Protection and Productivity: Evidence from the 2018–19 U.S. Tariffs

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Abstract: I ask whether the U.S. tariffs of 2018–19 changed the productivity of the industries that they shielded. I compare manufacturing industries by how much of their home market the tariffs covered. Measured against long-run trends, total factor productivity in the more exposed industries had fallen by about 1.6 percent relative to the less exposed by 2019. Output prices rose in the same industries, so higher markups could mask a decline in measured productivity, not create one. Assessments of the welfare effects of tariffs hold technology fixed and leave out this decline.

Keywords: tariffs, trade policy, total factor productivity, manufacturing, markups

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I am interested in evidence of how policy changes affect productivity. The U.S. tariffs of 2018–19 provide a natural setting to obtain it. By the end of 2019 the tariffs on imports from China alone covered roughly $350 billion (Fajgelbaum and Khandelwal, 2022), in what Fajgelbaum et al. (2020) call a return to protectionism unprecedented in the postwar era. I ask whether the tariffs changed the productivity of the industries that they shielded.

I cannot simply compare protected and unprotected industries, because tariffs are not handed out at random. Adão et al. (2026) estimate that redistributive motives account for about a third of the variation across U.S. tariff lines in 2017. The added tariff was nearly uniform, 25 percent on most covered goods, so I cannot identify its effect from differences in the rate. However, the share of the home market supplied by newly tariffed imports differed widely across industries. Following Flaaen and Pierce (2026), I measure the exposure of an industry to the tariffs by the added duty on its imports as a share of the value of its home market. I compare industries by that exposure in a difference-in-differences design that nets out the long-run trend of each industry and controls for how much each industry trades. My outcome measure is the index of total factor productivity (TFP) that the Bureau of Labor Statistics (BLS) publishes for 86 manufacturing industries.

After the tariff surge, the TFP of the more exposed industries fell relative to that of the less exposed industries. Take two industries, one at the 75th percentile of protection, where the added duty came to about 2 percent of the value of its home market, and one at the 25th, where it came to about one-tenth of a percent. By 2019, TFP in the first had fallen about 1.6 percent relative to the second, measured against their long-run trends. In two years, the more exposed industries lost more ground than the average industry used to gain in a full year. After 2019, my estimates are too imprecise to show whether the decline lasts.

The size of the decline depends on how long the catch-up of the more exposed industries before the tariff war would have lasted. In 2014 and 2015 these industries sat below their long-run trend, and by 2017 they were back on it. If that faster growth had continued without the tariffs, the decline by 2019 would have been about 3 percent. I take the smaller number as the more cautious estimate. With either trend, the decline does not reflect a simple reversion of growth rates to their mean. The fastest risers among the more protected industries were still below their long-run trend in 2017, and by 2019, instead of catching up to it, they had fallen further below it.

The TFP decline is of similar size regardless of the measure of tariff exposure that I consider, including the change in the statutory tariff, which averages the tariff schedule without weighting by imports. The estimates change little with controls for the business cycle and the pandemic, and the break also appears in output per hour, although less precisely. Hours per worker, one proxy for capacity utilization, did not fall in the more exposed industries.

The TFP that I use is built from revenues that BLS deflates with detailed price indexes at the product-class level. Studies that deflate revenues with broader price indexes obtain measures that mix movements in markups with movements in physical productivity (Foster et al., 2008), and much of the evidence on trade policy and productivity rests on such measures. The distinction shows up in my estimates. The output prices of the more exposed industries rose relative to those of the less exposed. With a revenue-based measure, that rise would be counted as productivity, and the estimated decline would be smaller. With the BLS measure, the rise is divided out, unless the product-class indexes miss part of it. In that case, the decline in physical productivity would be larger than the one that I estimate.

