Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector *

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Abstract

This paper estimates the relationship between the U.S. tariff increases of 2018-2019 and outcomes in domestic manufacturing. Despite being intended to boost manufacturing activity, we find U.S. industries more exposed to tariff increases experience relative reductions in employment, as a small positive effect from import protection is offset by larger negative effects from rising input costs and retaliatory tariffs. Higher tariffs are also associated with relative increases in producer prices due to rising input costs. Lastly, we document broader labor market impacts, as counties more exposed to rising tariffs exhibit relative increases in unemployment and declines in labor force participation.

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1 Introduction

The unprecedented increase in tariffs imposed by the United States against its major trading partners in 2018-2019 has brought renewed attention to the economic effects of tariffs. While vast theoretical and empirical literatures document the effects of changes in trade policy, it is not clear how prior estimates apply when there are virtually no modern episodes of a large, advanced economy raising tariffs in a way comparable to the U.S. during this period. Further complicating estimation of the effects of tariffs is the rapid expansion of globally interconnected supply chains, in which tariffs can have impacts through channels beyond their traditional effect of limiting import competition.

Another important feature of these tariffs is that they were imposed, in part, to boost the U.S. manufacturing sector by protecting against what were deemed to be the unfair trade practices of trading partners, principally China. Thus, understanding the impact of tariffs on manufacturing is vitally important, as some may view the negative consequences of tariff increases documented in existing research—including higher prices, lower consumption, and reduced business investment—as an acceptable cost for boosting manufacturing activity in the United States.

This paper provides the first comprehensive estimates of the effect of recent tariffs on the U.S. manufacturing sector, while also considering spillovers to the broader labor market. A key feature of this analysis is simultaneously accounting for the different channels through which tariffs could affect manufacturers in the presence of global trade and supply chain linkages. On the one hand, U.S. import tariffs may protect some U.S.-based manufacturers from import competition in the domestic market, allowing them to gain market share at the expense of foreign competitors. On the other hand, U.S. tariffs have also been imposed on intermediate inputs, and the associated increase in costs may hurt U.S. firms' competitiveness in producing for both the export and domestic markets. Moreover, U.S. trade partners have imposed retaliatory tariffs on U.S. exports of certain goods, which could again put U.S. firms at a disadvantage in those markets, relative to their foreign competitors. Disentangling the effects of these three channels and determining which effect dominates is an empirical question of critical importance.

Toward this end, we construct industry-level measures of exposure to each of these three channels. We measure the import protection channel as the tariff rate impact on the share of domestic absorption covered by newly imposed tariffs. We account for an industry's exposure to retaliatory tariffs by U.S. trading partners based on the share of industry-level shipments subject to new retaliatory tariffs. Finally, we measure possible increases in production costs associated with tariffs on imported inputs as the tariff rate impact on the share of industry costs subject to new tariffs.[1] We then relate the measures for these three channels of tariff exposure to monthly data on manufacturing employment, output, and producer prices.

We begin by regressing the industry-month-level outcomes on interactions of measures of the three channels with a set of month dummies, using the approach from Finkelstein (2007) to difference out pre-existing industry-level trends, which are important in this setting. Industry and month fixed effects in the regressions control for time-invariant characteristics of industries and aggregate shocks. In addition, we include interactions of month dummies with a set of industry-level characteristics whose relationship with the dependent variable may change over time. Interactions of month dummies with measures of an industry's general international exposure allow for the possibility, for example, that more internationally exposed industries respond differently to international shocks other than tariffs, such as exchange rate or international business cycle fluctuations. Interactions with measures of

[1] Analogues for each of these measures can be derived from standard theoretical models of international trade with input-output linkages, and we discuss how our measures compare with responses to bilateral trade shocks in the model of Adão et al. (2020) in Appendix A. Appendix Section D.2 shows that our main results are robust to alternate measures of exposure to tariffs, including measures based solely on tariff rates and measures that do not normalize by absorption or shipments.

industry-level capital intensity allow for similar differences for industries that vary in the extent to which they use labor or capital in their production activities.

We find that tariff increases enacted since early 2018 are associated with relative reductions in U.S. manufacturing employment and relative increases in producer prices. In terms of manufacturing employment, rising input costs and retaliatory tariffs account for the negative relationship, and the contribution from these channels more than offsets a small positive effect from import protection. For producer prices, the relative increases associated with tariffs are due primarily to the rising input cost channel. We find little evidence for a relationship between industrial production and any of the three tariff channels considered and provide evidence that this lack of a response is due to the historically high orders backlog that manufacturers built up in the two years prior to imposition of the tariffs.

In terms of economic significance, we find that shifting an industry from the 25th percentile to the 75th percentile in terms of exposure to each of these channels of tariffs is associated with a relative reduction in manufacturing employment of 2.7 percent, with the positive contribution from the import protection effects of tariffs (0.4 percent) more than offset by the negative effects associated with rising input costs (-2.0 percent) and retaliatory tariffs (-1.1 percent). For producer prices, we find that an interquartile shift in exposure to tariffs is associated with a 3.3 percent relative increase in factory-gate prices, which is primarily due to the rising input cost channel.

To consider potential broader effects of the tariffs beyond the manufacturing sector, we estimate the relationship between county-level labor force participation and unemployment rates and geographic measures of exposure to the three tariff channels. We find that counties with higher exposure to tariffs experience relative increases in unemployment rates and relative decreases in labor force participation. These findings suggest that workers who lose employment in the manufacturing sector due to tariffs are not readily absorbed into employment in other sectors.

Our results suggest that the traditional use of trade policy as a tool for the protection and promotion of domestic manufacturing is complicated by the presence of globally interconnnected supply chains and the retaliatory actions of trade partners. Indeed, we find the impact from the traditional import protection channel is completely offset in the short-run by reduced competitiveness from retaliation and especially by higher costs in downstream industries. As such, this is the first paper to document the interplay between these potentially offsetting channels and show that their net effect is a relative reduction in manufacturing employment. In addition, our results provide important context for the influential "China Shock" literature (Autor et al., 2013; Pierce and Schott, 2016; Autor et al., 2021), which has found that increased import competition from China was associated with substantial declines in manufacturing employment. Here, we find that attempts to decrease import competition and boost manufacturing employment via tariffs aimed primarily at China have, in the short run, been unsuccessful.

All results in this paper necessarily represent short-term effects of tariffs, and the longer-term implications may differ from those estimated here. For example, adjustment to the imposition of tariffs may take time as firms re-evaluate contracts and relationships with customers and suppliers. To a large extent, the longer-term effects of the tariffs will depend on firms' continuing evaluation of how long they are likely to remain in place. While a Phase One trade agreement between the U.S. and China in early 2020 temporarily halted the imposition of new tariffs, all of the tariffs examined in this paper remain in effect through early 2023. Moreover, with the tariffs now spanning two Presidential administrations and tensions between the U.S. and China remaining high, the prospect of their quick removal appears slim, highlighting their continued relevance for researchers and policymakers. A complication for considering the longer-term effects of the tariffs, however, is the onset of

COVID-19 and the associated disruption in international trade, particularly US-China trade.

This paper contributes to the evolving literature examining the effects of recent global trade tensions on the U.S. economy. Early work in this literature includes Amiti et al. (2019) and Fajgelbaum et al. (2020) who find near-complete pass-through of U.S. tariff increases to domestic prices, implying welfare losses, though of a relatively small magnitude. Cavallo et al. (2021) show that product composition appears to be a key determinant in the differences in tariff pass-through between U.S. imports and U.S. exports during the 2018-2019 tariff escalation, while also showing that the majority of U.S. tariff increases are being absorbed by U.S. retailers. Flaaen et al. (2020) examine the case of U.S. tariffs imposed on washing machines, showing that tariffs on individual countries can lead to the relocation of production across borders, while tariffs on broader sets of countries lead to substantial retail price increases for both targeted products and complementary goods.

Another example of the importance of the rising input cost channel is found in concurrent work by Handley et al. (2020) who find that U.S. import tariffs on inputs lead to reduced *exports* for firms in affected industries. While Handley et al. (2020) examines an indirect effect of tariffs on output, via exports, our paper provides a direct and comprehensive view of the effects of the tariffs on overall manufacturing activity, including the highly policy-relevant outcome of employment. Bown et al. (2020) also show that tariffs imposed since the 1980s have lowered sales and employment while increasing prices in downstream industries. Unlike these papers, which focus on the input cost channel, we estimate the relative magnitudes of the various ways that tariffs have impacted U.S. manufacturing and, ultimately, their net effect on the sector. Our results, therefore, highlight the importance of multi-directional global value chains and networks for evaluating the effects of tariffs (Antràs et al., 2017; Antràs and Chor, 2018; Alfaro et al., 2019; Bernard and Moxnes, 2018).

Focusing on geographic exposure to tariffs, Waugh (2019) finds that counties specializing in industries subject to Chinese retaliatory tariffs experience reductions in new auto sales, Goswami (2020) finds that commuting zones subject to higher retaliatory tariffs experience lower employment growth, with no effect from import protection, and Blanchard et al. (2019) show that retaliatory tariffs can explain a shift in voting away from Republican House candidates in the 2018 election. In terms of financial impacts, Huang et al. (2023) and Amiti et al. (2020) find that the effects of tariffs carry through to firms' financial performance, with firms more engaged in trade with China experiencing lower stock returns and, in turn, higher default risk and lower investment, respectively, after the announcement of new rounds of tariffs targeting China. Lastly, Reyes-Heroles et al. (2020) note that the effects of tariff actions by major trading countries can also have implications for the trade patterns of emerging market economies.

Although we highlight the recent and rapidly expanding literature on the 2018-2019 tariffs, the ideas of accounting for retaliatory tariffs and supply chain effects of tariffs go back decades. Early examinations of optimal tariffs given the potential for retaliation can be found in Kaldor (1940) and Johnson (1953). The counteracting effect of tariffs on intermediate inputs used in further domestic production—the rising input cost channel described above—was highlighted in Balassa (1965) and Corden (1966), and is present in a wide range of more recent empirical research such as Amiti and Konings (2007) and Topalova and Khandelwal (2011), among others.[2] However, the scale of the 2018-2019 tariffs, the increased availability of data, and the immensely expanded network of global supply chains permits a quantitative examination of these channels that has not been possible before.

Our paper makes several contributions to the existing literatures. First, we explicitly measure and estimate the effects of several channels through which tariffs could affect man-

[2] The effects of changes in tariffs on an industry's output—the import protection channel we examine—have been examined in an extensive empirical literature including, for example, Pavcnik (2002), Trefler (2004), Fernandes (2007), and Artuç et al. (2010).

ufacturing industries, which we find to be important given that tariffs can simultaneously protect an industry's output, while raising prices for its inputs, and subjecting it to retaliation in its export markets. Second, we focus specifically on the manufacturing sector, the sector whose output and employment were targeted to be boosted by tariffs, and find that the tariffs have been a drag on employment and have failed to increase output, providing context for decision-makers evaluating the efficacy of the tariffs. Third, we provide the first simultaneous examination of the output, employment, and price effects of the 2018-2019 tariffs in a particular sector, and highlight that the tariffs have been associated with price increases, even as they have failed to boost activity in the sector. And finally, we consider the possibility of spillover effects from the manufacturing sector to the broader economy and find that manufacturing workers who lose employment due to tariffs have not been quickly absorbed into employment in other sectors, as indicated by increases in unemployment and decreases in labor force participation in more-affected counties, consistent with findings for other trade shocks (e.g. Autor et al. (2013), Dix-Carneiro and Kovak (2017)).

The remainder of the paper proceeds as follows. Section 2 describes the timing of the relevant trade actions by the U.S. and its trading partners, lists data sources, and details the calculation of the three measures of exposure to tariffs. Section 3 presents our baseline empirical strategy, results, and robustness checks, and Section 4 examines potential spillovers from the manufacturing sector to the broader economy. Section 5 concludes.

