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

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October 13, 2022

First Version: December 2019

Abstract

This paper estimates the relationship between the unprecedented U.S. tariff increases of 2018-2019 and outcomes in the domestic manufacturing sector. Despite being intended, in part, to boost manufacturing activity, we find that 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, the tariffs have broader impacts, as counties more exposed to rising tariffs exhibit relative increases in unemployment rates.

*We are grateful to Vivi Gregorich for superb research assistance. We thank Costas Arkolakis, Matilde Bombardini, Lorenzo Caliendo, Samuel Kortum, Ryan Monarch, Paola Conconi, Aksel Erbahar, Peter Schott, Lorenzo Trimarchi and participants in various seminars and conferences for useful comments. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the Board of Governors or its research staff.

1 Introduction

The unprecedented increase in tariffs imposed by the United States against its major trading partners since early 2018 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. in 2018-2019. 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 share of domestic absorption covered by newly imposed tariffs. We account for possible increases in production costs associated with tariffs on imported inputs as the share of industry costs subject to new tariffs. Finally, we measure an industry's exposure to retaliatory tariffs by U.S. trading partners as the share of industry-level shipments subject to new retaliatory tariffs.[1] We

[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, Arkolakis and Esposito (2020) in Appendix A. Appendix Section C.2 shows

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. 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 three measures of an industry's general international exposure—the import share of domestic absorption, export share of shipments, and import share of costs—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 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.

Next, we conduct two exercises to consider the possibility of broader effects of the tariffs outside the manufacturing sector. First, we estimate the impact of manufacturing tariff increases on employment in downstream non-manufacturing industries. Based on this approach, we find only limited evidence of a negative relationship between exposure to rising

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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.

input costs and overall nonmanufacturing employment. However, we find clear evidence for broader labor market effects of the manufacturing tariffs when we estimate the relationship between county-level unemployment rates and geographic measures of exposure to the three tariff channels that are based on industry composition. Specifically, we find that counties with higher exposure to tariffs experience relative increases in unemployment rates that are highly statistically significant. This finding suggests 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 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 only 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, Dorn and Hanson, 2013; Pierce and Schott, 2016; Autor, Dorn and Hanson, 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, so far, 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. 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, Redding and Weinstein (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, Hortaçsu and Tintelnot (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, Kamal and Monarch (2020) who find that U.S. import tariffs on inputs lead to reduced *exports* for firms in affected industries. While Handley, Kamal and Monarch (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 the trade war impacted U.S. manufacturing and, ultimately, its 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, Fort and Tintelnot (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, Bown and Chor (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. (2019) and Amiti, Kong and Weinstein (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, in research focusing on uncertainty regarding tariff rates, Caldara et al. (2019) find that increases in measured trade policy uncertainty reduce investment in firm-level and aggregate data, and Reyes-Heroles, Traiberman and Van Leemput (2019) 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 manufacturing 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 trade war has been a drag on employment and has 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 rates in more affected counties, a relationship that has not been previously documented.

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 the data sources used in the analysis, 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.

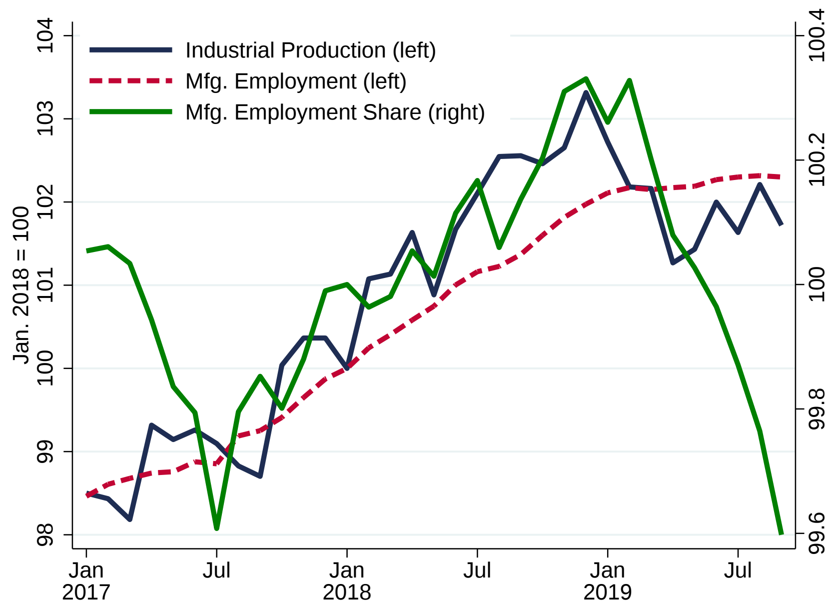
2 Background, Data, and Industry-Level Measurement

We begin by providing some brief background on recent trends in manufacturing activity in the period leading up to and during the imposition of tariffs. Toward that end, 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

[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, Chaudhuri and McLaren (2010).

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 decline in the manufacturing share of employment from late 2018 through the end of the sample period 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.

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.

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

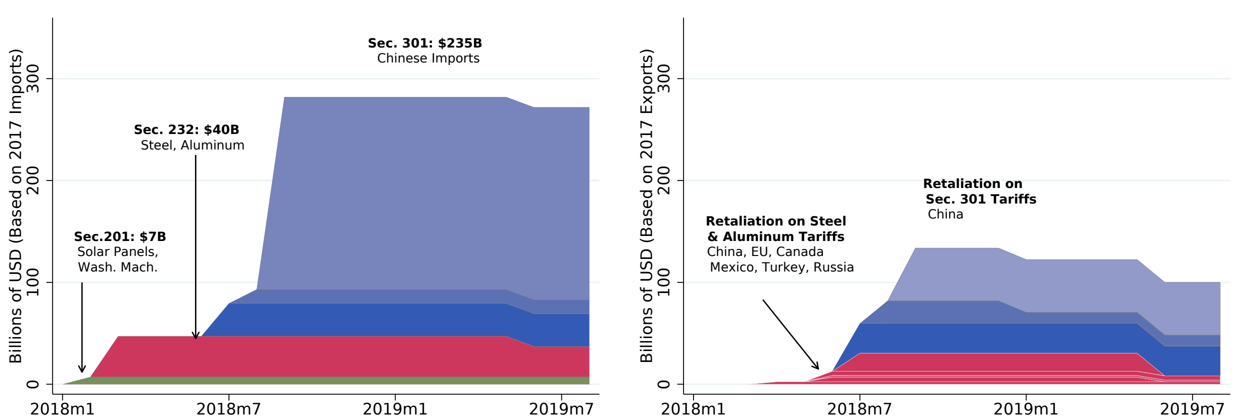
2.1.1 U.S. Import Tariffs

The first tariff action was initiated by the Trump administration and enacted by the U.S. in early February 2018 against large residential washing machines and solar panels/modules based on the rarely used Section 201 of the Trade Act of 1974 (U.S. Code: Title 19, Code 2252). These safeguard tariffs apply to all countries and were scheduled to last for several years before automatically expiring.[3] The value of 2017 U.S. imports affected by these tariffs is shown by the green area in Figure 2a.

The second major tariff action affected steel and aluminum imports beginning in March 2018. In only the third instance of its use by the United States, the U.S. administration self-initiated an investigation under Section 232 of the Trade Expansion Act of 1962, which determines whether a product is being imported "in certain quantities or under such circumstances as to impair or threaten to impair U.S. national security" (U.S. Code: Title 19, Code 1862). The announced tariff rates were applied at 25 percent on steel and certain steel products and 10 percent on aluminum. The administration initially exempted the imports of several countries, including Canada, Mexico, Korea, and the countries comprising the European Union; however, in June 2018 these exemptions were removed.[4] The value of imports affected by these tariffs is shown by the red area in Figure 2a.

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.

The third and most significant tariff action imposed tariffs on U.S. imports from China

[3]Each of these Section 201 tariff actions were tariff rate quotas, where an initial quantity of imports was subject to lower tariff rates than subsequent quantities. Ultimately, the effective tariff rates applied via these tariff rate quotas were around 30 percent, very similar to those applied in later tariff actions (Fajgelbaum et al. (2020)). Despite plans for automatic expiration, the washing machine tariffs were extended in early 2021 and the solar panels tariffs were extended in early 2022.

[4]The Republic of Korea secured a permanent exemption after agreeing to stringent import quotas for the U.S. market.

based on Section 301 of the Trade Act of 1974. This provision provides enforcement mechanisms against a wide range of trade practices deemed to be unjustifiable, unreasonable, discriminatory, or that violate trade agreements. The initial Section 301 investigation against Chinese trade practices focused on intellectual property and technology transfer, and the results of the investigation were released in March of 2018. New tariffs were announced and applied in several phases as both the United States and China retaliated against import tariffs imposed on one another. Phase 1 of U.S. tariffs on imports from China occurred in July 2018, targeting $34 billion of Chinese imports, with additional Phase 2 tariffs on $16 billion following in August. Each of these initial phases were set at a rate of 25 percent. The largest set of tariffs, which covered nearly $200 billion of Chinese imports, went into effect in late September 2018 at a rate of 10 percent, which was later raised to 25 percent in May 2019. These phases of the section 301 tariffs can be seen as the blue areas of Figure 2a.[5]

2.1.2 Retaliatory Tariffs

The retaliatory tariffs imposed in response to these U.S. actions are summarized in Figure 2b. In response to the Section 232 tariffs on steel and aluminum, China announced retaliatory tariffs on U.S. exports in April of 2018, while the European Union, Canada, and Mexico imposed their own retaliatory tariffs in June and July of 2018. These tariffs focused on aluminum waste, scrap, pork and various agricultural products for the case of China, and steel, aluminum and other agricultural goods for the cases of the E.U., Canada, and Mexico. The value of 2017 U.S. exports subject to these retaliatory tariffs is shown by the red portion of Figure 2b.

