicated in the first column of the table, the negative effects on manufacturing employment of a one standard deviation increase in exposure to either rising input costs or export retaliation are more than twice as large as the positive effect of a one standard deviation increase in import protection. Among the independent variables, the impact of rising input costs is largest in absolute value terms, as a one standard deviation increase yields a 0.6 standard deviation relative decrease in manufacturing employment. As shown in the third column, the same one standard deviation increase in exposure to rising input costs yields a 1 standard deviation increase in producer prices.

Table D16: Point Estimates of Cumulative Effect by Channel: Standardized Regression Coefficients

Variable	Employment	Industrial Production	Producer Prices
Import Protection	0.206*	-0.123	-0.525
	(0.114)	(0.255)	(0.315)
Export Retaliation	-0.511**	0.152	0.178
	(0.191)	(0.133)	(0.353)
Rising Input Costs	-0.590***	-0.116	1.012***
	(0.166)	(0.255)	(0.292)
Industry Fixed Effects	yes	yes	yes
Month Fixed Effects	yes	yes	yes
Number of Industries	76	84	82
Observations	2,508	2,772	2,706

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays standardized coefficient estimate and standard error equivalents of the Finkelstein (2007) estimates presented in Table 1. Each coefficient estimate indicates the change in the relevant dependent variable (in terms of its standard deviation) associated with a one standard deviation change in the relevant independent variable. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

D.10 Distribution of Net Effects of Tariffs Across Industries

In Section 3, we describe the economic significance of our baseline results by comparing outcomes for a hypothetical industry that is at the 75th percentile of exposure to all three channels to another hypothetical industry that is at the 25th percentile of exposure to all three channels. A concern with this approach is that, hypothetically, the mass of industries near the 75th percentile benefiting from import protection may be large, whereas the mass of industries near the 25th percentile being harmed by rising input costs may be small. If this is the case, the net effects of exposure to tariffs may differ from those suggested by our straightforward interquartile calculation. More generally, calculating the effect of an interquartile shift in each tariff channel treats their distributions as independent, while ignoring their joint distribution.

To address this concern, we perform an exercise in which we multiply the estimated baseline coefficients from Table 1 by each industry's actual exposure to each of the three tariff channels. Next, we sum the estimated effects of the three channels for each industry and display the densities of the net effects for employment, IP, and PPI in Figure D6.

As indicated in the left panel of the Figure, the mass of the net effect of tariffs is overwhelmingly negative for manufacturing employment, and the median (unweighted) industry experiences an employment loss of 2.8 percent due to tariffs. By contrast, the mass for effects on PPI is overwhelmingly in positive territory, and the median (unweighted) industry experiences an increase in PPI of 2.8 percent. The mass for the effect of tariffs on IP is centered around zero. Subject to the usual caveat that these estimates do not account for the general equilibrium effects of tariffs, Figure D6 provides further evidence of the negative net effects of tariffs on manufacturing employment, with positive net effects on producer prices.

D.11 Margins of Employment Adjustment and the Differing Responses of Employment and Industrial Production

In this section, we describe additional information related to margins of employment adjustment and provide insights into differences between the effects of tariffs on employment, where we find a strong negative relationship, and industrial production, where we find little response.

First, as background to the more formal analysis of margins of employment adjustment in Section 3.4, we discuss aggregate data on hiring and layoffs in the manufacturing sector from the BLS's Job Openings and Labor Turnover Survey at the time that tariffs begin to be imposed. As indicated in the left panel of Figure D7, the moving average of layoffs in the manufacturing sector moves roughly sideways from mid-2018 forward, even as tariffs are imposed. By contrast, after increasing throughout 2017, hires peak in 2018 and then move steadily down. This larger reaction for hires in the aggregate data is consistent with the more formal findings in Section 3.4, in which the effects of tariff exposure on hires are roughly twice the size of the effects on separations.

To the extent that the effect on hires dominates that for separations, these results also provide the first of two pieces of information that is helpful for considering a puzzling feature of our results in section 3.2: negative impacts of the tariffs on employment combined with little impact on measures of industrial production.

The second piece of information for this puzzle is the state of manufacturers' order backlogs during this time. As shown in Figure D7b, the tariffs were imposed at a time when manufacturers held historically high levels of unfilled orders—the dashed red line in the figure—which support output.[30] When the index for *new* orders of manufactured goods (black line in Figure D7b) plunged as new tariffs were imposed, manufacturers faced a situation of high current demand from orders already on their books, combined with sharply declining future demand.

One potential response by firms in this situation would be to maintain production to fulfill existing orders, while forgoing hiring that would have otherwise taken place, with the

[30] The Institute for Supply Management's (ISM) Manufacturing Orders Backlog Index reached its highest level in 14 years in the first half of 2018. This index is constructed based on survey responses of purchasing and supply executives indicating whether their level of orders backlogs had increased, decreased, or remained the same over the past month. Industry detail is not available within broad industry classes that are roughly equivalent to three-digit NAICS industry groups. See Institute for Supply Management (2020) for further information.

extent of this response varying according to exposure to tariffs. The results in Table 1 and Figure D7 are consistent with this interpretation.

D.12 Evaluating the Role of Regression Weights

When estimating equation 6 for employment we use December 2017 employment levels as weights to arrive at estimates that can scale up to a manufacturing aggregate. Similarly, when estimating equation 6 for either IP or PPIs we use 2016 value added weights. To evaluate the role of weights in our results, we re-run our baseline specification for employment but instead use each industry's 2016 average level of employment, and then remove the weights entirely. The results are shown below in Table D17.