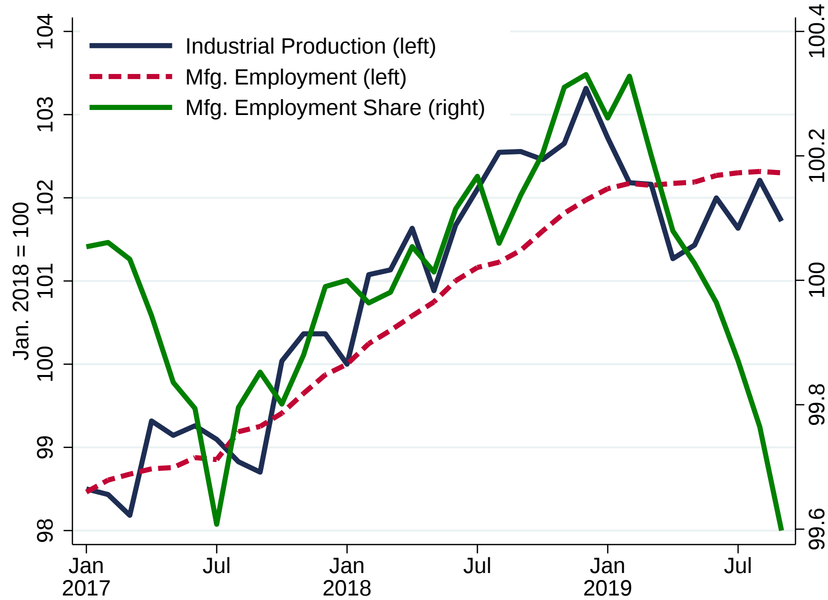
2 Background, Data, and Industry-Level Measurement

We begin by providing some brief background on trends in manufacturing activity in the period leading up to and during the imposition of tariffs. Figure 1 displays manufacturing production, employment, and the share of manufacturing in private employment from January 2017 to September 2019, with each data series converted to an index that equals 100 in January 2018, just before the imposition of the first round of new tariffs. As indicated in the Figure, manufacturing employment and output increased at a steady pace in 2017 and, indeed, through much of 2018. Toward the end of 2018, however, growth in manufacturing employment and output stalled. Moreover, the concomitant decline in the manufacturing share of employment indicates that the weakness in manufacturing employment was specific to that sector, as nonmanufacturing employment continued to grow steadily throughout this time period. Given the inflection point in manufacturing activity, which came after the imposition of substantial tariffs by the U.S. and its trading partners, it seems reasonable to ask whether the tariffs implemented in 2018 played some role in this manufacturing slowdown. Indeed, media and other anecdotal reports from the time are rife with worries about tariffs, especially among manufacturers. The Federal Reserve's July 2018 Beige Book, for example, notes that "[m]anufacturers in all Districts expressed concern about tariffs and in many Districts reported higher prices and supply disruptions that they attributed to the new trade policies," while the September 2018 version reports that "[t]ariffs were reported to be contributing to rising input costs, mainly for manufacturers."

2.1 Timing and Features of U.S. and Retaliatory Tariffs

To evaluate the effects of recent tariffs, it is first important to understand their timing, their scope, and the characteristics of products targeted by tariffs. The tariffs imposed by the U.S. and its trading partners since 2018 can be classified under three separate actions, with the largest round of U.S. tariffs occurring in late September 2018. As described in detail below, Figures 2a and 2b display the magnitude and timing of these three trade actions, and Figure 3 shows that U.S. tariffs were focused overwhelmingly on the intermediate and

Figure 1: Measures of Manufacturing Activity: Jan. 2017 to Sep. 2019



Sources: Federal Reserve Board (FRB) for industrial production; U.S. Department of Labor, Bureau of Labor Statistics for employment.
Notes: Figure displays manufacturing industrial production, manufacturing employment, and the manufacturing share of private employment, each indexed to be 100 in January 2018.

capital goods used by U.S. manufacturers in their production processes.

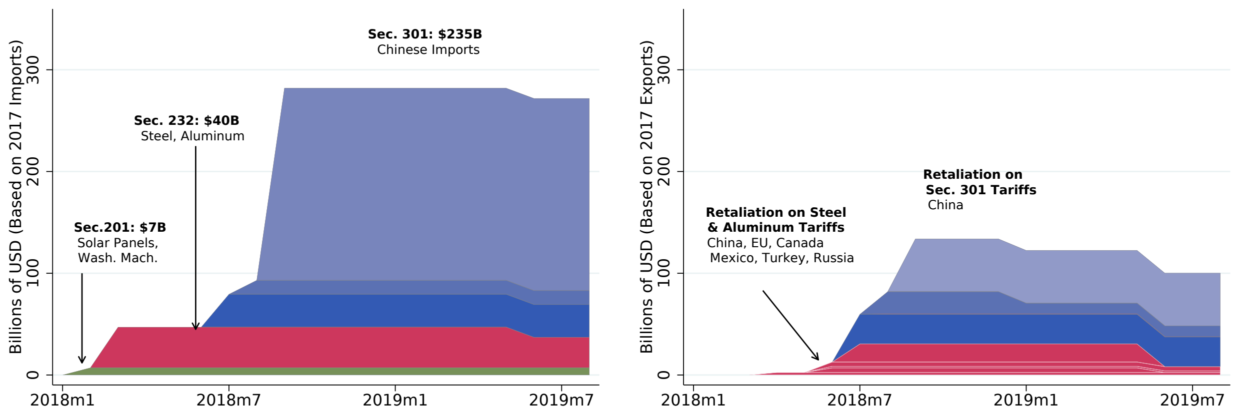
2.1.1 U.S. Import Tariffs

Figure 2a displays the magnitude and timing of the three main U.S. tariff actions—which were initiated by the U.S. government, as opposed to being requested by industries or firms—in 2018 and 2019. The first of these actions, shown in green, entailed "Section 201" tariff rate quotas with effective rates of around 30 percent, which were enacted in February 2018 against imports of washing machines and solar panels from all countries. The second major tariff action, shown in red, affected steel and aluminum imports beginning in March 2018. These rarely-used "Section 232" tariffs, which were justified on national security grounds, were applied at 25 percent on steel and 10 percent on aluminum, and covered nearly all countries, with limited exceptions. The third and most significant action—shown in shades of blue—followed a "Section 301" investigation that concluded that certain Chinese intellectual property and technology transfer policies were illegal under U.S. trade law. The original U.S.

tariffs resulting from this investigation were imposed in July 2018 and covered $34 billion of imports from China at a 25 percent rate. However, in a series of back-and-forth retaliations between the U.S. and China, the U.S. expanded the list of covered imports by $16 billion in August and then by nearly $200 billion in September. This latter round of U.S. tariffs was initially imposed at a rate of 10 percent, which was later raised to 25 percent in May 2019.

Figure 2: Timeline of New Tariffs Imposed: 2018-2019

(a) New U.S. Import Tariffs **(b)** Retaliatory Tariffs on U.S. Exports

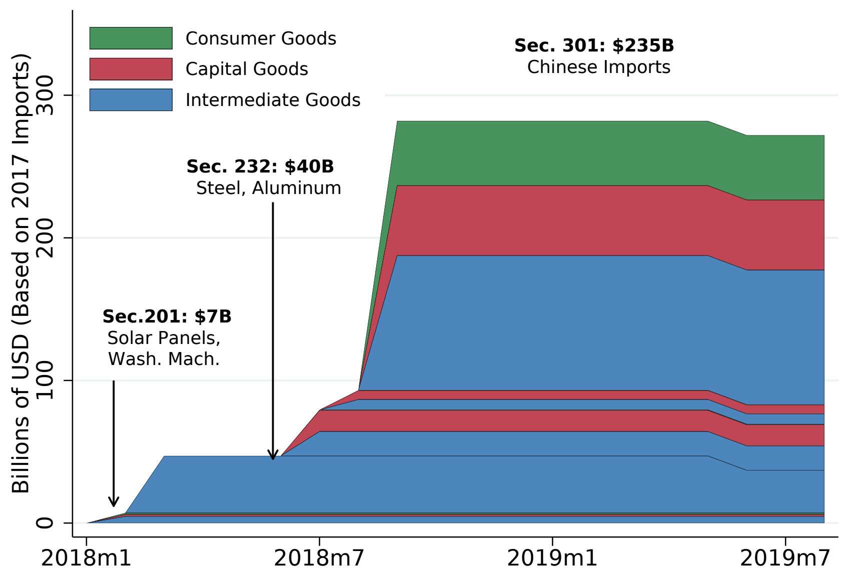


Sources: United States International Trade Commission (USITC) for 2017 import and export values.
Notes: See Tables B1 and B2 for details on the set of relevant products and trade values. In Panel (2a), the decline in mid-2019 reflects Canada and Mexico being removed from the steel and aluminum tariffs.

2.1.2 Retaliatory Tariffs

U.S. trading partners responded to these actions with retaliatory tariffs on U.S. exports, which are summarized in Figure 2b. As shown in red, in response to the Section 232 tariffs on steel and aluminum, China announced tariffs on U.S. exports in April of 2018, while other countries imposed retaliatory tariffs in June and July. In response to the Section 301 tariffs, China imposed retaliatory tariffs in three phases shown in shades of blue. The equal scale of the axes in the two panels makes clear that the value of U.S. exports subject to retaliatory tariffs was substantially smaller than the value of U.S. imports subject to U.S. tariffs.

Figure 3: 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).

2.1.3 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 (see also Bown et al. (2019b) for a similar breakdown). As shown in Figure 3, 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). Recalling the prominence of imported inputs among the set of goods subject to tariffs will be helpful when considering the effects of the three channels of tariffs in Section 3.

Lastly, 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.

2.2 Data and Measurement

This section describes the data sources and measurement for the empirical analysis presented in Section 3. We use publicly available data on the lists of products covered by U.S. import tariffs and foreign retaliatory tariffs.[3] For U.S. tariffs, product lists are from the United States Trade Representative and the U.S. Federal Register. For retaliatory tariffs by U.S. trade partners, data are drawn from the relevant government agencies including the Canadian Department of Finance, the European Commission, as well as the World Trade Organization. These lists of affected products have been helpfully collected by other researchers who have made them available for public use.[4] Table B1 provides links to all lists of affected products.

We map the Harmonized System (HS) codes covered by tariffs described above 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

[3] We use statutory rather than effective tariff rates for several reasons. Statutory rates are the salient policy change influencing firm behavior, and measures of effective tariff rates for export retaliation aren't readily available. For more discussion, including the prospect of tariff exemptions affecting our analysis, see Appendix B

[4] See, for example, Bown and Kolb (2019) and the website maintained by the Crowell-Moring International Trade law firm.

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 evaluate the validity of the assumption in Appendix B and find that it is justified, because the value of U.S. exports that we classify as being covered by retaliatory tariffs lines up extraordinarily well with those announced by U.S. trade partners (USD 185.9 billion with our approach; USD 185.7 billion in government announcements), as well as those calculated by other researchers.

Our measures of exposure to the various rounds of tariffs imposed by the U.S. and its trading partners also require industry-level data on the value of overall imports, exports and shipments. We collect data on the dollar value of U.S. imports and exports from the USITC and on industry shipments from the Annual Survey of Manufactures (ASM) for a pre-tariff year, 2016. Data on the input usage of each industry are drawn from the BEA's detailed input-output tables for 2012.[5]

Lastly, we draw monthly values of the dependent variables for our analysis—industry output, employment, and producer prices—from three sources. Our measures of monthly industry output come from the Federal Reserve's G.17 Release on Industrial Production and Capacity Utilization. For monthly data on employment at the industry-level, we utilize data from the Current Employment Statistics (CES) program of the Bureau of Labor Statistics. Finally, we use the producer price index, also from the Bureau of Labor Statistics, to measure

[5]We use the NAICS-IO concordance provided by BEA as the foundation for further concording of these detailed codes to both our industry measures and our commodity trade measures.

monthly changes in prices across industries. As mentioned above, our sample extends from January 2017 to September 2019. A key feature of these data, relative to confidential plant- and firm-level data from the Census Bureau, is their higher frequency (monthly). By contrast, to study output and employment outcomes with Census Bureau data, one would have to rely on the ASM, which provides *annual* information and hence would not be ideal for observing the timing of higher-frequency responses to tariffs, the goal of this paper. This limitation would be particularly problematic for 2018 when tariffs were only imposed for portions of the year that differed by industry.

2.3 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).[6] 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.[7] While there is almost certainly heterogeneity in the extent of exposure to each of the three tariff channels for the finer

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

[7] 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.

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.

2.4 Industry-Level Measures of Trade Policy Impact

This section describes the measures we construct to quantify the industry-level effects of the trade policies enacted by the U.S. and its trading partners since 2018. A range of theoretical models that involve input-output linkages could be used to motivate the channels we highlight empirically below. We describe one useful example from Adão et al. (2020) in detail in Appendix A and discuss how their measures of the various responses to bilateral trade cost shocks compare with the measures we employ.[8] Our focus in constructing these measures is capturing the effect of realized changes in tariffs on forces likely to affect outcomes in the manufacturing sector, including the amount of import competition in the U.S. market, the competitiveness of U.S. exports in foreign markets, and input costs. In particular, we construct three industry-level measures capturing each of these channels of potential trade policy impact. As shown by the densities displayed in Appendix Figure C1, the three measures of exposure to tariffs we construct vary substantially across industries, driven by variation in the share of imports of each product sourced from or exported to China, the share of products within an industry subject to US or retaliatory tariffs, the tariff increase applied to U.S. imports or exports, and, in the case of the rising input cost channel, the intensity with which each input is used in the production process. Appendix Tables C3 and C4 provide unweighted and weighted summary statistics for the three exposure measures.

[8]In addition, we show in Section D.2 of the Appendix that our main results are robust to alternate measures of exposure to tariffs, including measures based solely on tariff rates and measures that do not normalize by absorption or shipments.