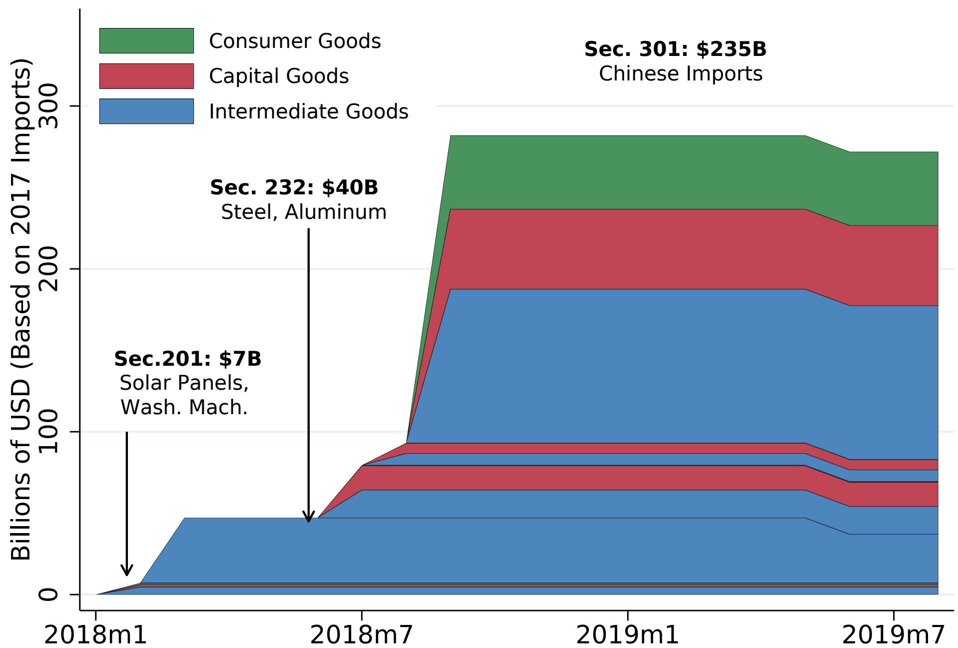
In response to the Section 301 tariffs against U.S. imports from China, China imposed retaliatory tariffs on U.S. exports associated with each of the three phases of U.S. tariffs. Retaliation on Phases 1 and 2 covered dollar values of U.S. exports that were equivalent to the dollar values covered by U.S. tariffs on imports from China, and at identical rates. China's Phase 3 retaliation covered $60 billion of U.S. exports, initially at rates ranging from 5-10 percent, which were then increased in 2019 in response to the U.S. raising its Phase 3 tariff rates. These values of U.S. exports subject to Chinese retaliatory tariffs are shown in the blue areas of Figure 2b. The equal scale of the axes in Figures 2b and 2a makes clear that the value of U.S. exports subject to retaliatory tariffs has been substantially smaller

[5] A notable feature of the Section 301 tariffs against China was the potential for U.S. firms to file requests for tariff exemptions to the Office of the U.S. Trade Representative (USTR) (See Flaaen, Langemeier and Pierce (2021) for further technical details of the exemption process). Although such granted requests could, in principle, alter the effective tariffs imposed against U.S. firms, these exemptions are unlikely to materially affect our results due to the timing of the exemption process. The number of industries affected by tariffs, combined with the extensive detail required for these petitions, led to long delays in decision notices on tariff exemptions by the USTR. For Phase 1 of the Section 301 tariffs, these decisions were announced on a rolling basis between December 2018 and October 2019; decisions on Phase 2 and Phase 3 didn't begin until July 2019 and August 2019, respectively, at the very end of our sample period. Hence, the vast majority of tariffs were not affected by exemptions during the period we study in this paper.

than the value of U.S. imports subject to U.S. tariffs.

2.1.3 Characteristics of Products and Industries 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).

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, Jung and Lu (2019*b*) for a similar breakdown).[6] 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.

[6]Of course, the BEC classification does not substitute for analysis using input-output tables, as one U.S. industry's output can be another industry's intermediate input.

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 of the tariffs examined in this paper in place, underscoring their continued importance. Second, while the Phase One trade deal did decrease tariff 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. 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.[7] 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 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, Bown and Chor (2019), Waugh (2019) and Bown, Jung and Lu (2019*a*). We find that this assumption is justified because the value of U.S. exports that we classify as being covered by retaliatory tariffs lines up well with those calculated by other researchers as well as those announced by U.S. trade partners, as reported in Table B2.

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. For annual levels of industry shipments, we use the Annual Survey of Manufactures (ASM) for a pre-tariff year, 2016. Data on the input usage of each industry are drawn from the

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

BEA's detailed input-output tables for 2012, the most recent vintage available.

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 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. This limitation would be particularly problematic for 2018 when tariffs were only imposed for portions of the year that differed by industry. Therefore, while the confidential plant-level data will be useful for examining heterogeneity in the responses of plants and firms to tariffs at an annual frequency, our monthly industry-level data are well suited to providing information on the nature and timing of the relationship between tariffs and overall industry-level outcomes.

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).[8] 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.[9] While there is almost certainly heterogeneity in the extent of exposure to each of the three tariff channels for the finer

[8] Results are qualitatively identical if NAICS 315 and 316 are excluded from the sample, given their small size.

[9] 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, Arkolakis and Esposito (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.[10] 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.[11] As shown in Figure C2, 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, variation in the share of products within an industry subject to US or retaliatory tariffs, variation in the tariff increase applied to U.S. imports or exports, and, in the case of the rising input cost channel, variation in the intensity with which each input is used in the production process.

Import Protection

One of the most salient ways that tariffs could affect an industry's economic activity is by restricting foreign competition. To measure the extent of this potential protection, we relate the value of imports of an industry's output affected by new tariffs to the level of domestic absorption (domestic production + imports - exports). Formally, 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. $\Delta\tau_{ipc}$ measures the change in the tariff rate (in percentage points) for a particular trade policy action. Using these definitions, our measure of import protection is given by:

[10] In addition, we show in Section C.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.

[11] Uncertainty regarding trade policy may have led to additional effects (Caldara et al. (2019)), and we explore robustness of our estimates to inclusion of measures of trade policy uncertainty later in section 3.3.

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

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, multiplying the value of those imports by the applicable increase in tariff rates, and then dividing that sum by the value of domestic absorption.[12] Throughout the remainder of the paper, we typically 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 tariff actions described in Section 2.1, and define $\Delta\tau_{ipc}$ based on the tariff rates in effect at the end of our sample period.[13]

Table 1 lists the top ten industries for this measure of new import protection and Panel (a) of Figure C2 displays its distribution across industries. 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.

Table 1: 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.

[12]Equation (A4) in Appendix A is an example of a model-derived analogue of this measure from an extension of Adão, Arkolakis and Esposito (2020) (see Appendix C.5).

[13]Measures of export retaliation and rising input costs are also based on the cumulative set of tariffs. In Appendix C.5 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—which we refer to as an industry's exposure to "export retaliation"—as the following:[14]

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

The ten industries most affected by new foreign retaliatory tariffs are shown in Table 2, with the industry-level distribution shown in Panel (b) of Figure C2. 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.[15]

Table 2: 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.

[14] Adão, Arkolakis and Esposito (2020) contains an analogous expression (see equation (A2) in Appendix A).

[15] 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.

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 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 (implied) import share of costs in industry i from commodity j.[16] 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, the most recent year available, updated with 2016 information on values of imports and shipments to calculate the import shares in equation 4.[17]

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

[16] 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.

[17] 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.[18]

Table 3 lists the top U.S. industries affected by increased costs from recent import 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 Figure C2. As is apparent in the table, all of these industries are heavily dependent on various metals for domestic production. In addition, the above tables highlight the value in jointly analyzing these channels. For the case of household appliance manufacturing (NAICS 3352), our measures indicate that the industry was highly exposed to all three channels.[19]

Table 3: 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.

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.

[18]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).

[19]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.

3.1 Empirical Strategy

As indicated in Tables 1, 2, and 3, some industries are 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. Any bivariate relationship between an outcome measure and one of the channels identified above could end up conflating multiple, 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, and determining which tariff channel dominates. The correlations between the three tariff measures are: rising input costs and import protection (0.38), rising input costs and export retaliation (0.08), and import protection and export retaliation (0.23).[20]

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.[21] 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:

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

where the outcome of interest, y_{it}, is either log employment, log output, or the log of the producer 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$_i$, Input Cost$_i$,

[20] Section C.4 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.

[21] 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, the most recent year of data available for industry-level shipments. (The input cost shares come from the most recent detailed input-output tables, which is 2012.) Our measure of the capital intensity of each industry is the capital per worker as measured by the NBER CES manufacturing database.

and Foreign Retaliation$_i$ 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.

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 their treatment 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 U.S. 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. 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 trade war, rather than on short-run industry-specific trends in employment, output, or prices.[22]

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. We utilize two approaches to explicitly account for pre-trends. 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

[22]In addition, Fajgelbaum et al. (2020) examine the relationship between industry-level protection and 2016 campaign contributions, and actually find a somewhat negative relationship, implying that tariffs were not directed toward politically connected industries.

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 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. 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.

3.2 Results

We report results in two ways. Table 4 reports estimates from the Finkelstein (2007) approach (equation 8). Figure 4 provides a visual representation of the alternative results of estimating equation 7 for each of the three detrended outcomes of interest. Specifically, the three panels of the figure display coefficient estimates and 90 percent confidence intervals for the interactions of the tariff channel measures with month dummies for the dependent variables of employment (Panel (a)), industrial production (Panel (b)), and producer prices (Panel (c)).[23]

Estimates for employment are reported in column 1 of Table 4 and Panel (a) of Figure 4. 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 4 (left column of Panel (a)) as a downward shift of coefficient estimates following the imposition of tariffs. Table 4 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 right column of Panel (a) of Figure 4. Lastly, we find a positive and marginally statistically significant relationship between import protection and employment in Table 4, which manifests itself as a subtle and imprecisely estimated shift up in coefficient estimates once tariffs begin to be imposed in the middle column of Panel (a). The results in Panel (a) of Figure 4 also indicate intuitive differences in the timing of observed effects for

[23] Appendix Section C.3 presents results for the non-detrended version of Equation 7. As shown in Figure C3, coefficient patterns sometimes indicate the presence of differing pre-existing trends for more- versus less-exposed industries, followed by breaks in trend that occur as tariffs are put into place. As discussed in Finkelstein (2007), these breaks in trend represent the impact on the dependent variables that can be attributed to tariffs, with our two approaches representing alternative ways to capture these impacts by netting out pre-existing trends.

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.

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. 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 economic significance of these estimates is to consider the effect of shifting to an alternative scenario with zero tariff exposure. In this scenario, eliminating exposure to rising input costs is associated with a 1.8 percent relative increase in employment (or around 230,000 jobs); adding in the other two channels increases this estimated effect to 2.6 percent (or around 320,000 jobs). We caution, however, that 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).

Table 4: 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)
Rising Input Costs	-3.085***	-1.216	6.538***
	(0.867)	(2.690)	(1.888)
Foreign Retaliation	-4.479**	2.732	1.954
	(1.679)	(2.370)	(3.868)
Industry 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. Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Column 2 of Table 4 and Panel (b) of Figure 4 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 4 are not statistically different from zero, and coefficients displayed in Figure 4 are little-changed, on net, following the imposition of tariffs, a finding that we explore in depth in Section 3.4.

Finally, column 3 of Table 4 indicates that new tariffs are associated with a statistically significant relative increase in producer prices due to exposure to rising input costs. In terms of economic significance, an interquartile shift in exposure to rising input costs is 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, Redding and Weinstein (2019) who find a role for input tariffs, in addition to tariffs on output, in increasing U.S. prices. In terms of timing, the left column of Panel (c) of Figure 4 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]

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 5, with the baseline estimates from Table 4 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 (Pierce and Schott (2016), Handley and Limao (2017), Crowley and Exton (2018)). 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).