As is clear from the table, the use of 2016-average employment (in column 2) has a very small effect. This is not surprising as the relative movements would have changed little during that time period, and averaging across months also should have minimal effects since each industry's monthly estimate is seasonally adjusted. Removing weights entirely increases the positive effect from import protection and lowers the negative effect of export retaliation, suggesting that industries benefiting from protection tend to be smaller, while those negatively affected by retaliation tend to be somewhat larger.

Table D17: Point Estimates of Cumulative Effect by Channel:

	Employment		
Variable	Baseline	2016-weights	No Weights
Import Protection	0.310*	0.310*	0.598*
	(0.171)	(0.175)	(0.309)
Export Retaliation	-4.479**	-4.387**	-3.912*
	(1.679)	(1.678)	(2.196)
Rising Input Costs	-3.085***	-3.078***	-3.054***
	(0.867)	(0.856)	(0.924)
Industry Fixed Effects	yes	yes	yes
Month Fixed Effects	yes	yes	yes
Number of Industries	76	84	82
Observations	2,508	2,772	2,706

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Baseline results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

D.13 Comparison of Magnitude of Estimated Effects With Existing Literature

Other papers, including Acemoglu et al. (2016) examine the effects on employment of trade shocks to input-producing industries. In this section, we use elasticities from this and other papers to compare the magnitudes estimated in our paper to those in the existing literature. We also discuss caveats inherent in this type of comparison exercise. Among the most important caveats is that the existing literature (Acemoglu et al., 2016; Pierce and Schott, 2016) has not found statistically significant effects of shocks to input costs on downstream employment. This lack of a response in the existing literature highlights the importance of our paper's finding of a clear effect of the input channel on employment. It also fits with the discussion in Amiti et al. (2019), noting that other aspects of the 2018-2019 tariffs—particularly the finding of complete pass-through of tariffs—differ from prior trade shocks. However, the use of imprecise coefficient estimates from elsewhere in the literature indicates that these comparisons must be taken with a grain of salt.

We consider two approaches of comparing magnitudes of our estimates to those in the existing literature, with each approach making use of the estimate from Acemoglu et al. (2016) of the effect of the China shock on input-producing industries on downstream US manufacturing employment. This estimated elasticity is 2.3 (Table 6a, column 2), so that a 1 percentage point increase in input import penetration is associated with 2.3 percent increase in manufacturing employment. As mentioned above, however, this estimate is not statistically different from zero (in fact, the standard error is larger than the coefficient).

One way to use the Acemoglu et al. (2016) estimates in our setting is simply to apply this elasticity to the observed decrease in U.S. penetration of imports from China, which declined from 7.6 percent in 2017 to 6.5 percent in 2019. The implied decline in US manufacturing employment associated with this fall in the import penetration of inputs is 2.5 percent, somewhat larger than the 1.8 percent decline in manufacturing employment that we attribute to the rising input cost channel.

A second approach is to calculate the response of imports to tariffs using existing estimates of that elasticity and then calculate the effect of the implied decrease in imported inputs on employment, again using the estimates from Acemoglu et al. (2016). To do this, we use the estimated elasticity of imports with respect to tariffs from Amiti et al. (2019) (Table 1, column 2), which implies a decline in U.S. imports from China of USD 160 billion, or a decrease in import penetration of 1.7 percentage points. Applying the elasticity from Acemoglu et al. (2016), this yields a decrease in U.S. manufacturing employment of 4.0 percent, a little more than twice as large as our estimated effect of the rising input cost channel.

Additional caveats are important in this calculation. First, Amiti et al. (2019) contains alternative estimates of the elasticity of imports with respect to tariffs (e.g. columns 3 and 5) that are even larger. However, all the elasticities estimated in Amiti et al. (2019) are with respect to *varieties* (particular goods imported from a particular country), and as noted in that paper, the response of total U.S. imports to tariffs will be much smaller than that implied by these elasticities as imports increase from non-targeted countries.

D.14 Quarterly Employment

The baseline results in Section 3.2 make use of monthly employment data from the the BLS's CES. The analysis of hires and separations in Section 3.4, however, uses quarterly data from the Census Bureau's QWI. To provide a comparison between these two sets of results, we construct a measure of quarterly employment as the average of the monthly industry-level data in the CES and then use these transformed data to estimate the quarterly specification.

As shown in Table D18, we find results that are highly similar in terms of sign, significance, and magnitude, to those based on the monthly employment data in Table 1. We continue to find that higher exposure to rising input costs or export retaliation is associated with a relative decline in manufacturing employment. The positive relationship between the import protection channel and employment loses statistical significance in this quarterly specification.

Table D18: Quarterly Average of CES Employment

Variable	Employment
Import Protection	0.273
	(0.187)
Export Retaliation	-2.042**
	(0.579)
Rising Input Costs	-3.517***
	(1.404)
Industry Fixed Effects	yes
Quarter Fixed Effects	yes
Number of Industries	76
Observations	836

Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach, where the dependent variable is average quarterly employment, calculated using monthly industry-level employment from the BLS's CES program. Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

D.15 Univariate Results

Table D19 presents results of regressions of the three outcome variables on individual tariff channel measures, one at a time, as opposed to including the three channels together in the same regression. There are some similarities between these "univariate" regression results and the main results shown in Table 1. Table D19 still reports a negative relationship between the rising input cost and channel and employment, with a positive relationship for producer prices. There are also important differences, however. The results for industrial production actually report a positive relationship between export retaliation and industrial production, but this effect is not present when the other channels are present, highlighting the importance of controlling for all tariff channels together.