Import Protection

One of the most salient ways that tariffs could affect an industry's economic activity is by restricting foreign competition. Let Ω^I be the list of U.S. imported product-country pairs (pc) subject to new tariffs. The variables imp_i and exp_i identify total industry i imports and exports, and Q_i equals domestic production, each measured as of 2016. $\Delta\tau_{ipc}$ is the change in the tariff rate (in percentage points) for a particular trade policy action from the beginning to end of our sample period. Using these definitions, our measure of import protection is given by:

$$\text{Import Protection}_i = \frac{\sum_{pc \in \Omega^I} imp_{ipc} \Delta\tau_{ipc}}{Q_i + imp_i - exp_i}, \tag{1}$$

As indicated in the equation, this measure is calculated for each industry, i, by summing the value of tariff-affected imports from country c of product p, dividing that sum by the value of domestic absorption, and then multiplying the value of those imports by the applicable increase in tariff rates.[9] Throughout the remainder of the paper, we refer to this measure as an industry's degree of "import protection" from tariffs. In our baseline analysis, we calculate equation (1) based on the cumulative set of products covered by all tariffs described in Section 2.1, and define $\Delta\tau_{ipc}$ based on the tariff rates in effect at the end of our sample period.[10] Appendix Table C5 lists the top ten industries for this measure of new import protection, and Panel (a) of Appendix Figure C1 displays its distribution across industries.

[9] Equation (A4) in Appendix A is an example of a model-derived analogue of this measure from an extension of Adão et al. (2020) (see Appendix C.5).

[10] Measures of export retaliation and rising input costs are also based on the cumulative set of tariffs. In Appendix D.16 we describe additional results in which we calculate separate measures of import protection for each individual wave of tariffs.

Export Retaliation

While U.S. tariffs may reduce competition for some industries in the domestic market, U.S. trading partners responded to these tariffs by imposing retaliatory tariffs. These retaliatory tariffs may harm U.S. manufacturers by decreasing their competitiveness in foreign markets.

We measure this potential effect for each industry as the value of U.S. exports subject to new retaliatory tariffs, multiplied by the applicable increase in tariff rates, and divided by the value of U.S. output. In particular, defining Ω^E to be the list of U.S. exported product-country pairs (pc) subject to retaliatory tariffs, we calculate a measure of an industry's exposure to "export retaliation" as the following:[11]

$$\text{Export Retaliation}_i = \frac{\sum_{pc \in \Omega^E} exp_{ipc} \Delta \tau_{ipc}}{Q_i}. \tag{2}$$

The ten industries most affected by new export retaliation tariffs are shown in Appendix Table C6, with the industry-level distribution shown in Panel (b) of Appendix Figure C1.

Rising Input Costs

The final channel we study traces the impact of U.S. tariffs on input costs via supply chain linkages with foreign countries. The principal data on an industry's sources of inputs used in U.S. production come from the "use" table of the Bureau of Economic Analysis's (BEA) input-output tables. This table consists of a matrix with elements use_{ij}—the dollar value of commodity j used in industry i production. With information on industry i's use of total intermediate inputs M_i and compensation of employees $Comp_i$, it is straightforward to

[11] Adão et al. (2020) contains an analogous expression (see equation (A2) in Appendix A).

construct a matrix SC_{ij} with the share of input costs of commodity j in industry i:

$$S_{ij} = \frac{use_{ij}}{M_i + Comp_i}, \tag{3}$$

Then, we define IS_j as the import share of domestic absorption of commodity j:

$$IS_j = \frac{imp_j}{Q_j + imp_j - exp_j}, \tag{4}$$

where here the variables imp_j, Q_j, and exp_j are imports, output, and exports of commodity j, respectively. By multiplying the terms from equations (3) and (4) we arrive at the import share of costs in industry i from commodity j.[12] Summing across commodities j yields the total import share of costs for industry i. This implied import share of costs is given by:

$$\begin{aligned} ISC_i &= \sum_j ISC_{ij} \\ &= \sum_j \underbrace{\frac{use_{ij}}{M_i + Comp_i}}_{\substack{\text{product share} \\ \text{of costs}}} \underbrace{\frac{imp_j}{Q_j + imp_j - exp_j}}_{\substack{\text{product import} \\ \text{share}}} . \end{aligned} \tag{5}$$

As mentioned above, we use data from the "use" table in the BEA's benchmark 2012 input-output tables, updated with 2016 information on values of imports and shipments to calculate the import shares in equation 4.[13]

Finally, we construct our measure of exposure to rising input costs as the share of an industry's costs that is covered by new U.S. import tariffs, multiplied by the corresponding

[12] Without additional detail on the sources of inputs across industries, here we must use the "proportionality assumption," i.e. that the distribution of the uses of imported commodities in an industry is proportional to overall commodity usage.

[13] We are only able to update the shares in equation (4) for manufactured goods, as annual output measures for non-manufacturing commodities are unavailable. For non-manufacturing commodities, we use the 2012 shares from the input-output tables.

change in tariff rates as follows:

$$\text{Rising Input Costs}_i = \sum_j \frac{use_{ij}}{M_i + Comp_i} \frac{\sum_{pc \in \Omega^I} imp_{jpc} \Delta\tau_{jpc}}{Q_j + imp_j - exp_j}, \tag{6}$$

where, as before, the term Ω^I denotes the list of U.S. imported product-country pairs (pc) subject to new tariffs, and $\Delta\tau_{jpc}$ represents the relevant change in tariff rates.[14] Appendix Table C7 lists the top U.S. industries in terms of exposure to increased costs from recent input tariffs, again based on the cumulative effects from all new tariffs in our sample period, with the industry-level distribution shown in Panel (c) of Appendix Figure C1.

3 Short-Run Impacts of Tariffs on Manufacturing

This section discusses the generalized difference in differences empirical strategy we use to estimate the relationship between recent tariffs and outcomes in the manufacturing sector and presents our baseline results.

3.1 Empirical Strategy

Some industries may be highly protected with respect to their output, while also being highly subject to tariffs on their inputs or exports, underscoring the need for a systematic approach to disentangle the impacts of tariffs on the manufacturing sector. In particular, the weighted (unweighted) correlation coefficient is 0.37 (0.39) for rising input costs and import protection, 0.08 (0.07) for rising input costs and export retaliation, and 0.24 (0.23) for import protection and export retaliation. As a result, any univariate relationship between an outcome measure and one of the channels identified above could end up conflating multiple,

[14] In a similar way to the other measures, Appendix A provides theoretical background for this measure, and highlights equation (A6) as a model-derived analogue to equation (6). One interpretation of this measure is as a re-weighted version of the import protection channel. We explore the implications of this interpretation in Appendix D.3.

potentially offsetting effects on an industry. Therefore, we will control for all channels of exposure to tariffs in our baseline specification, allowing us to calculate estimates of the effect of each channel holding the others constant.[15]

We adopt a flexible setup that allows the effects of each of the channels to vary over time. In particular, we interact the industry-level measures for each of the tariff channels with a full set of month dummies. This approach allows us to observe the exact timing of any change in trend associated with the three tariff channels and subsequently control for any pre-trends in outcome variables across industries. Recognizing that industries with varying exposure to international trade may respond differently to shocks even in the absence of changes in trade policy, we include additional controls that account for a baseline level of export exposure, import exposure, input cost exposure, and capital intensity for each industry.[16] These controls account for general exposure to international conditions such as changes in the value of the dollar and foreign GDP growth, as well as allowing for the possibility that industries with different levels of exposure to trade and capital intensity behave differently at different points in the business cycle. Our estimating equation is given by:

$$\begin{aligned} y_{it} = \quad & \alpha + \sum_t \gamma_t \mathbf{1}(M_t = t)(\text{Import Protection}_i) + \sum_t \lambda_t \mathbf{1}(M_t = t)(\text{Export Retaliation}_i) \ \ldots \\ & + \sum_t \theta_t \mathbf{1}(M_t = t)(\text{Input Cost}_i) + \sum_t \Big(\mathbf{1}(M_t = t) \times \mathbf{X_i'}\boldsymbol{\beta}_\mathbf{t}\Big) + \delta_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{7}$$

where the outcome of interest, y_{it}, is either log employment, log output, or the log of the pro-

[15] Section D.15 of the Appendix provides equivalent results in which the dependent variables are regressed separately on each individual tariff channel measure. The results highlight the importance of estimating the effects of all tariff channels simultaneously.

[16] Our export exposure measure is the export share of output, our import exposure measure is the import share of domestic absorption, and our import cost exposure is the fraction of an industry's input costs coming from imported goods. Each of these measures is calculated using data from 2016. Input cost shares are from the 2012 detailed input-output tables. Our measure of the capital intensity of each industry is the capital per worker as measured by the NBER CES Manufacturing Industry Database.

ducer price index of industry i in time t. The $\mathbf{1}(M_t = t)$ terms indicate a set of month dummies (spanning February 2017 to September 2019). Import Protection$_i$, Export Retaliation$_i$, and Input Cost$_i$ are the three tariff channel measures described above, and the term $\mathbf{X_i'}$ contains the general controls for international conditions (including overall import share of absorption, export share of output, and import cost share) as well as capital intensity. The δ_i and δ_t terms are industry and month fixed effects, respectively. Standard errors are calculated using clustering at the three-digit NAICS level.

3.1.1 Assignment of Tariffs

One concern with this approach is the potential for tariffs to have been assigned to specific industries based on trends in the dependent variables we examine, i.e., employment, production, or prices. Several aspects of how the 2018-2019 tariffs were determined, however, make detailed targeting of industries based on these outcomes unlikely, and our treatment of tariffs in equation (7) is consistent with that in the existing literature (i.e. Fajgelbaum et al. (2020) and Cavallo et al. (2021)). First, the bulk of the 2018-2019 tariffs resulted from investigations initiated *by the U.S. government* for the purpose of addressing longstanding complaints against trading partners, especially treatment of intellectual property in China. This process stands in contrast to that associated with temporary tariffs like antidumping duties, where industries experiencing negative shocks apply for assistance from the government. Second, the tariffs imposed were largely uniform—91 percent of the value of targeted imports was subject to a 25 percent ad valorem duty rate—and covered broad groups of industries, with nearly all imports from China ultimately subject to tariffs. Third, tariff lists were assembled quickly, with the timing of tariffs imposed and magnitude of trade covered largely determined by the tit-for-tat responses of U.S. trading partners, particularly China.

One particular concern is that tariffs may have been assigned based on political economy considerations to reward preferred or politically connected industries. Assessing this possibility, Fajgelbaum et al. (2020) highlight the generally uniform level of tariffs granted across industries, as well as a somewhat negative relationship between industry-level protection and campaign contributions, and conclude that "...tariff changes are unlikely to have been driven by specific interest groups." A feature of our focus on the separate effects of three tariff channels is that it provides additional evidence relevant to considering the role of political economy considerations in the government's tariff setting. In particular, the most likely way that the government might try to protect particular industries would be by providing import protection to industries experiencing positive or negative shocks, which would manifest as pre-existing trends in terms of our outcome variables of employment, output, or prices for industries more exposed to the import protection channel.[17] Importantly, however, Figure 4 indicates a lack of pre-trends for the import protection channel for all three outcome variables, which is confirmed in a formal hypothesis test in Section D.6 of the Appendix. In sum, while products subject to tariffs were clearly not chosen randomly, there is substantial evidence that they were chosen primarily based on strategic considerations of the tariff escalation, rather than on short-run industry-specific trends in employment, output, or prices.

3.1.2 Accounting for Pre-Trends

Another feature of difference in differences analysis is the need to address differing trends across industries prior to the implementation of new tariffs, which we find to be important in our analysis. To illustrate the relevance of accounting for pre-trends in this setting, Figure 4 presents results from estimating equation (7) in unadjusted form. The three panels of the figure display coefficient estimates and 90 percent confidence intervals for the interactions of

[17] It seems much less likely that the U.S. government would be in the position to assign tariffs based on trends in input costs, especially given the rapid rollout of rounds of tariffs described above.

the tariff channel measures with month dummies for the dependent variables of employment (Panel (a)), IP (Panel (b)), and producer prices (Panel (c)). Estimates are weighted by either December 2017 employment (for employment) or value-added (for IP and PPI).

Two aspects of the results stand out. First, we find evidence of differing pre-trends across industries prior to the introduction of tariffs, which appear, for example, as the pre-tariff upward trend in coefficient estimates for the relationship between exposure to rising input costs and employment in the right column of Panel (a).[18]

Second, the figure highlights clear breaks in pre-existing trends that occur at the time that tariffs are put into place, as seen by the flattening and ultimate decline in coefficient estimates in the same right column of Panel (a). As discussed in Finkelstein (2007), it is these *breaks in trend* that represent the impact on the outcome variables attributable to the change in policy.