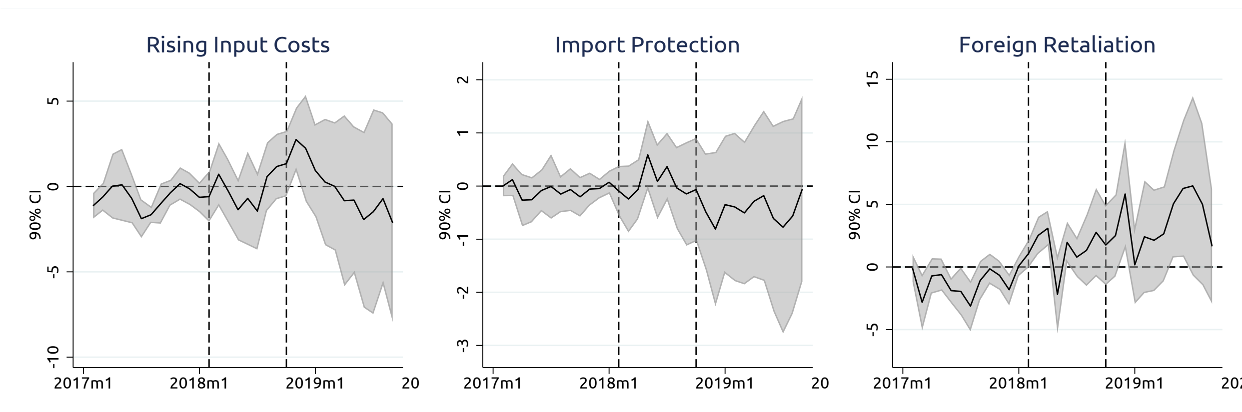
Caldara et al. (2019)'s measure of trade policy uncertainty is based on a textual analysis of the quarterly earnings calls of publicly traded U.S. firms. After classifying firms according to their Fama-French 12 industry definition, Caldara et al. (2019) measure the frequency of references to trade policy and uncertainty-related terms by industry, for each quarter. Because Caldara et al. (2019)'s measure of trade policy uncertainty is only defined through

[24]The results in Table C4 of section C.4 of the appendix highlight the importance of controlling for all three tariff channels simultaneously. For example, while there is a positive 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.

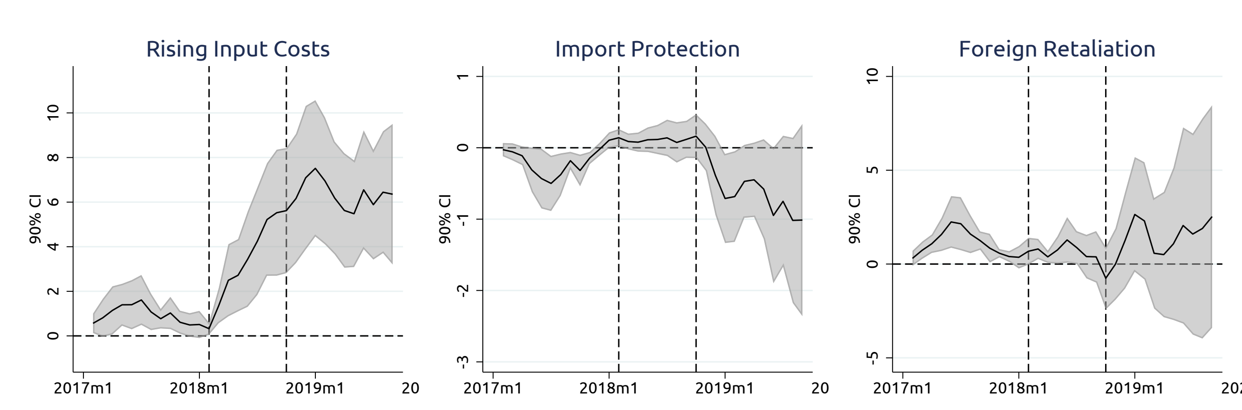
Figure 4: Effects of Cumulative Tariffs (Detrended)

(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 employment as of December 2017 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.

the second quarter of 2019, our analysis in this robustness check ends in June 2019, versus

Table 5: 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)
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)
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)
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 foreign 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 4, 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. Results are weighted by employment as of December 2017. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

September 2019 in our baseline results. Results are presented in column 2 of Table 5.

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 estimates in column 1, and the coefficient on the measure of trade policy uncertainty is not statistically significant at conventional levels. Therefore, while 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 time frequency (quarterly) than our dependent variable, these results provide support for 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 5 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: As noted above, 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 and the Differing Responses of Employment and Industrial Production

In this section, we examine whether the employment effects of tariffs identified above result from increased layoffs or slowdowns in hiring by affected firms. This analysis provides important supporting information about how employment adjusts in response to trade shocks, which is relevant for evaluating the effects of job loss on affected workers. In addition, when combined with information on manufacturers' unfilled orders, it provides 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.

Aggregate data on hiring and layoffs in the manufacturing sector at the time that tariffs begin to be imposed provide some initial information. As indicated in the left panel of Figure 5, 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. While these declines in hiring align with the employment decline in section 3, the aggregate information is only suggestive.

To more formally examine whether the tariff channels we examine are related to this decline in hiring, we make use of data from the Census Bureau's Quarterly Workforce Indicators (QWI). The QWI is based on linked employer-employee data, and reports the number of hires and separations, by quarter, for all U.S. manufacturers at the four-digit NAICS industry level.[25] While these data are available at a lower frequency (quarterly) than the dependent variables in Section 3, they provide information on employer-employee adjustment that is otherwise unavailable.

We employ the same estimation strategy as in Section 3, adapted to quarterly data:

$$\begin{aligned} y_{iq} = \quad & \alpha + \sum_q \gamma_q \mathbf{1}(Q_q = q)(\text{Import Protection}_i) + \sum_q \theta_q \mathbf{1}(Q_q = q)(\text{Input Cost}_i) \ ... \\ & + \sum_q \lambda_q \mathbf{1}(Q_q = q)(\text{Foreign Retaliation}_i) + \sum_q \Big(\mathbf{1}(Q_q = q) \times \mathbf{X_i'}\boldsymbol{\beta_q}\Big) + \delta_i + \delta_q + \varepsilon_{iq} \end{aligned} \tag{9}$$

Here, the dependent variable is the log level of either hires or separations for industry i in quarter q. The industry-level exposure measures for import protection, rising input costs, foreign retaliation, and the general international exposure and capital intensity 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 6 reports results of applying the Finkelstein (2007) approach to the coefficients from estimating equation 9. The results indicate that exposure to tariffs is indeed associated with a reduction in hiring. In particular, as shown in the first column of the Table, we find that the rising input cost channel of tariffs is associated with relative declines in hiring, as it was associated with relative declines in employment. Coefficient estimates for the remaining relationships are not statistically significant, but take the expected signs, and are consistent with the employment results in Table 4. Table 6 also reveals that the negative employment result for the foreign retaliation channel is largely due to worker separations. Nevertheless, from a quantitative perspective—using the inter-quartile shift of each channel described above—the effect of these tariffs on hires is about twice the magnitude of the effect on separations.

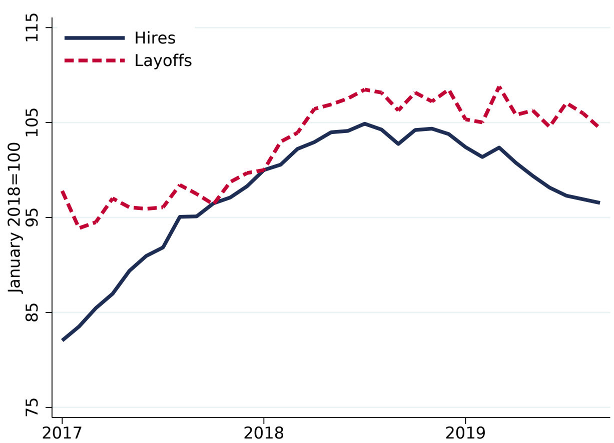
These results also provide an explanation for what may be a puzzling feature of our results

[25] We aggregate the state-NAICS4-quarter-level data to the NAICS4-quarter-level. Five percent of total U.S. hires and separations are suppressed for data confidentiality reasons at the state-NAICS4-quarter level in 2017 and 2018.

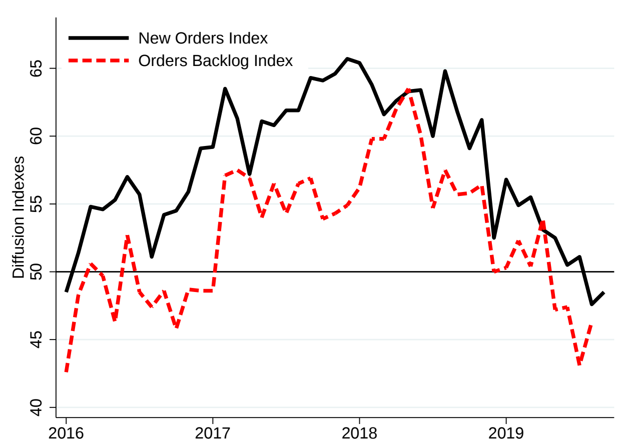
in section 3.2: negative impacts of the tariffs on employment combined with little impact on measures of industrial production. The state of manufacturers' order backlogs during this time, when paired with our decomposition of employment into hires vs separations, sheds some light on this potential puzzle. As shown in Figure 5b, 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.[26] When the index for *new* orders of manufactured goods (black line in Figure 5b) 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 extent of this response varying according to exposure to tariffs. The results in Tables 4 and 6 are consistent with this interpretation.

Figure 5: 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.

3.5 Discussion

This analysis is necessarily short-run in nature, and the longer-term effects of the 2018-2019 tariffs may differ from those that we find here. On the one hand, there may be more

[26] 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.

Table 6: Hires, Separations, and Tariffs:

Variable	Hires	Separations
Import Protection	0.469	0.156
	(1.540)	(1.511)
Rising Input Costs	-17.351**	3.369
	(6.336)	(2.160)
Foreign Retaliation	-5.190	13.155***
	(9.385)	(4.350)
Industry Fixed Effects	yes	yes
Number of Industries	76	76
Observations	836	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 applied to equation (9) in the text. Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

substantial expansion of U.S. manufacturing activity in the longer-term as firms fully adjust their supply chains to avoid U.S. import tariffs. That said, there is suggestive evidence that the United States is not typically the immediate destination for production relocation from China due to increased tariffs. In the washing machine case studied in Flaaen, Hortaçsu and Tintelnot (2020), firms first moved production to other East Asian countries (Thailand and Vietnam) following China-specific antidumping duties imposed in mid-2017. After the later Section 201 tariffs against *worldwide* imports of washing machines (discussed above), these same firms did indeed shift some sizable production to the United States, though this occurred with substantial costs to consumers via rising prices.

