The Price of Protectionism

Effects of Tariffs on U.S. Manufacturing Employment, Industrial Production, and Producer Prices, 2018–2024

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March 29, 2026

Abstract

Over the last decade, protectionism has come back into vogue in the United States. Starting in 2018, both Republican and Democratic administrations have imposed new tariffs on US imports; some trading partners have responded with tariffs on US exports. The stated justification for this return to protectionism is to bolster manufacturing employment. Following the methodology of Flaaen and Pierce (2024), I analyze the impact of tariffs on U.S. manufacturing employment, industrial production, and producer prices from 2018 to 2024. Import tariffs have a negative effect on manufacturing employment that is significant at the 1% level across all sample definitions and robust to controlling for sector-month fixed effects. My estimates imply that tariffs reduced manufacturing employment by approximately 274,000 jobs over the full sample period, relative to a baseline of 11.87 million manufacturing workers in January 2018. The impact of all three (import, input, and retaliatory) tariff channels on industrial production is not statistically significant. Import tariffs have a positive and significant effect on producer prices. Combined with the results on employment, this suggests that tariffs left capital better off relative to labor.

*Senior essay written for the Economics Department. My thanks to the Mellon Forum for providing a grant for this project, and to Professor Amit Khandelwal for advising it. I would also like to thank my parents, Rupinder Singh and Sharmila Sen, for reading the first draft and providing some helpful comments. Any remaining errors are my own.

1 Introduction

> "I think, in the end, we're going to have a lot of great jobs, we're going to have a lot of great companies, all coming back into our country."
> —*Donald Trump, remarks at signing ceremony for Section 232 steel and aluminum tariffs, March 8, 2018*

> "That's why today I'm announcing new tariffs in key sectors of the economy that are going to ensure that our workers are not held back by unfair trade practices."
> —*Joe Biden, remarks announcing new tariffs on Chinese steel, aluminum, and electric vehicles, May 14, 2024*

> "Jobs and factories will come roaring back into our country, and you see it happening already. We will supercharge our domestic industrial base."
> —*Donald Trump, remarks at "Liberation Day" signing ceremony for Executive Order 14257 imposing 10% tariffs on nearly all countries, April 2, 2025*

The last decade has seen a return to protectionism in the United States. Proponents of protectionism argue that free trade agreements caused the offshoring of manufacturing jobs—Ross Perot's "giant sucking sound"—with large negative consequences for communities that depend on blue-collar employment in tradeable industries. Tariffs, the argument goes, can bring these manufacturing jobs back home.

In 2016, Donald Trump and Bernie Sanders ran for president as opponents of the North American Free Trade Agreement (NAFTA). In the general election, Hillary Clinton reversed her support for the Trans-Pacific Partnership (TPP), a proposed free trade agreement between the United States and 11 Asian countries, which she had helped negotiate as Secretary of State. In his first term as president, Trump formally withdrew the United States from the TPP in January of 2017 and renegotiated NAFTA (though the updated trade agreement, USMCA, made few substantive changes). Starting in January of 2018, President Trump invoked Section 232 of the Trade Expansion Act of 1962 and Section 301 of the Trade Act of 1974 to impose tariffs on imported solar panels, washing machines, steel, aluminum, and select Chinese imports (Bown, 2019). In remarks at a signing ceremony for the tariffs, President Trump argued that they would bring "a lot of great jobs. . . back into our country."

These tariffs represented a major shift in American trade policy and were met with retaliatory tariffs from the Chinese government. As a candidate for president in 2019, Joe Biden opposed Trump's tariffs on China, writing on X that "Trump doesn't get the basics" and that "any freshman econ student could tell you that the American people are paying [the cost of] his tariffs."[1] However, as president, Biden did not deviate much from his predecessor's trade policy. In the spring of 2024, Biden invoked Section 301 to impose 25% tariffs on Chinese steel, aluminum, and electric vehicle batteries; 50% tariffs on Chinese semiconductors and solar panels; and 100% tariffs on Chinese electric vehicles. In his remarks announcing the tariffs, President Biden made a similar argument about employment, saying that his new tariffs "ensure that our workers are not held back by unfair trade practices."

Figure 1 illustrates the protectionist shift in U.S. trade policy since 2018.

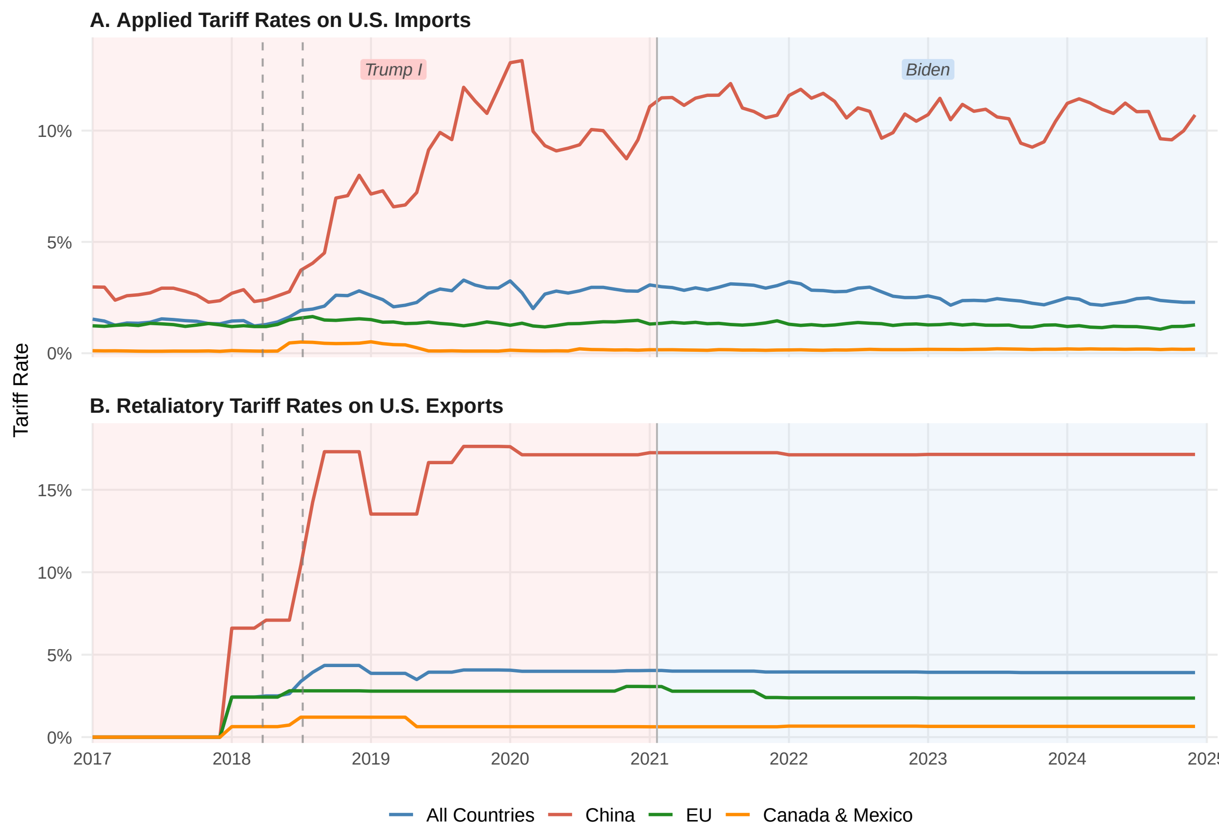


Figure 1: Tariff Rates on US Trade, 2017–2024.
Notes: Applied tariff rates on U.S. imports from China rose from ∼3% to ∼13%, all countries from ∼1.5% to ∼3.3%. Retaliatory tariff rates on U.S. exports to China rose from 0% to ∼17%, all countries from 0% to ∼4%. Vertical dashed lines mark Section 232 and Section 301 implementation dates during first Trump administration.

This essay analyzes the impact of tariffs from 2018 through 2024 on manufacturing employment. I apply the framework of Flaaen and Pierce (2024), with some methodological changes, such as using applied import tariffs rather than statutory import tariffs and extending the

[1] https://x.com/JoeBiden/status/1138506137697959939

time period being analyzed from 2018–2019 to 2018–2024. Thus, the impact of tariff changes during the second Trump administration (including the "Liberation Day" tariffs) is outside the scope of this essay.

Data from the Census Bureau compiled by Peter K. Schott[2] is used to construct monthly applied tariff rates at the HS level. Data on employment in manufacturing industries are obtained from the Bureau of Labor Statistics Current Employment Statistics. Data on industrial production are obtained from the Federal Reserve Board, and data on producer prices are obtained from the Bureau of Labor Statistics. Data on statutory retaliatory tariffs—tariffs applied to U.S. exports by other countries—are obtained from the Global Tariff Database maintained by Feodora Teti[3] and used to calculate a trade-weighted average of retaliatory tariffs imposed by U.S. trading partners on exports of a given industry's products.

These data are used to run a two-way fixed effects panel regression of manufacturing employment, industrial production, and producer price index on import, input, and retaliatory tariffs. Input tariffs are constructed following the methodology used in Topalova and Khandelwal (2011). The analysis includes a binary treatment event study, classifying industries as "high treatment" or "low treatment" based on whether changes in import, input, and retaliatory tariff levels applied to that industry exceed the median change in tariff levels. Finally, to test whether "purely protected" industries—those facing high import tariffs without similarly high input-cost or retaliatory penalties—experience employment gains, a six-cell classification is used to allow for interactions between the three tariff channels.

For robustness, three different sample specifications are used in these regressions: the full sample, pre-COVID only (up through February of 2020), and excluding COVID (full sample minus March 2020 to December 2020). I benchmark my results against Flaaen and Pierce (2024) by re-estimating the baseline panel regression for their sample period only and comparing estimated coefficients for each outcome variable and tariff channel. The panel regression is estimated using different time frequencies (monthly, quarterly, and semiannual) to account for noise, and using lagged and leading tariffs, to see whether tariffs operate with a delayed effect or whether industries anticipate future tariff changes.

Import tariffs have a negative effect on manufacturing employment that is significant at the 1% level across all sample definitions and robust to controlling for sector-level time trends via NAICS2×month fixed effects. In particular, my analysis finds that over the full period (2018–2024), a 1 percentage point increase in the applied import tariff rate on an industry is

[2] https://sompks4.github.io/sub_data.html

[3] https://feodorateti.github.io/data.html

associated with a 1.16% decline in that industry's manufacturing employment, holding input[4] and retaliatory tariffs constant. Multiplying the coefficient for import tariffs on employment by the average percentage point change in import tariffs implies that import tariffs reduced manufacturing employment by approximately 274,000 jobs over the full sample period (90% CI: 171,000 to 378,000), relative to a baseline of 11.87 million manufacturing workers in January 2018.

Import tariffs have a positive and significant effect on producer prices as expected from standard trade theory. However, the input and retaliatory tariff channels are underpowered in this framework due to limited independent variation across the three tariff measures. The input tariff measure covers approximately 66% of manufacturing industries' input cost shares, with the remaining third consisting of services inputs for which no import tariff data exists. This measurement gap, combined with the high correlation with import tariffs, makes it difficult to isolate a separate input-cost effect.

The coefficient for input tariffs on manufacturing employment is not significant at conventional norms in the main specification. In the log tariff specification, input tariffs have a significant and *positive* effect on manufacturing employment, and a significant and *negative* effect on producer prices. That is, industries with higher input tariff exposure experience *higher* employment growth and *lower* producer price growth. This result is consistent across specifications, but is counterintuitive and likely the result of data limitations.

Coefficients for all three tariff channels on industrial production are not statistically significant across regression specifications.

Section 2 provides an overview of existing literature on this subject. Section 3 describes data sources. Section 4 describes the empirical strategy. Section 5 presents results. Section 6 discusses the results and Section 7 concludes.

2 Literature Review

Several recent papers study the employment effects of trade liberalization with China. Autor et al. (2013) and Pierce and Schott (2016) both find that trade liberalization reduced U.S. manufacturing employment, albeit through different mechanisms (import competition vs. reduced trade policy uncertainty). Autor et al. (2024) investigates whether the 2018 tariffs reversed those employment losses, concluding that they did not.

[4] Note that "input tariffs" refers to tariffs on imported goods used as inputs in the production processes of U.S. manufacturing firms. For an automaker, input tariffs would include tariffs on steel and aluminum.

Amiti et al. (2019), Amiti et al. (2020), Fajgelbaum et al. (2020), and Cavallo et al. (2021) all find that the 2018 tariffs were nearly fully passed through to U.S. consumer and retail prices—though Cavallo et al. (2021) find less evidence of pass-through at the retail level, suggesting that retailers were at least partially absorbing tariffs by lowering their profit margins on tariffed goods. Near-complete pass-through of tariffs to prices is consistent with protectionism lowering consumer welfare. Handley and Limão (2017) find that trade liberalization with China increased U.S. consumer welfare, lining up with Fajgelbaum et al. (2020), which finds that the 2018 tariffs reduced U.S. consumer welfare.

Trade policy uncertainty (TPU) affects investment and employment. Caldara et al. (2020) measure TPU using three metrics—newspaper coverage, firm earnings calls, and tariff rates—finding that uncertainty shot up in 2017 and 2018 to levels not seen since the 1970s across all three measurement types. Firm-level estimates suggest that uncertainty about trade policy in 2018 may have lowered aggregate U.S. investment by 1%, with both higher tariffs and increased TPU deterring investment. Pierce and Schott (2016) find a link between China gaining Permanent Normal Trade Relations status and a decline in TPU, which in turn led to declines in U.S. manufacturing employment. Because my regressions do not fully capture TPU, they may understate the cumulative effect of tariffs on manufacturing employment from 2018 to 2024; see Section 5.3 for further discussion.