Therefore, in our baseline results, we utilize two approaches to explicitly account for these pre-trends in our baseline results, each of which yields similar results. First, we estimate equation (7) and then follow Finkelstein (2007) by differencing out the pre-trend path for each coefficient, thereby arriving at a point estimate that isolates the impact of each tariff channel, net of any pre-existing trends. Specifically, for a given set of coefficients (say, the γ_t coefficients above) we calculate the following:

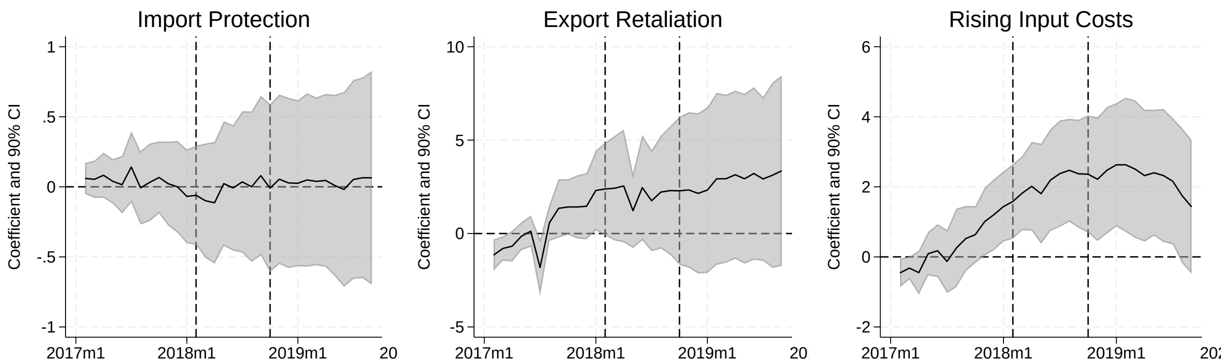
$$\Delta y_{it}^{\gamma} = \quad (\overline{\gamma}_{\text{Jul-Sep19}} - \overline{\gamma}_{\text{Dec17-Feb18}}) - \kappa(\overline{\gamma}_{\text{Dec17-Feb18}} - \overline{\gamma}_{\text{Feb17-Apr17}}). \tag{8}$$

This calculation compares changes in average coefficients over two periods: A post-tariff period spanning just before tariffs were put in place (December 2017 - February 2018) to the final three months of our sample (July-September 2019); and a pre-tariff period from the

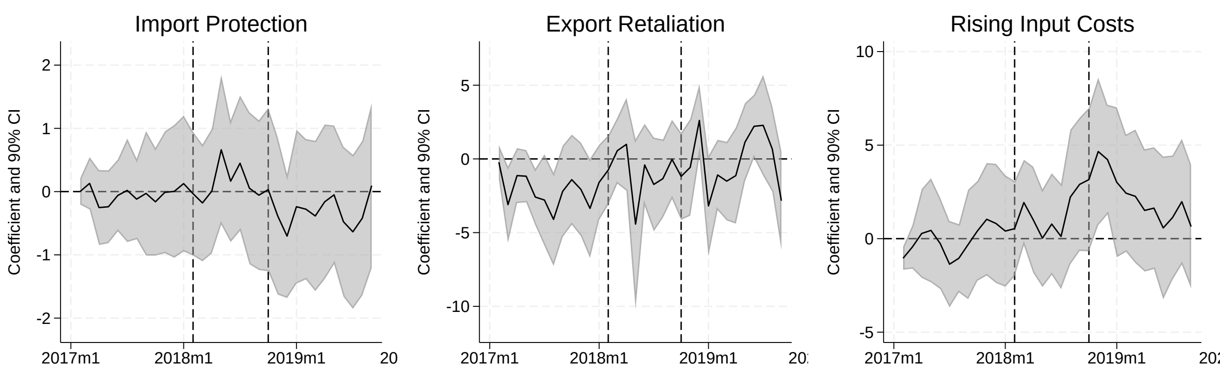
[18]Appendix Section D.6 formally tests for the presence of pre-trends and finds that they are present for the rising input cost and export retaliation channels for both the employment and PPI regressions.

Figure 4: Effects of Cumulative Tariffs, Non-Detrended Outcome Variables

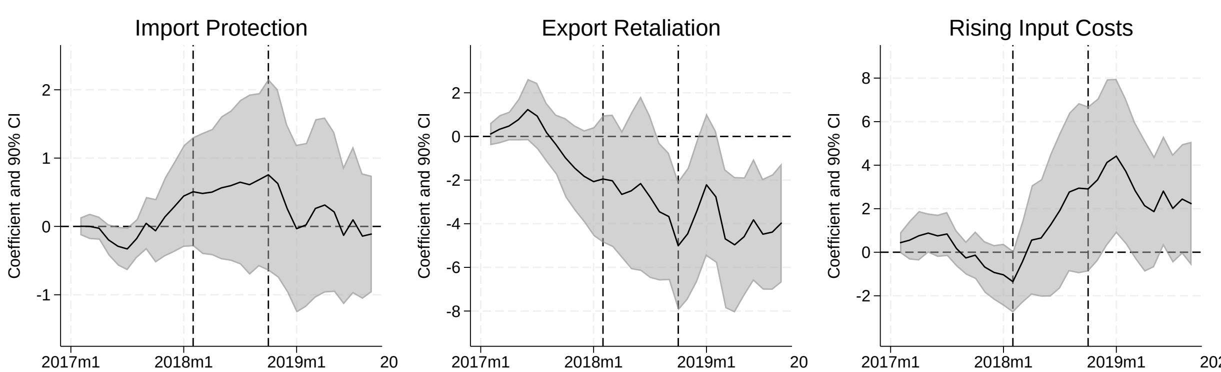
(a) Employment



(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 results of a separate regression for the noted dependent variable, with each column corresponding to the three tariff channels in equation (7). Solid lines indicate coefficient estimates and shaded areas represent 90 percent confidence intervals. The two vertical dashed lines are at February 2018 and September 2018, the times of the first and last waves of 2018 tariffs we study. 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.

start of the sample (February - April 2017) to just before tariffs were put in place (December 2017 - February 2018). The κ term adjusts for the differing lengths of the post-tariff and pre-tariff periods.

Second, as an alternative approach for netting out pre-trends, we replace the outcome variable y_{it} in equation 7 with the equivalent measure after removing an industry-specific linear trend for the period from January 2017 to January 2018, the last full year before the implementation of new tariffs. One attractive feature of this approach is that it allows us to observe the precise timing of any change in relationship between exposure to the tariff channels and manufacturing outcomes.

We note that estimated results in Section 3.2 should be interpreted as short-term effects of tariffs, both in terms of the duration of outcomes we observe after tariffs are put in place, as well as the comparison with the pre-existing trend. Appendix Section D.7 describes the manufacturing trends in the pre-period, estimates a placebo test during a pre-tariff period, and provides estimates with an extended pre-tariff period.

3.2 Results

This sub-section provides baseline results accounting for the presence of pre-trends. Table 1 reports estimates from the Finkelstein (2007) approach (equation 8) and Figure 5 presents results of estimating equation (7) with de-trended dependent variables.

Estimates for employment are reported in column 1 of Table 1 and Panel (a) of Figure 5. As shown in the first column of the table, we find statistically significant relationships between manufacturing employment and all three tariff channels, with each relationship taking the expected sign. First, we find a negative and highly statistically significant relationship between manufacturing employment and exposure to the rising input cost channel capturing tariffs on imported inputs. The timing of this impact is shown in Figure 5 (right column of Panel (a)) as a downward shift of coefficient estimates following the imposition of tariffs. Table 1 also reveals a negative and statistically significant relationship between exposure to export retaliation and manufacturing employment, which appears as a downward turn of coefficient estimates in the middle column of Panel (a) of Figure 5. Lastly, we find a positive and marginally statistically significant relationship between import protection and employment in Table 1, which manifests itself as a subtle and imprecisely estimated shift up in coefficient estimates once tariffs begin to be imposed in the left column of Panel (a).[19] The results in Panel (a) of Figure 5 also indicate intuitive differences in the timing of observed effects for each of the channels. Coefficient estimates for the retaliatory tariff channel begin to shift almost immediately after those tariffs are imposed, while the relationship with exposure to rising input costs takes longer to appear given that these effects only arise as the impacts of tariffs are passed through supply chains.[20]

We calculate the economic significance of these estimates by comparing an industry at the 75th percentile of exposure to the three tariff channels to an industry at the 25th percentile, where these and other summary statistics are reported in Section C.1 of the Appendix.[21] In this comparison, the industry more exposed to the rising input cost channel experiences a relative reduction in manufacturing employment of -2.0 percent, relative to the less exposed industry. Including the other two channels boosts this effect to a -2.7 percent relative reduction in manufacturing employment, as the negative contribution from retaliatory tariffs (-1.1 percent) more than outweighs the (somewhat less precisely estimated) positive contribution from the import protection effect (0.4 percent). Another way of calculating the

[19] Appendix Section D.5 reports results of an alternative specification in which the dependent variable is transformed to first differences. Estimates are qualitatively similar to those reported here.

[20] As discussed in Appendix Section D.8, our measurement of industries' tariff exposure based on *cumulative* tariffs imposed over the sample period side-steps some of the main concerns of staggered treatment highlighted in Goodman-Bacon (2021) and Callaway and Sant'Anna (2021).

[21] As an alternative approach to expressing economic significance, Section D.9 of the Appendix presents standardized coefficient estimates, which report the changes in the dependent variables (measured in standard deviations) associated with one standard deviation changes in the independent variables.

economic significance of these estimates is to consider the effect of shifting to an alternative scenario with zero tariff exposure. This scenario indicates that exposure to rising input costs is associated with a 1.8 percent relative decrease in employment (or around 230,000 jobs); incorporating the other two channels increases the estimated effect to 2.6 percent (or around 320,000 jobs).[22] A test of joint significance of the three tariff channel variables similarly indicates a negative and statistically significant relationship with employment.

While these alternative estimates do not account for additional general equilibrium effects that might be associated with the tariffs, which have been examined in existing work by Fajgelbaum et al. (2020), exploratory work in Appendix D.18 suggests such effects may amplify the negative effects. Indeed, contrary to results found elsewhere, Appendix D.18 does not find significant positive impacts coming from the import protection channel when also accounting for general equilibrium effects.

Column 2 of Table 1 and Panel (b) of Figure 5 present estimates pertaining to the relationship between tariffs and industrial production. Here, we see little evidence of significant impacts from the tariffs. Estimates in column 2 of Table 1 are not statistically different from zero, and coefficients displayed in Figure 5 are little-changed, on net, following the imposition of tariffs. As discussed in Appendix Section D.11, we find evidence that the difference is due to the presence of historically high orders backlogs for manufacturers before the tariffs were put in place, which supported production in the short term.

Finally, column 3 of Table 1 indicates that new tariffs are associated with a statistically significant relative increase in producer prices due to exposure to rising input costs.[23] In terms of economic significance, an interquartile shift in exposure to rising input costs is

[22] In Section D.10 of the Appendix, we perform a similar exercise for all three dependent variables in which we multiply the coefficient estimates from Table 1 by each industry's actual exposure to the three tariff channels and plot the distribution of the net estimated effects across industries. This approach yields highly similar estimated net effects of tariffs. Another exercise in Section D.13 of the Appendix compares our estimates of the magnitude of the rising input cost channel to those based on existing work.

[23] The joint test statistic for the three tariff exposure measures is also positive and statistically significant.