The longer-run effects of the tariffs will also depend on the extent to which firms view them as being temporary or part of a new trade regime favoring domestic and regional supply chains. Notably, the "Phase One" trade deal signed by the U.S. and China in January 2020 left all of the tariffs examined in this paper in place and unchanged, and they have now persisted across Presidential administrations of each of the major political parties.[27] Given the continued tensions between the U.S. and China, immediate progress on eliminating trade restrictions seems unlikely, implying that firms may begin to view them as a permanent feature of the trading environment.

[27] In terms of U.S. actions, the Phase 1 trade agreement lowered the ad valorem rates applied on a fourth round of tariffs imposed by the U.S. in September 2019, while indefinitely suspending a fifth round scheduled to be imposed in December 2019.

4 Examining 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 conducting two exercises, each with a differing focus. First, we examine whether tariffs on the manufacturing sector have spillover effects to downstream nonmanufacturing industries via input-output linkages. Second, we consider whether the negative relationship between tariffs and manufacturing employment is sufficiently large to have implications for county-level unemployment rates. This second exercise also provides information on the difficulty with which manufacturing workers displaced by tariffs were able to find employment in other sectors.

4.1 Examining Potential Spillovers to Downstream Nonmanufacturing Industries

In the same way that manufacturing firms are affected by tariffs on imported intermediate inputs, nonmanufacturing industries that use manufactured goods as inputs may face similar effects. In this section, we estimate the relationship between exposure to rising input costs and employment in nonmanufacturing industries. We focus on employment as the outcome variable because detailed data on producer prices and monthly output are unavailable for nonmanufacturing industries. We focus on exposure to rising input costs because services industries are neither protected by U.S. tariffs nor subject to retaliatory tariffs by U.S. trading partners.[28] We address the case of retaliatory tariffs on non-manufacturing goods-producing industries—particularly agriculture—in further detail below.

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

$$y_{it} = \alpha + \sum_t \theta_t \mathbf{1}(M_t = t)(\text{Input Cost}_i) + \delta_i + \delta_t + \varepsilon_{it}. \tag{10}$$

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 7 displays coefficient estimates and standard errors based on the application of the Finkelstein (2007) approach to equation (10).

[28]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.

For comparison purposes, the first column of Table 7 reports results for manufacturing industries, and column two reports results for nonmanufacturing industries.[29] 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 non-manufacturing industries, a relationship that is substantially less precisely estimated than that for manufacturing industries.[30]

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.[31]

4.2 Examining County-Level Unemployment Rates

An alternative 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, leading to more severe employment effects that would not be apparent in the industry-level analysis of non-manufacturing industries described above. Several recent papers have analyzed this geographic dimension of the 2018-2019 tariffs. Fajgelbaum et al. (2020) and Blanchard, Bown and Chor (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

[29]Note that estimates for manufacturing industries in the first column of Table 7 are the result of estimating equation 10. Because these results are based on only the rising input cost channel, they naturally differ from those reported in Table 4, which include all three tariff channels simultaneously.

[30]The negative relationship between input tariffs and nonmanufacturing employment aligns with Bown et al. (2020) and Barattieri and Cacciatore (2020), 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.

[31]We provide extensive additional results on the relationship between the rising input cost channel and nonmanufacturing employment in section C.6 of the appendix. These results include estimates based on augmenting the manufacturing sample with nonmanufacturing sectors that use manufactured goods more intensively in their production processes, as well as robustness checks examining the importance of industry aggregation and non-linear employment growth in certain industries for the nonmanufacturing estimates.

Table 7: 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
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 (10). Results are weighted by employment as of December 2017. Standard errors (in parentheses) are clustered by 3-digit NAICS industry. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

retaliatory tariffs influenced the 2018 Congressional elections.[32] 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.[33] Specifically, for an individual county k, we define exposure to each of the three tariff channels as the employment-weighted averages of exposure of the industries present in each county:

$$\text{Channel}_k = \sum_i \left(\frac{m_{ik}}{m_k}\right) \text{Channel}_i, \tag{11}$$

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 foreign retaliation.

When constructing these county-level measures, all industries, whether manufacturing

[32] 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*.

[33] 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).

or nonmanufacturing, have varying levels of exposure to the rising input cost channel via their input-output structures, as discussed in Section 4.1. 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 non-manufacturing 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.[34] 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). In this sense, our estimates of the impact of foreign retaliation may be conservative.

The county-level distributions of the three tariff channels are summarized in Figure 6. 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 foreign 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.

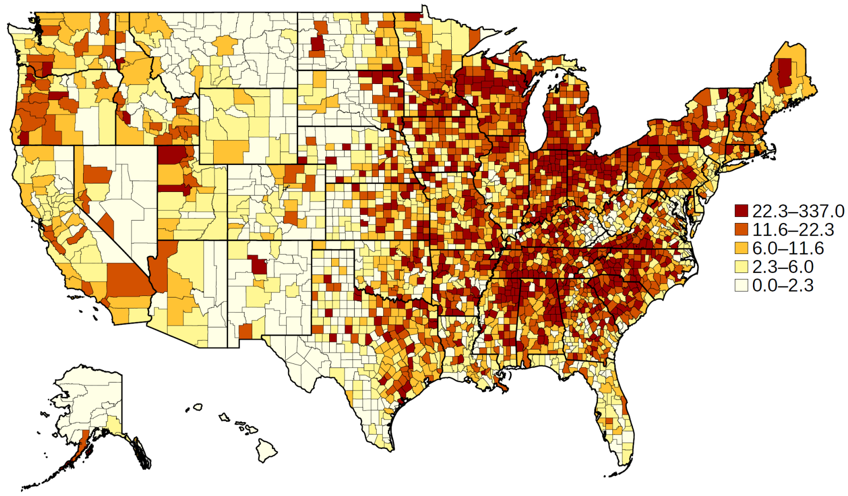
These correlations are higher than their industry-level analogues because each county-level measure of tariff exposure is related, in part, to the extent of manufacturing activity in a county. Therefore, to ensure that we accurately estimate the relationship between exposure to *tariffs* and the unemployment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

We use these county-level measures of each channel to examine the relationship between exposure to tariff changes and a broader measure of labor market outcomes, the unemploy-

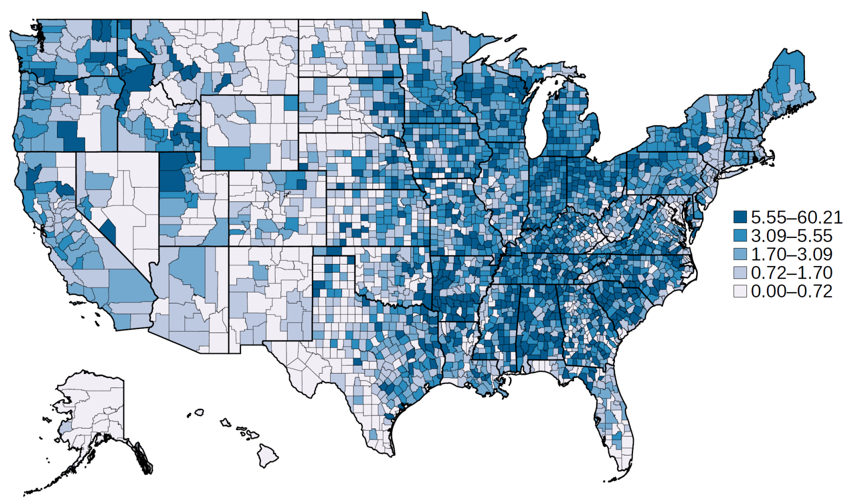
[34] Waugh (2019) and Goswami (2020) use an alternative approach to measure exposure to tariffs, based on employment-weighted average changes in tariffs for the industries in each county. That measure does not account for the value of imports or exports covered by tariffs and is not normalized by the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

Figure 6: County-Level Distribution of Tariffs

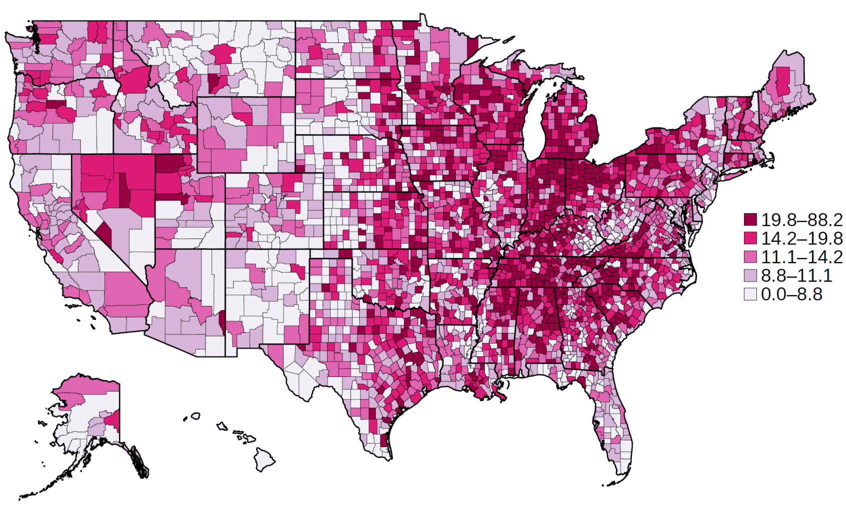
(a) Manufacturing Import Protection, by County



(b) Foreign 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 (11)) of industry-level exposure defined in equations (6), (2), and (1) above.

ment rate. Unemployment rate data are from the BLS's Local Area Unemployment Statistics (LAUS), which collects information on labor market outcomes at the county-level.[35] 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:

$$\begin{aligned} y_{kt} = \quad & \alpha + \sum_t \gamma_t \mathbf{1}(M_t = t)(\text{Import Protection}_k) + \sum_t \theta_t \mathbf{1}(M_t = t)(\text{Input Cost}_k) \; ... \\ & + \sum_t \lambda_t \mathbf{1}(M_t = t)(\text{Foreign Retaliation}_k) + \sum_t \Big(\mathbf{1}(M_t = t) \times \mathbf{X_k'} \boldsymbol{\beta_t} \Big) + \delta_k + \delta_t + \varepsilon_{kt} \end{aligned} \tag{12}$$

The dependent variable (y_{kt}) is the county-month-level unemployment rate, and the independent variables are interactions of month dummies with the county-level measures of each of the three tariff channels, the three measures of international exposure described above, and the manufacturing employment share. Equation 12 also includes county and month fixed effects. Standard errors are clustered at the state level.