I build directly on the Flaaen and Pierce framework, adopting the same three-channel structure and generalized difference-in-differences approach. Their analysis is expanded in several ways: by using trade-weighted *applied* tariff rates rather than statutory rate changes, which captures actual tariff burdens inclusive of exemptions and exclusions; and by extending the sample through 2024, covering the Biden administration's continuation of most Trump-era tariffs; and I use time-varying monthly tariff measures rather than cumulative end-of-period measures, allowing tariff exposure to change as new rounds of tariffs are imposed. Appendix A presents a direct comparison of my results to Flaaen and Pierce's.

Note that this essay does not consider the impacts of tariffs imposed during the second Trump administration; for analysis of the "Liberation Day" tariffs, see Ignatenko et al. (2025), Rodríguez-Clare et al. (2026), and Gopinath and Neiman (2026).

3 Data

This section discusses data sources and the construction of tariff measures.

3.1 Outcome Variables

I examine three outcome variables at the four-digit NAICS industry level, measured monthly:

- **Employment** (`lemp`): Log manufacturing employment from the Bureau of Labor Statistics Current Employment Statistics[5] at the NAICS 3–5 digit levels, seasonally adjusted. The sample is restricted to manufacturing industries (NAICS codes beginning with 3), covering 64 industries.
- **Industrial Production** (`lip`): Log industrial production index from the Federal Reserve Board[6], covering 66 industries at the NAICS 3–4 digit levels.
- **Producer Prices** (`lppi`): Log producer price index from the Bureau of Labor Statistics[7], covering 80 industries, at the NAICS 3–6 digit levels, monthly. The sample period runs from January 2017 through December 2024 (96 months), with 2017 serving as the pre-treatment period.

3.2 Tariff Measures

I construct three time-varying tariff measures, each expressed as an applied tariff rate[8] in percentage points:

Import tariff (τ_{jt}^{imp}): The applied tariff rate on imports in industry j at time t, computed from detailed HS-level tariff data[9] aggregated to the NAICS-4 level using trade weights. This captures the direct competitive pressure from tariffs on an industry's own output. The weighted average import tariff rate across manufacturing industries rose from approximately 1.3 percentage points in 2017 to 3.3 percentage points by 2019 and remained near that level through 2024 (Table 1).

Input tariff (τ_{jt}^{input}): Constructed following the Topalova and Khandelwal (2011) methodology:

$$\tau_{jt}^{input} = \sum_{s} \alpha_{js} \cdot \tau_{st}^{imp} \tag{1}$$

where α_{js} is the cost share of input industry s in the production of industry j, obtained

[5] https://www.bls.gov/ces/
[6] https://www.federalreserve.gov/releases/g17/
[7] https://www.bls.gov/ppi/
[8] Applied tariffs are calculated as the duties collected at customs as a share of the value of a good, which may differ from the statutory tariff set out by legislation or executive order because of exemptions for specific goods.
[9] Tariff data sourced from the Census Bureau via Peter K. Schott: https://sompks4.github.io/sub_data.html.

from the BEA input-output tables[10], and τ_{st}^{imp} is the applied import tariff rate in the input industry. Note that the α_{js} are not renormalized to sum to 1; they reflect raw cost shares, so the input tariff measure is naturally larger for material-intensive industries than for labor-intensive ones. Cost shares are adjusted for many-to-many concordance mappings between IO industry codes and NAICS codes by redistributing shares proportionally across matched industries. To validate the IO-based construction, I verify that the input tariff measure correctly transmits the Section 232 steel and aluminum tariffs to known downstream users. As expected, the industries with the highest input tariff exposure in 2019 are steel products (NAICS code 3312, tariffs of 3.87 percentage points), forging and stamping (3321, 3.46 pp), boilers and tanks (3324, 3.25 pp), and motor vehicle parts (3363, 2.96 pp)—all heavy users of steel and aluminum inputs. More broadly, the 15 metal-using industries in the sample have a median input tariff rank of 14 out of 76, confirming that the IO linkages correctly identify downstream exposure.

Retaliatory tariff (τ_{jt}^{ret}): A trade-weighted average of retaliatory tariffs imposed by U.S. trading partners on exports of industry j's products:

$$\tau_{jt}^{ret} = \sum_{c} w_{jc} \cdot \tau_{jct} \tag{2}$$

where w_{jc} is the share of country c in industry j's exports and τ_{jct} is the retaliatory tariff imposed by country c on industry j at time t, based on 2017 baseline export values.[11] Note that this measure captures the average tariff rate conditional on exporting, but does not scale by the industry's export intensity. In the panel regression framework, cross-industry differences in export-to-output ratios are absorbed by the industry fixed effects. This measure captures the demand-side effect of foreign retaliation.

Figure 2 displays a histogram of tariff changes across manufacturing industries from 2017 to 2024.

[10] I use the 2012 detailed input-output "use" tables from the Bureau of Economic Analysis: https://www.bea.gov/industry/input-output-accounts-data.

[11] Statutory retaliatory tariffs are sourced from the Global Tariff Database maintained by Feodora Teti: https://feodorateti.github.io/data.html.

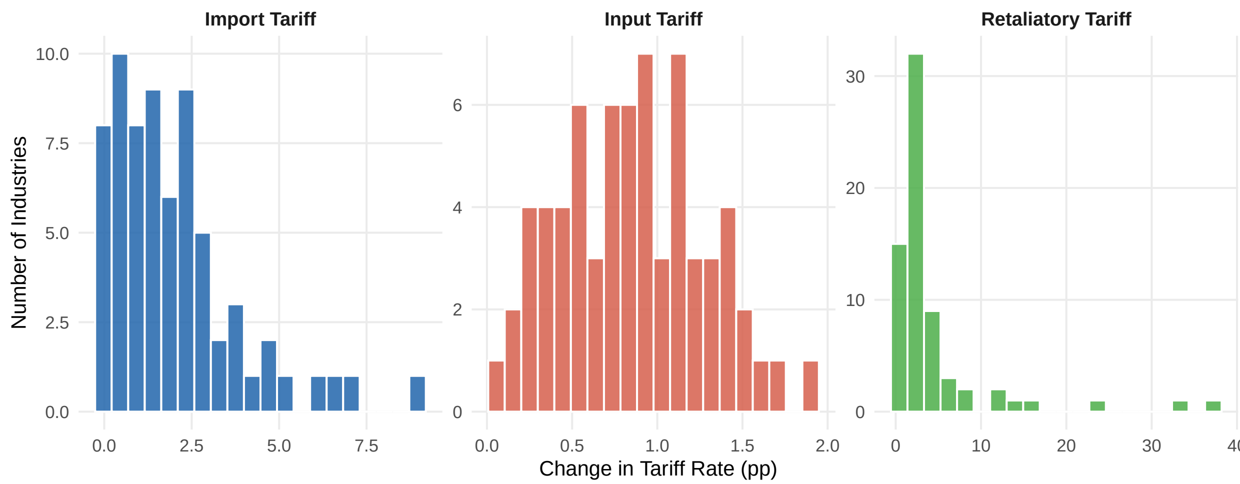


Figure 2: Distribution of Tariff Changes Across Manufacturing Industries, 2017–2024
Notes: Each panel shows the distribution of the change in the indicated tariff measure (2024 annual average minus 2017 annual average) across four-digit NAICS manufacturing industries. Import and input tariff rates are applied rates in percentage points; retaliatory tariff rates are trade-weighted statutory rates converted to percentage points. Sample restricted to industries with nonmissing data on all three channels ($N = 68$).

For import tariffs, the average increase from 2017 to 2024 was 2 percentage points. Most industries saw increases of 0 to 3 percentage points, with some (such as steel and aluminum) seeing increases of around 9 percentage points. The average increase in input tariffs was 0.86 percentage points over the same period, with most industries seeing increases of between 0.5 and 1 percentage points. Retaliatory tariffs were heavily right-skewed, with most industries facing very small increases (of 0 to 2 percentage points), but a few being hit very hard with increases up to 37 percentage points. Across industries, the mean change in retaliatory tariffs from 2017 to 2024 was 4.38 percentage points, with a median increase of 2.08 percentage points.

Figure 3 shows correlations between the three tariff channels.

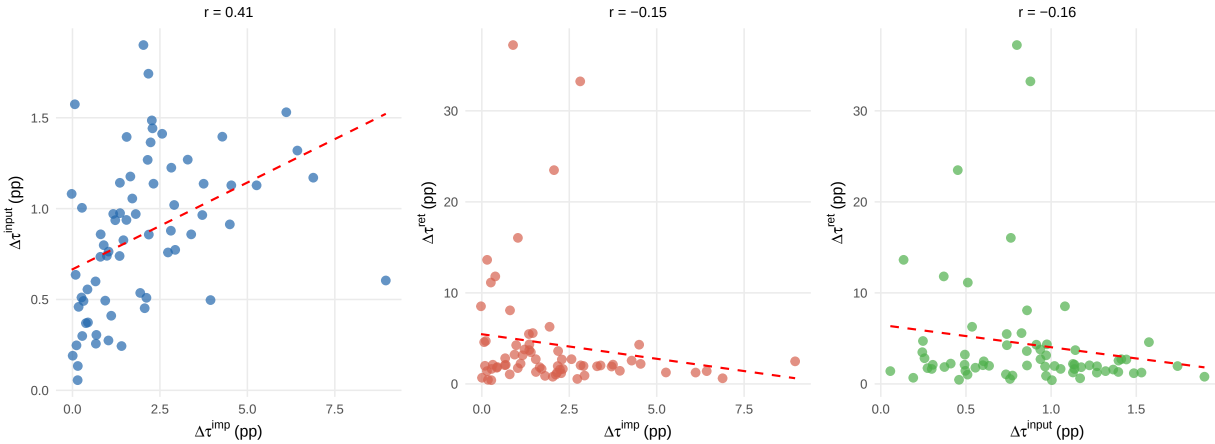


Figure 3: Pairwise Tariff Change Correlations Across Manufacturing Industries, 2017–2024
Notes: Each panel plots the 2017-to-2024 change in one tariff channel against another for the 68 manufacturing industries with nonmissing data on all three channels. Dashed red lines show OLS best-fit lines. Correlation coefficients (r) are shown above each panel.

Import and input tariffs are positively correlated ($r = 0.41$), with industries that face higher import tariffs—such as steel-using industries—often tending to use more heavily tariffed inputs. Import and retaliatory tariffs have a weak negative correlation ($r = -0.15$), implying that retaliation was not targeted towards U.S. industries protected by import tariffs. Similarly, input and retaliatory tariffs have a weak negative correlation ($r = -0.16$), implying that upstream tariff exposure and exposure to retaliation are largely independent.

Table 1: Tariff Measure Summary Statistics

	Import Tariff (τ^{imp})	Input Tariff (τ^{input})	Retaliatory Tariff (τ^{ret})
Mean (pp)	3.12	0.83	0.04
Std. Dev.	2.72	0.62	0.06
Min	0.00	0.02	0.00
Max	16.05	6.55	1.19

Notes: Summary statistics computed across all industry×month observations in the regression sample. All measures are applied tariff rates expressed in percentage points. The pre-trade-war (2017) baseline import tariff averaged approximately 1.3 pp.

The notably small mean and standard deviation of the retaliatory tariff measure reflect the structure of retaliatory tariffs during this period. China imposed the largest retaliatory tariffs, averaging 10.4 percentage points across covered industries, but these were concentrated on specific products—primarily agricultural goods, certain metals, and automobiles—rather than applied uniformly across all U.S. exports. More importantly, China accounts for a very small share of most industries' total exports: the median industry sends only 0.8% of its exports to China, with no industry exceeding 8%. After trade-weighting, even a 25 percentage point Chinese retaliatory tariff translates to only $25 \times 0.008 \approx 0.2$ percentage points at the industry level. Other retaliating countries (or trading blocs)—the EU, Turkey, India, and Canada—imposed even smaller incremental tariffs. As a result, 53 of 106 industries have trade-weighted retaliatory tariff changes below 0.01 percentage points, and only nine industries exceed 0.05 percentage points. This limited cross-industry variation constrains the precision of the retaliatory tariff channel estimates.

It is also worth noting that the sample ends in December 2024 and therefore does not capture any retaliatory tariffs imposed on U.S. exports during President Trump's second term, beginning in January 2025.

4 Empirical Strategy

4.1 Binary Treatment Event Study

I estimate event studies following the binary treatment design:

1. For each tariff channel, compute the total tariff change per industry as the difference between the 2019 and 2017 annual averages.

2. Classify industries as "high treatment" if their tariff change exceeds the sample median (baseline specification) or the sample mean (robustness check). The mean split produces a somewhat unbalanced grouping due to the right-skewed distribution of tariff changes.

3. Estimate a single *joint* regression with all three binary treatments interacted with month dummies:

$$y_{jt} = \sum_{t \neq \text{Jan 2018}} \left(\delta_t^{imp} \cdot \mathbf{1}[\text{High}_j^{imp}] + \delta_t^{input} \cdot \mathbf{1}[\text{High}_j^{input}] + \delta_t^{ret} \cdot \mathbf{1}[\text{High}_j^{ret}] \right) + \alpha_j + \gamma_t + \varepsilon_{jt} \quad (3)$$

Industries in the $(0, 0, 0)$ cell—those below the threshold on all three channels—serve as the control group. The coefficients $\hat{\delta}_t^{imp}$ trace the average difference in log outcomes between "high" and "low" import tariff industries in month t, relative to the reference period (January 2018). This approach provides a visualization of pre-trends and dynamic treatment effects without relying on the continuous tariff variation, while simultaneously controlling for the other tariff channels. Figures 4 and 5 present results using the median split (mean split results are reported in Appendix G).