I adapt the empirical design of Flaaen and Pierce (2026) to a different context. A strength of their design is that it separates the protection that an industry receives from the higher cost of its imported inputs and from retaliation against its exports. They study employment, industrial production, and producer prices. Productivity cannot be derived from their estimates, because TFP also depends on capital and intermediate inputs and because the correction for trends before the tariff war is specific to each outcome measure. That correction carries more weight for productivity. Their outcome measures followed no distinct path before the tariffs, whereas the TFP of the more exposed industries was rising. Therefore, I fit the trend of each industry over every year before the tariff war and compare the break with breaks in earlier years and with random assignments of exposure. I also rebuild the measure of exposure from the Federal Register for each of the 86 industries, some of which they combine into groups, and I add a measure of the tariff that depends on the tariff schedule alone.

Syverson (2011) surveys the evidence on how regulation, competition, and trade affect productivity. Within that evidence, studies of tariffs and quantity-based productivity are scarce. The main exception is Pierce (2011), who measures physical productivity for U.S. plants that report output in physical units. Among those plants, physical productivity fell under antidumping duties, while revenue productivity barely moved. At the industry level, Bernard et al. (2006) link falling U.S. trade costs to faster growth of TFP. Per point of tariff, the size of the decline that I estimate lies between the estimates of these two studies. My evidence comes from a broad tariff increase in an advanced economy, at a time when the assessments of its costs hold productivity fixed.

Studies that measure revenue productivity are more numerous, and most come from liberalizations in developing economies. Holmes and Schmitz (2010) review the evidence from industry studies and trade liberalizations and conclude that in most of them increased competition raised industry productivity. Pavcnik (2002) documents that revenue productivity rose after liberalization in Chilean import-competing plants. Konings and Vandenbussche

(2008) report that it also rose under antidumping measures at the average protected European firm, the same direction of policy as in Pierce (2011). Studies of increases in import competition reach different conclusions. Bloom et al. (2016) find that more import competition raised TFP within exposed European firms. By contrast, Autor et al. (2020) find that it reduced patenting among exposed U.S. firms. The industry TFP that I measure is built from product-level deflators, which divide out the output price of the industry.

The finding bears on the welfare effects of tariffs. In trade theory, the case for a unilateral tariff rests on terms-of-trade effects (Costinot and Rodríguez-Clare, 2014). For the 2018–19 tariffs, studies of their incidence find that those effects were modest and that import prices rose nearly one for one with the tariffs (Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021). The assessments of the episode, which Fajgelbaum and Khandelwal (2022) survey, find that the aggregate loss was small. By their authors' own accounts, the assessments are short-run and static by design.[1] They hold technology and the set of producers fixed, so they leave out a lasting fall in the productivity of the protected industries. By comparing more and less exposed industries, I identify only a relative effect; accordingly, I need additional assumptions to draw conclusions about the change in TFP for manufacturing as a whole. Moreover, the welfare consequences depend on how long the decline lasts, which I cannot estimate precisely.

I. Exposure and Productivity

I adapt the empirical design of Flaaen and Pierce (2026) to the study of the effects of tariffs on total factor productivity. I build the analysis on a yearly panel of the 86 four-digit NAICS manufacturing industries that BLS covers in its detailed-industry productivity accounts. I estimate the response of productivity to the tariffs over the years 2013 to 2022. I use earlier years, back to 1987, to fit the trend of each industry before the tariff war and to compare the break in 2019 with breaks in earlier years.[2]

A. Exposure to the 2018 Tariffs

I measure the exposure of an industry to the 2018 tariffs by the added duty on its imports. Let Ω denote the set of product–country pairs newly covered by a 2018 U.S. tariff action, and

[1] Fajgelbaum et al. (2020) analyze "the short-run impact" of the tariffs (page 1) and describe their aggregate result as "a ballpark estimate" (page 4); Amiti et al. (2019, page 200) note that their approach "makes a number of simplifying assumptions, including partial equilibrium and perfect competition"; and Fajgelbaum and Khandelwal (2022, page 222) report, as one possible explanation of the gap between stock-market and static estimates, that "static models do not incorporate potentially important mechanisms, such as dynamic losses or growing uncertainty."