We report results of estimating equation 12 in terms of the Finkelstein (2007) hypothesis test described above, with results reported in Table 8.[36] The first column shows results without time-varying controls for a county's manufacturing share of employment, while the second column—our preferred specification—includes these controls. Focusing on column (2), 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 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 and isn't robust when applying the Borusyak, Hull and Jaravel (2021) adjustment (as discussed below). In terms of economic significance, these estimates imply that a county in the 75th percentile of the distribution for each tariff channel experiences a 0.17 percentage point increase in the county-level unemployment rate, relative to a county in the 25th percentile. While this increase is modest in size, it is not trivial. Furthermore, it suggests that the decline in manufacturing employment due to the imposition of tariffs is not readily absorbed by gains in other industries. This result, therefore, provides further evidence of the presence of substantial adjustment costs for workers attempting to move between industries or geographic areas (Ebenstein et al. (2014), Artuç, Chaudhuri and McLaren (2010), Caliendo and Parro (2015), and Acemoglu et al. (2016)).

[35] 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 seasonally adjust these data using the standard Census Bureau X-13 seasonal adjustment program available at https://www.census.gov/srd/www/x13as/.

[36] We report raw coefficient estimates and confidence intervals from estimating equation 12 in Section C.7 of the appendix.

Table 8: Point Estimates of Cumulative Effect by Channel:

Variable	Unemployment Rate (1)	(2)
Rising Input Costs	88.35***	64.17***
	(17.97)	(17.81)
Import Protection	12.05**	9.75*
	(5.49)	(5.48)
Foreign Retaliation	100.32***	51.67*
	(27.85)	(31.08)
Manufacturing Share Controls	no	yes
Capital Intensity Controls	no	no
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: Table 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. See Appendix C.8 for results translated to a shock-level (industry) basis following Borusyak, Hull and Jaravel (2021). Estimates are weighted by December 2017 labor force. Standard errors (in parentheses) are clustered at the state-level. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

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, Hull and Jaravel (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.[37] In Appendix C.8 we follow the correction procedures outlined in Borusyak, Hull and Jaravel (2021) and convert employment weighted averages across counties to then run industry-level regressions with corrected standard errors. The results are qualitatively similar in that the rising input channel cost remains highly statistically significant. By contrast, the positive effect from import protection noted above becomes insignificant, and the export retaliation effect is sensitive to the controls used.

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

5 Conclusion

This paper provides the first estimates of the effect of the tariff increases imposed since 2018 on outcomes in the U.S. manufacturing sector, the sector intended to benefit from U.S. tariffs. We calculate measures of each industry's exposure to tariff changes via three channels: the import protection that comes when an industry's output is subject to U.S. tariffs, 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 to tariffs and manufacturing employment, output, and producer prices.

We find that the recent tariffs are associated with relative reductions in manufacturing employment and relative increases in producer prices. For manufacturing 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. While we find little evidence of effects of the tariffs on downstream nonmanufacturing industries, we find a clear positive relationship with county-level unemployment rates. This relationship mirrors that found for manufacturing employment, as counties more exposed to rising input costs experience relative increases in unemployment rates.

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 have not boosted manufacturing employment or output, 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.

References

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

Adão, Rodrigo, Costas Arkolakis, and Federico Esposito. 2020. "General Equilibrium Effects in Space: Theory and Measurement." Working Paper.

Alfaro, Laura, Pol Antràs, Davin Chor, and Paola Conconi. 2019. "Internalizing Global Value Chains: A Firm-Level Analysis." *Journal of Political Economy*, 127(2): 508–559.

Amiti, Mary, and Jozef Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *American Economic Review*, 97(5): 1611–1638.

Amiti, Mary, Sang Hoon Kong, and David Weinstein. 2020. "The Effect of the U.S.-China Trade War on U.S. Investment." National Bureau of Economic Research Working Paper 27114.

Amiti, Mary, Stephen J. Redding, and David Weinstein. 2019. "The Impact of the 2018 Trade War on U.S. Price and Welfare." *Journal of Economic Perspectives*, 33(4): 187–210.

Antràs, Pol, and Davin Chor. 2018. "Chapter 5 - On the Measurement of Upstreamness and Downstreamness in Global Value Chains." In . *World Trade Evolution: Growth, Productivity and Employment*, , ed. Lili Yan Ing and Mioajie Yu. Routledge.

Antràs, Pol, Teresa C. Fort, and Felix Tintelnot. 2017. "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms." *American Economic Review*, 107(9): 2514–64.

Artuç, Erhan, Shubham Chaudhuri, and John McLaren. 2010. "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review*, 100(3): 1008–45.

Autor, David, David Dorn, and Gordon H Hanson. 2021. "On the Persistence of the China Shock." National Bureau of Economic Research Working Paper 29401.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121–68.

Balassa, Bela. 1965. "Tariff Protection in Industrial Countries." *Journal of Political Economy*, 73(6): 573–94.

Barattieri, Alessandro, and Matteo Cacciatore. 2020. "Self-Harming Trade Policy? Protectionism and Production Networks." National Bureau of Economic Research Working Paper 27630.

Bernard, Andrew B., and Andreas Moxnes. 2018. "Networks and Trade." *Annual Review of Economics*, 10(1): 65–85.

Blanchard, Emily J., Chad P. Bown, and Davin Chor. 2019. "Did Trump's Trade War Impact the 2018 Election?" National Bureau of Economic Research Working Paper 26434.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2021. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies*, 89(1): 181–213.

Bown, Chad P., and Melina Kolb. 2019. "Trump's Trade War Timeline: An Up-to-Date Guide." Peterson Institute for International Economics.

Bown, Chad, Paola Conconi, Aksel Erbahar, and Lorenzo Trimarchi. 2020. "Trade Protection Along Supply Chains." Working Paper.

Bown, Chad P., Euijin Jung, and Zhiyao Lu. 2019*a*. "China's Retaliation to Trump's Tariffs." Peterson Institute for International Economics.

Bown, Chad P., Euijin Jung, and Zhiyao Lu. 2019*b*. "Trump, China, and Tariffs: From Soybeans to Semiconductors." Peterson Institute for International Economics.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo. 2019. "The Economic Effects of Trade Policy Uncertainty." *Journal of Monetary Economics.*

Caliendo, Lorenzo, and Fernando Parro. 2015. "Estimates of the Trade and Welfare Effects of NAFTA." *The Review of Economic Studies*, 82(1): 1–44.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang. 2021. "Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy." *American Economic Review: Insights*, 3(1): 19–34.

Corden, W.M. 1966. "The Structure of a Tariff System and the Effective Protective Rate." *Journal of Political Economy*, 74(3): 221–237.

Crowley, Meredith, Lu Han, and Oliver Exton. 2018. "Renegotiation of Trade Agreements and Firm Exporting Decisions: Evidence from the Impact of Brexit on UK Exports." Working Paper.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips. 2014. "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys." *The Review of Economics and Statistics*, 96(4): 581–595.

Eckert, Fabian, Teresa C. Fort, Peter K. Schott, and Natalie J. Yang. 2020. "Imputing Missing Values in the US Census Bureau's County Business Patterns." National Bureau of Economic Research.

Fajgelbaum, Pablo D., Pinelopi K. Goldberg, Patrick J. Kennedy, and Amit K. Khandelwal. 2020. "The Return to Protectionism." *Quarterly Journal of Economics*, 135(1): 1–55.

Fernandes, Ana M. 2007. "Trade policy, trade volumes and plant-level productivity in Colombian manufacturing industries." *Journal of International Economics*, 71(1): 52 – 71.

Finkelstein, Amy. 2007. "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare." *Quarterly Journal of Economics*, 122(1): 1–37.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. "The Production Relocation and Price Effects of U.S. Trade Policy: The Case of Washing Machines." *American Economic Review*, 110(7): 2103–2127.

Flaaen, Aaron, Katyrn Langemeier, and Justin Pierce. 2021. "Factors Affecting Recent U.S. Tariffs on Imports from China." Federal Reserve Board FEDS Notes 29401.

Goswami, Sanjana. 2020. "Employment Consequences of U.S. Trade Wars." Working Paper.

Handley, Kyle, and Nuno Limao. 2017. "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States." *American Economic Review*, 107(9): 2731–83.

Handley, Kyle, Fariha Kamal, and Ryan Monarch. 2020. "Rising Import Tariffs, Falling Export Growth: When Modern Supply Chains Meet Old-Style Protectionism." International Finance Discussion Papers Working Paper 1270.

Huang, Yi, Chen Lin, Sibo Liu, and Heiwei Tang. 2019. "Trade Networks and Firm Value: Evidence from the U.S.-China Trade War." Centre for Economic Policy Research Working Paper DP14173.

Institute for Supply Management. 2020. "Manufacturing ISM Report on Business." Working Paper.

Johnson, Harry G. 1953. “Optimum Tariffs and Retaliation.” *The Review of Economic Studies*, 21(2): 142–53.

Kaldor, N. 1940. “A Note on Tariffs and the Terms of Trade.” *Economica*, 7(28): 377–80.

Lawder, David, and Howard Schneider. 2018. “Surprises Lurk in Trump’s Tariff List, from Thermostats to Vaping Devices.” *Reuters*.

Pavcnik, Nina. 2002. “Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants.” *The Review of Economic Studies*, 69(1): 245–276.

Pierce, Justin, and Peter Schott. 2012. “A Concordance Between U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries.” *Journal of Economic and Social Measurement*, 37(1-2): 61–96.

Pierce, Justin R., and Peter K. Schott. 2016. “The Surprisingly Swift Decline of US Manufacturing Employment.” *American Economic Review*, 106(7): 1632–62.

Reyes-Heroles, Ricardo, Sharon Traiberman, and Eva Van Leemput. 2019. “Emerging Markets and the New Geography of Trade: The Effects of Rising Trade Barriers.” Working Paper Working Paper.

Topalova, Petia, and Amit Khandelwal. 2011. “Trade Liberalization and Firm Productivity: The Case of India.” *The Review of Economics and Statistics*, 93(3): 995–1009.

Trefler, Daniel. 2004. “The Long and Short of the Canada-U. S. Free Trade Agreement.” *American Economic Review*, 94(4): 870–895.

Waugh, Michael E. 2019. “The Consumption Response to Trade Shocks: Evidence from the US-China Trade War.” National Bureau of Economic Research Working Paper 26353.

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, Arkolakis and Esposito (2020), which examines the effect of international trade shocks on spatially connected markets. Most relevantly for our purposes, Adão, Arkolakis and Esposito (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, Arkolakis and Esposito (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, Arkolakis and Esposito (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, Arkolakis and Esposito (2020). Specifically, Adão, Arkolakis and Esposito (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, Arkolakis and Esposito (2020) details how changes in bilateral trade costs affecting sector k output impact revenues in country j. It is given by

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

where $y_{ji,k}$ is the share of sector k revenue of country j that comes from country i, and x is defined similarly in terms of spending. In the application to the tariff escalation highlighted in this paper, we focus on the first term only as the second term ends up being second order in magnitude.[38] Focusing on this first term:

[38]To see this, consider the example of Chinese retaliatory tariffs on the U.S., with $\hat{\tau}_{ji,k} > 0$ for $j = \{U.S.\}$

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

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 foreign retaliation in equation (2) in the main text.