Table D19: Univariate Point Estimates of Cumulative Effect by Channel:

Variable	Employment			Industrial Production			Producer Prices		
Import Protection	0.061			0.187			1.508		
	(0.174)			(0.692)			(1.027)		
Export Retaliation			-2.904			4.928***			2.957
			(2.501)			(1.533)			(5.415)
Rising Input Costs		-2.456***			-1.632			8.077*	
		(0.853)			(1.961)			(4.542)	

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Employment results are weighted by employment as of December 2017 and results for IP and PPI are weighted by value-added. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \ p < 0.10$, $** \ p < 0.05$, $* * * \ p < 0.01$.

D.16 Results by Tariff Wave

The main results presented in Table 1 calculate exposure to three tariff channels based on cumulative values of affected trade, covering all tariffs imposed during our sample period. Table D20, on the other hand, shows the results of regressions that include interactions of month dummies with separate measures for each of the individual waves of tariffs. Each column of Table D20, therefore, shows the results of a single regression.

The table yields several findings on the effects of individual tariff waves. First, in terms of employment (column 1) we find that exposure to rising input costs from the March 2018 steel and aluminum tariffs is associated with a relative decline in employment, as is export retaliation to those tariffs in the following month. These results align very closely with the baseline results presented in Table 1. Regarding industrial production (column 2)—for which we do not find any relationship with tariffs in the baseline results—we find that exposure to rising input costs from the September 2018 U.S. Section 301 tariffs on China is associated with a relative decrease in IP, while import protection from the March 2018 steel and aluminum tariffs is associated with a relative increase, as is the export retaliation in August 2018. Lastly, in terms of PPIs, we find that exposure to rising input costs from the September 2018 U.S. tariffs are associated with a relative increase in producer prices, that foreign retaliatory tariffs in April and August are associated with a relative decline in producer prices (while those in July are associated with a relative gain), and that higher import protection in August and September is associated with a relative decrease in PPIs.

Despite the increased detail shown in Table D20, we report the cumulative values of affected trade as the baseline in the main text due to the inherent uncertainty in choosing specific dates to identify the effects of the range of tariff waves, and because these estimates may be sensitive to the correlation between exposure across different waves.

D.17 Examining Potential Spillovers to Downstream Nonmanufacturing Industries

In the same way that manufacturing firms are affected by tariffs on imported intermediate inputs, nonmanufacturing industries that use manufactured goods as inputs may face similar effects. In this section, we estimate the relationship between exposure to rising input costs and employment in nonmanufacturing industries. We focus on employment as the outcome variable because detailed data on producer prices and monthly output are unavailable for nonmanufacturing industries. We focus on exposure to rising input costs because services industries are neither protected by U.S. tariffs nor subject to retaliatory tariffs by U.S. trading partners.[31] We address the case of retaliatory tariffs on non-manufacturing goods-producing industries—particularly agriculture—in further detail below.

Our empirical approach is similar to that used to examine the manufacturing sector, but restricted to the input costs channel given the data limitations described above:

$$y_{it} = \alpha + \sum_t \theta_t \mathbf{1}(M_t = t)(\text{Input Cost}_i) + \delta_i + \delta_t + \varepsilon_{it}. \tag{D9}$$

Here, y_{it} is industry-month-level employment and Input Cost_i is industry-level exposure to the rising input cost channel. The sample includes all nonmanufacturing industries. Table D21 displays coefficient estimates and standard errors based on the application of the Finkelstein (2007) approach to equation (D9).

For comparison purposes, the first column of Table D21 reports results for manufacturing industries, and column two reports results for nonmanufacturing industries.[32] As indicated in the second column, we find a negative but statistically insignificant (p-value of 0.15) relationship between exposure to rising input costs and employment at downstream nonmanufacturing industries, a relationship that is substantially less precisely estimated than that for manufacturing industries.[33]

[31] There were some instances of non-tariff retaliation by U.S. trading partners, such as China's brief effective banning of imports of U.S. crude oil, which could have also affected nonmanufacturing industries. Because these non-tariff barriers were small relative to the size of tariff increases, and because they are often exceedingly difficult to detect and measure, they are not explicitly included in this analysis.

[32] Note that estimates for manufacturing industries in the first column of Table D21 are the result of estimating equation D9. Because these results are based on only the rising input cost channel, they naturally differ from those reported in Table 1, which include all three tariff channels simultaneously.

[33] The negative relationship between input tariffs and nonmanufacturing employment aligns with Bown

Table D20: Point Estimates by Tariff Wave

Variable	Employment	Industrial Production	Producer Prices
Import Protection Feb. 2018	-2.242	-3.838	8.944
	(2.679)	(13.113)	(6.148)
Import Protection Mar. 2018	0.668	5.900***	-3.103
	(1.497)	(1.678)	(1.875)
Import Protection Jul. 2018	2.741	-2.038	5.720*
	(4.751)	(3.930)	(2.866)
Import Protection Aug. 2018	-3.017	-1.352	-8.106*
	(2.307)	(5.244)	(4.043)
Import Protection Sep. 2018	0.214	0.053	-1.840**
	(0.384)	(0.731)	(0.764)
Export Retaliation Apr. 2018	-60.919***	41.714	-100.726**
	(19.760)	(63.249)	(40.310)
Export Retaliation Jun. 2018	17.254	-2.627	10.296
	(11.518)	(14.156)	(6.395)
Export Retaliation Jul. 2018	-1.613	-6.097	12.284***
	(3.579)	(5.916)	(4.178)
Export Retaliation Aug. 2018	-2.372	19.882**	-12.727**
	(5.543)	(8.053)	(5.329)
Export Retaliation Sep. 2018	-1.011	-0.227	-9.757
	(1.170)	(3.302)	(6.912)
Rising Input Costs Feb. 2018	18.674	-15.441	-17.986
	(17.830)	(95.166)	(38.130)
Rising Input Costs Mar. 2018	-3.214***	-0.881	4.848
	(0.960)	(2.133)	(3.433)
Rising Input Costs Jul. 2018	-10.655	1.272	-1.418
	(15.509)	(19.517)	(17.034)
Rising Input Costs Aug. 2018	-2.250	14.410	-6.074
	(8.718)	(16.741)	(18.796)
Rising Input Costs Sep. 2018	-4.531*	-11.379*	11.080**
	(2.460)	(6.001)	(4.394)

Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (7) in the text. Column (1) results are weighted by employment (as of December 2017) whereas columns (2) and (3) are weighted by value-added. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

et al. (2020) and Barattieri and Cacciatore (2023), who find that downstream nonmanufacturing industries experience notable effects on employment related to antidumping duties on manufacturing industries. The comparative strength and precision of these other findings may be due in part to the large magnitude of the duty rates applied in antidumping investigations, which can exceed 100 percent, as well as to the sample period spanning multiple decades.

There are a number of reasons why one might expect the input cost measure of tariff exposure to be less salient for non-manufacturing industries than for manufacturing industries. First, manufactured goods make up a far lower share of input costs for nonmanufacturing industries than for manufacturing industries. The average manufacturing industry has an exposure to input tariffs that is nearly an order of magnitude higher than that for the average nonmanufacturing industry (2.8 percent of costs vs. 0.4 percent of costs, respectively), and the top 43 industries in terms of exposure to tariffs via input costs are all manufacturing industries. Second, it may simply take more time for tariffs on manufactured goods to work their way through supply chains and yield tangible effects on nonmanufacturing industries. Therefore, the impact on these industries may become more precisely estimated or larger in magnitude as input tariffs are sustained for a longer period of time.

Table D21: Effects of Exposure to Rising Input Costs Via Tariffs on Nonmanufacturing Employment

Variable	Mfg. Industries	Nonmfg. Industries
Rising Input Costs	-2.456***	-2.928
	(0.853)	(2.003)
Industry Fixed Effects	yes	yes
Month Fixed Effects	yes	yes
Number of Industries	76	175
Observations	2,508	5,775

Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented applied to results from estimating equation (D9). Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Next, we provide additional results related to analyzing the relationship between exposure to the rising input cost channel and employment at downstream nonmanufacturing industries. In particular, we estimate equation (D9) using detrended employment, providing visual representations of the results in Figure D8. The upper left panel of the Figure displays results based on all nonmanufacturing industries, equivalent to the results based on the Finkelstein (2007) approach in the second column of Table D21. As in the table, we see only limited evidence for a negative relationship between the input cost channel of tariffs and employment in the nonmanufacturing sector, although coefficient estimates do move down in 2019—after the largest round of US tariffs went into effect—unwinding a pre-tariff increase. The remaining panels of Figure D8 examine whether the relationship between exposure to rising input costs and employment that is present for manufacturing industries persists in broader groupings of sectors, especially including those nonmanufacturing sectors that use manufactured goods more intensively in their production processes. As shown in the Figure D8, a negative relationship between exposure to rising input costs and employment remains apparent when the manufacturing sample is augmented with construction (upper right panel) and, to a lesser extent, with mining (lower left panel), or with all goods-producing industries (lower right panel).[34] The Finkelstein (2007) approach indicates that this relationship is negative and statistically significant for manufacturing plus construction and negative and marginally insignificant for manufacturing plus mining (p-value 0.16) and all goods producing industries (p-value 0.25). In sum, the results indicate that while the relationship between tariffs and non-manufacturing employment is weak, the relationship between tariffs and manufacturing employment is strong enough to show through when broader groups of sectors are considered.

D.18 Approximate General Equilibrium Effects on Local Labor Markets

One important limitation of the results in this paper is that they are all partial equilibrium in nature. A potential method for achieving implied general equilibrium results—for our spatial results on unemployment—is the empirical approach described in Adão et al. (2020). We implement their specification of spatial links by weighting indirect exposure to the shocks we study via a gravity representation. Specifically, we employ their equation (4) for each of the three channels X_j we study to arrive at indirect estimate IX_i:

$$IX_i =_{j\neq i} \frac{D_{ij}^{-\delta}}{_{k\neq i} D_{ik}^{-\delta}} X_j \tag{D10}$$

with D_{ij} being the distance between counties i and j and using the preferred measure of trade elasticity δ from Adão et al. (2020) of 5. We then include these indirect measures in our baseline specification to examine the role, if any, of indirect links in the effect on unemployment from the tariffs. As is clear in the second column of Table D22, the qualitative magnitude of our direct channels remains the same, with additional positive (increases) impacts on the unemployment rates, on net, from the indirect channels, though the significance is generally weak.

If one were to incorporate these implied general equilibrium effects (abstracting away from statistical significance), then the net effect (overall) for a county in the 75th percentile of the distribution of each tariff channel relative to a county in the 25th percentile is an increase of 0.24 percentage points. This is an increase of roughly 40 percent relative to our baseline estimate of 0.17 percentage points.

For another perspective, these estimates show that there is no measurable beneficial impact on domestic producers coming from the import protection channel, even when factoring in general equilibrium features. When combining the direct and approximated G.E. effects of this channel, the resulting coefficient is slightly positive (hence, leading to greater unem-

[34] Goods-producing industries include industries whose NAICS codes begin with 1, 2, or 3. Because agriculture is excluded from the BLS's Current Employment Statistics, NAICS code 1 represents only logging.

ployment) but not statistically significant.[35] These results differ from model-based estimates, such as those in Fajgelbaum et al. (2020) in which there are positive welfare impacts on the U.S. economy through implied gains from domestic producers. While our measure of the impact on unemployment rates is not a perfect analogue to notions of welfare captured by Fajgelbaum et al. (2020) and others, it is notable that we find no such offsetting impacts were present during the tariff episode we study here.