Table 1: Point Estimates of Cumulative Effect by Channel

Variable	Employment	Industrial Production	Producer Prices
Import Protection	0.310*	-0.491	-1.266
	(0.171)	(1.004)	(0.758)
Export Retaliation	-4.479**	2.714	1.954
	(1.679)	(2.380)	(3.868)
Rising Input Costs	-3.085***	-1.216	6.538***
	(0.867)	(2.690)	(1.888)
Test of Joint Significance	-7.255***	1.026	7.225**
	(1.966)	(2.473)	(3.444)
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

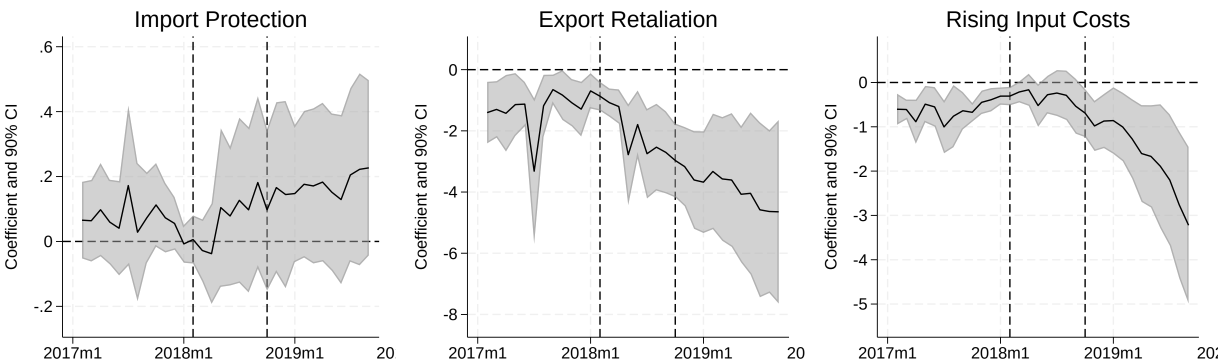
Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach presented in equation (8) in the text, along with the test statistic for a test of the joint significance of all three tariff channels. Results are weighted by December 2017 employment (for employment regression) or value added (for IP and producer prices). Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

associated with a 3.9 percent relative increase in factory-gate prices. Including the other statistically insignificant channels implies a 3.3 percent relative increase in factory-gate prices. These results are consistent with Amiti et al. (2019) who find a role for input tariffs, in addition to tariffs on output, in increasing U.S. prices. In terms of timing, the right column of Panel (c) of Figure 5 indicates that the positive relationship between exposure to rising input costs and producer prices becomes apparent almost immediately after the first round of U.S. tariffs is imposed.[24]

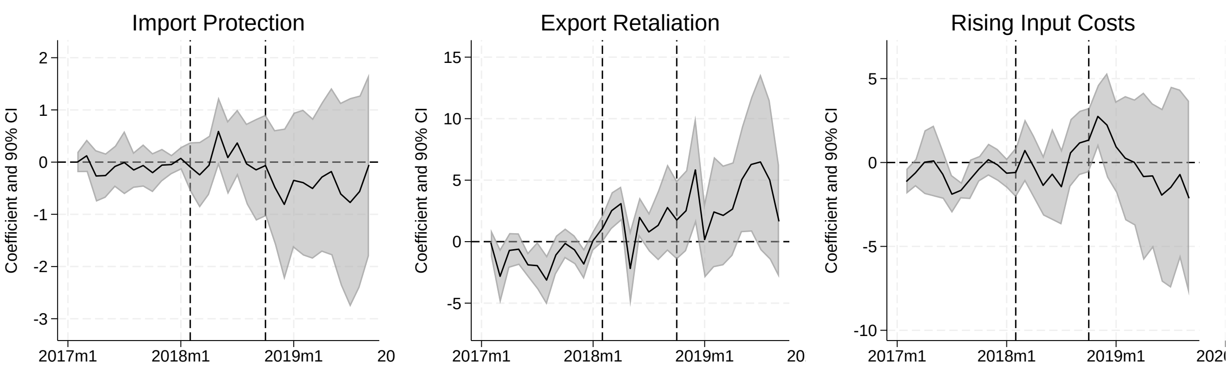
[24] The results in Table D19 of Section D.15 of the Appendix highlight the importance of controlling for all three tariff channels simultaneously. For example, while there is a positive and nearly statistically significant univariate relationship between the import protection channel and producer prices, that relationship is not present once we control for the stronger impact of the rising input cost channel.

Figure 5: Effects of Cumulative Tariffs (Detrended)

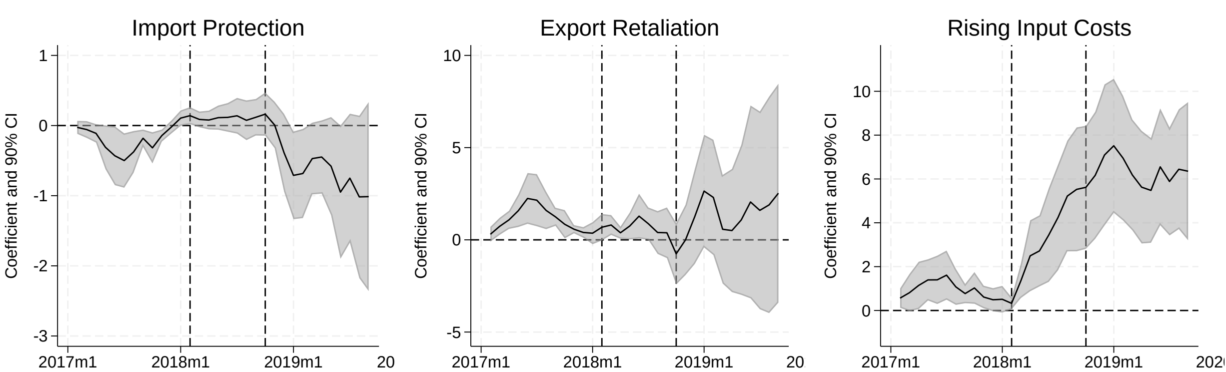
(a) Employment



(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 results of a separate regression for the noted detrended dependent variable, with each column corresponding to the three tariff channels in equation (7). Solid lines indicate coefficient estimates and shaded areas represent 90 percent confidence intervals. The two vertical dashed lines are at February 2018 and September 2018, the times of the first and last waves of new 2018 tariffs. Results are weighted by December 2017 employment (for employment regression) or value added (for IP and producer prices). Standard errors are clustered at the three-digit NAICS level.

3.3 Robustness Checks

In this section, we consider a range of robustness checks designed to examine the sensitivity of the baseline results. As described below, results are stable across a range of specifications that include controlling for trade policy uncertainty, dropping some or all of the control variables included in the baseline, and clustering of standard errors at different levels. Results for employment are reported in Table 2, with the baseline estimates from Table 1 replicated in column 1 for comparison. Results for other dependent variables are available on request.

Trade Policy Uncertainty: Much of the discussion of the effects of the 2018-2019 tariffs has focused on the role of uncertainty about trade policy (Caldara et al. (2019)), and a recent literature has documented substantial effects on economic activity of trade policy uncertainty and its resolution, particularly with respect to U.S.-China trade (Pierce and Schott (2016), Handley and Limao (2017), Crowley et al. (2018), Alessandria et al. (2019), Bianconi et al. (2021)). Here, we explore the effects of augmenting equation (7) with a commonly-cited measure of trade policy uncertainty related to the 2018-2019 tariffs from Caldara et al. (2019).

Caldara et al. (2019)'s measure of trade policy uncertainty is based on a textual analysis of the quarterly earnings calls of publicly traded U.S. firms. After classifying firms according to their Fama-French 12 industry definition, Caldara et al. (2019) measure the frequency of references to trade policy and uncertainty-related terms by industry, for each quarter. Because Caldara et al. (2019)'s measure of trade policy uncertainty is only defined through the second quarter of 2019, our analysis in this robustness check ends in June 2019, versus September 2019 in our baseline results. Results are presented in column 2 of Table 2.

As indicated in column 2 of the Table, relationships between realized tariff changes and employment when controlling for trade policy uncertainty are highly similar to the baseline

Table 2: Robustness Checks

	Dep. Var: Log Employment						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Import Protection	0.31*	0.225	0.304	0.52***	0.516***	0.31	0.31**
	(0.171)	(0.159)	(0.21)	(0.16)	(0.16)	(0.305)	(0.138)
Export Retaliation	-4.479**	-3.553**	-4.821***	-3.148	-3.283	-4.479**	-4.479***
	(1.679)	(1.429)	(1.678)	(2.345)	(2.277)	(2.184)	(0.875)
Rising Input Costs	-3.085***	-1.942***	-2.876***	-3.045***	-2.982***	-3.085***	-3.085***
	(0.867)	(0.616)	(0.842)	(0.86)	(0.83)	(0.92)	(0.699)
Trade Policy Uncertainty		-0.01					
		(0.024)					
Intl. Exposure Controls	Yes	Yes	Yes	No	No	Yes	Yes
Cap. Intensity Controls	Yes	Yes	No	Yes	No	Yes	Yes
Clustering	N3	N3	N3	N3	N3	N4	N3, Mo.
Observations	2,508	2,508	2,508	2,508	2,508	2,508	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 (8) in the text. For trade policy uncertainty, the table displays the coefficient estimate and standard error of the time-varying industry-level measure of trade policy uncertainty based on Caldara et al. (2019). Column 1 reproduces the baseline estimates from Table 1, and column 2 adds the control for trade policy uncertainty. Columns 3 through 5 vary the sets of control variables included, and columns 6 and 7 consider alternate levels of clustering standard errors. All regressions include industry and month fixed effects. Results are weighted by employment as of December 2017. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

estimates in column 1, and the coefficient on the measure of trade policy uncertainty is not statistically significant at conventional levels. We caution that the Caldara et al. (2019) measure of trade policy uncertainty is defined at a more aggregate industry level (Fama-French 12) and frequency (quarterly) than our dependent variable, and that a more disaggregated measure of trade policy uncertainty may yield a stronger effect on manufacturing employment. Nonetheless, these results support the idea that actual changes in tariffs are associated with changes in economic activity that are distinct from effects of trade policy uncertainty.

Evaluating the Importance of Control Variables: As noted in Section 3.1, our baseline specification includes controls for three measures of industry-level international exposure that are *unrelated* to recent tariff increases, as well as industry-level capital intensity (capital-labor ratio). Inclusion of these controls increases confidence that the baseline estimates are not due to other factors that might be correlated with tariff exposure. For example, if slowing international growth led to reductions in exports, and therefore domestic employment, failing to account for overall international exposure measures (such as an industry's pre-tariff ratio of exports to shipments), might lead us to inaccurately attribute some of the employment decline to the effects of tariffs. Similarly, if more labor-intensive industries were more susceptible to import supply shocks, failing to account for an industry's capital-to-labor ratio might lead us to conflate some effects of an import supply shock with the effects of tariffs.

Despite the relevance of these control variables, however, it's also important to understand the extent to which the baseline results depend on their inclusion. Results in columns 3 to 5 of Table 2 show that estimates of the effects of the three tariff channels are not substantially affected by varying the groups of control variables included. Indeed, we continue to find negative and highly significant effects of the rising input cost channel in every specification, with modest variation in the magnitude and precision of the negative effect of export retaliation and positive effect of import penetration.

In column 3, which drops controls for industry-level capital intensity, coefficient estimates are highly similar to the baseline (column 1), with a very small decrease in precision for import protection, and a very small increase in precision for export retaliation. In column 4, which instead drops controls for general non-tariff international exposure, estimates of the positive effect of import protection are modestly larger and more precise—though they are still more than outweighed by the negative contribution of rising input costs—while the coefficient for export retaliation becomes smaller and loses statistical significance. Estimates in column 5, which drops both international exposure and capital intensity are similar to those in column 4.

Evaluating Clustering at Different Levels of Aggregation: Our baseline estimates include clustering at the three-digit NAICS (sector) level, which accounts for correlation of errors across industries within sectors. To examine whether the choice of level of clustering is important for our results, we re-estimate with clustering at the four-digit NAICS (column 6) or two-way clustering at the three-digit NAICS and month level (column 7). As shown in the table, the precision of the results is little-changed due to these different levels of clustering, with slightly larger standard errors when clustering at the four-digit NAICS level and slightly smaller standard errors when two-way clustering for three-digit NAICS and month.

3.4 Margins of Employment Adjustment

The employment effects we identify above could result from increased layoffs or slowdowns in hiring by affected firms, and analyzing differences along these margins provides important supporting information on employment adjustments to tariff shocks. To explore which of these margins accounts for our results, we use data from the Census Bureau's Quarterly Workforce Indicators, which reports the number of hires and separations, by quarter, for all U.S. manufacturers at the four-digit NAICS industry level.

We employ the same estimation strategy as in Section 3, adapted to quarterly data. Here, the dependent variable is the log level of either hires or separations for industry i in quarter q. The industry-level measures are identical to those in equation 7, but are interacted with quarter dummies, rather than month dummies. We continue to cluster standard errors at the three-digit NAICS level.

Table 3 displays results of applying the Finkelstein (2007) approach to the resulting coefficient estimates. The estimates indicate that exposure to tariffs is associated with a reduction in hiring due to higher exposure to the rising input cost channel and an increase in separations due to export retaliation. In terms of the relative importance of the hiring and separation margins, the impact of an interquartile shift in exposure to each channel on hires is about twice the magnitude of the effect on separations, though the relationship for hires is a bit less precisely estimated.[25]

Table 3: Hires, Separations, and Tariffs

Variable	Hires	Separations
Import Protection	0.469	0.156
	(1.540)	(1.511)
Export Retaliation	-5.190	13.155***
	(9.385)	(4.350)
Rising Input Costs	-17.351**	3.369
	(6.336)	(2.160)
Industry Fixed Effects	yes	yes
Quarter Fixed Effects	yes	yes
Number of Industries	76	76
Observations	836	836

Sources: U.S. Census Bureau; authors' calculations.
Notes: Table displays coefficient estimates and standard errors of the Finkelstein (2007) approach applied to quarterly equivalent of equation (7). Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \; p < 0.10$, $** \; p < 0.05$, $* * * \; p < 0.01$.

4 Broader Effects of Tariffs on Manufacturing

Given the relationship between tariffs and activity in the manufacturing sector described above, we next examine whether this relationship has broader implications outside the sector. We do this by considering whether the negative relationship between tariffs and manufacturing employment is sufficiently large to have implications for other labor market measures, such as county-level labor force participation and unemployment rates. This exercise also provides information on the difficulty with which manufacturing workers displaced by tariffs were able to find employment in other sectors. Appendix Section D.17 provides an industry-level analysis of the relationship between exposure to the rising input costs channel and

[25] In subsequent work, Javorcik et al. (2022) find that exposure to input tariffs and retaliatory tariffs decreases online job postings in the U.S., consistent with this finding of effects of tariffs on the hiring margin.

employment for the nonmanufacturing sector.