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

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

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

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

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

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

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

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

Once again, this equation simply weights the changes in bilateral trade costs by the respective country shares within a given sector. In the context of our focus on the manufacturing sector,

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.

the change in bilateral trade costs owing to a rise in own-country tariffs ($\hat{\tau}_{oi,k}$ above) implies the higher prices by domestic firms that forms the basis of import protection. Equation (A4), therefore, is similar to our empirical measure for import protection in equation (1) in the main text.

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

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

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

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

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

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

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

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

Retaliatory Tariff	Reference for Affected Products	2017 Export Volume	Reported by Government	Other Estimates	Source for Other Estimates
		Billions of U.S. Dollars			
China on US – Apr. 2018	Link	2.44	2.4	2.39	Source
EU on US – Jun. 2018	Link	4.23	3.2	3.24	Source
Canada on US – Jul. 2018	Link	17.8	12.8	12.76	Source
China on US – Jul. 2018	Link	29.2	34		
China on US – Aug. 2018	Link	21.9	16		
China on US – Jul.+Aug.		51.1	50	49.8	Source
China on US – Sep. 2018	Link	52	60	53.4	Source
Mexico on US – Jun. 2018	Link	4.51	3.8		
India on US – Jan. 2019	Link	0.89	1.3	1.3	Source
Turkey on US – Jun. 2018	Link	1.56	1.8		
Russia on US – Aug. 2018	Link	0.27	0.43		
China on US – Sep. 2019	Link		112		
China on US – Dec. 2019	Link		160		

C Additional Results

C.1 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 and 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 C1 reports these results pertaining to employment, industrial production, and PPIs.

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

C.2 Alternative Measures of Tariff Exposure

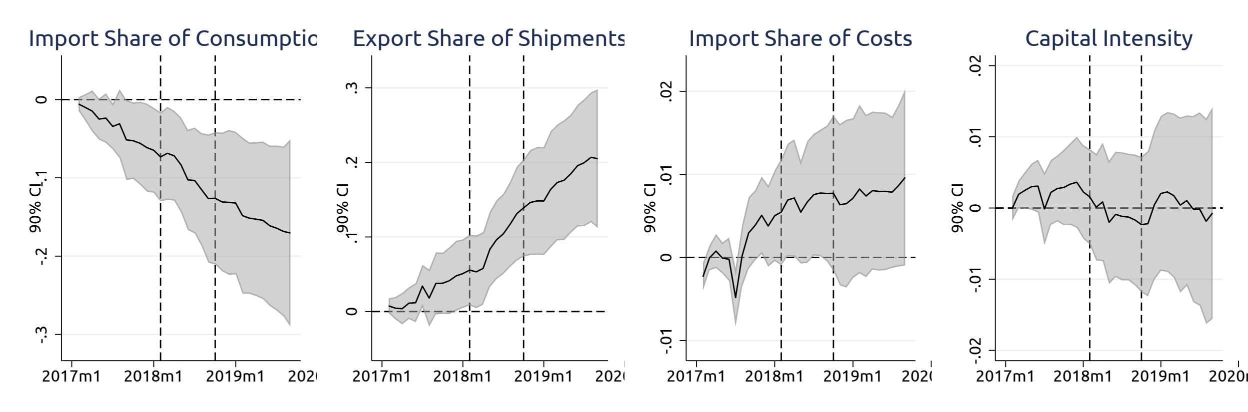
Our baseline measures of exposure to tariffs described in Section 2.4 account for the magnitude of tariff increases, the value of trade flows affected, and the relevance of those trade flows to an industry's output (shipments) or domestic market (absorption, or $output + exports - imports$). In this 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 C3 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.

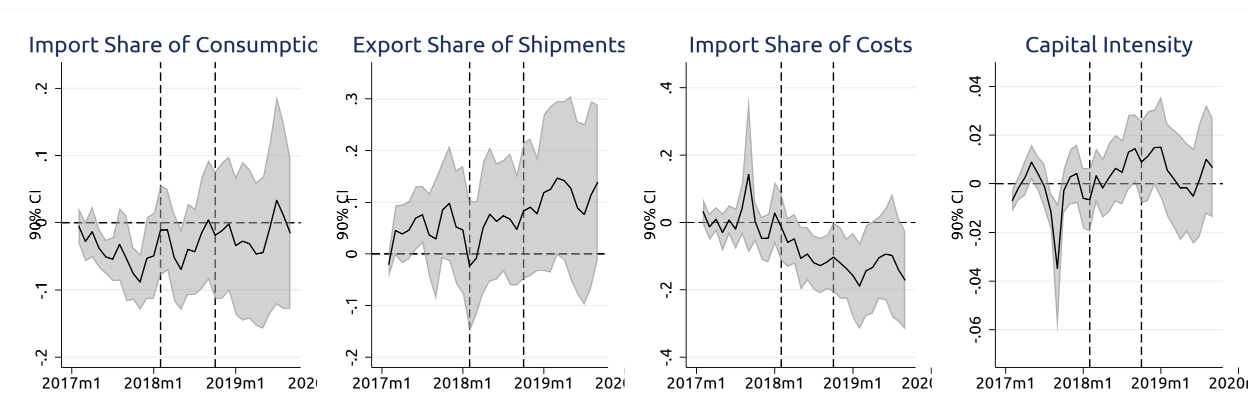
Exposure Only To Changes in Tariff Rates: Another approach to measuring exposure to tariff changes is to simply calculate industry-level average changes in ad-valorem rates on output, exports, and inputs. This approach is straightforward, but it does not account for either the value of trade flows affected or the size of those affected trade flows relative to the industry's output or domestic market. Column 2 of Table C3 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

Figure C1: Coefficient Estimates for Control Variables

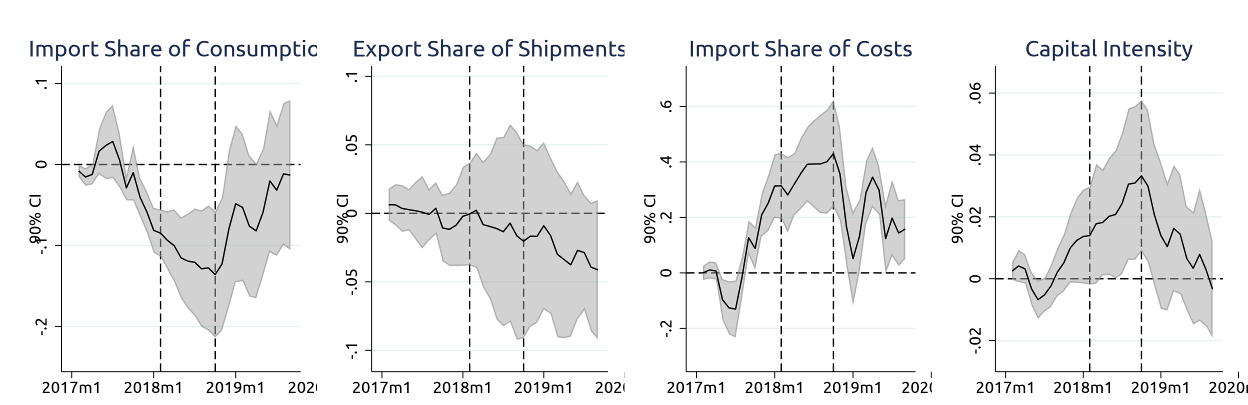
(a) Employment



(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.

accounting for the importance of tariff changes either to trade flows or industry size.

Table C3: Robustness Results: Alternative Exposure Measures

Variable	Dep. Var: Log Employment (1)	(2)
Import Protection	-0.001	-0.003
	(0.002)	(0.070)
Rising Input Costs	-0.009**	-0.692***
	(0.004)	(0.219)
Foreign Retaliation	-0.005***	0.006
	(0.002)	(0.082)
Industry Fixed Effects	yes	yes
Number of Industries	76	76
Observations	2,475	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 foreign 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. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

C.3 Alternative Specifications

Figure C3 presents the raw results from estimating equation (7) without accounting for pre-trends in the dependent variable. As indicated in the figure, we find clear evidence of differing pre-trends across industries prior to the introduction of tariffs, which appears, for example, as the pre-tariff upward trend in coefficient estimates for the relationship between exposure to rising input costs and employment in the left column of Panel (a). The figure also 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 left column of Panel (a). As discussed in Finkelstein (2007), these *breaks in trend* represent the impact on the outcome variables that is attributable to the change in policy. In the main text, we use either the approach developed in Finkelstein (2007) or industry-level detrending to isolate this impact of the tariff changes by netting out pre-trends.

C.4 Univariate Results

Table C4 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 4. Table C4 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 foreign retaliation and industrial production, but this effect is not present when the other channels are present, highlighting the importance of controlling for all tariff channels together.

Table C4: 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)		
Rising Input Costs		-2.456***			-1.635			8.077*	
		(0.853)			(1.962)			(4.542)	
Foreign Retaliation			-2.904			4.943***			2.957
			(2.501)			(1.524)			(5.415)

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

C.5 Results by Tariff Wave

The main results presented in Table 4 calculate exposure to three tariff channels based on cumulative values of affected trade, covering all tariffs imposed during our sample period. Table C5, 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 C5, therefore, shows the results of a single regression.

The table yields several findings on the effects of individual tariff waves. First, in terms of employment (column 1) we find that exposure to rising input costs from the March 2018 steel and aluminum tariffs is associated with a relative decline in employment, as is foreign retaliation to those tariffs in the following month. These results align very closely with the baseline results presented in Table 4. 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 foreign 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 C5, 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.

C.6 Robustness Checks for the Nonmanufacturing Industry Sample

This sub-section provides 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 (10) using detrended employment, providing visual representations of the results in Figure C4. 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 7 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 C4 examine whether the relationship between exposure to rising input costs and employment that is present for manufacturing industries persists in broader groupings of sectors, especially including those nonmanufacturing sectors that use manufactured goods more intensively in their production processes. As shown in the Figure C4, 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).[39] 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.

[39] 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.