[2] I place all series on the 2012 NAICS basis. Appendix A documents the construction and validation of every series.

a_{pc} the tariff rate added on pair pc.[3] The protection measure has two parts, both measured in 2017. The first is the added duty on the imports of an industry as a share of those imports. The second is the share of imports in the home market of the industry. The terms M, X, and Q are, respectively, the imports, domestic exports, and shipments of an industry, so that

$$\text{Protection}_j = \sum_{pc \in \Omega} a_{pc} \frac{M_{j,pc}}{M_j} \cdot \frac{M_j}{Q_j + M_j - X_j}. \tag{1}$$

The denominator of the second factor is domestic absorption, the size of the home market. The protection measure is therefore the added duty on the imports of an industry as a share of the value of its home market. I build it from the product lists in the Federal Register notices, the import and export data of Schott (2025), and the shipments of the NBER–CES database (Becker et al., 2021).[4]

Exposure varies across industries. The added duty came to 4.1 percent of the value of the home market, on average, in the most exposed quartile of industries and 0.05 percent in the least exposed quartile. Because nearly every covered import faced the same additional 25 percent tariff, the protection measure varies mostly with how much of the home market of an industry the tariffs reached. Accordingly, the protection measure ranks industries almost exactly as the share of the home market newly covered by the tariffs does.[5]

The specification also includes two other channels: the higher cost of imported inputs and retaliation by trading partners. The first is the rise in the costs of an industry if the duties on its imported inputs passed through in full, and the second is the added duty that foreign retaliation placed on the exports of an industry, as a share of its output.[6]

B. Productivity Measures

I measure productivity with the BLS index of total factor productivity for detailed industries (U.S. Bureau of Labor Statistics, 2026). BLS computes the index as sectoral output

[3]The actions are the Section 232 tariffs on steel and aluminum (The White House, 2018b), the Section 201 safeguard tariffs on solar cells and large residential washers (The White House, 2018a), and the Section 301 tariffs of Lists 1 to 3 on imports from China (Office of the United States Trade Representative, 2018a,b,c). Because I sum the added duty over product–country pairs, the exposure of an industry to the tariffs differs from its exposure to imports from China.

[4]I rebuild the protection measure rather than use the one that Flaaen and Pierce (2026) publish because they combine some industries into groups. On the 83 industries that the two constructions share, the two protection measures correlate at 0.997. I compare the two protection measures in Section A.3 of the Appendix. I measure both factors of the protection measure in equation (1), the added duty as a share of imports and the import share of the home market, on 2017 data, whereas the code of Flaaen and Pierce takes the import share from 2016.

[5]I report the estimate with the share of the home market newly covered by the tariffs as the measure of exposure in Section II.C.

[6]To construct the measures of the higher cost of imported inputs and of retaliation, I adapted the replication codes of Flaaen and Pierce (2024) by eliminating the steps that group some industries.

divided by a Törnqvist index of combined capital, labor, energy, and intermediate inputs. It distributes nominal sectoral output across detailed product categories and deflates each by the producer price index of that product before aggregating, so the output price of an industry is divided out by construction (Cunningham et al., 2023). With these data I cannot separate a change in technology, a shift of production toward less productive firms, and the way output is valued in the published series, all of which move measured TFP together.

As an alternative measure of productivity, I use real sectoral output per hour from BLS. I also use the output price of each industry, measured by the implicit deflator of its sectoral output.[7]