4.1 Examining County-Level Labor Market Measures

One way to examine whether the 2018-2019 tariffs have spillover effects beyond the manufacturing sector is to construct measures of geographic exposure to the tariffs and relate those measures to broader labor market outcomes. This is particularly important as the impact of tariffs could be concentrated in specific areas of the United States. Several recent papers have analyzed this geographic dimension of the 2018-2019 tariffs. Fajgelbaum et al. (2020) and Blanchard et al. (2019) consider the political economy aspects of the tariffs, with the former finding that import protection favored politically competitive counties and the latter finding that retaliatory tariffs influenced the 2018 Congressional elections.[26] Waugh (2019) calculates a measure of employment-weighted county-level exposure to tariff changes and finds that counties more exposed to retaliatory tariffs exhibit relative declines in consumption expenditures. Goswami (2020) uses Waugh (2019)'s approach of calculating geographic exposure to tariffs and finds that retaliatory tariffs are associated with a decline in commuting zone-level employment growth, while import tariffs had no immediate effect.

Here, we calculate county-level measures of exposure to each of the three tariff channels described above. To do so, we apply the industry-level measures of each tariff channel described in Section 2.2 to each county's industrial structure based on data from the Census Bureau's County Business Patterns.[27] Specifically, for an individual county k, we define exposure to each of the three tariff channels as the employment-weighted averages of exposure

[26] While these papers note that tariffs may have been targeted based on *future political considerations*, there is no evidence that tariffs were targeted—either by the U.S. or its trading partners—based on *industry performance*.

[27] We use CBP data from a pre-tariff year, 2016. To address the well-known issues of data suppression due to confidentiality requirements, we use the CBP version with imputations created by Eckert et al. (2020).

of the industries present in each county:

$$\text{Channel}_k = \sum_i \left(\frac{m_{ik}}{m_k}\right) \text{Channel}_i, \tag{9}$$

where m_{ik} is employment in industry i in county k in 2016, and the three channels are once again exposure to rising input costs, import protection, and export retaliation.

When constructing these county-level measures, all industries, whether manufacturing or nonmanufacturing, have varying levels of exposure to the rising input cost channel via their input-output structures, as discussed in Appendix Section D.17. Manufacturing industries are also exposed to the import protection and export retaliation channels via U.S. tariffs on their output, and retaliatory tariffs on their exports. Services industries, by contrast, have zero exposure to these channels, by definition, as their output is not subject to tariffs. While nonmanufacturing goods-producing industries—i.e. logging, mining, and agriculture—received very modest import protection and were subject to export retaliation, we are unable to include their exposure to these channels because there is not a readily comparable analogue of the Annual Survey of Manufactures to measure industry-level shipments for these industries.[28] While new U.S. import protection on these industries was inconsequential (less than 1 percent of the value of trade covered by new tariffs, based on 2017 value), this is more relevant for retaliatory tariffs, as a large component of these tariffs targeted agricultural products (roughly 15 percent of the value of new retaliatory tariffs on exports by 2017 value). Therefore, while our county-level analysis accounts well for spillovers of manufacturing tariffs to other sectors, it will not reflect the direct effects of the retaliatory tariffs on agriculture and mining that have been found to be important in Waugh (2019).

[28] Waugh (2019) and Goswami (2020) use an alternative approach to measure exposure to tariffs, based on employment-weighted average changes in tariffs for the industries in each county. That measure does not account for the value of imports or exports covered by tariffs and is not normalized by the value of shipments or apparent consumption.

In this sense, our estimates of the impact of export retaliation may be conservative. The county-level distributions of the three tariff channels are displayed in Appendix Figure C2.

We use these county-level measures of each channel to examine the relationship between exposure to tariffs and broader measures of labor market outcomes, including labor force participation and the unemployment rate. These data come from the BLS's Local Area Unemployment Statistics (LAUS), which collects information on labor market outcomes at the county-level.[29] Our approach mirrors that used to estimate equation (7) in Section 3, but using county-month-level data in place of industry-month-level data:

$$\begin{aligned} y_{kt} = \quad & \alpha + \sum_t \gamma_t \mathbf{1}(M_t = t)(\text{Import Protection}_k) + \sum_t \lambda_t \mathbf{1}(M_t = t)(\text{Export Retaliation}_k) \ ... \\ & + \sum_t \theta_t \mathbf{1}(M_t = t)(\text{Input Cost}_k) + \sum_t \Big(\mathbf{1}(M_t = t) \times \mathbf{X}_{\mathbf{k}}^{'} \boldsymbol{\beta}_{\mathbf{t}} \Big) + \delta_k + \delta_t + \varepsilon_{kt} \end{aligned} \tag{10}$$

The dependent variable (y_{kt}) is either the county-month labor force participation rate or unemployment rate, and the independent variables are interactions of month dummies with the county-level measures of each of the three tariff channels, the measures of international exposure described above, and the manufacturing employment share. Equation (10) also includes county and month fixed effects. Standard errors are clustered at the state level.

We report results of estimating equation 10 in terms of the Finkelstein (2007) hypothesis test described above, with results reported in the first column of Table 4. We find a positive and statistically significant relationship between the county-level unemployment rate and exposure to the rising input cost channel. The other two channels channels have marginally

[29]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/.

Table 4: Point Estimates of Cumulative Effect by Channel: Labor Market Measures

Variable	Unemployment Rate (1)	Unemployment Rate (2)	Labor Force Participation (3)	Labor Force Participation (4)
Import Protection	9.76*	9.95*	0.47	0.47
	(5.48)	(5.85)	(0.72)	(1.11)
Export Retaliation	51.67*	52.70*	1.42	0.98
	(31.08)	(29.93)	(3.16)	(3.48)
Rising Input Costs	64.18***	64.08**	-8.57***	-9.01***
	(17.81)	(27.10)	(2.60)	(2.23)
Manufacturing Share Controls	yes	yes	yes	yes
County Fixed Effects	yes	N.A.	yes	N.A.
Month Fixed Effects	yes	yes	yes	yes
Number of Counties	3,131	N.A.	3,131	N.A.
Number of Industries	N.A.	250	N.A.	250
Observations	103,323	8,250	103,323	8,250

Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Columns (1) and (3) display results of the Finkelstein (2007) approach described in equation 8, based on OLS regressions of unemployment or labor force participation rates on measures of exposure to the rising input cost, import protection, and export retaliation channels of tariffs. Columns (2) and (4) are the equivalent regressions translated to a shock-level (industry) basis following Borusyak et al. (2021). Estimates are weighted by December 2017 labor force. Standard errors (in parentheses) are clustered at the state-level in columns (1) and (3), and NAICS-3 level in columns (2) and (4). $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

significant effects on unemployment, and while the effect coming from import protection is positive (and hence, contrasts with the industry-level results above), the implied magnitude is small.[30] We similarly find a negative and statistically significant relationship between labor force participation and the rising input cost channel, whereas the other two channels are small in magnitude and statistically insignificant. In terms of economic significance, these estimates imply that a county in the 75th percentile of the distribution for each tariff channel experiences a 0.2 percentage point increase in the county-level unemployment rate, relative to a county in the 25th percentile (and a smaller decrease in overall labor force participation). While these effects are modest in size, they are not trivial. Furthermore, it suggests that the decline in manufacturing employment due to the imposition of tariffs is

[30]Moreover, when accounting for implied general equilibrium effects in Appendix D.18, the joint effect of this channel becomes even smaller and insignificant.

not readily absorbed by gains in other industries. These results, therefore, provide further evidence of the presence of substantial adjustment costs for workers attempting to move between industries or geographic areas (Ebenstein et al. (2014), Artuç et al. (2010), Caliendo et al. (2019), and Acemoglu et al. (2016)).

In a setting where we use prior-year employment shares to allocate the industry-level shock, this exercise has a natural interpretation that follows the growing literature utilizing Bartik or shift-share instruments. In particular, Borusyak et al. (2021) argue that standard errors associated with estimates coming from regressions at the level of geography could be under-stated, as they do not properly account for the variance of the quasi-experimental shocks.[31] We show results from applying the suggested re-weighting approach in the second and fourth columns of Table 10.[32] The statistical significance is qualitatively unchanged using this "shock-level" version: the standard errors corresponding to the rising input cost channel on unemployment rates increase somewhat while those corresponding to labor force participation decline slightly.

5 Conclusion

This paper provides the first estimates of the effect of tariffs imposed since 2018 on outcomes in the U.S. manufacturing sector, the sector intended to benefit from U.S. tariffs. We calculate measures of industries' exposure to tariffs via three channels: the import protection from tariffs on an industry's output, the increase in production costs resulting from tariffs on imported inputs, and the reduction in foreign competitiveness due to retaliatory tariffs in U.S. export markets. We then estimate the relationship between these measures of exposure

[31] Although our setting is a shift-share in reduced form, unlike the IV applications highlighted in their paper, Borusyak et al. (2021) emphasize that the re-weighting approach is valid in either case.

[32] As is clear from the table, the equivalence result highlighted in Borusyak et al. (2021) holds in our case, subject to some slight discrepancies, which we attribute to differences in numerical precision given the presence of multiple sets of shocks and a host of controls (including time-varying county-level controls) that we pull through to apply the Finkelstein (2007) hypothesis test.

to tariffs and manufacturing employment, output, and producer prices.

The tariffs are associated with relative reductions in manufacturing employment and relative increases in producer prices. For employment, a small and imprecisely estimated boost from the import protection effect of tariffs is more than offset by larger drags from the effects of retaliatory tariffs and, especially, exposure to rising input costs. Exposure to rising input costs is also associated with relative increases in producer prices.

We consider the possibility of spillover effects of tariffs from the manufacturing sector to the broader economy and find a positive relationship between tariff exposure and county-level unemployment rates and a negative relationship with labor force participation rates. These relationships mirror that found for manufacturing employment, as counties more exposed to rising input costs experience relative worsening in broader labor market measures.

These results have implications for evaluating the effects of recent U.S. trade policy. While one may view the negative welfare effects of tariffs found by other researchers to be an acceptable cost for a more robust manufacturing sector, our results suggest that the tariffs did not boost manufacturing employment or output in the short run, even as they increased producer prices. While the longer-term effects of the tariffs may differ from those that we estimate here, the results indicate that the tariffs, thus far, have not led to increased activity in the U.S. manufacturing sector.

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Appendix

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 2.4 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

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

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.[33] Focusing on this 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

[33] 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.

inputs, is ($\hat{\eta}_i^C$). This measure is defined at the overall market level as

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

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

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

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 $\hat{\eta}_{i,k}^C$ as follows:

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

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

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

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 (6) 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.

B.1 Assumptions for Retaliatory Tariffs

We focus, in particular, 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.

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

B.2 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

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).

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.

C Additional Information on Independent Variables

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

C.1 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.

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.

For further detail on the distribution of exposure to the three tariff channels considered in this paper, Figure C1 shows density estimates across the 76 manufacturing industries for which manufacturing employment data are available.

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.

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.[34] 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

[34] 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.

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.[35]

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 (6) in the text.
Notes: This measure corresponds to the cumulative coverage of all three 2018-2019 tariff actions.

C.2 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 C2. The 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.

[35] 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.

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 (7). 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 D3 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 2.4 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 6) 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 7) 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

Variable	Dep. Var: Log Employment (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 (8) 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 (8) 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 (8) 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 7 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 7) 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 (8) 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 (7). 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 8 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 5 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 4 and 5, 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	0.072	0.421
	(0.187)	(0.486)	(0.370)
Export Retaliation	2.927*	-0.417	-2.251*
	(1.538)	(0.895)	(1.243)
Rising Input Costs	1.818***	0.990	-1.687**
	(0.420)	(1.185)	(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 D4, 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 (8) 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 6 are based on the *cumulative* set of tariffs imposed by the U.S. and its trading partners. Thus, when they enter Equation 7, 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	-0.341	-1.154
	(0.140)	(0.946)	(0.707)
Export Retaliation	-3.423**	3.314	1.165
	(1.388)	(2.669)	(3.756)
Rising Input Costs	-2.413***	-1.121	5.730***
	(0.927)	(3.105)	(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 Normalized 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*	-0.124	-0.525
	(0.114)	(0.254)	(0.315)
Export Retaliation	-0.511**	0.153	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 D5.

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 D5 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 D6, 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 D6b, 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.[36] When the index for *new* orders of manufactured goods (black line in Figure D6b) 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

[36] 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 D6 are consistent with this interpretation.

D.12 Evaluating the Role of Regression Weights

When estimating equation 7 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 7 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 (8) 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	Hires
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.

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.