4.2 Panel Regressions

The baseline specification is a two-way fixed effects panel regression:

$$y_{jt} = \beta_1 \tau_{jt}^{imp} + \beta_2 \tau_{jt}^{input} + \beta_3 \tau_{jt}^{ret} + \alpha_j + \gamma_t + \varepsilon_{jt} \tag{4}$$

where y_{jt} is the log of the outcome variable for industry j in month t, the τ variables are tariff rates in levels (percentage points), α_j are industry fixed effects, and γ_t are month fixed effects. Standard errors are clustered at the three-digit NAICS level. Four specifications are estimated: (1a) import tariff only, (1b) import plus input tariffs, (1c) all three channels, and (1d) all three channels with two-digit NAICS $\times$ month fixed effects replacing the separate month fixed effects. The NAICS2$\times$month specification absorbs sector-level time-varying shocks, forcing identification from within-sector cross-industry tariff variation.

To examine the dynamics of tariff effects, the study estimates time-interacted specifications where each tariff measure is interacted with quarter or half-year indicators, with the reference period set to 2017 Q4 or 2017 H2.

All regressions are estimated using weighted least squares. Employment regressions are weighted by baseline (December 2017) employment levels, so that estimated coefficients reflect aggregate employment impacts—meaning that a 1 percentage point tariff increase in a 500,000-worker industry receives proportionally more weight than the same increase in a 5,000-worker industry. Industrial production and producer price regressions are weighted by Federal Reserve relative importance weights, which measure each industry's share of total manufacturing output. These weights are conceptually analogous to the employment weights: both ensure that estimates are representative of aggregate outcomes rather than giving equal influence to every four-digit industry regardless of size. The two weighting schemes are positively correlated across industries (Spearman $\rho = 0.75$), reflecting the fact that industries with more workers also tend to produce more output, though the correspondence is imperfect because capital-intensive industries can have high production shares with moderate employment. Flaaen and Pierce (2024) similarly use weighted regressions in their baseline specifications. An alternative approach—unweighted OLS—would estimate the average causal effect across industries of equal size; I prefer weights because the policy question motivating this paper concerns aggregate manufacturing employment, not the average effect on a randomly chosen industry.

In the main panel regressions (Specifications 1a–1d), $\hat{\beta}$ gives the percent change in the outcome associated with a 1 percentage point increase in the tariff rate. As a robustness check, the panel regressions are re-estimated using $\log(1+\tau/100)$ in place of the tariff rate in levels (Specifications 3a–3d, mirroring the structure of 1a–1d). Dividing by 100 converts the tariff from percentage points to a proportion, so $\log(1+\tau/100)$ is the log of the gross tariff factor. Since the outcome variables are already in logs, the coefficients have an elasticity interpretation: $\hat{\beta}$ gives the percent change in the outcome associated with a 1% increase in the gross tariff factor. See Appendix C for further details.

4.3 Sample Restrictions

To address potential confounding from the COVID-19 pandemic, I estimate all specifications on three samples:

- **Full sample**: January 2017 – December 2024
- **Pre-COVID**: January 2017 – February 2020
- **Excluding COVID**: Full sample minus March 2020 – December 2020

Note that for all samples, 2017 serves as the pre-treatment reference period. In the event study and six-cell specifications (Section 4.1 and Appendix B), tariff changes are calculated as the difference between the 2019 and 2017 annual averages.

4.4 Identification

A key identification concern is whether tariff changes are endogenous to industry outcomes—for example, if import tariffs were targeted to protect industries that were already declining, the estimated negative coefficients could reflect pre-existing trends rather than causal effects.

As a direct test, I regress the 2017-to-2019 change in each tariff channel on pre-period (January 2017 to January 2018) log employment growth across the 64 manufacturing industries. For the import tariff channel—the basis for the main results—the coefficient is statistically insignificant ($p = 0.56$), as is the retaliatory tariff channel ($p = 0.57$). The input tariff channel shows a marginally significant positive coefficient ($p = 0.06$), meaning that faster-growing industries tended to face larger input tariff increases; this is the opposite of what reverse causality would predict and would bias against finding negative employment effects from input tariffs. A joint F-test across all three channels fails to reject the null of no relationship ($p = 0.54$). Combined with the clean pre-trends in the event study (Figure 4), these results support the assumption that tariff assignment is conditionally exogenous to pre-existing industry-level employment trends.

5 Results

5.1 Event Study Evidence

The binary treatment event studies provide visual evidence on pre-trends and dynamic treatment effects. Figure 4 shows the combined three-channel event study for employment in the full sample. The import tariff channel (blue) displays clean pre-trends—coefficients are indistinguishable from zero throughout 2017—followed by a steady divergence after February 2018, reaching approximately -0.04 by 2024 (meaning that by 2024, industries in the "high" import tariff group experienced approximately 4% lower employment than those in the "low" group, relative to the January 2018 baseline). This pattern supports the causal interpretation of the panel regression results shown in Table 2.

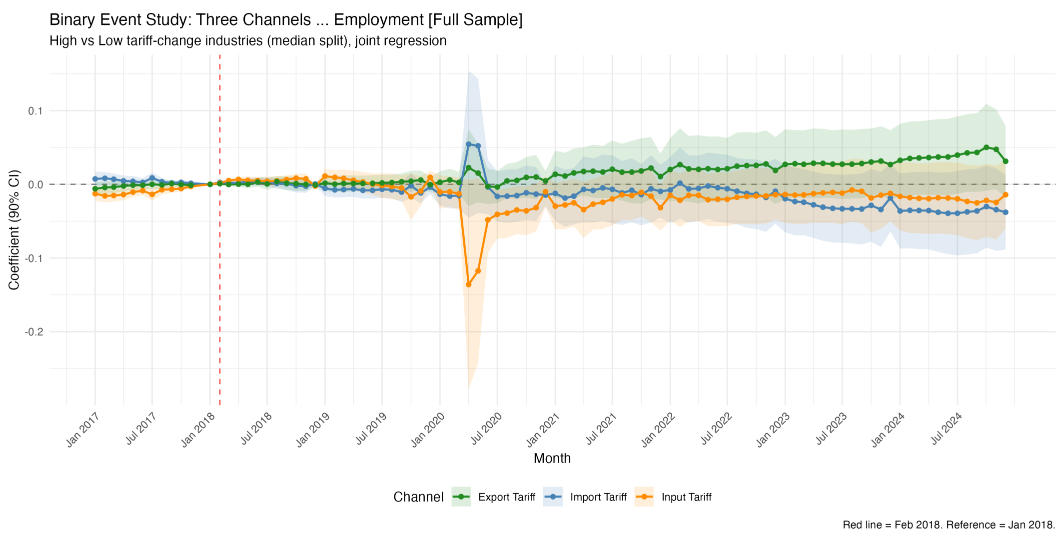
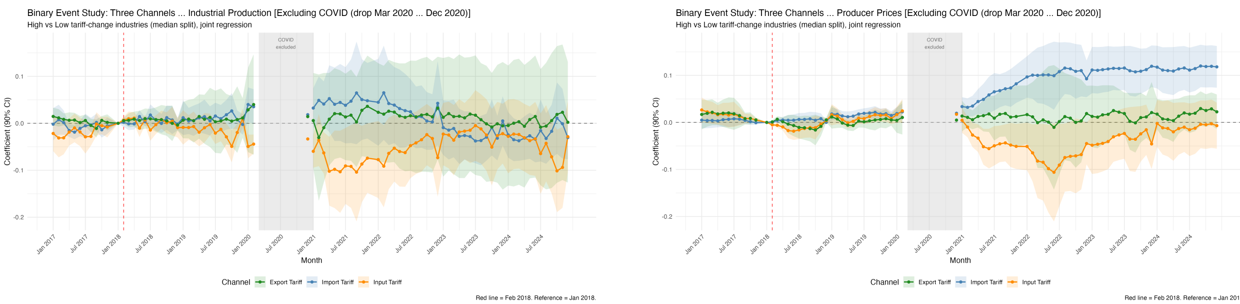


Figure 4: Binary Event Study: Three Channels, Employment (Full Sample)

Notes: Industries classified as "high" vs. "low" tariff change based on whether the 2017-to-2019 change exceeds the median. All three channels are estimated jointly in a single regression; industries in the $(0, 0, 0)$ cell serve as the control group. Shaded areas show 90% confidence intervals. Reference period is January 2018. Red dashed line marks February 2018. See Appendix G for results using the mean split.

The input tariff channel (orange) shows pre-treatment coefficients that are already negative before February 2018, indicating that the "high input tariff" and "low input tariff" groups were on different trends prior to the trade war. Though the difference between pre-treatment coefficients for the input tariff channel and the other two channels is small, this pre-trend violation may undermine the causal interpretation of the input tariff channel in the event study framework and may partly explain the puzzling positive sign in the panel regressions. That is, it may be the case that industries subjected to high input tariffs were already seeing declines in employment before the imposition of tariffs, causing the input tariff variable to be positively correlated with the pre-existing negative trend in employment. The retaliatory tariff channel (green) shows no clear pre-trend violation but also no detectable post-treatment effect, consistent with the limited variation in this measure.

Figure 5 shows the event studies for industrial production and producer prices, excluding the COVID period. For IP, removing the COVID months eliminates the extreme spike that dominated the full-sample plot, but no clear tariff effect emerges. For PPI, the import tariff channel shows a gradual upward drift post-treatment, consistent with tariffs raising domestic prices, though with wider confidence intervals than the employment results.



(a) Industrial Production

(b) Producer Prices

Figure 5: Binary Event Study: IP and PPI (Excluding COVID, Median Split)
Notes: Same methodology as Figure 4 (joint regression with all three channels, median split). COVID period (March–December 2020) excluded. Gray shading indicates the excluded COVID window. See Appendix G for results using the mean split.

While Figures 4 and 5 are based on the binary event study design (Section 4.1), where industries are split into "high" and "low" tariff groups and the coefficients trace the level difference between groups over time, Figures 6–8 take a complementary approach based on the panel regression framework (Equation 4). Specifically, each figure plots coefficients from Specification 2b, where all three continuous tariff measures are interacted with quarterly indicators in a single regression. Each point estimates the coefficient on a given tariff channel in a given quarter—that is, the percent change in the outcome associated with a 1 percentage point higher tariff rate in that quarter, holding the other channels constant. If tariff effects are constant over time, all points should be similar; if effects build or fade, the trajectory for each channel will slope upwards or downwards. The reference period is 2017 Q4, so pre-treatment points near zero indicate that the continuous tariff variation is not picking up pre-existing differential trends.

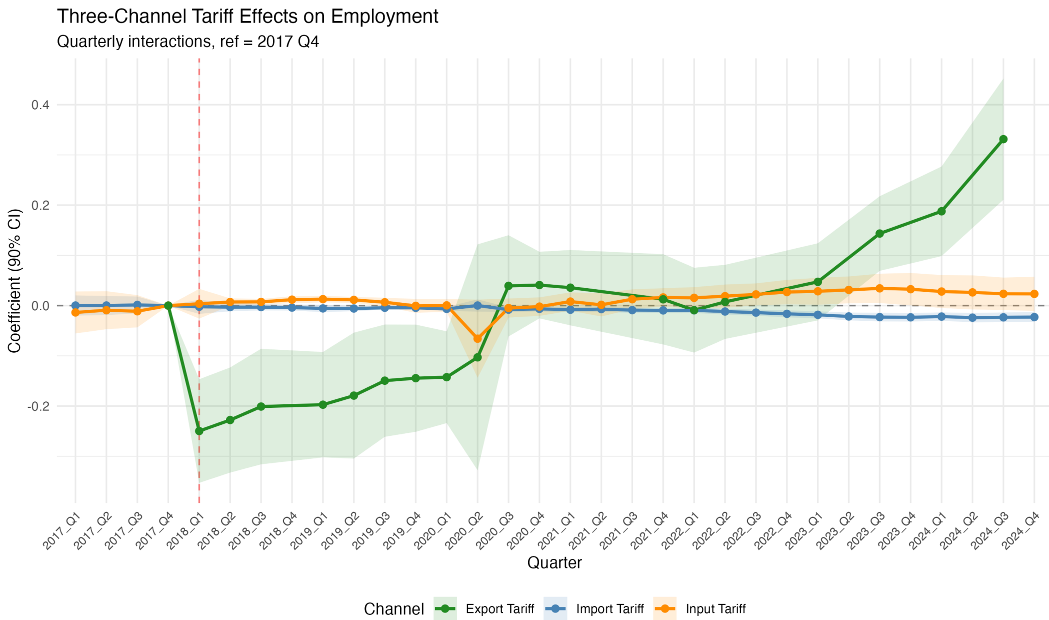


Figure 6: Quarterly Tariff Interaction Coefficients: Employment (Full Sample)
Notes: Coefficients from a panel regression with all three continuous tariff measures interacted with quarterly indicators (reference: 2017 Q4). Shaded areas show 90% confidence intervals. Red dashed line marks 2018 Q1. Some quarterly retaliatory tariff interactions are dropped due to collinearity (limited variation). Compare with Figures 4–5, which use binary treatment splits.