C. The Empirical Specification

Tariffs are not assigned at random, so industries with higher tariffs may differ from the others for reasons that predate the tariffs. For the 2018 tariffs the concern is concrete, because the more exposed industries were already gaining on the others in productivity before the tariff war.[8] Accordingly, I compare industries by their exposure while allowing for their paths before the tariff war. I regress detrended log TFP on each measure of exposure and each control, with a separate coefficient for every year. For industry j in year t,

$$\begin{aligned} \tilde{y}_{jt} \;=\; & b_t^P \,\text{Protection}_j \;+\; b_t^I \,\text{InputCost}_j \;+\; b_t^R \,\text{Retaliation}_j \\ & +\; b_t^M \,\text{ImpShare}_j \;+\; b_t^X \,\text{ExpShare}_j \;+\; b_t^C \,\text{ICShare}_j \;+\; b_t^K \ln(K/L)_j \\ & +\; b_t^B \,\text{Cycle}_j \;+\; c_j \;+\; d_t \;+\; e_{jt}, \end{aligned} \tag{2}$$

where InputCost_j and Retaliation_j measure the two other channels of Section I.A, the higher cost of imported inputs and retaliation by trading partners, the five terms from ImpShare_j to Cycle_j are controls, c_j and d_t are industry and year fixed effects, and e_{jt} is the error term. The regressors carry only the industry subscript j, because each takes a single value for an industry, the same in every year of the sample. The three exposure measures apply the 2018 tariff actions to trade before the tariff war, and the five controls are measured before the tariff war. Only the coefficients carry the year subscript t. Each is a path of year-specific slopes, normalized to zero in 2017, the base year. I estimate the equation on the 86 industries over 2013–2022 and weight industries by value added in 2017.[9] Following Flaaen and Pierce (2026), I cluster standard errors by three-digit sector.

[7] I validate the BLS TFP series against the five-factor TFP index of the NBER–CES database, which is constructed independently. On the overlapping industry-years the two series correlate at 0.77 in within-industry variation.

[8] I report the estimates without removing the trend of each industry in Section B.1 of the Appendix.

[9] Among the 86 industries, coating, engraving, and heat treating (NAICS 3328) imports nothing and has no tariff lines, so all its exposure measures are zero, as in the data of Flaaen and Pierce (2024).

The outcome $\tilde{y}_{jt}$ is log TFP with the linear trend of each industry removed. Using monthly data, Flaaen and Pierce (2026) remove an industry-specific linear trend fitted over the last year before the tariff increases. With yearly data, I fit the trend of each industry on all the observations available before the tariff war, which run from 1987 through 2017. In Section II I also report the estimates with the pre-trend fitted over a shorter period, from 2014 through 2017. I report both rather than choose between them with a test for pre-trends, because such tests can have low power and choosing a specification by their result can distort estimation and inference (Roth, 2022).

I control for four characteristics of each industry, so that the effects of shocks falling more heavily on trade-exposed industries are not attributed to the tariffs. Year fixed effects absorb a shock only if it hits every industry equally, whereas a movement in the dollar or a slowdown in foreign demand could fall mostly on the protected industries. In the second line, ImpShare_j is the import share of the home market of each industry, ExpShare_j the export share of its shipments, ICShare_j the share of imported inputs in its costs, and $\ln(K/L)_j$ its log capital per worker, all measured before the tariff war. The protection measure, Protection_j, is the product of the added duty on the imports of an industry, as a share of those imports, and the import share of its home market in 2017. Because ImpShare_j has its own coefficient for every year, those coefficients absorb any shock that falls on import-intensive industries in general, whether or not the tariff lists covered their products. Cleaned of such shocks, the coefficients on Protection_j reflect what sets apart the industries whose imports the tariff lists covered. The fifth control, Cycle_j, measures how strongly the TFP of each industry moves with the business cycle. This sensitivity is the slope of the annual TFP growth of the industry on the growth of manufacturing output in all other industries, from 1988 through 2017.[10]

II. The 2019 Break

A. The Break by Year

The TFP of the more exposed industries fell relative to that of the less exposed industries once the tariffs were imposed. In Table 1, the coefficients on the protection measure trace that gap year by year, relative to 2017, the last year before the tariffs. After the tariff surge, the coefficients are negative. They are statistically significant at the 10 percent level in 2018 and at the 5 percent level in 2019, and imprecise afterward. In 2020, the first year of the pandemic, the coefficient is close to zero. The coefficients for 2014 and 2015 are also negative and statistically significant. In those years the more exposed industries were below

[10] I describe the construction of the value-added weights and of the cyclical sensitivity in Section A.6 of the Appendix.

their long-run trend and catching up to it, as I show in Section II.B. I measure the decline in 2019, the year by which the tariffs were fully in place and the last year before the pandemic.