Table D22: Point Estimates of Cumulative Effect by Channel:

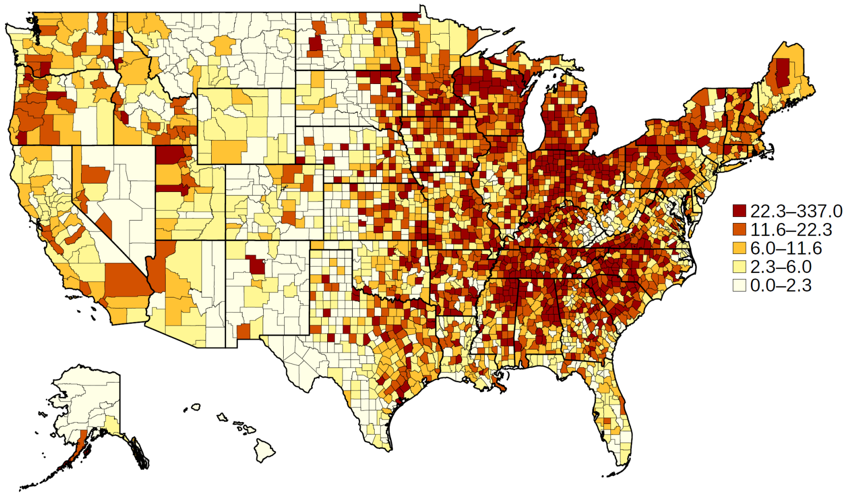
Variable	Unemployment Rate (1)	(2)
Import Protection	9.75*	12.72**
	(5.48)	(5.90)
Export Retaliation	51.67*	62.34*
	(31.08)	(32.91)
Rising Input Costs	64.17***	48.01***
	(17.81)	(17.19)
(Indirect)		
Import Protection		-3.64
		(9.85)
Export Retaliation		9.13
		(72.94)
Rising Input Costs		37.78
		(31.12)
Manufacturing Share Controls	yes	yes
County Fixed Effects	yes	yes
Month Fixed Effects	yes	yes
Number of Counties	3,131	3,131
Observations	103,323	103,323

Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Column (1) displays results of the Finkelstein (2007) approach described in equation 7, based on OLS regressions of unemployment rates on measures of exposure to the rising input cost, import protection, and export retaliation channels of tariffs. Column (2) also adds in approximated general equilibrium effects following Adão et al. (2020). Estimates are weighted by December 2017 labor force. Standard errors (in parentheses) are clustered at the state-level in column (1), and NAICS-3 level in column (2). $* \ p < 0.10$, $** \ p < 0.05$, $* * * \ p < 0.01$.

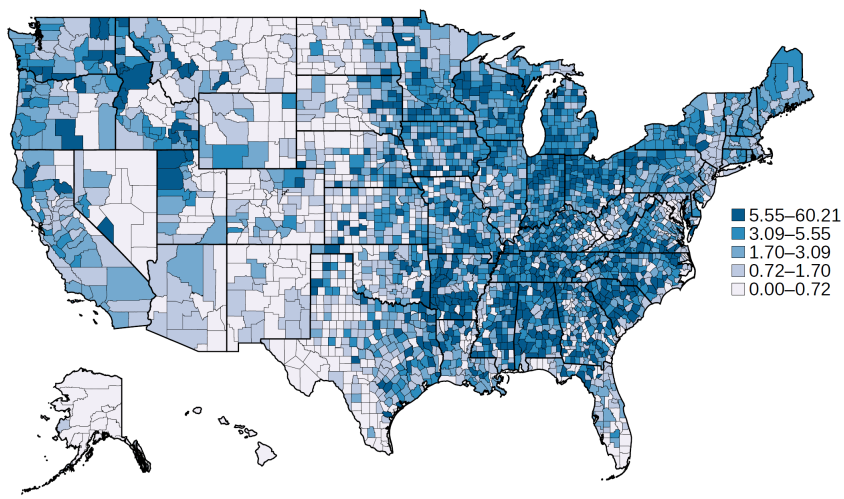
[35] Specifically, a coefficient of 9.08 with a standard error of 10.35.

Figure C3: County-Level Distribution of Tariffs

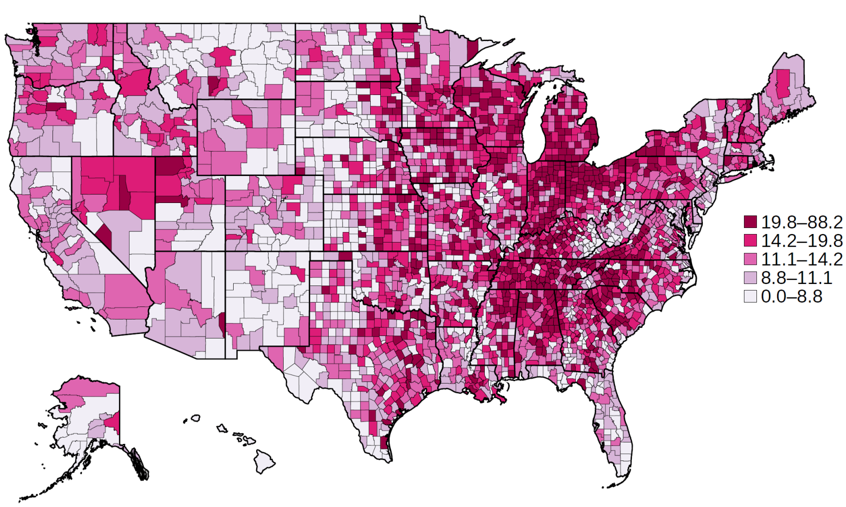
(a) Manufacturing Import Protection, by County