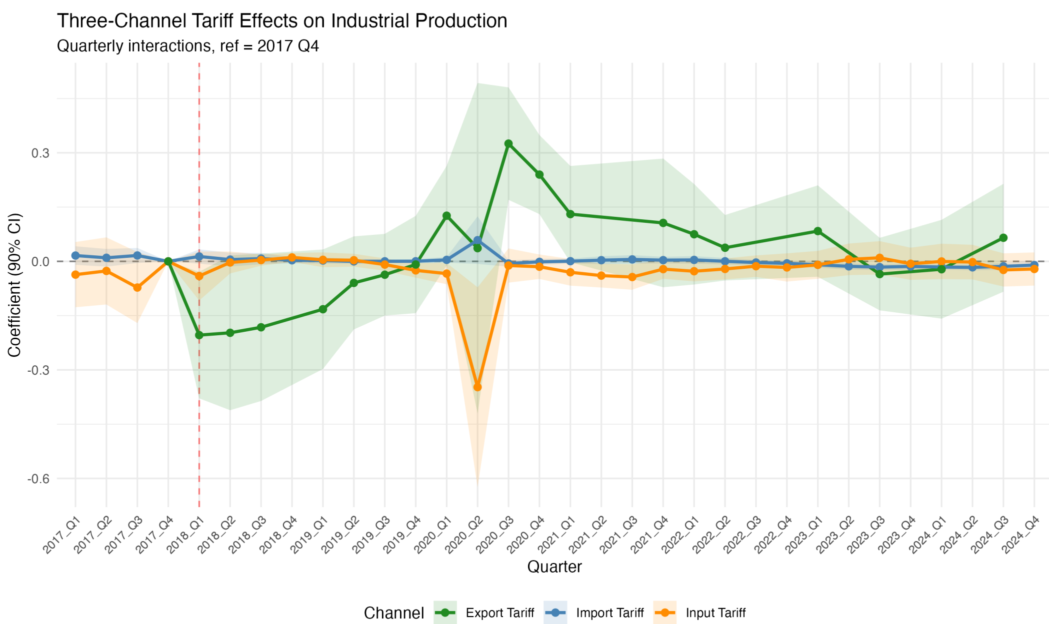


Figure 7: Quarterly Tariff Interaction Coefficients: Industrial Production (Full Sample)
Notes: Same specification as Figure 6. The large spike in 2020 Q2–Q3 reflects the COVID-19 pandemic interacting with the tariff variation rather than a genuine tariff effect; see Figure 5 for the excluding-COVID event study.

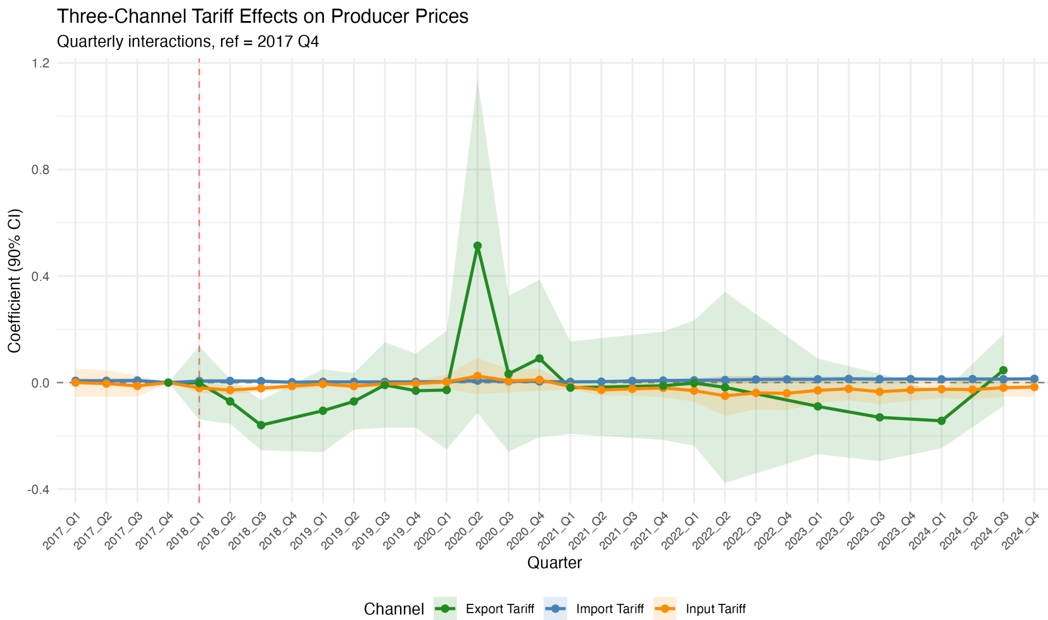


Figure 8: Quarterly Tariff Interaction Coefficients: Producer Prices (Full Sample)
Notes: Same specification as Figure 6. The import tariff channel (blue) shows a small but steady positive effect, consistent with tariff cost pass-through to domestic producer prices.

Per Figure 6, the effect of the import tariff channel on manufacturing employment is negative and builds over time; the effect of the retaliatory tariff channel on employment starts out negative and then becomes positive at the start of 2023; and the effect of the input tariff channel is constant over time and indistinguishable from zero.

Per Figure 7, the effects of the import and input tariff channels on industrial production are indistinguishable from zero (except for the COVID window). The effect of the retaliatory tariff channel on industrial production is noisier, but is also indistinguishable from zero, except for three quarters of the pandemic.

Per Figure 8, the effects of the import and input tariff channels on producer prices are consistent over time and indistinguishable from zero. The effect of the retaliatory tariff channel is noisier, but also indistinguishable from zero.

5.2 Panel Regression Results

Table 2 presents the main panel regression coefficients for the three-channel model (Specifications 1c and 1d) across all outcomes and sample periods. Coefficients represent the effect of a 1 percentage point higher tariff rate on the log of the outcome variable.[12]

[12] Recall that for Specifications 1a–1d, $\hat{\beta}$ gives the percent change in the outcome associated with 1 percentage point increase in the tariff rate.

Table 2: Panel Regression Results: Three-Channel Model

Outcome	Sample	Import Coef.	Import SE	Input Coef.	Input SE	Export Coef.	Export SE	N
Specification 1c: Industry + Month FE								
Employment	Full	-0.012^{***}	(0.003)	0.013	(0.007)	-0.049^{**}	(0.021)	6,144
	Pre-COVID	-0.005^{***}	(0.001)	0.008	(0.004)	0.019	(0.015)	2,432
	Excl. COVID	-0.012^{***}	(0.003)	0.018	(0.005)	-0.057^{**}	(0.022)	5,504
Industrial Production	Full	-0.004	(0.007)	-0.028	(0.030)	0.010	(0.023)	6,336
	Pre-COVID	-0.003	(0.002)	0.013	(0.006)	0.042	(0.035)	2,508
	Excl. COVID	-0.006	(0.006)	0.008	(0.014)	0.003	(0.024)	5,676
Producer Prices	Full	0.007^{**}	(0.003)	-0.017	(0.008)	-0.042	(0.025)	7,410
	Pre-COVID	0.004^{**}	(0.001)	-0.001	(0.005)	-0.118^{***}	(0.030)	2,964
	Excl. COVID	0.007^{*}	(0.004)	-0.023	(0.012)	-0.062^{***}	(0.022)	6,630
Specification 1d: Industry + NAICS2×Month FE								
Employment	Full	-0.011^{***}	(0.003)	0.009	(0.006)	-0.020	(0.049)	6,144
	Pre-COVID	-0.005^{***}	(0.002)	0.003	(0.005)	0.037	(0.031)	2,432
	Excl. COVID	-0.011^{***}	(0.003)	0.015	(0.006)	-0.030	(0.051)	5,504
Industrial Production	Full	-0.002	(0.007)	-0.031	(0.026)	-0.039	(0.043)	6,240
	Pre-COVID	-0.003	(0.002)	0.008	(0.012)	0.059	(0.050)	2,470
	Excl. COVID	-0.004	(0.007)	0.005	(0.024)	-0.065	(0.053)	5,590
Producer Prices	Full	0.008^{**}	(0.003)	-0.020^{**}	(0.008)	-0.010	(0.031)	7,410
	Pre-COVID	0.004^{**}	(0.001)	0.004	(0.004)	-0.113^{***}	(0.020)	2,964
	Excl. COVID	0.009^{**}	(0.004)	-0.024^{**}	(0.011)	-0.021	(0.026)	6,630

Notes: Tariff variables are in levels (applied rates in pp). Specification 1c includes industry and month fixed effects. Specification 1d replaces month FEs with two-digit NAICS × month FEs to absorb sector-level time trends. Standard errors (in parentheses) are clustered at the three-digit NAICS level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The import tariff coefficient for employment is negative and highly significant across all three samples, ranging from −0.005 in the pre-COVID sample to −0.012 in the excluding-COVID sample. The pre-COVID coefficient is smaller in magnitude, consistent with tariff effects building gradually over the first two years. The NAICS2×month FE specification (1d) yields very similar import tariff coefficients (−0.011 vs. −0.012 in the full sample), indicating that the result is not driven by sector-level time trends.

The import tariff coefficient for industrial production is negative, but not significant at conventional levels. Still, these results are consistent with the coefficient for import tariffs on employment. It is possible that the regression is picking up increased TPU, with firms becoming less willing to invest in new capacity, consistent with Caldara et al. (2020).

For producer prices, the import tariff coefficient is positive and significant in the full and pre-COVID samples, indicating that tariffs raise domestic producer prices—the expected cost pass-through effect. One interpretation of these results is that producers were better off as a result of tariffs causing consumers to substitute away from imports and toward domestic producers, consistent with Fajgelbaum et al. (2020). Combined with the negative import tariff coefficient for employment, this suggests that tariffs left capital better off relative to labor.

Recall that the input tariff is constructed as an IO-weighted average of import tariffs in upstream industries (Equation 1). This means that import and input tariff measures are positively correlated: the cross-sectional correlation between 2017-to-2019 import and input tariff changes is 0.50 across the 64 manufacturing industries in the sample. Note that the import tariff coefficient becomes more negative when the input tariff is added as a control (-0.008 in the import-only specification versus -0.009 with both channels), suggesting that the omitted input tariff is attenuating the import tariff estimate through their positive correlation. This pattern implies that the import tariff coefficient in the three-channel model likely captures some input-cost effects that the input tariff measure fails to pick up due to measurement limitations. That is, when an industry faces a high (applied) import tariff rate, this both reduces competitive pressure from imports and signals that the industry is embedded in a supply chain where upstream input costs have risen; the regression cannot fully separate these two mechanisms.

The input tariff coefficient itself has a puzzling positive sign for employment. This likely reflects measurement limitations rather than a true economic effect. Specifically, the input tariff measure understates true input tariff exposure for industries with high service intensity.

Across manufacturing industries in the BEA input-output table, approximately 42% of input cost shares come from non-manufacturing sectors—wholesale trade, logistics, finance, legal services, IT, and utilities—for which no import tariff exists. The input tariff measure constructed in Equation 1 can therefore only cover the remaining 58% of inputs. In practice, after accounting for the IO-to-NAICS concordance and tariff data availability, median coverage across the 64 industries in the employment regression sample is 64.6%, ranging from 16.4% (NAICS code 3241, Petroleum Refining, which relies heavily on mining and energy inputs) to 83.2% (NAICS code 3116, Animal Slaughtering and Processing, which relies heavily on manufactured inputs such as packaging materials and processing equipment).

Because the missing coverage is roughly constant within industry over time, industry fixed effects absorb the level bias. However, the 0.50 correlation between import and input tariff changes means that after conditioning on the import tariff (which partly captures input-cost effects), the residual variation in the input tariff measure may no longer reflect true cost-channel exposure. Instead, it may proxy for "how much of an industry's inputs come from observable manufacturing sectors"—a compositional characteristic that could correlate positively with supply-chain resilience or other unobserved determinants of employment growth. The binary event study provides further evidence of this problem: the "high input tariff" and "low input tariff" groups show divergent pre-trends before 2018 (Figure 4), indicating that the treatment split is confounded by pre-existing differences. Together, these findings suggest that the three-channel decomposition cannot cleanly separate the import protection channel from the input-cost channel with the available data, and the import tariff coefficient should be interpreted as a reduced-form composite of both mechanisms.

The retaliatory tariff coefficient is significant in some specifications (notably -0.049 for employment in the full sample under Specification 1c), but its significance is sensitive to the inclusion of NAICS2×month FEs and has very limited cross-industry variation (standard deviation of only 0.06 percentage points, as discussed in Section 3.2). Interestingly, the retaliatory tariff is *negatively* correlated with both the import tariff ($\rho = -0.23$) and the input tariff ($\rho = -0.25$) across industries—different industries were targeted by foreign retaliation than by Section 301 tariffs—which provides some independent identifying variation, but the small magnitude of the retaliatory tariff measure limits the precision of its estimates.

5.3 Cumulative Effects

Table 3 translates the statistically significant coefficients into cumulative economic magnitudes by multiplying the estimated coefficient by the employment-weighted average tariff change over each sample window.