Table C5: Point Estimates by Tariff Wave

Variable	Employment	Industrial Production	Producer Prices
Foreign Retaliation Apr. 2018	-53.331**	41.801	-100.726**
	(21.172)	(63.326)	(40.310)
Foreign Retaliation Aug. 2018	-1.880	19.904**	-12.727**
	(5.472)	(8.048)	(5.329)
Foreign Retaliation Jul. 2018	-2.666	-6.161	12.284***
	(3.633)	(5.916)	(4.178)
Foreign Retaliation Jun. 2018	15.867	-2.647	10.296
	(12.224)	(14.178)	(6.395)
Foreign Retaliation Sep. 2018	-1.216	-0.237	-9.757
	(1.870)	(3.301)	(6.912)
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)
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. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Lastly, we conduct two robustness checks to examine potential explanations for the imprecise relationship between exposure to the input cost effects of tariffs and non-manufacturing employment. First, we examine the importance of limitations on the industry detail of data for specific non-manufacturing industries. Data for nonmanufacturing industries are, in general, less detailed than for manufacturing industries, especially in the input-output tables. This lack of disaggregated data is particularly acute for some nonmanufacturing industries that are likely to be affected by tariffs, especially construction, for which all detailed industries in the input-output tables match to a single two-digit NAICS code (NAICS 23). As shown in the middle panel of Figure C5, excluding construction from the analysis of nonmanufacturing industries substantially changes the contour of the coefficients, while still indicating a lack of a statistically significant relationship between tariff exposure and nonmanufacturing employment. Second, we examine the relevance of short-term trends in employment for non-manufacturing industries in the pre-tariff period. The step up in coefficients in 2017 shown in the upper left panel of Figure C4, even after linear detrending, indicates that employment for some of the more-exposed nonmanufacturing industries was increasing at a non-linear rate in the months before tariffs were announced or implemented. In the right panel of Figure C5, we display results of estimating equation 10 after subtracting a quadratic trend from the dependent variable, based on each industry's 2017 data. As shown in the panel, accounting for the more-than-linear employment growth observed in 2017 reveals a substantial slowing that occurs at the time the tariffs begin to be imposed, and which deepens as additional rounds of tariffs take effect. Nonetheless, we caution that the implied assumption that the non-linear growth in employment would continue for any extended period of time is aggressive, and would be likely to reveal under-performance relative to this trend.

C.7 Visual Representation of County-Level Unemployment Rate Results

This sub-section presents visual representations of the results for county-level unemployment rates presented in Section 4.2.

C.8 Shock-Level Results for Effect on Unemployment

In this appendix we follow the growing literature that seeks to translate diff-in-diff specifications with shift-share measures of exposure into direct shock-level regressions using the approach from Borusyak, Hull and Jaravel (2021). Recall that while our setting is a shift-share in reduced form—unlike the IV applications highlighted in their paper—Borusyak, Hull and Jaravel (2021) emphasize that the re-weighting approach is valid in either case. We note that implementing the Borusyak, Hull and Jaravel (2021) approach in our setting differs from that in standard IV applications due to the presence of multiple sets of shocks and a host of controls, including time-varying county-level controls.

We present shock-level results based on the Borusyak, Hull and Jaravel (2021) approach in Table C6. Beginning in column (1), which excludes control variables, coefficient estimates are nearly identical to the analogous OLS results in column (1) of Table 8. This similarity of coefficient estimates aligns with the equivalence result from Borusyak, Hull and Jaravel (2021). The main difference in the shock-level results relative to the baseline is that the import protection channel is no longer statistically significant due to larger standard errors in the shock-level analysis. Column (2), which includes additional control variables, first residualizes based on a county's manufacturing share of employment before translating to the industry-level specification, to be consistent with column (2) of Table 8. The results in column (2) of Table C6 reinforce the primary role played by rising input costs, as now the export retaliation channel also loses statistical significance. It is worth pointing out that the equivalence result does not hold in this case, which is likely the result of the complication of re-weighting when incorporating the time-varying impact of manufacturing share controls.

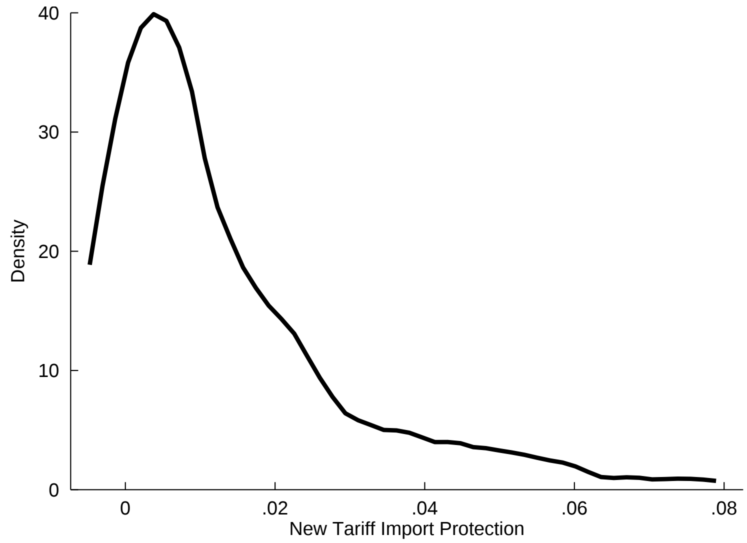
Table C6: Industry-Level Point Estimates of Unemployment Rate Effects:

Variable	Unemployment Rate	
	(1)	(2)
Rising Input Costs	87.63***	223.06***
	(16.67)	(45.80)
Import Protection	12.21	25.24
	(7.98)	(26.14)
Foreign Retaliation	100.68***	376.62
	(30.71)	(280.76)
Manufacturing Share Controls	no	yes
Capital Intensity Controls	no	no
Industry Fixed Effects	yes	yes
Month Fixed Effects	yes	yes
Observations	8,250	8,250

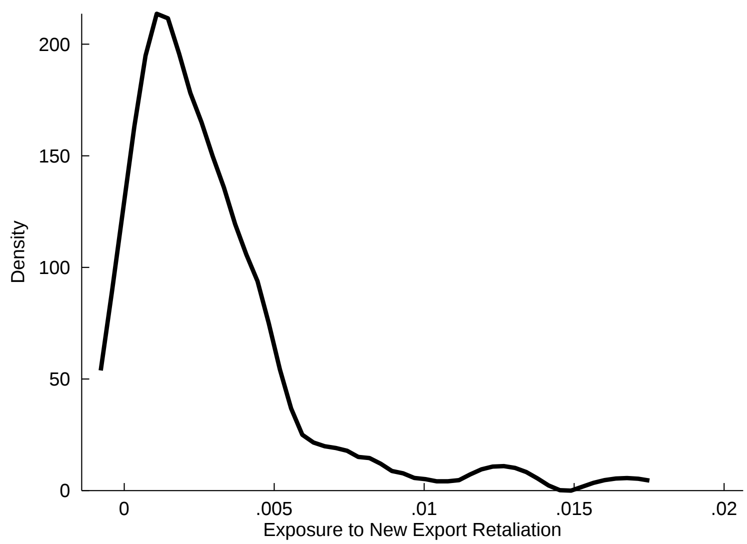
Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Table displays results of the Finkelstein (2007) approach described in equation 8, based on OLS regressions of unemployment rates on measures of exposure to the rising input cost, import protection, and export retaliation channels of tariffs. These specifications reports results analogous to Table 8 after translating to a shock-level (industry-level) specification following Borusyak, Hull and Jaravel (2021). Estimates are weighted by December 2017 labor force. Standard errors (in parentheses) are clustered at the 3-digit NAICS industry level. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

Figure C2: Density Estimates of Tariff Exposure Channels Across Manufacturing

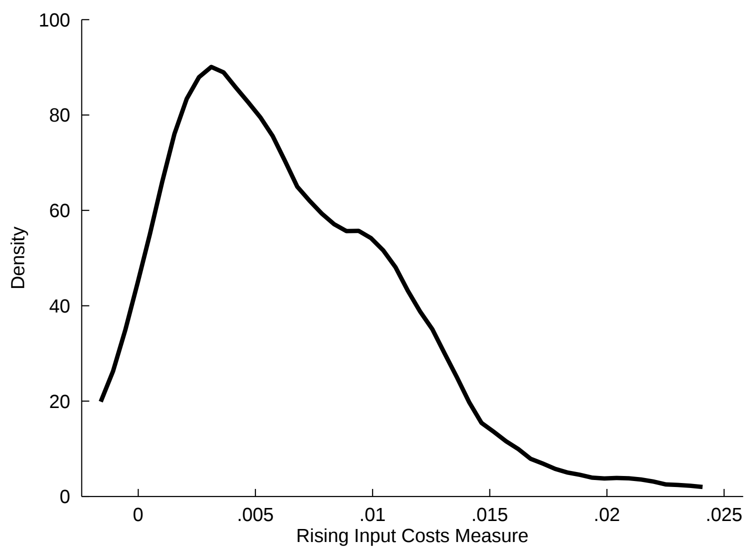
(a) Import Protection



(b) Foreign Retaliation



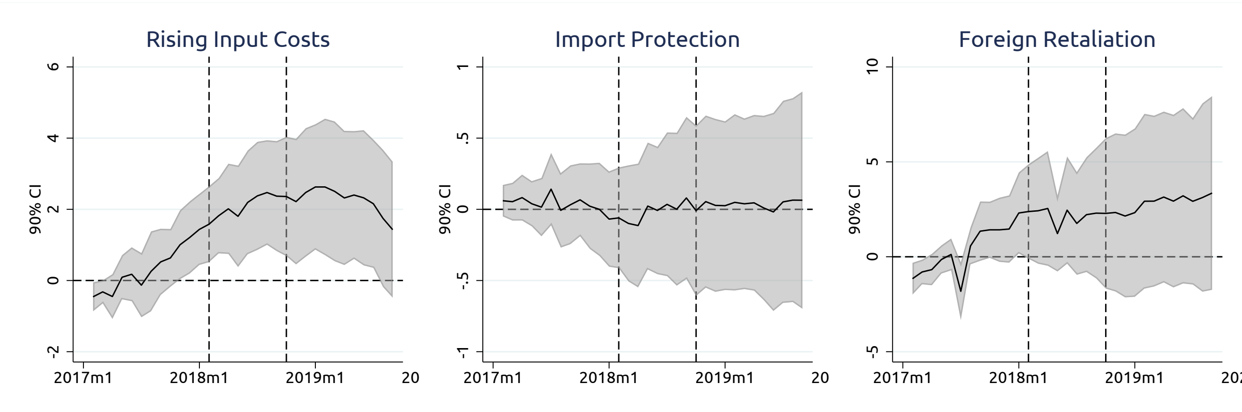
(c) Rising Input Costs



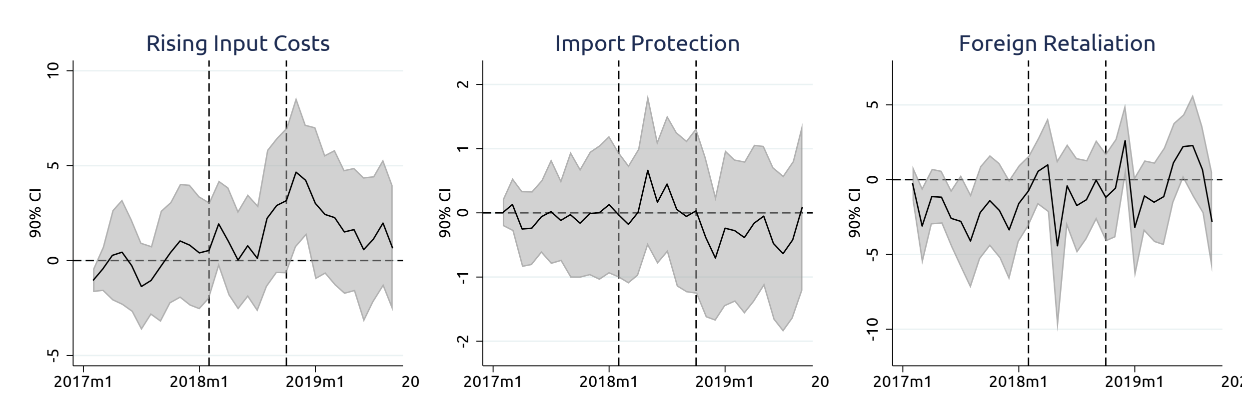
Sources: Figures display densities of industry-level measures of exposure to each tariff channel.