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

Variable	Employment	Industrial Production	Producer Prices
Import Protection	0.061	0.183	1.508
	(0.174)	(0.692)	(1.027)
Export Retaliation	-2.904	4.943***	2.957
	(2.501)	(1.524)	(5.415)
Rising Input Costs	-2.456***	-1.635	8.077*
	(0.853)	(1.962)	(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 (8) 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. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

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

Table D20: Point Estimates by Tariff Wave

Variable	Employment	Industrial Production	Producer Prices
Import Protection Aug. 2018	-1.648	-1.380	-8.106*
	(3.095)	(5.240)	(4.043)
Import Protection Feb. 2018	-3.416	-3.853	8.944
	(3.357)	(13.108)	(6.148)
Import Protection Jul. 2018	2.080	-2.045	5.720*
	(4.914)	(3.935)	(2.866)
Import Protection Mar. 2018	0.898	5.901***	-3.103
	(1.516)	(1.677)	(1.875)
Import Protection Sep. 2018	0.123	0.045	-1.840**
	(0.401)	(0.730)	(0.764)
Export Retaliation Apr. 2018	-53.331**	41.801	-100.726**
	(21.172)	(63.326)	(40.310)
Export Retaliation Aug. 2018	-1.880	19.904**	-12.727**
	(5.472)	(8.048)	(5.329)
Export Retaliation Jul. 2018	-2.666	-6.161	12.284***
	(3.633)	(5.916)	(4.178)
Export Retaliation Jun. 2018	15.867	-2.647	10.296
	(12.224)	(14.178)	(6.395)
Export Retaliation Sep. 2018	-1.216	-0.237	-9.757
	(1.870)	(3.301)	(6.912)
Rising Input Costs Aug. 2018	-2.846	14.646	-6.074
	(8.798)	(16.728)	(18.796)
Rising Input Costs Feb. 2018	25.296	-15.257	-17.986
	(21.933)	(95.052)	(38.130)
Rising Input Costs Jul. 2018	-7.008	1.257	-1.418
	(16.342)	(19.527)	(17.034)
Rising Input Costs Mar. 2018	-3.469***	-0.885	4.848
	(1.071)	(2.133)	(3.433)
Rising Input Costs Sep. 2018	-5.706*	-11.376*	11.080**
	(2.996)	(5.991)	(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 (8) 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. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

partners.[37] We address the case of retaliatory tariffs on non-manufacturing goods-producing

[37] 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.

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.[38] 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.[39]

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.

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 D7. 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 of the main text. 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 D7 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 nonmanufactur-

[38] 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.

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

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

Variable	Mfg. Industries	Nonmfg. Industries
Rising Input Costs	-2.455***	-2.928
	(0.853)	(2.002)
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. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

ing sectors that use manufactured goods more intensively in their production processes. As shown in the Figure D7, 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).[40] 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

[40]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.

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 unemployment) but not statistically significant.[41] 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.

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

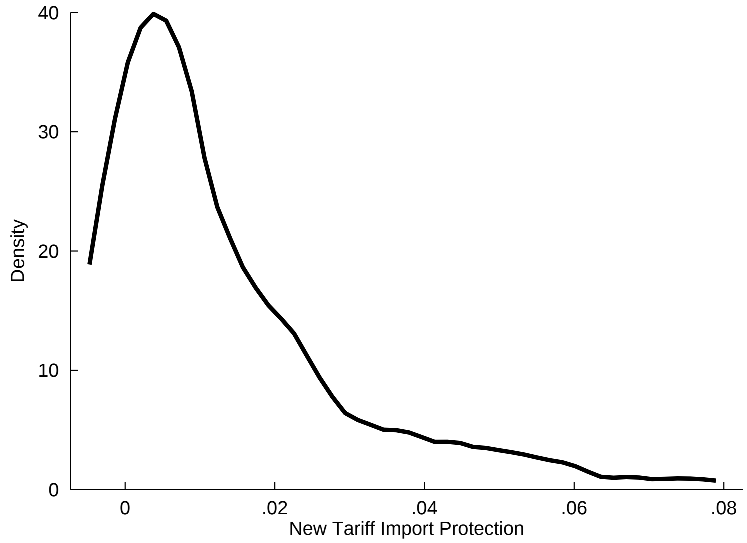
Table D22: Point Estimates of Cumulative Effect by Channel:

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

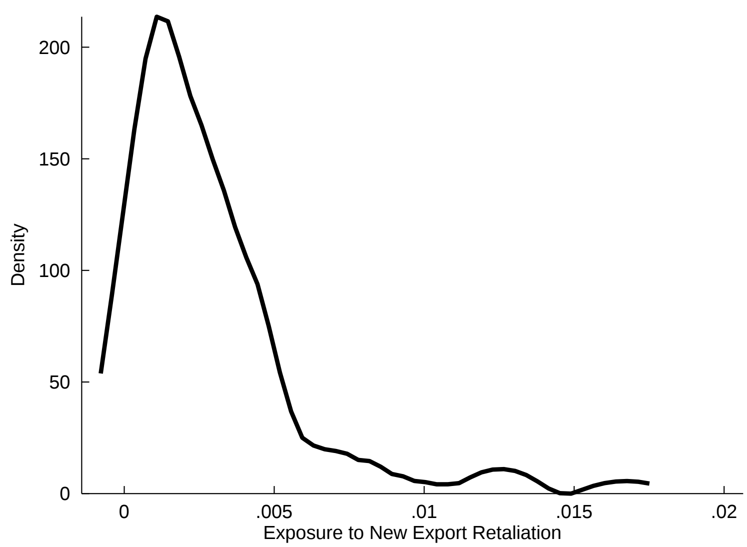
Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Column (1) displays results of the Finkelstein (2007) approach described in equation 8, based on OLS regressions of unemployment rates on measures of exposure to the rising input cost, import protection, and 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). $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Figure C1: Density Estimates of Tariff Exposure Channels Across Manufacturing

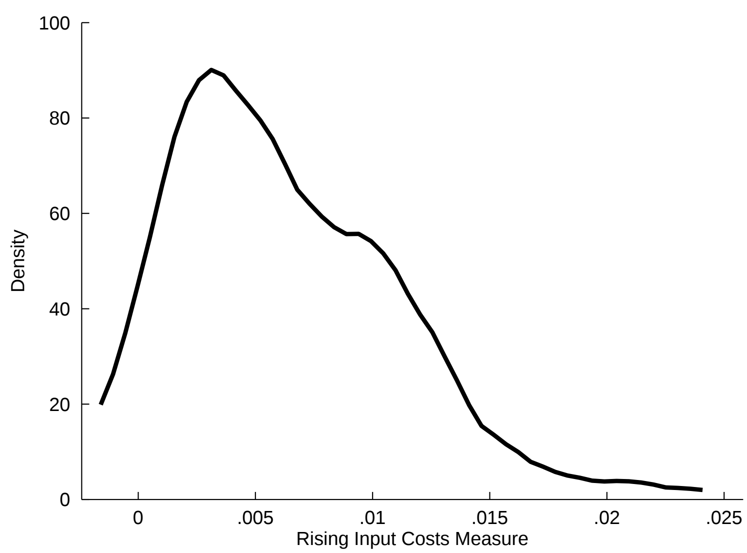
(a) Import Protection



(b) Export Retaliation



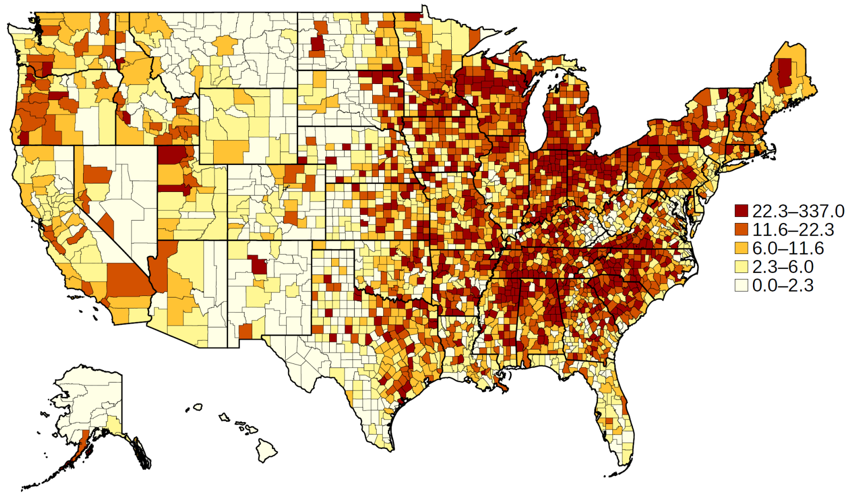
(c) Rising Input Costs



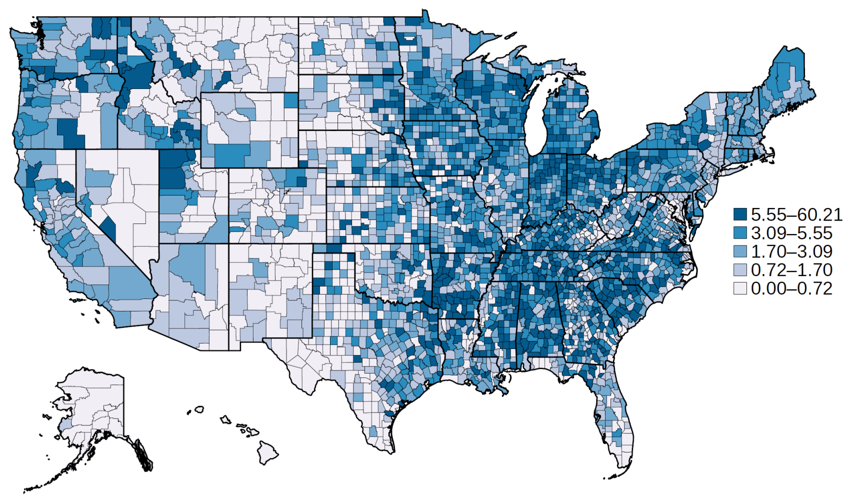
Sources: Figures display densities of industry-level measures of exposure to each tariff channel.

Figure C2: County-Level Distribution of Tariffs

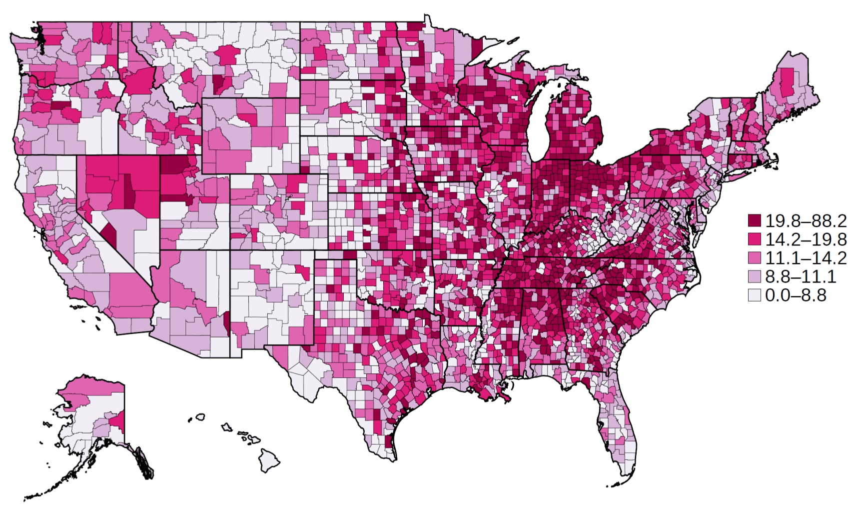
(a) Manufacturing Import Protection, by County



(b) Export Retaliation on Manufacturing, by County



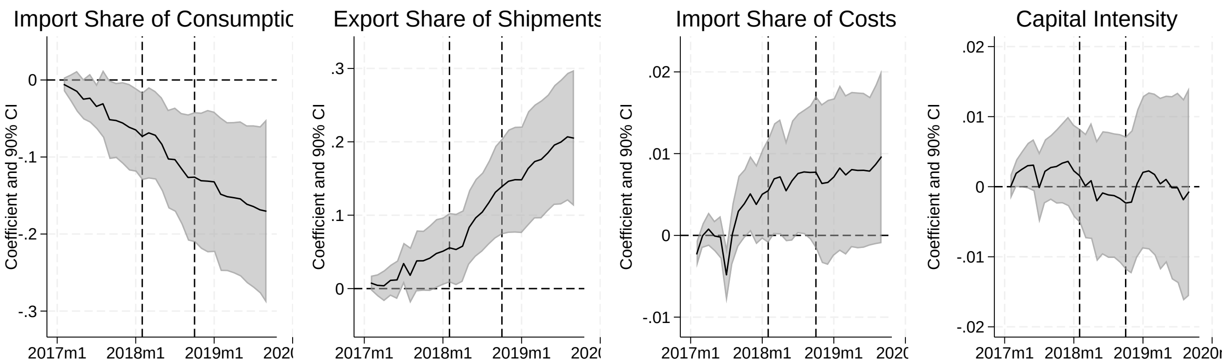
(c) Rising Input Costs, by County



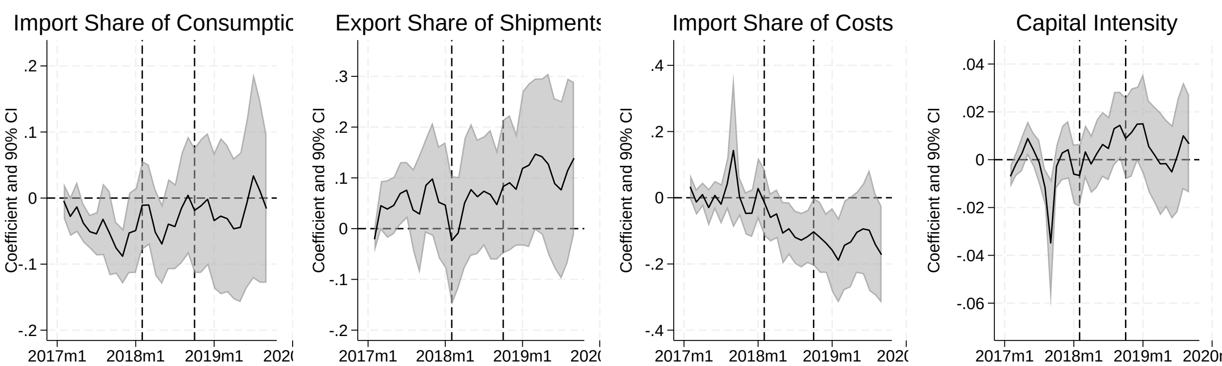
Sources: Author's calculations using County Business Patterns (U.S. Census Bureau), Eckert et al. (2020) and sources highlighted in Section 2.2.
Notes: Maps display county-level measures of exposure to the import protection, export retaliation and rising input cost tariff channels. Note that measures are multiplied by 100 for greater legibility. County-level measures are employment weighted-averages (as shown in equation (9)) of industry-level exposure defined in equations (6), (2), and (1) above.