Table 3: Cumulative Effects of Import Tariffs

Outcome	Sample	$\hat{\beta}$	Avg. $\Delta\tau$ (pp)	Effect (%)	90% CI
Employment	Full (Jan 18–Dec 24)	−0.012	2.00	−2.31%	[−3.18, −1.44]%
	Pre-COVID (Jan 18–Feb 20)	−0.005	1.41	−0.71%	[−1.05, −0.36]%
	Excl. COVID	−0.012	1.96	−2.35%	[−3.25, −1.46]%
Producer Prices	Full (Jan 18–Dec 24)	+0.007	1.58	+1.16%	[+0.42, +1.90]%
	Pre-COVID (Jan 18–Feb 20)	+0.004	1.06	+0.38%	[+0.01, +0.75]%

Notes: Cumulative effect $= \hat{\beta} \times \bar{\Delta\tau}$ over the post-treatment window, where $\bar{\Delta\tau} = \bar{\tau}_{\text{post}} - \bar{\tau}_{\text{pre}}$. Average tariff changes are employment-weighted (for employment) or relative-importance-weighted (for PPI). Confidence intervals are constructed from 90% CIs on $\hat{\beta}$. Only statistically significant coefficients are shown.

These estimates imply that tariffs reduced manufacturing employment by approximately 274,000 jobs over the full sample period (90% CI: 171,000 to 378,000), relative to a baseline of 11.87 million manufacturing workers in January 2018. In the pre-COVID window, the estimated job loss is approximately 84,000 (90% CI: 43,000 to 125,000). These job loss estimates apply to the 64 four-digit NAICS industries in the regression sample, which account for approximately 11.87 million of the roughly 12.8 million total manufacturing workers in January 2018. The remaining industries are excluded due to missing tariff or outcome data.

The strength of using this kind of back-of-the-envelope calculation to scale up estimates to the aggregate level is that it is simple and relatively easy to do—there is no need to write down and solve a general equilibrium model. However, there are also limitations to this approach. As discussed by Moll and Haney (2025), this simple scaling-up procedure suffers from the "missing intercept" problem. The estimated $\hat{\beta}$ coefficients in Table 3 identify relative effects—roughly, how manufacturing employment changed in industries exposed to higher import tariffs compared to how manufacturing employment changed in industries exposed to lower import tariffs. At the aggregate level, however, what we want are absolute effects, i.e., the number of jobs lost. The panel regression uses cross-sectional variation—that is, differences in import tariff levels faced by different industries—to recover estimates of the slope of the aggregate relationship between import tariffs and manufacturing employment. But the panel regression is unable to recover the intercept of the aggregate relationship.

Thus, it is possible that the cumulative analysis either overstates or understates job losses caused by tariffs. If the aggregate effect of tariffs is to make imports more expensive across the board, then consumers and firms may substitute toward domestically produced goods in all manufacturing industries, not just the most-tariffed ones. In this case, the cumulative estimates would overstate the job losses attributable to tariffs.

On the other hand, if the aggregate effect of tariffs is to raise consumer prices across the economy, then purchasing power would fall and demand for all manufactured goods—not just tariffed goods—would decrease. Reductions in import demand might strengthen the dollar, hurting export competitiveness for all U.S. manufacturers. And uncertainty about trade policy or supply chain disruptions may cause firms to slow hiring. In this case, the cumulative estimates would understate the job losses attributable to tariffs.

On balance, the evidence suggests that the cumulative analysis understates the number of tariff-induced job losses. If the protective channel were generating a positive common effect via broad import substitution, one would expect to see "purely protected" industries gain employment; as shown in the six-cell analysis (Appendix B), they do not. The literature finds a near-complete pass-through of tariffs to prices (see Amiti et al., 2019; Fajgelbaum et al., 2020), which implies that tariffs depress aggregate demand by reducing purchasing power; and also finds that both higher tariffs and increased TPU reduce investment (Caldara et al., 2020).

See Appendix for robustness checks and comparison with Flaaen and Pierce (2024).

6 Discussion

This paper finds that tariffs reduced U.S. manufacturing employment from 2018 to 2024. It also finds that tariffs raise producer prices, as expected from standard trade theory. The positive and significant PPI coefficients indicate that industries facing higher import tariffs experience increases in domestic producer prices, consistent with reduced competitive pressure from imports and cost pass-through from tariffed inputs. I am unable to identify the effects of tariffs on industrial production: coefficients are, for the most part, not statistically significant. My results are consistent with Flaaen and Pierce (2024) despite methodological differences, as shown in Table A1.

Over the full sample period, my estimates imply that tariffs reduced manufacturing employment by approximately 274,000 jobs (Section 5.3), relative to a baseline of 11.87 million manufacturing workers in January 2018. In the pre-COVID window, the estimated job loss was approximately 84,000. Import tariffs have a negative but statistically insignificant effect on industrial production, which suggests that increased trade policy uncertainty may cause firms to scale back investment as discussed by Caldara et al. (2020). Import tariffs have a positive effect on producer prices, consistent with Fajgelbaum et al. (2020); combined with the negative effects on employment, this suggests that tariffs left capital better off relative to labor.

The effect of import tariffs on manufacturing is the most robust result: it is negative and significant at the 1% level across all sample definitions and robust to controlling for sector-level time trends. The magnitude of the import tariff penalty on employment increases with the sample length, from -0.50% per percentage point of tariffs in the pre-COVID window to -1.16% per percentage point of tariffs over the full seven-year period, which suggests that adjustment costs accumulate over time.

Why might tariffs lower manufacturing employment? The intuition is that in the modern, globally-integrated manufacturing sector, the protective effects of tariffs—shielding domestic producers from foreign competition—are dominated by the costs of tariffs. The costs of tariffs can operate through multiple channels, such as higher prices for imported intermediate inputs, which raise production costs for downstream industries; retaliatory tariffs imposed by trading partners, which reduce export demand; supply chain disruption and policy uncertainty, which discourage investment and hiring; and reduced competitiveness in export markets due to higher input costs, even beyond explicit retaliation.

As discussed in Section 5.2, the import tariff coefficient in practice captures a composite of the direct competitive-pressure effect and the input-cost channel. The input tariff measure covers approximately 66% of manufacturing industries' input cost shares, with the remaining third consisting of services inputs for which no import tariff data exists. This measurement gap, combined with the high correlation with import tariffs, makes it difficult to isolate a separate input-cost effect. The import tariff coefficient should therefore be interpreted as a reduced-form effect of tariff exposure broadly defined, rather than a clean estimate of the protection channel alone.

The six-cell analysis (see Table B1 in Appendix B) sheds light on how the three tariff channels interact, by assigning each combination of channels its own coefficient. The "import only" cell industries $(1, 0, 0)$—that is, firms receiving high import protection without proportional input-cost or retaliatory penalties—show negative but statistically insignificant employment effects under both the median (-0.047) and 75th percentile (-0.015) splits. Thus, even under the most favorable conditions for detecting a positive protective effect, tariffs do not appear to boost employment. Meanwhile, the "input only" $(0, 1, 0)$ cell—representing firms facing higher input costs without proportional import protection or retaliatory penalties—has the largest negative coefficient (-0.072, $p < 0.05$) on employment. This suggests that supply-chain cost increases are a primary driver of the employment declines observed in the panel regressions.

The temporal structure of tariff effects provides some additional insight into adjustment mechanisms. The frequency robustness exercise (Table E1) shows that import tariff coefficients increase slightly in magnitude when monthly data is collapsed to quarterly or semi-annual frequency, consistent with measurement noise in the monthly data attenuating the estimates. The lag/lead analysis (Table F1) reveals that in the longer samples, import tariff effects persist for at least 6 months beyond the contemporaneous response, suggesting that adjustment costs—layoffs, supply chain reorganization, and investment reductions—unfold gradually. In the pre-COVID sample, lags are insignificant and effects are purely contemporaneous, consistent with the initial tariff shock producing an immediate response before cumulative adjustment processes had time to materialize. The significant leading tariff coefficients may indicate that firms anticipate announced tariff changes before their effective dates.

Besides reshoring manufacturing jobs, three other justifications are typically offered for protectionism: forcing exporters to reduce their before-tariff prices,[13] winning votes, national security.

As discussed in Section 2, Blanchard et al. (2019) found that tariffs reduced support for Republicans in 2018. It is possible that any electoral benefits of protectionism operate with a lag: Autor et al. (2024) find that despite being economically costly, import tariffs increased support for the Republican Party in 2020. During the 2024 campaign, Donald Trump's protectionist policies were popular. One survey of registered voters found a 10% tariff on all imports polling at +23 net support, a 60% tariff on all Chinese imports polling at +20 net support, and "[phasing] out Chinese imports of essential goods, including electronics, steel, and pharmaceuticals" polling at +33 net support (Roth Smith and Cass, 2024).[14] Does this mean that the electorate is clamoring for an end to free trade? Not quite. For the last ten years, a majority of the American public has viewed foreign trade as more of an "opportunity for economic growth" than a "threat to the economy," per Gallup's time series polling (Brenan, 2026). The share of voters viewing trade positively has increased from 61% of voters at the end of the Biden presidency to 82% in 2026. Other polling data shows that a large majority of the public disapproves of Trump's second term trade policy (Van Green et al., 2026; Brenan, 2025; Igielnik, 2026), and that evaluations of Trump's handling of trade fell sharply after the "Liberation Day" tariff announcements (Silver, 2026). Thus, to the extent that the public prefers protectionism, that preference is weak. Voters—particularly those from communities that lost employment because of trade with China—may appreciate the symbolism of tariffs, but they do not appreciate having to pay higher costs for that symbolism.

Tariffs on China in particular are often justified by invoking national security concerns. Importing cheap Chinese electric vehicles and solar panels would lower energy costs for American consumers and lower U.S. greenhouse gas emissions. Nonetheless, the Biden administration imposed new tariffs on imports of Chinese electric vehicles and solar panels. The underlying logic is that allowing Chinese firms to dominate the market for clean energy technologies would undermine American national security; similarly, Biden-era restrictions on selling advanced computer chips to Chinese firms were aimed at protecting America's

[13]The intuition behind the first justification is straightforward: if exporters (to the US) do not reduce their before-tariff prices, then prices for consumers will rise and demand for imported goods will fall. Tariffs imposed by the US will have an above-average impact on foreign exporters' pricing decisions because the US economy's size gives it market power.

[14]Disclosure: I worked at the firm that conducted this survey during the 2024 campaign.

edge in artificial intelligence (Alper and Nellis, 2026).

Whether tariffs on specific goods maintain an American edge in strategic industries is beyond the scope of this essay. What this essay shows is that tariffs are economically costly. To the extent that there is a national security justification for tariffs on specific goods, those benefits must be weighed against economic costs, not benefits.

7 Conclusion

This essay studies the effects of tariffs on U.S. manufacturing from 2018 to 2024, using three channels (import, input, and retaliatory tariffs), finding that import tariffs reduce manufacturing employment (statistically significant at the 1% level across all sample definitions). My estimates imply that import tariffs led to a loss of 274,000 manufacturing jobs over the full sample period, and a loss of 84,000 manufacturing jobs in the pre-COVID period. The effect of import tariffs on employment accumulates over time: the impact of a 1 percentage point increase in import tariff rates on employment goes from -0.5% in the pre-COVID period to -1.16% in the full sample period. Import tariffs raise producer prices; effects on industrial production are not statistically significant. Despite methodological differences (i.e., using applied tariff rates rather than statutory tariff rates), my results line up with Flaaen and Pierce (2024)—see Appendix A for further detail.

I close by noting a few caveats. First, the results in this paper should be interpreted as partial-equilibrium effects that do not account for general equilibrium reallocation across sectors: the "jobs lost" figures represent employment declines relative to a no-tariff counterfactual, not necessarily net job losses for the economy as a whole. Second, the paper does not analyze the effects of tariffs on retail or consumer prices, or on total welfare. Third, I do not account for changes in trade policy uncertainty driven by the 2018 trade war and subsequent tariff increases. Finally, this analysis does not cover tariffs imposed during the second Trump administration. These tariffs are far larger in both scope and magnitude than the 2018–2024 tariffs studied in this essay, and are an important topic for future research.

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Appendix

A Comparison with Flaaen and Pierce (2024)

To benchmark the results of this paper, I re-estimate the baseline specifications on the Flaaen and Pierce (2024) (hereafter F&P) sample period (January 2017 through September 2019). Table A1 compares my three-channel coefficients with F&P's published estimates from their Table 4, Column 3.

Table A1: Coefficient Comparison: F&P Sample Period

		This Paper		F&P (2024)	
Outcome	Channel	Coef.	SE	Coef.	SE
Employment	Import	-0.004^{**}	(0.002)	-0.002^{**}	—
	Input	$+0.008^{***}$	(0.003)	$+0.003$	—
	Export	$+0.015$	(0.015)	-0.008^{***}	—
Industrial Production	Import	-0.002	(0.002)	-0.006^{**}	—
	Input	$+0.015^{**}$	(0.006)	$+0.010$	—
	Export	$+0.030$	(0.029)	-0.011^{***}	—
Producer Prices	Import	$+0.003^{**}$	(0.001)	*not reported*	
	Input	-0.002	(0.006)	*not reported*	

Notes: "This paper" reports Specification 1c (three-channel, industry + month FE) estimated on the F&P sample period (January 2017 – September 2019). My standard errors are clustered at the three-digit NAICS level. F&P coefficients are from their Table 4, Column 3, which uses statutory tariff changes (Δpp) as regressors and clusters at the industry level. Direct magnitude comparison is limited because I use applied tariff *levels* while F&P uses statutory tariff *changes*; focus should be on sign comparison and qualitative patterns. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The import tariff coefficient for employment matches F&P in both sign and significance (-0.004 vs. -0.002, both significant at the 5% level), confirming that applied tariff levels capture similar variation to statutory tariff changes. The input tariff coefficients also share the same positive sign for both employment and industrial production, though mine are larger in magnitude and more precisely estimated, likely because the applied tariff measure has more continuous cross-sectional variation than F&P's discrete statutory changes. The retaliatory tariff channel shows a sign discrepancy: my coefficient is positive but insignificant, while F&P estimate a significantly negative effect. This difference likely reflects differences in measurement (trade-weighted applied levels vs. statutory retaliatory tariff changes), combined with the very limited retaliatory tariff variation in my data (see Section 3.2). My positive and significant PPI import tariff coefficient (+0.003) provides results that F&P do not report, documenting tariff cost pass-through to domestic producer prices even in the initial 2017–2019 window.