(b) Export Retaliation on Manufacturing, by County



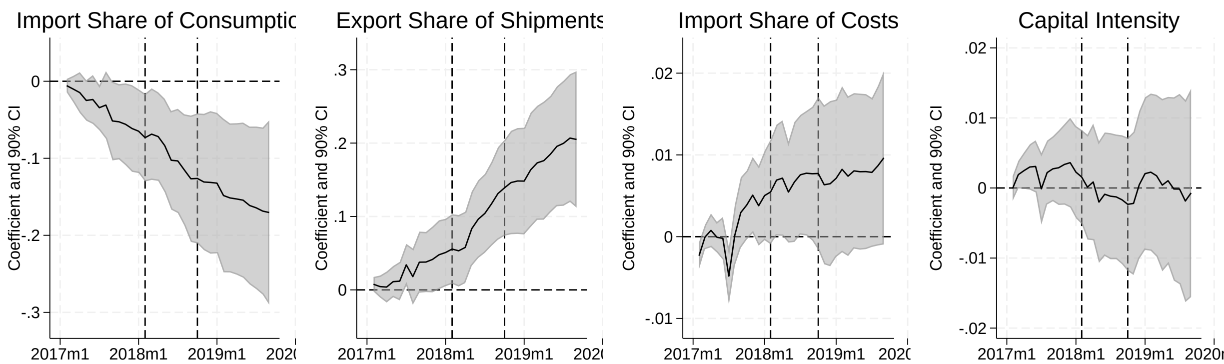
(c) Rising Input Costs, by County



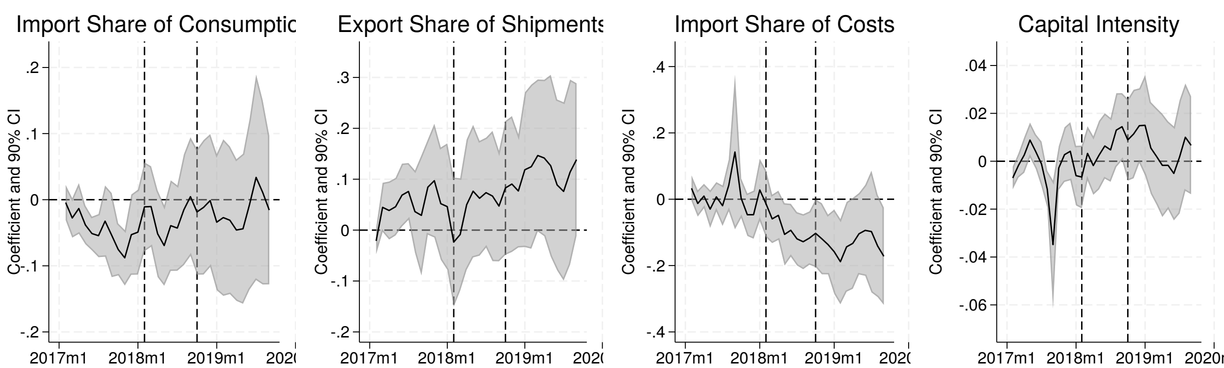
Sources: Author's calculations using County Business Patterns (U.S. Census Bureau), Eckert et al. (2020) and sources highlighted in Section 2.2.
Notes: Maps display county-level measures of exposure to the import protection, export retaliation and rising input cost tariff channels. Note that measures are multiplied by 100 for greater legibility. County-level measures are employment weighted-averages (as shown in equation (8)) of industry-level exposure defined in equations (5), (2), and (1) above.

Figure D4: Coefficient Estimates for Control Variables

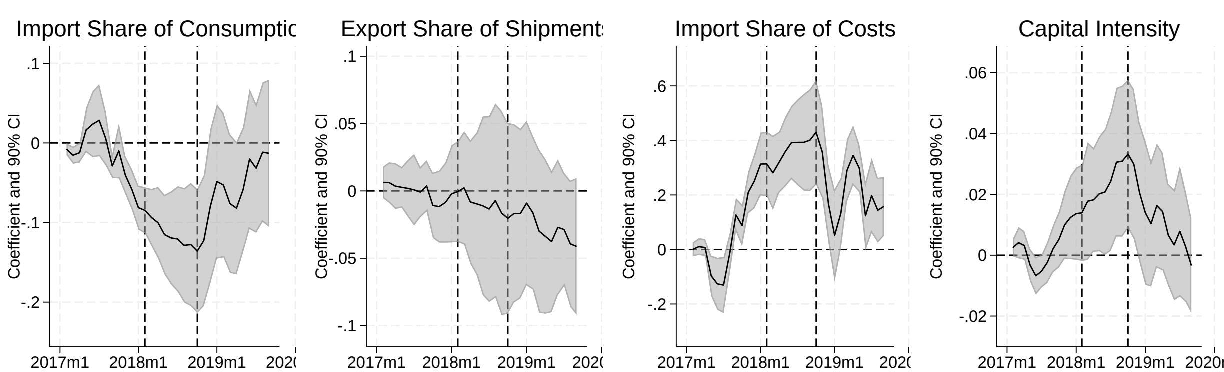
(a) Employment



(b) Industrial Production (Output)