Figure D3: Coefficient Estimates for Control Variables

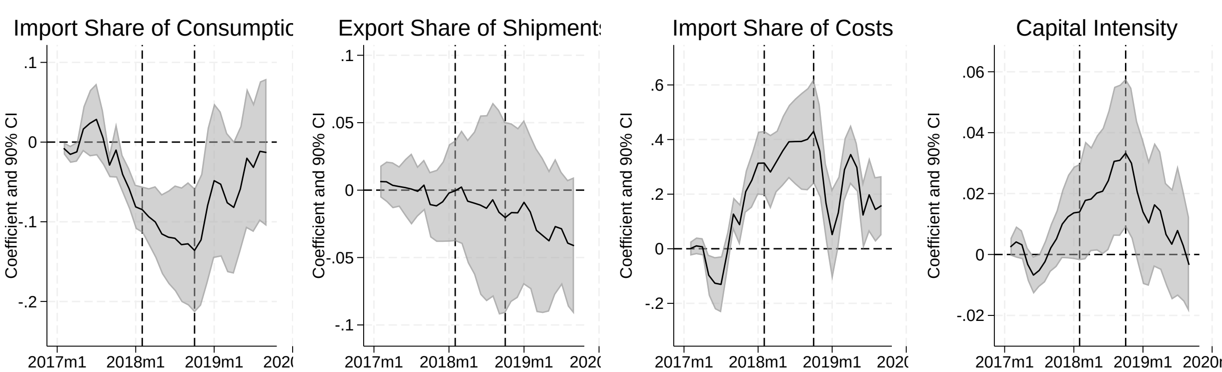
(a) Employment



(b) Industrial Production (Output)

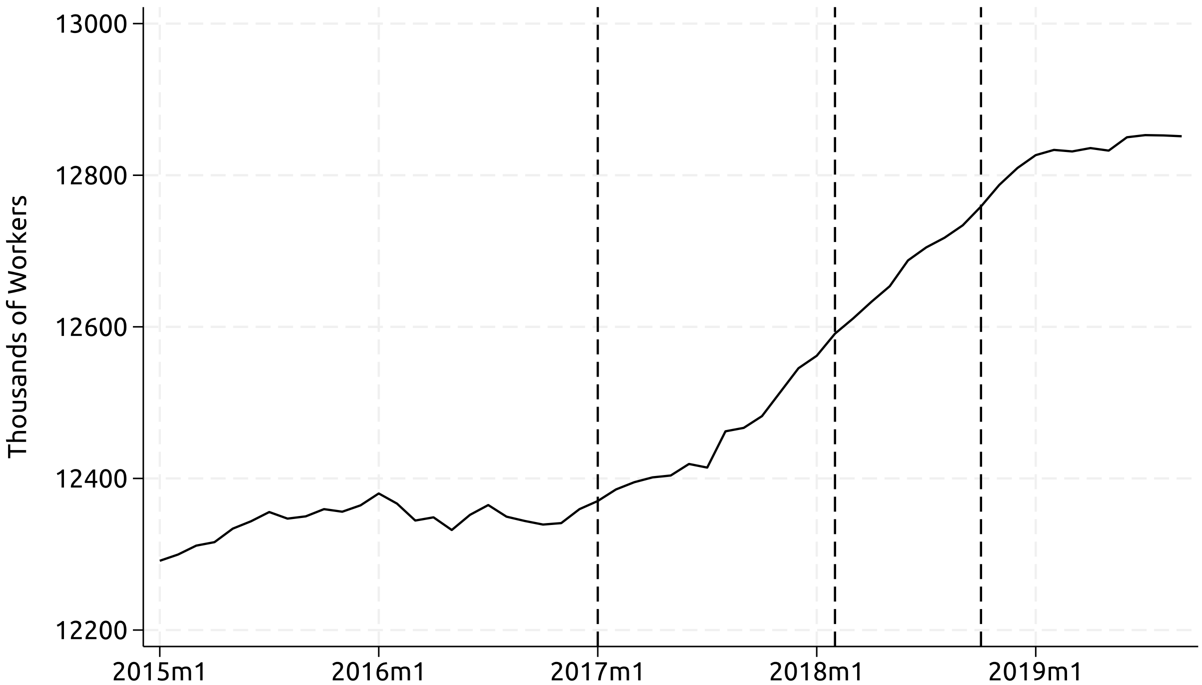


(c) Producer Price Index



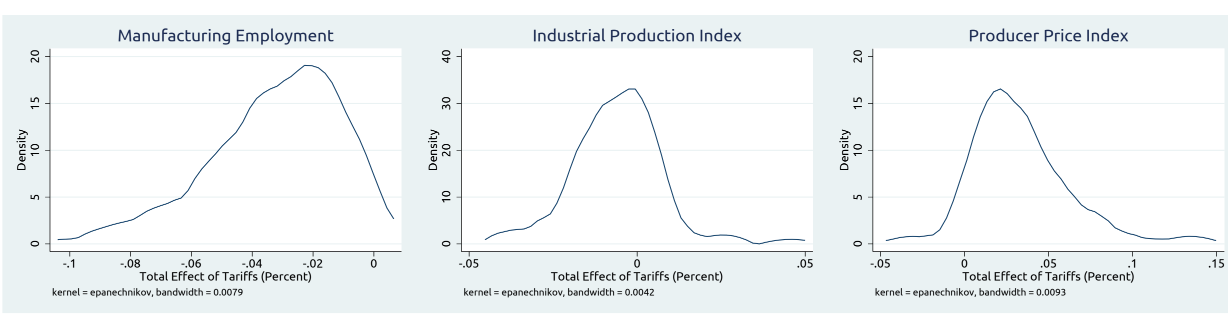
Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Each panel displays coefficient estimates (solid lines) and 90 percent confidence intervals (shaded areas) of interactions of month dummies with import share of absorption, export 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 D4: 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.

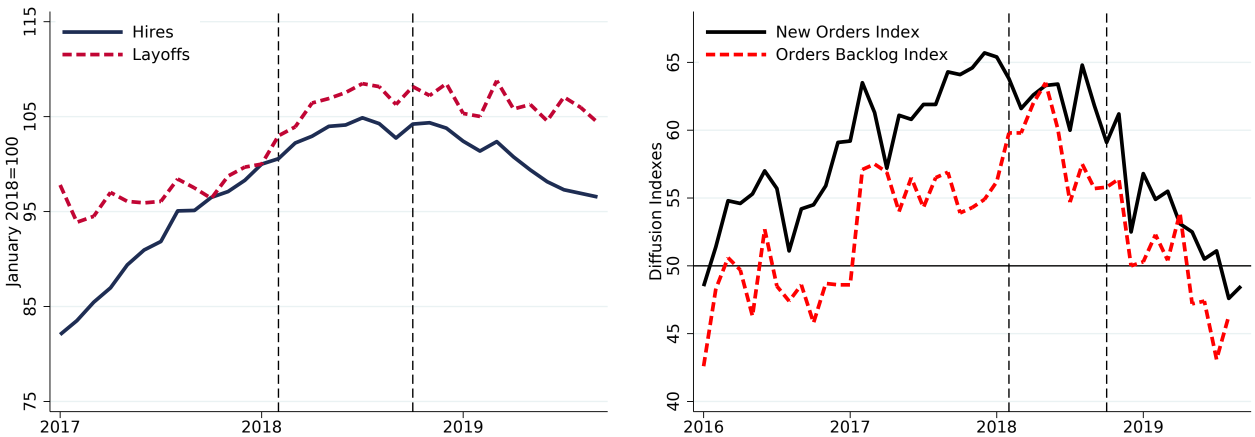
Figure D5: Distributions Across Industries of Net Effects of Three Tariff Channels



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.

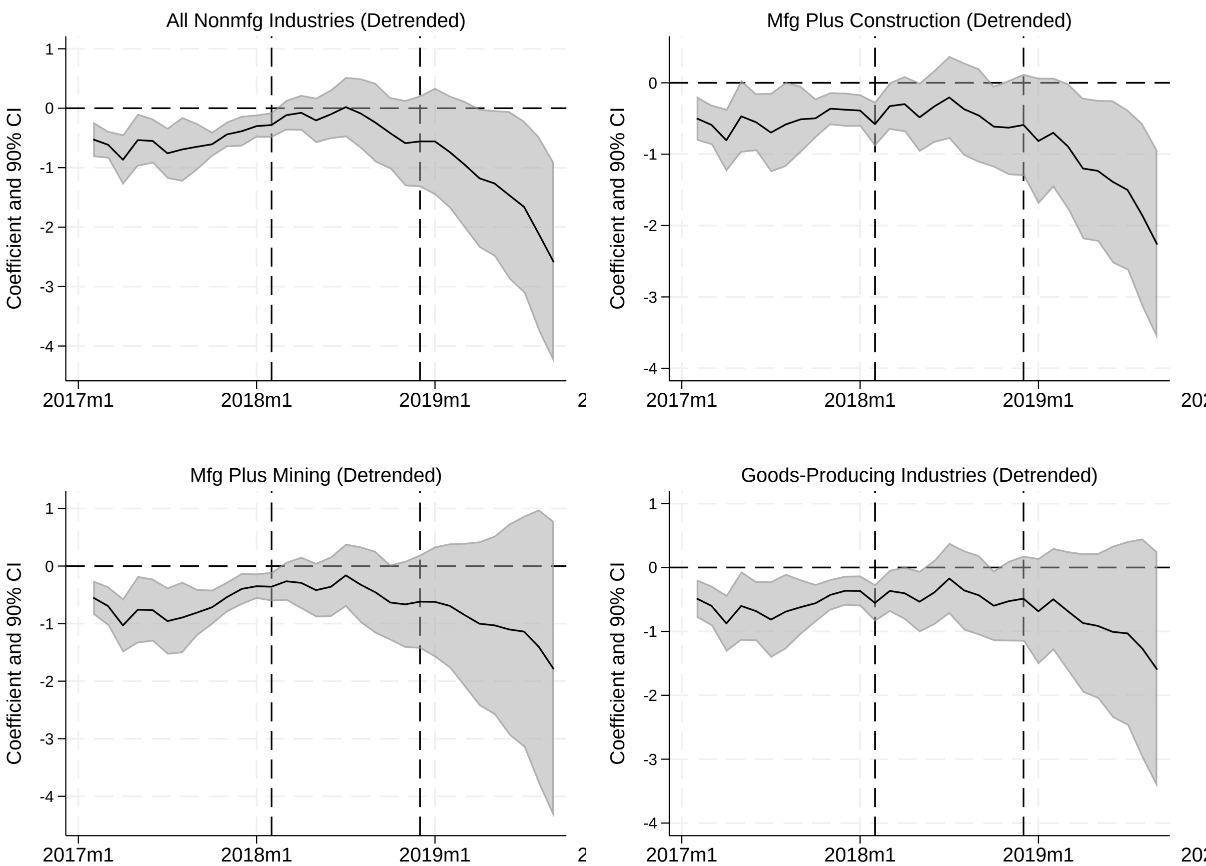
Figure D6: Manufacturing Orders, Hires, and Layoffs

(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 D7: 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.