Because I remove the trend that each industry followed before the tariff war, the coefficient for 2019 measures the break directly. It is the gap that opened between the more and the less exposed industries from 2017 to 2019, beyond what their long-run trends would have produced. According to Table 1, each additional percentage point of protection is associated with TFP about 0.9 percent lower in 2019, relative to the long-run trend. Between industries at the 75th and 25th percentiles of protection, the difference is about 1.6 percent.[11] The estimate is statistically significant at the 5 percent level.

This decline is sizable relative to the productivity growth of these industries. Over the decade to 2007, the TFP of the average industry rose by about 12 percent, or 1.2 percent a year, and over the following decade it barely changed. In two years, the more exposed industries lost more ground than the average industry used to gain in a full year.

The decline is also in line with the effects of trade barriers on productivity that earlier studies find. Those studies report effects per point of tariff, and the comparable estimate in my design uses the statutory output tariff, the legal tariff rate on the products of an industry when they come from China, as the measure of exposure. As shown in Table 2, each additional percentage point of that tariff is associated with TFP about a quarter of a percent lower in 2019. Two of those studies measure productivity in a way that is comparable with mine. Both find, as I do, that higher trade barriers are associated with lower productivity. Among U.S. plants that report quantities, Pierce (2011) finds that physical productivity fell under antidumping duties by more per point of duty than the quarter of a percent per point of statutory tariff that I estimate. Bernard et al. (2006) measure the TFP of U.S. manufacturing industries much as I do and find that falling trade costs raised it by less per point than my estimate.[12] Because the horizons of the three estimates differ, I conclude only that my estimate lies within the range of the earlier evidence.

B. The Catch-Up before the Tariff War

In Figure 1, I contrast the gap in exposure across industries with the gap in TFP growth, for the industries at the 75th and 25th percentiles of protection. Panel A shows the gap in the protection measure by year, with each 2018 action counted from the day it took effect. The gap opens in 2018 and reaches its full size, about 1.9 percentage points of the home market, in 2020, the first full year with all the tariffs at their final rates. Panel B shows

[11] The industries at the 25th and 75th percentiles of protection are aerospace products and parts (NAICS 3364) and engine, turbine, and power transmission equipment (NAICS 3336), where the added duties amounted to 0.13 and 2.02 percent of the value of the home market.

[12] I compare the three estimates and their horizons in Section B.3 of the Appendix.

Table 1: The TFP of the More Exposed Industries Declined in Relative Terms after the 2018 Tariffs