Overall, the alignment with F&P on the import and input channels—despite different tariff measurement approaches, different industry coverage (64 vs. ∼407 NAICS-4 industries), and different clustering choices—provides external validation that my applied tariff framework captures the same underlying economic mechanisms.

B Six-Cell Analysis

The binary event study (Section 4.1) implicitly assumes that the effects of the three tariff channels are additive: each channel's high/low indicator enters the regression separately, so the estimated effect for an industry that is "high" on both import and input tariffs is simply the sum of the two individual channel effects. This restriction may not hold if the channels interact—for example, if the cost burden of input tariffs is particularly harmful for industries that are *also* exposed to import competition, or if import protection is beneficial only for industries that are not simultaneously hit by higher input costs.

To allow for such interactions, I classify industries into $2^3 = 8$ cells based on whether their 2017-to-2019 tariff change on each of the three channels exceeds a threshold. Each cell is denoted by a triple $(d^{imp}, d^{input}, d^{ret}) \in \{0,1\}^3$, where 1 indicates above-threshold and 0 indicates below. The $(0,0,0)$ cell—industries below the threshold on all three channels—serves as the omitted baseline. I then estimate:

$$y_{jt} = \sum_{c \neq (0,0,0)} \beta_c \cdot \mathbf{1}[\text{cell}_j = c] \cdot \text{Post}_t + \alpha_j + \gamma_t + \varepsilon_{jt} \tag{5}$$

where $\text{Post}_t = \mathbf{1}[t \geq \text{Feb 2018}]$. Because the cell indicators are time-invariant (determined by 2017–2019 tariff changes), they are absorbed by the industry fixed effects α_j; identification comes from the cell × Post interaction. Each coefficient $\hat{\beta}_c$ gives the average post-treatment difference in log outcomes between industries in cell c and the $(0,0,0)$ baseline, conditional on industry and month fixed effects.

I consider two threshold configurations. The primary specification uses the *median* tariff change on each channel, which produces a relatively balanced distribution of industries across cells. As a robustness check, I use the *75th percentile*, which concentrates most industries in the $(0,0,0)$ baseline and isolates the most heavily treated industries in each channel. The 75th percentile split is particularly useful for testing whether "purely protected" industries—those with high import tariffs but below-threshold input and retaliatory tariffs, i.e., the $(1,0,0)$ cell—experience employment gains. I also estimate event study variants of

Equation 5 by interacting the cell indicators with month dummies rather than a single Post indicator.

Table B1 reports the six-cell regression results for employment, with the $(0,0,0)$ cell—industries below the median tariff change on all three channels—as the omitted baseline. Each coefficient shows the average post-February-2018 difference in log employment between the indicated cell and the baseline; for example, $\hat{\beta}_{(1,0,0)} = -0.047$ means that "import only" industries experienced approximately 4.7% lower employment growth than the $(0,0,0)$ group (though this difference is not statistically significant).

Table B1: Six-Cell Static Regression: Employment

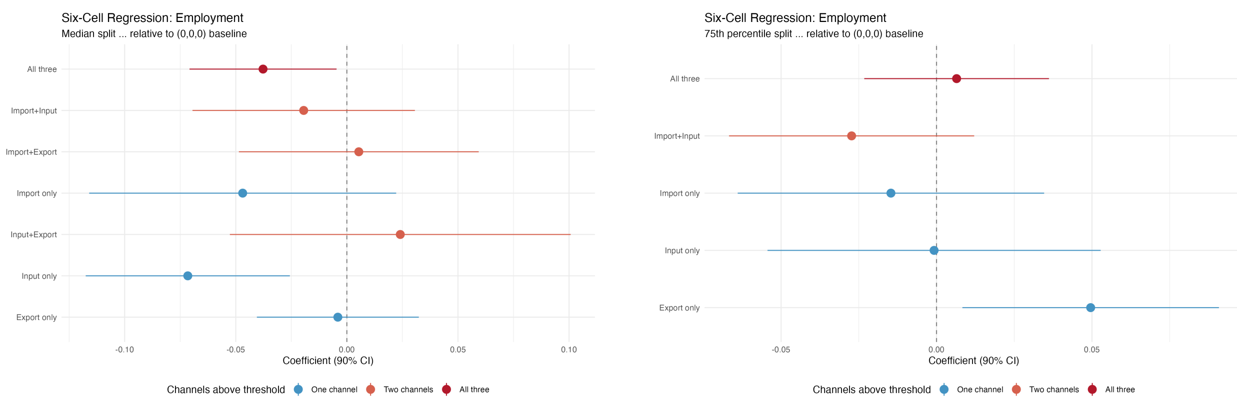
		Median Split			75th Percentile Split		
Cell	Label	Full	Pre-COVID	Excl. COVID	Full	Pre-COVID	Excl. COVID
(1,0,0)	Import only	−0.047	−0.026	−0.045	−0.015	−0.008	−0.013
		(0.040)	(0.016)	(0.040)	(0.028)	(0.013)	(0.028)
(0,1,0)	Input only	−0.072**	−0.013	−0.065**	−0.001	0.015	0.004
		(0.026)	(0.019)	(0.027)	(0.031)	(0.015)	(0.030)
(0,0,1)	Export only	−0.004	−0.015	−0.002	0.050*	0.009	0.054**
		(0.021)	(0.009)	(0.022)	(0.024)	(0.009)	(0.026)
(1,1,0)	Imp+Input	−0.019	−0.010	−0.015	−0.027	−0.002	−0.026
		(0.029)	(0.014)	(0.030)	(0.023)	(0.010)	(0.023)
(1,0,1)	Imp+Export	0.005	−0.008	0.008			
		(0.031)	(0.016)	(0.032)			
(0,1,1)	Input+Export	0.024	0.006	0.037			
		(0.044)	(0.013)	(0.048)			
(1,1,1)	All three	−0.038*	−0.001	−0.034	0.007	0.019**	0.006
		(0.019)	(0.011)	(0.020)	(0.017)	(0.007)	(0.017)
Observations		6,144	2,432	5,504	6,144	2,432	5,504

Notes: Each coefficient is the interaction of a cell indicator with Post_t ($= \mathbf{1}[t \geq \text{Feb 2018}]$), estimated from Equation 5. The $(0,0,0)$ cell is the omitted baseline. Standard errors (in parentheses) clustered at three-digit NAICS. The 75th percentile split produces empty cells for (1,0,1) and (0,1,1) due to insufficient industries above the threshold on those channel combinations. Cell counts for the median split: (0,0,0) = 8, (1,0,0) = 6, (0,1,0) = 5, (0,0,1) = 14, (1,1,0) = 13, (1,0,1) = 4, (0,1,1) = 5, (1,1,1) = 9. For the 75th percentile: (0,0,0) = 26, (1,0,0) = 7, (0,1,0) = 7, (0,0,1) = 15, (1,1,0) = 8, (1,1,1) = 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Under the median split, the most striking result is that the $(0,1,0)$ "input only" cell has the largest and most statistically significant negative coefficient (-0.072, $p < 0.05$). Industries exposed primarily to higher input tariffs—but not to high import tariffs on their own output or high retaliatory tariffs—experienced the steepest employment declines relative to the baseline. The $(1,1,1)$ "all three" cell is also negative and marginally significant (-0.038,

$p < 0.10$), consistent with multiple channels compounding. By contrast, the $(1, 0, 0)$ "import only" cell—which isolates industries receiving the most import protection without proportional input-cost or retaliatory penalties—shows a negative but statistically insignificant coefficient (-0.047, $p = 0.24$). Even industries that are "purely protected" do not show employment gains from tariffs. The remaining cells—$(0, 0, 1)$ "export only" (-0.004), $(1, 0, 1)$ "import + export" ($+0.005$), $(0, 1, 1)$ "input + export" ($+0.024$), and $(1, 1, 0)$ "import + input" (-0.019)—all have statistically insignificant coefficients. The small cell sizes (4–14 industries per cell) limit statistical power for these interaction terms, and the near-zero retaliatory tariff variation makes it difficult to distinguish cells that differ only in their retaliatory tariff classification.

Figure B1 presents coefficient plots for the median and 75th percentile splits, displaying all cell coefficients with 90% confidence intervals.



(a) Median Split

(b) 75th Percentile Split

Figure B1: Six-Cell Coefficient Plots: Employment (Full Sample)

Notes: Point estimates and 90% confidence intervals from the static six-cell regression (Equation 5). The $(0, 0, 0)$ baseline is normalized to zero. Median split (left) uses channel-specific medians as thresholds; 75th percentile split (right) uses the 75th percentile.

The 75th percentile split (Figure B1b) concentrates most industries in the $(0, 0, 0)$ baseline (26 of 64) and isolates only the most heavily treated industries in each channel. Under this more extreme split, the $(1, 0, 0)$ cell coefficient moves closer to zero (-0.015), providing further evidence against any protective employment effects from tariffs. The $(0, 0, 1)$ "retaliatory only" cell is positive and marginally significant ($+0.050$, $p < 0.10$). Still, this cell contains 15 industries that are above the 75th percentile on retaliatory tariff changes yet below the threshold on both import and input tariffs. This combination likely reflects idiosyncratic industry characteristics rather than a meaningful economic channel.

Figure B2 shows the event study variant of the six-cell analysis, tracing the dynamic evolution of three key cells—$(1,0,0)$ "import only," $(1,1,0)$ "import + input," and $(1,1,1)$ "all three"—relative to the $(0,0,0)$ baseline over time.

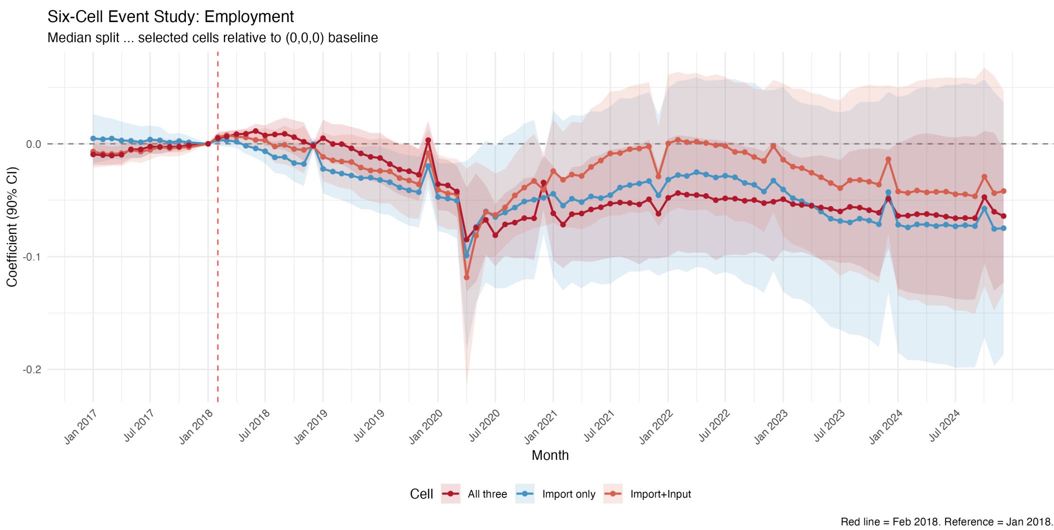


Figure B2: Six-Cell Event Study: Employment (Full Sample, Median Split)

Notes: Monthly coefficients for selected cells from the event study variant of Equation 5, with the $(0,0,0)$ cell as the baseline. Reference month is January 2018. Shaded areas show 90% confidence intervals. Red dashed line marks February 2018.

Note that industries with above-median exposure on all three tariff channels (the red line) experienced progressively lower employment relative to the $(0,0,0)$ baseline, with the gap growing in magnitude over time and statistically significant for most post-treatment months.

C Log Tariff Specification

Tables C1–C3 report results from the log tariff specification (Specifications 3a–3d), where tariff rates enter as $\log(1+\tau/100)$, for all three outcome variables. Since the dependent variable is also in logs, the coefficients have an elasticity interpretation: each coefficient gives the percent change in the outcome variable associated with a 1% increase in the gross tariff factor.[15]

[15]Compare to Specifications 1a–1d, where coefficients give the percent change in the outcome variable associated with a 1 percentage point increase in the tariff level.