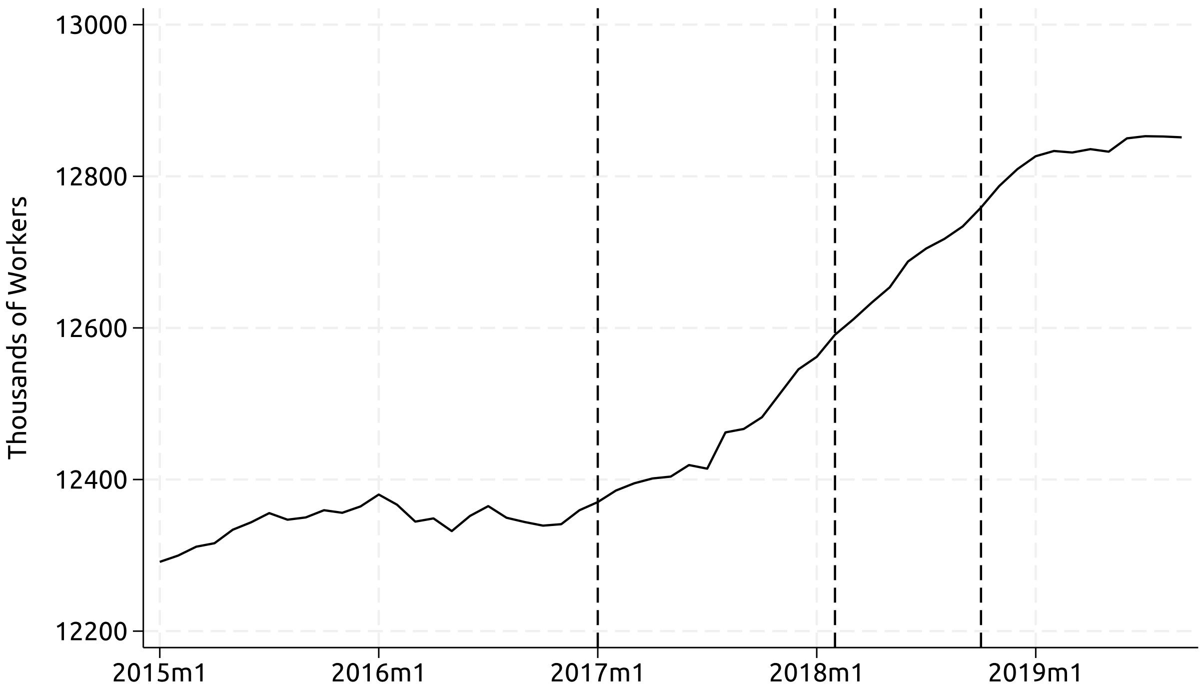
(c) Producer Price Index



Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.

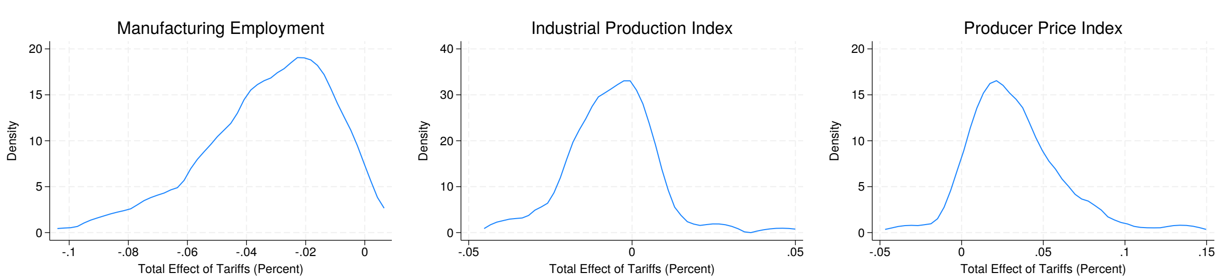
Notes: Each panel displays coefficient estimates (solid lines) and 90 percent confidence intervals (shaded areas) of interactions of month dummies with import share of absorption, export share of shipments, import share of costs, and capital intensity. Each panel represents the result of a different regression, and dependent variables for each regression are noted in panel titles. The two vertical dashed lines are at February 2018 and September 2018, the times of the first and last waves of new 2018 tariffs. Estimates for employment are weighted by December 2017 employment and estimates for industrial production and producer prices are weighted by December 2017 value added. Standard errors are clustered at the three-digit NAICS level.

Figure D5: U.S. Manufacturing Employment, Jan. 2015 - Sep. 2019



Notes: Figure displays U.S. manufacturing employment from January 2015 to September 2019. The dashed vertical line at January 2017 is the start of the pre-tariff period in the baseline. The two dashed vertical lines in 2018 denote the first and last rounds of U.S. import tariffs examined in this paper. Source: U.S. Department of Labor, Bureau of Labor Statistics.

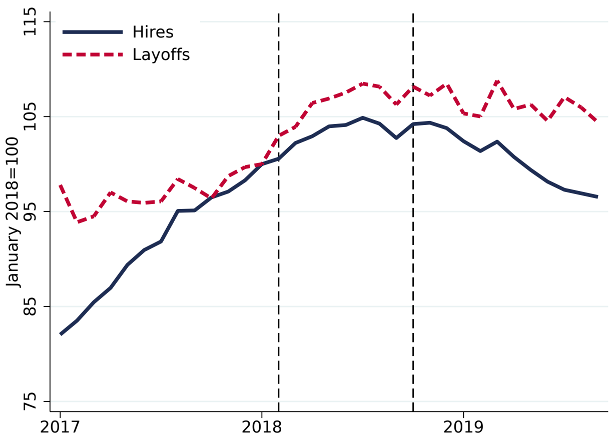
Figure D6: Distributions Across Industries of Net Effects of Three Tariff Channels