Figure C3: Effects of Cumulative Tariffs, Non-Detrended Outcome Variables

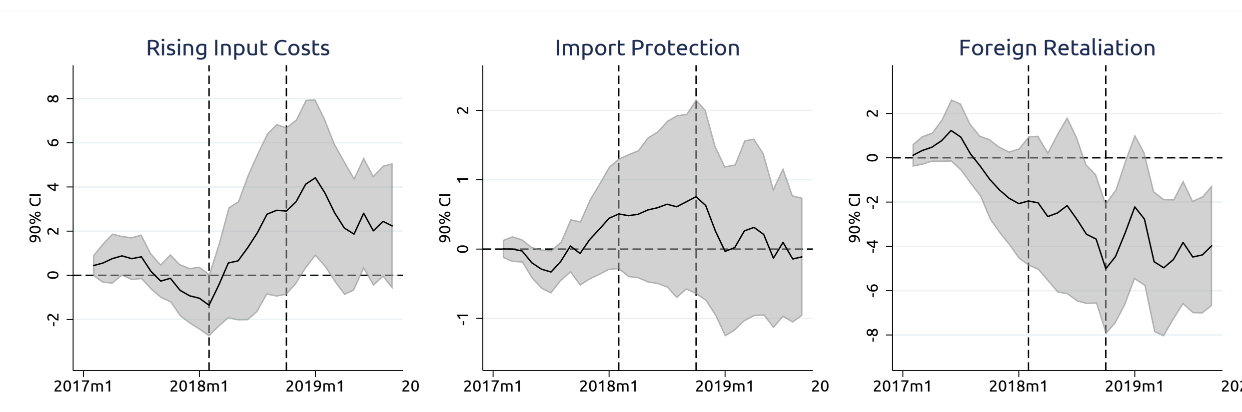
(a) Employment



(b) Industrial Production (Output)



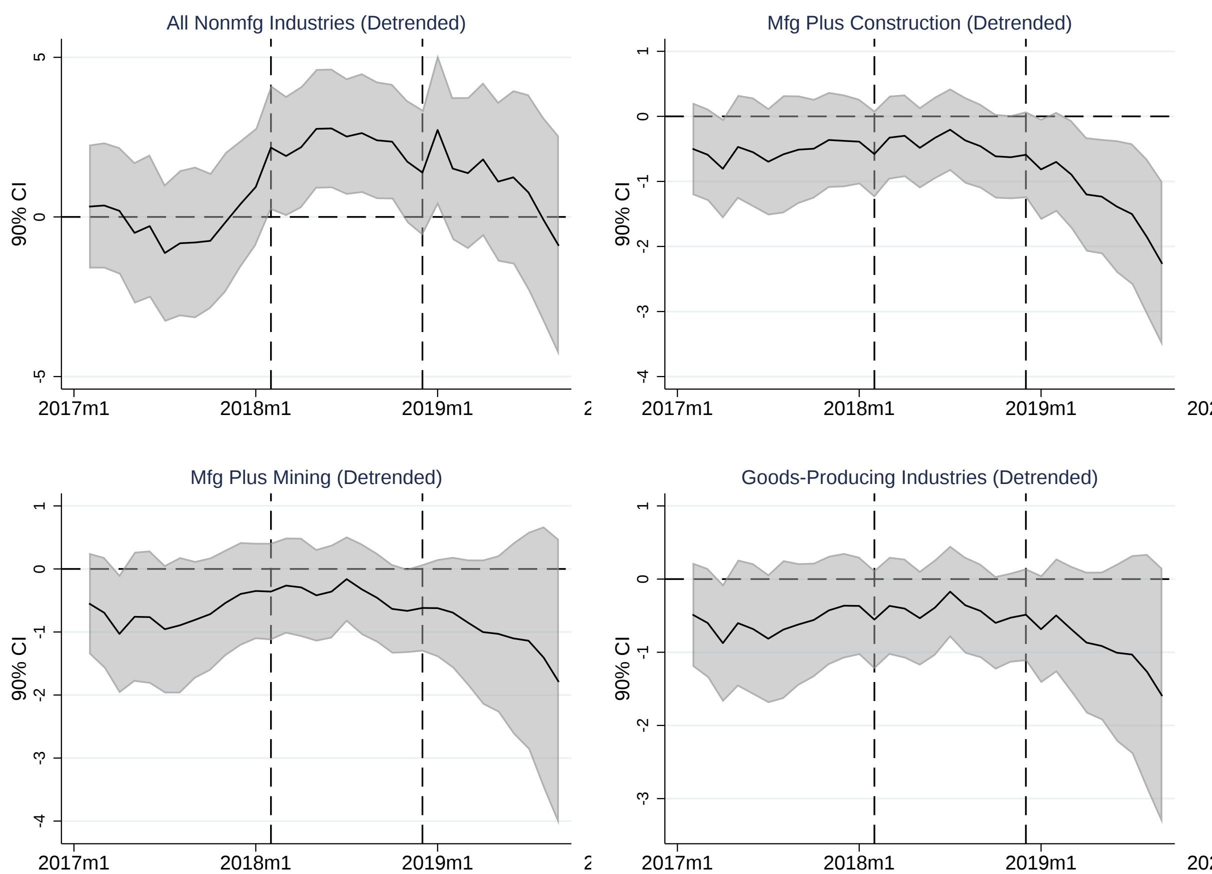
(c) Producer Price Index



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

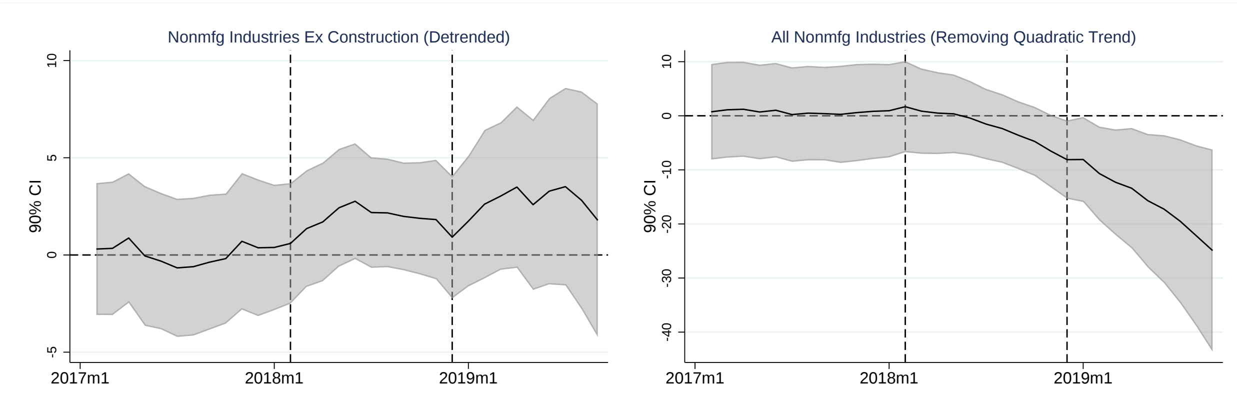
Notes: Each panel displays results of a separate regression for the noted dependent variable, with each column corresponding to the three tariff channels in equation (7). Solid lines indicate coefficient estimates and shaded areas represent 90 percent confidence intervals. The two vertical dashed lines 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.

Figure C4: Effects of Exposure to Rising Input Costs Via Tariffs on Nonmanufacturing Employment



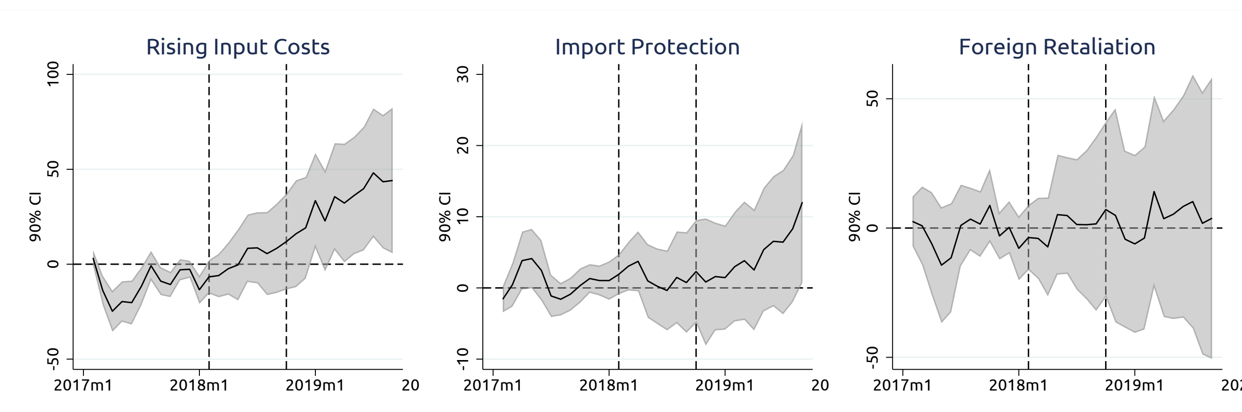
Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Each chart in the figure displays results of a separate regression of nonmanufacturing employment on exposure to rising input costs via tariffs. Solid lines indicate coefficient estimates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

Figure C5: Relationship Between Exposure to Rising Input Costs Via Tariffs and Non-manufacturing Employment



Sources: Federal Reserve Board (FRB), U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Each column in the figure represents results of a separate regression of nonmanufacturing employment on exposure to rising input costs via tariffs. The left panel displays results using linearly-detrended nonmanufacturing employment, but excludes the construction sector (NAICS 23). The right panel uses nonmanufacturing employment de-trended with a quadratic term. 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.

Figure C6: Exposure to Tariffs and County-Level Unemployment



Sources: U.S. Department of Labor, Bureau of Labor Statistics; authors' calculations.
Notes: Figure displays results of an OLS regression of the detrended county-level unemployment rate on interactions of month dummies and each of the three county-level channels of exposure to the 2018-2019 tariffs. 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.