Table C1: Panel Regression Results: Log Tariff Specification, Employment

	(3a) Import	(3b) Imp+Input	(3c) Three-Ch	(3d) NAICS2×Mo FE
Full Sample				
$\log(1+\tau^{imp})$	-1.067^{***}	-1.229^{***}	-1.231^{***}	-1.164^{***}
	(0.308)	(0.282)	(0.282)	(0.281)
$\log(1+\tau^{input})$		1.340^{*}	1.316^{*}	0.930
		(0.669)	(0.672)	(0.611)
$\log(1+\tau^{ret})$			-4.908^{**}	-2.060
			(2.086)	(4.906)
N	6,144	6,144	6,144	6,144
Pre-COVID				
$\log(1+\tau^{imp})$	-0.391^{**}	-0.527^{***}	-0.528^{***}	-0.488^{***}
	(0.185)	(0.156)	(0.156)	(0.164)
$\log(1+\tau^{input})$		0.828^{**}	0.836^{**}	0.323
		(0.376)	(0.377)	(0.535)
$\log(1+\tau^{ret})$			1.881	3.691
			(1.465)	(3.108)
N	2,432	2,432	2,432	2,432
Excluding COVID				
$\log(1+\tau^{imp})$	-1.038^{***}	-1.275^{***}	-1.277^{***}	-1.208^{***}
	(0.311)	(0.296)	(0.296)	(0.305)
$\log(1+\tau^{input})$		1.928^{***}	1.901^{***}	1.588^{**}
		(0.567)	(0.561)	(0.613)
$\log(1+\tau^{ret})$			-5.708^{**}	-3.060
			(2.237)	(5.136)
N	5,504	5,504	5,504	5,504

Notes: Tariff variables enter as $\log(1+\tau/100)$. With log outcomes, coefficients are elasticities: $\hat{\beta}$ gives the percent change in the outcome per 1% increase in the gross tariff factor. Specifications 3a–3d mirror 1a–1d. Standard errors (in parentheses) clustered at three-digit NAICS. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

For employment (Table C1), the log import tariff coefficient is -1.231 in the full-sample three-channel specification (3c), implying that a 1% increase in the gross import tariff factor is associated with a 1.23% decline in employment. This result is significant at the 1% level across all samples and specifications. The magnitude is smaller in the pre-COVID sample (-0.528), consistent with tariff effects accumulating over time.

Table C2: Panel Regression Results: Log Tariff Specification, Industrial Production

	(3a) Import	(3b) Imp+Input	(3c) Three-Ch	(3d) NAICS2×Mo FE
Full Sample				
$\log(1+\tau^{imp})$	−0.681	−0.391	−0.391	−0.190
	(0.596)	(0.686)	(0.685)	(0.730)
$\log(1+\tau^{input})$		−2.875	−2.869	−3.130
		(3.036)	(3.038)	(2.670)
$\log(1+\tau^{ret})$			1.047	−3.883
			(2.276)	(4.273)
N	6,336	6,336	6,336	6,240
Pre-COVID				
$\log(1+\tau^{imp})$	−0.109	−0.292	−0.295	−0.259
	(0.241)	(0.249)	(0.248)	(0.259)
$\log(1+\tau^{input})$		1.310**	1.330**	0.800
		(0.557)	(0.572)	(1.210)
$\log(1+\tau^{ret})$			4.157	5.874
			(3.519)	(5.049)
N	2,508	2,508	2,508	2,470
Excluding COVID				
$\log(1+\tau^{imp})$	−0.558	−0.636	−0.636	−0.454
	(0.680)	(0.641)	(0.640)	(0.684)
$\log(1+\tau^{input})$		0.780	0.782	0.537
		(1.459)	(1.454)	(2.410)
$\log(1+\tau^{ret})$			0.284	−6.553
			(2.380)	(5.332)
N	5,676	5,676	5,676	5,590

Notes: Same specification as Table C1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

For industrial production (Table C2), the log import tariff coefficient is negative but statistically insignificant across all samples and specifications, consistent with the levels results. The only significant coefficient is the log input tariff in the pre-COVID sample (+1.33, $p < 0.05$), which likely reflects the same measurement issues discussed in Section 5.2.

Table C3: Panel Regression Results: Log Tariff Specification, Producer Prices

	(3a) Import	(3b) Imp+Input	(3c) Three-Ch	(3d) NAICS2×Mo FE
Full Sample				
$\log(1+\tau^{imp})$	0.611*	0.778**	0.777**	0.871**
	(0.346)	(0.301)	(0.302)	(0.357)
$\log(1+\tau^{input})$		−1.760**	−1.775**	−2.074**
		(0.790)	(0.789)	(0.855)
$\log(1+\tau^{ret})$			−4.213	−1.011
			(2.551)	(3.142)
N	7,410	7,410	7,410	7,410
Pre-COVID				
$\log(1+\tau^{imp})$	0.359**	0.371**	0.376**	0.366**
	(0.149)	(0.142)	(0.145)	(0.154)
$\log(1+\tau^{input})$		−0.098	−0.141	0.445
		(0.535)	(0.531)	(0.435)
$\log(1+\tau^{ret})$			−11.82***	−11.34***
			(3.021)	(2.007)
N	2,964	2,964	2,964	2,964
Excluding COVID				
$\log(1+\tau^{imp})$	0.557	0.786*	0.783*	0.929*
	(0.515)	(0.422)	(0.424)	(0.445)
$\log(1+\tau^{input})$		−2.354*	−2.377*	−2.495**
		(1.194)	(1.196)	(1.129)
$\log(1+\tau^{ret})$			−6.158**	−2.056
			(2.188)	(2.616)
N	6,630	6,630	6,630	6,630

Notes: Same specification as Table C1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

For producer prices (Table C3), the log import tariff coefficient is positive and significant across all samples (+0.777 in the full sample, $p < 0.05$; +0.376 pre-COVID, $p < 0.05$), confirming tariff cost pass-through to domestic prices. The log input tariff coefficient is negative and significant in the full and excluding-COVID samples (−1.775, $p < 0.05$). As with the puzzling positive input tariff coefficient for employment, this likely reflects the measurement limitations discussed in Section 5.2 rather than a genuine economic channel. The retaliatory tariff coefficient is implausibly large and negative in the pre-COVID sample (−11.82, $p < 0.01$), likely driven by the extremely limited cross-industry variation in this measure (standard deviation of 0.06 pp). Overall, the sign and significance patterns are consistent with the levels specification (Table 2), providing evidence that the main results are not sensitive to the functional form of the tariff variable.

D Robustness: Manufacturing Input Share Controls

The input tariff measure τ_{jt}^{inp} is constructed as $\sum_s \alpha_{js}\tau_{st}^{imp}$, where the IO cost shares α_{js} sum to each industry's manufacturing input share of total costs rather than to one. This means that variation in τ_{jt}^{inp} reflects both changes in upstream tariffs and cross-sectional differences in manufacturing input intensity. If industries that rely more heavily on manufacturing inputs experience differential time trends in outcomes—for instance, because they are more exposed to global supply chain disruptions—the input tariff coefficient could be confounded.

To address this concern, I augment the baseline specification with $\text{mfg\_input\_share}_j \times \text{month}_t$ controls, which absorb any time-varying confounder proportional to an industry's manufacturing input intensity. Specifically, I interact the time-invariant manufacturing input share (the sum of IO cost shares from manufacturing suppliers) with month fixed effects, adding these as controls alongside the standard industry and time fixed effects.

Tables D1–D3 present the results for employment, industrial production, and producer prices, respectively. In each table, column (1) reproduces the baseline three-channel specification, column (2) adds NAICS2×month fixed effects, column (3) adds the manufacturing input share×month controls, and column (4) includes both.

Across all three outcomes, the import tariff coefficient is virtually unchanged by the inclusion of manufacturing input share controls. For employment, the coefficient moves from −0.012 in the baseline to −0.012 with the additional controls (column 3) and −0.011 with both sets of controls (column 4), remaining significant at the 1% level throughout. The input tariff coefficient attenuates modestly—from 0.013 to 0.012 in column (3) and to 0.005 in column (4)—consistent with some of its identifying variation being absorbed by the differential trends. Results for the pre-COVID and excluding-COVID samples are qualitatively identical: the import tariff coefficient is stable across all specifications, while the input tariff coefficient attenuates somewhat when both controls are included.[16]

[16]Full results for the pre-COVID and excluding-COVID samples are available in the replication package.

Table D1: Robustness to Manufacturing Input Share Controls: Employment

	(1) Baseline	(2) NAICS2×Mo	(3) MfgShare×Mo	(4) Both
Import Tariff	-0.012^{***}	-0.011^{***}	-0.012^{***}	-0.011^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Input Tariff	0.013^{*}	0.009	0.012^{*}	0.005
	(0.007)	(0.006)	(0.006)	(0.005)
Retaliatory Tariff	-0.049^{**}	-0.020	-0.061^{**}	-0.033
	(0.021)	(0.049)	(0.024)	(0.051)
Industry FE	Yes	Yes	Yes	Yes
Month FE	Yes	–	Yes	–
NAICS2×Month FE	–	Yes	–	Yes
MfgShare×Month	–	–	Yes	Yes
Observations	6,144	6,144	6,144	6,144
R^2	0.995	0.996	0.996	0.996

Notes: Dependent variable is log employment. Full sample (Jan 2017–Dec 2024). All tariff variables are in percentage points (applied rates). Regressions are weighted by baseline employment. Standard errors clustered at the NAICS-3 level in parentheses. MfgShare×Month denotes the interaction of each industry's time-invariant manufacturing input cost share with month fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table D2: Robustness to Manufacturing Input Share Controls: Industrial Production

	(1) Baseline	(2) NAICS2×Mo	(3) MfgShare×Mo	(4) Both
Import Tariff	-0.004	-0.002	-0.004	-0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Input Tariff	-0.028	-0.031	-0.005	-0.003
	(0.030)	(0.026)	(0.018)	(0.013)
Retaliatory Tariff	0.010	-0.039	0.017	-0.052
	(0.023)	(0.043)	(0.026)	(0.057)
Industry FE	Yes	Yes	Yes	Yes
Month FE	Yes	–	Yes	–
NAICS2×Month FE	–	Yes	–	Yes
MfgShare×Month	–	–	Yes	Yes
Observations	6,336	6,240	6,336	6,240
R^2	0.400	0.457	0.497	0.550

Notes: Dependent variable is log industrial production index. Full sample (Jan 2017–Dec 2024). All tariff variables are in percentage points (applied rates). Regressions are weighted by relative importance weights. Standard errors clustered at the NAICS-3 level in parentheses. MfgShare×Month denotes the interaction of each industry's time-invariant manufacturing input cost share with month fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table D3: Robustness to Manufacturing Input Share Controls: Producer Prices

	(1) Baseline	(2) NAICS2×Mo	(3) MfgShare×Mo	(4) Both
Import Tariff	0.007**	0.008**	0.008***	0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
Input Tariff	−0.017**	−0.020**	−0.016***	−0.022***
	(0.008)	(0.008)	(0.005)	(0.007)
Retaliatory Tariff	−0.042	−0.010	−0.034	−0.009
	(0.026)	(0.031)	(0.031)	(0.035)
Industry FE	Yes	Yes	Yes	Yes
Month FE	Yes	–	Yes	–
NAICS2×Month FE	–	Yes	–	Yes
MfgShare×Month	–	–	Yes	Yes
Observations	7,410	7,410	7,410	7,410
R^2	0.978	0.981	0.979	0.982

Notes: Dependent variable is log producer price index. Full sample (Jan 2017–Dec 2024). All tariff variables are in percentage points (applied rates). Regressions are weighted by relative importance weights. Standard errors clustered at the NAICS-3 level in parentheses. MfgShare×Month denotes the interaction of each industry's time-invariant manufacturing input cost share with month fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

E Robustness: Time Aggregation

The baseline regressions use monthly data, which may introduce high-frequency noise that attenuates coefficient estimates. To test sensitivity to the choice of time frequency, I collapse the monthly panels to quarterly and semi-annual averages and re-estimate the three-channel specification (1c). Table E1 reports the results for employment across all three sample periods.

Table E1: Employment Regressions at Different Time Frequencies (Spec. 1c)

		Import		Input		Export		
Frequency	Sample	Coef.	SE	Coef.	SE	Coef.	SE	N
Monthly	Full	-0.012^{***}	(0.003)	0.013	(0.007)	-0.049^{**}	(0.021)	6,144
	Pre-COVID	-0.005^{***}	(0.001)	0.008	(0.004)	0.019	(0.015)	2,432
	Excl. COVID	-0.012^{***}	(0.003)	0.018	(0.005)	-0.057^{**}	(0.022)	5,504
Quarterly	Full	-0.012^{***}	(0.003)	0.014^{*}	(0.007)	-0.085^{**}	(0.036)	2,048
	Pre-COVID	-0.006^{***}	(0.002)	0.009^{**}	(0.004)	0.037	(0.025)	832
	Excl. COVID	-0.013^{***}	(0.003)	0.020^{***}	(0.006)	-0.092^{**}	(0.036)	1,856
Semi-annual	Full	-0.013^{***}	(0.003)	0.016^{**}	(0.006)	-0.126^{*}	(0.071)	1,024
	Pre-COVID	-0.007^{***}	(0.002)	0.004	(0.010)	0.096^{*}	(0.048)	448
	Excl. COVID	-0.014^{***}	(0.003)	0.017^{**}	(0.006)	-0.139^{*}	(0.067)	960

Notes: All specifications include industry and period fixed effects with standard errors clustered at the three-digit NAICS level. Quarterly and semi-annual panels are constructed by averaging all variables within each industry×period cell. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The import tariff coefficient is remarkably stable across frequencies, remaining significant at the 1% level in all nine specifications. Magnitudes increase slightly at lower frequencies—from -0.012 (monthly) to -0.012 (quarterly) to -0.013 (semi-annual) in the full sample—consistent with high-frequency noise attenuating the monthly estimates. The input tariff coefficient also gains precision at lower frequencies, becoming statistically significant in several quarterly and semi-annual specifications where it was insignificant in the monthly data. Note that the sign on the input tariff coefficient on employment is still positive; as discussed in Section 5.2, this is counterintuitive. The retaliatory tariff coefficient grows larger in magnitude at lower frequencies but also becomes less precise as the number of time periods shrinks.