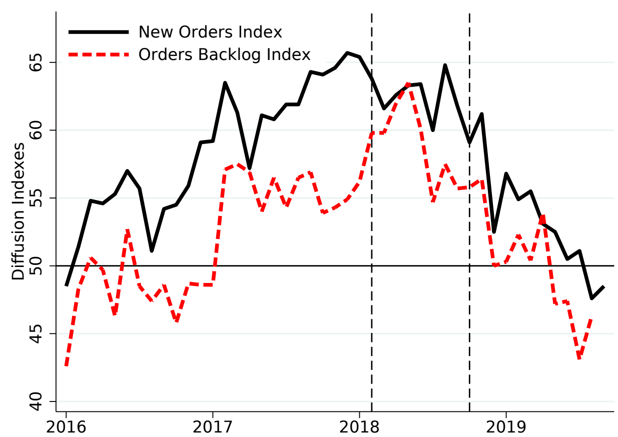
Notes: Figure distributions across industries of estimated net effects of tariffs on the noted dependent variables. Estimated net effects are calculated by multiplying each industry's actual exposure to each of three tariff exposure channels by the baseline coefficient estimates from Table 1.

Figure D7: Manufacturing Orders, Hires, and Layoffs

(a) Hires and Layoffs

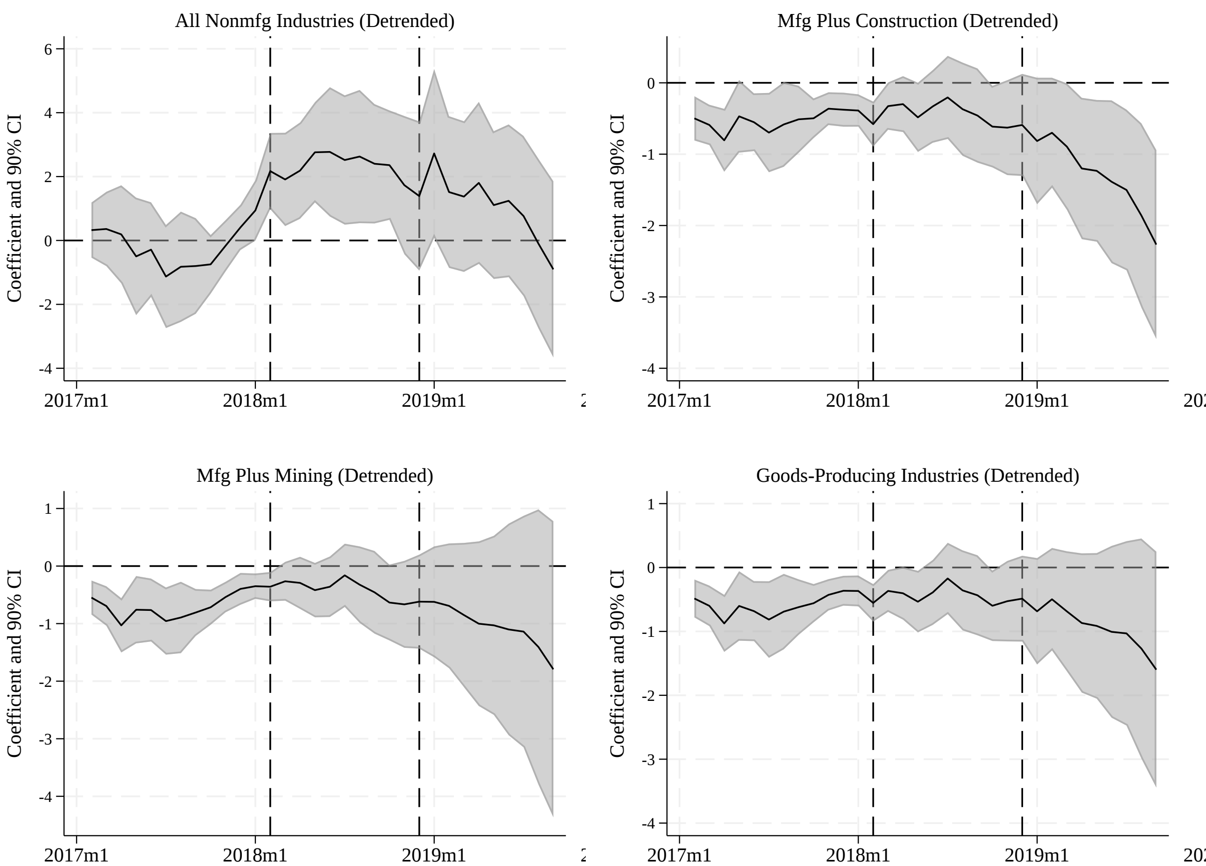


(b) Orders Backlog and New Orders Indexes



Source: Institute for Supply Management, Bureau of Labor Statistics.
Notes: Left panel displays the six-month moving average of manufacturing hires and layoffs from the BLS's Job Openings and Labor Turnover Survey, indexed to 100 in January 2018. Right panel displays diffusion indexes of Manufacturing Orders Backlog (red dashed line) and Manufacturing New Orders indexes (black line) for the period from January 2016 through September 2019.

Figure D8: Effects of Exposure to Rising Input Costs Via Tariffs on Nonmanufacturing Employment



Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Each chart in the figure displays results of a separate regression of nonmanufacturing employment on exposure to rising input costs via tariffs. Solid lines indicate coefficient estimates and shaded areas represent 90 percent confidence intervals based on clustering by 3-digit NAICS. The two vertical dashed lines are at February 2018 and September 2018, the times of the first and last waves of new 2018 tariffs.