Table E2 reports the results for industrial production across all three sample periods. Coefficients on import and retaliatory tariffs are not statistically significant across time frequencies and samples, while coefficients for input tariffs are statistically significant and positive at the monthly frequency in the pre-COVID sample.

Table E2: Industrial Production Regressions at Different Time Frequencies (Spec. 1c)

		Import		Input		Export		
Frequency	Sample	Coef.	SE	Coef.	SE	Coef.	SE	N
Monthly	Full	−0.004	(0.007)	−0.028	(0.030)	0.010	(0.023)	6,336
	Pre-COVID	−0.003	(0.002)	0.013**	(0.006)	0.042	(0.035)	2,508
	Excl. COVID	−0.006	(0.006)	0.008	(0.014)	0.003	(0.024)	5,676
Quarterly	Full	−0.003	(0.008)	−0.020	(0.025)	0.026	(0.042)	2,112
	Pre-COVID	−0.002	(0.003)	0.012*	(0.006)	0.095	(0.069)	858
	Excl. COVID	−0.007	(0.007)	0.008	(0.015)	0.016	(0.042)	1,914
Semi-annual	Full	−0.004	(0.008)	−0.009	(0.020)	0.109	(0.086)	1,056
	Pre-COVID	0.009	(0.013)	−0.039	(0.039)	0.257	(0.179)	462
	Excl. COVID	−0.004	(0.009)	−0.010	(0.021)	0.082	(0.080)	990

Notes: All specifications include industry and period fixed effects with standard errors clustered at the three-digit NAICS level. Quarterly and semi-annual panels are constructed by averaging all variables within each industry×period cell. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table E3 reports the results for producer prices across all three sample periods. Coefficients on import tariffs are consistently positive and significant across time frequencies and samples; coefficients on retaliatory tariffs are negative and significant for all time frequencies and samples except for the full sample at monthly and semi-annual frequencies. Coefficients on input tariffs are negative across time frequency and sample, but not always statistically significant.

Table E3: Producer Price Regressions at Different Time Frequencies (Spec. 1c)

		Import		Input		Export		
Frequency	Sample	Coef.	SE	Coef.	SE	Coef.	SE	N
Monthly	Full	0.007**	(0.003)	−0.017**	(0.008)	−0.042	(0.026)	7,410
	Pre-COVID	0.004**	(0.001)	−0.001	(0.005)	−0.118***	(0.030)	2,964
	Excl. COVID	0.007*	(0.004)	−0.023*	(0.012)	−0.062**	(0.022)	6,630
Quarterly	Full	0.009***	(0.003)	−0.024**	(0.010)	−0.103*	(0.058)	2,496
	Pre-COVID	0.004**	(0.002)	−0.003	(0.008)	−0.207***	(0.061)	1,014
	Excl. COVID	0.010**	(0.004)	−0.033*	(0.017)	−0.137***	(0.040)	2,184
Semi-annual	Full	0.009**	(0.003)	−0.027**	(0.012)	−0.138	(0.121)	1,248
	Pre-COVID	0.006*	(0.004)	−0.002	(0.006)	−0.331***	(0.081)	546
	Excl. COVID	0.011**	(0.005)	−0.033*	(0.016)	−0.197***	(0.067)	1,092

Notes: All specifications include industry and period fixed effects with standard errors clustered at the three-digit NAICS level. Quarterly and semi-annual panels are constructed by averaging all variables within each industry×period cell. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

F Temporal Dynamics: Lagged and Leading Tariffs

To examine whether tariff effects operate with a delay or whether industries anticipate future tariff changes, I augment the three-channel specification with lagged or leading tariff values. Table F1 reports results for employment.

Table F1: Lag/Lead Tariff Specifications: Employment

	Full Sample		Pre-COVID		Excl. COVID	
	Coef.	SE	Coef.	SE	Coef.	SE
Spec. 4a: Current + 1-month lag						
Import Tariff (t)	-0.005^{***}	(0.001)	-0.004^{***}	(0.001)	-0.006^{***}	(0.001)
Import Tariff ($t-1$)	-0.007^{***}	(0.002)	-0.001	(0.001)	-0.007^{***}	(0.002)
Spec. 4b: Current + 3-month lag						
Import Tariff (t)	-0.006^{***}	(0.002)	-0.004^{***}	(0.001)	-0.005^{***}	(0.001)
Import Tariff ($t-3$)	-0.006^{***}	(0.002)	-0.001	(0.001)	-0.008^{***}	(0.002)
Spec. 4c: Current + 6-month lag (import only)						
Import Tariff (t)	-0.007^{***}	(0.002)	-0.005^{***}	(0.001)	-0.005^{***}	(0.001)
Import Tariff ($t-6$)	-0.006^{**}	(0.002)	-0.000	(0.001)	-0.007^{**}	(0.003)
Spec. 4d: Current + 1-month lead						
Import Tariff (t)	-0.009^{***}	(0.003)	-0.003^{**}	(0.001)	-0.006^{***}	(0.002)
Import Tariff ($t+1$)	-0.003^{**}	(0.001)	-0.002^{**}	(0.001)	-0.006^{***}	(0.001)

Notes: Each specification includes the full set of contemporaneous tariff controls (import, input, retaliatory) plus the indicated lag or lead. Only import tariff coefficients are shown for brevity; input and retaliatory tariffs are included but not reported. Specs 4a–4c include the corresponding lags for all three channels; Spec 4c includes only the import tariff 6-month lag. Spec 4d includes 1-month leads for all three channels. Industry and month fixed effects; standard errors clustered at three-digit NAICS. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The lag structure reveals a clear difference between the pre-COVID and longer samples. In the full and excluding-COVID samples, lagged import tariffs are highly significant at all horizons—1, 3, and 6 months—with magnitudes comparable to the contemporaneous effect. This implies that a tariff increase continues to depress employment for at least half a year beyond its initial impact. In the pre-COVID sample, by contrast, lagged tariffs are uniformly insignificant, and the contemporaneous effect alone accounts for the employment response. This pattern is consistent with the interpretation that the initial 2018–2019 tariff shock produced an immediate employment response, while the persistent tariff regime over the longer 2018–2024 period generated additional lagged adjustment effects—such as supply chain reorganization, delayed investment responses, and gradual demand substitution—that are not captured in the shorter window.

The leading tariff specification (4d) shows significant forward-looking effects in all three samples: -0.003 ($p < 0.05$) in the full sample, -0.002 ($p < 0.05$) pre-COVID, and -0.006 ($p < 0.01$) excluding COVID. This could reflect anticipation effects—industries adjusting employment in advance of announced but not yet implemented tariff changes—or serial correlation in the tariff series combined with gradual employment adjustment. The fact that leads are significant even in the pre-COVID sample, where lags are not, lends some support to the anticipation interpretation: firms may have begun adjusting to announced tariffs before their effective dates, but the full cumulative effect had not yet materialized in the short pre-COVID window.

Table F2 reports results for the three-channel specification with lagged or leading tariff values on industrial production. Import tariff coefficients—both contemporaneous and lagged—are uniformly insignificant across samples and lag horizons, consistent with the null results for industrial production in the baseline specification (see Table 2 and Figure 7).

Table F2: Lag/Lead Tariff Specifications: Industrial Production

	Full Sample		Pre-COVID		Excl. COVID	
	Coef.	SE	Coef.	SE	Coef.	SE
Spec. 4a: Current + 1-month lag						
Import Tariff (t)	0.019	(0.018)	-0.004^{*}	(0.002)	-0.002	(0.003)
Import Tariff ($t-1$)	-0.026^{*}	(0.015)	0.001	(0.003)	-0.005	(0.005)
Spec. 4b: Current + 3-month lag						
Import Tariff (t)	-0.005	(0.006)	-0.002	(0.002)	-0.001	(0.003)
Import Tariff ($t-3$)	0.000	(0.010)	-0.001	(0.003)	-0.006	(0.006)
Spec. 4c: Current + 6-month lag (import only)						
Import Tariff (t)	-0.004	(0.004)	-0.002	(0.002)	0.001	(0.004)
Import Tariff ($t-6$)	-0.001	(0.011)	-0.004	(0.003)	-0.009	(0.008)
Spec. 4d: Current + 1-month lead						
Import Tariff (t)	-0.007	(0.004)	-0.001	(0.003)	-0.003	(0.004)
Import Tariff ($t+1$)	0.004	(0.008)	-0.002	(0.002)	-0.004	(0.002)

Notes: Each specification includes the full set of contemporaneous tariff controls (import, input, retaliatory) plus the indicated lag or lead. Only import tariff coefficients are shown for brevity; input and retaliatory tariffs are included but not reported. Specs 4a–4c include the corresponding lags for all three channels; Spec 4c includes only the import tariff 6-month lag. Spec 4d includes 1-month leads for all three channels. Industry and month fixed effects; standard errors clustered at three-digit NAICS. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F3 reports results for the three-channel specification with lagged or leading tariff values on producer prices. The contemporaneous import tariff coefficient remains positive and significant in most specifications, but lagged and leading import tariff coefficients are generally insignificant, suggesting that tariff pass-through to producer prices is largely contemporaneous.

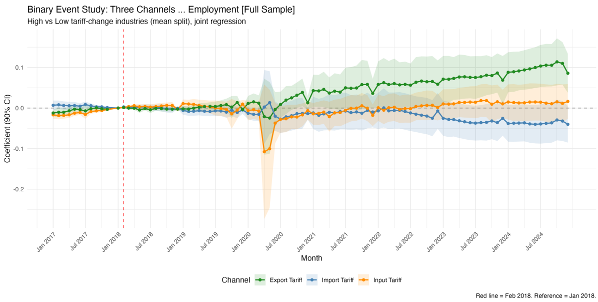
Table F3: Lag/Lead Tariff Specifications: Producer Prices

	Full Sample		Pre-COVID		Excl. COVID	
	Coef.	SE	Coef.	SE	Coef.	SE
Spec. 4a: Current + 1-month lag						
Import Tariff (t)	0.004**	(0.002)	−0.000	(0.003)	0.003	(0.002)
Import Tariff ($t-1$)	0.004	(0.003)	0.004	(0.004)	0.006	(0.003)
Spec. 4b: Current + 3-month lag						
Import Tariff (t)	0.003*	(0.002)	0.002	(0.002)	0.004*	(0.002)
Import Tariff ($t-3$)	0.006*	(0.003)	0.002	(0.003)	0.005	(0.005)
Spec. 4c: Current + 6-month lag (import only)						
Import Tariff (t)	0.003	(0.002)	0.004**	(0.002)	0.003	(0.003)
Import Tariff ($t-6$)	0.007	(0.004)	0.002	(0.002)	0.005	(0.007)
Spec. 4d: Current + 1-month lead						
Import Tariff (t)	0.006**	(0.003)	0.006	(0.005)	0.006***	(0.002)
Import Tariff ($t+1$)	0.002	(0.001)	−0.002	(0.004)	0.002	(0.004)

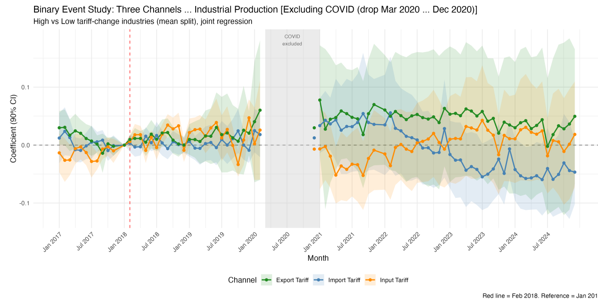
Notes: Each specification includes the full set of contemporaneous tariff controls (import, input, retaliatory) plus the indicated lag or lead. Only import tariff coefficients are shown for brevity; input and retaliatory tariffs are included but not reported. Specs 4a–4c include the corresponding lags for all three channels; Spec 4c includes only the import tariff 6-month lag. Spec 4d includes 1-month leads for all three channels. Industry and month fixed effects; standard errors clustered at three-digit NAICS. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

G Mean Split Event Study Figures

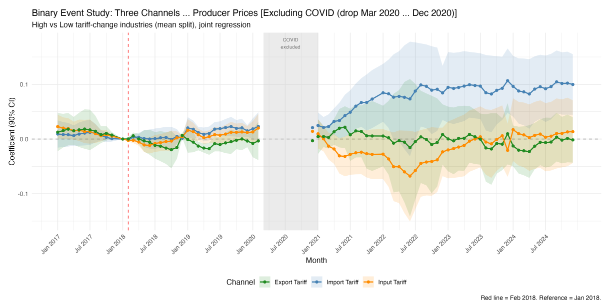
Figure G1 presents the binary event study results using the mean split (as opposed to the median split shown in the main text). Panel (a) shows employment over the full sample, panel (b) shows industrial production excluding COVID, and panel (c) shows producer prices excluding COVID.



(a) Employment (Full Sample)



(b) Industrial Production (Excl. COVID)



(c) Producer Prices (Excl. COVID)

Figure G1: Binary Event Study: Mean Split

Notes: Same methodology as Figure 4 and Figure 5, but with industries classified as “high” vs. “low” based on whether the 2017-to-2019 tariff change exceeds the sample mean rather than the median. The mean split produces a somewhat unbalanced grouping due to the right-skewed distribution of tariff changes.