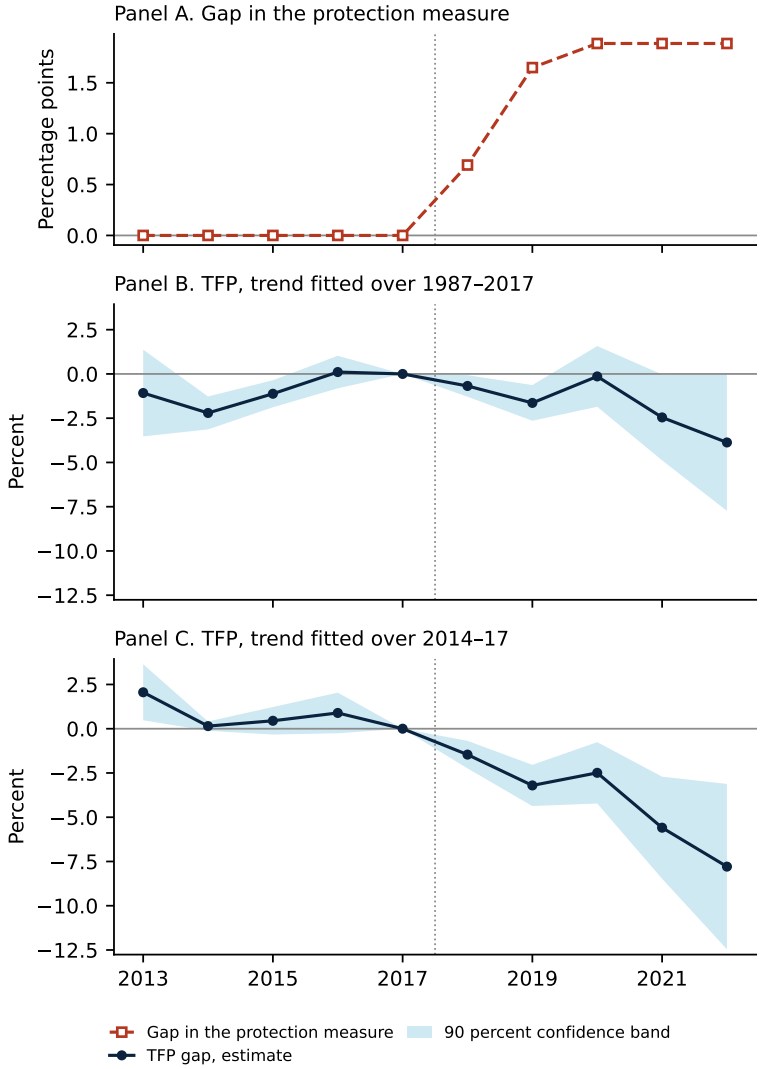
	Coefficient on the protection measure	Standard error
Panel A. Before the tariffs		
2013	−0.57	0.79
2014	−1.17	0.30
2015	−0.59	0.25
2016	0.06	0.30
Panel B. After the tariffs		
2018	−0.36	0.20
2019	−0.87	0.33
2020	−0.07	0.55
2021	−1.30	0.78
2022	−2.05	1.25
Panel C. The 2019 coefficient under two trends		
Trend fitted over 1987–2017 (baseline)	−0.87	0.33
Trend fitted over 2014–17	−1.70	0.38
Observations	860	

Notes: Coefficients on the protection measure from equation (2), relative to 2017. Panels A and B: the outcome is log BLS TFP net of the least-squares trend of each industry over 1987–2017. Panel C repeats the 2019 coefficient and adds the one with the trend fitted over 2014–17. Every regression includes InputCost, Retaliation, and the five controls, each interacted with year dummies, and industry and year fixed effects, with industries weighted by 2017 value added. Standard errors are clustered by the 21 three-digit sectors. I report the coefficients on the other regressors for 2018 and 2019 in Section B.2 of the Appendix. Sample: 86 industries, 2013–2022.

the coefficients of Table 1, scaled by the difference in protection between the two industries. The gap in TFP opens in 2018, together with the gap in protection. Before the tariff war, the same panel shows the more exposed industries below their long-run trend in 2014 and 2015 and back on it by 2017. Over those years their TFP grew faster than its trend. If that faster growth had continued without the tariffs, the decline by 2019 would have been larger. Panel C shows how much larger, with the trend of each industry fitted over 2014–17 alone. The decline by 2019 is then about 3.2 percent, twice the baseline. I take the baseline as the more cautious estimate and the 2014–17 version as an upper reading.[13] The baseline estimate relies on the full set of industries for its statistical significance; the estimate with

[13]To check whether the relative trend of the more exposed industries changed before the tariff war, I search for breaks in it over 1987–2017, following Bai and Perron (1998, 2003). The least-squares date of a single break falls after 2005. With the trend of each industry fitted over 2006–17, TFP is about 1.6 percent lower in 2019 at the interquartile difference in exposure, as in the baseline. A test that looks only at the trend of the protection measure places a break after 2012. With the trend fitted from then on, the decline is about 2.5 percent, closer to the 2014–17 version. I report the tests in Section B.4 of the Appendix.

Figure 1: TFP Growth in the More Exposed Industries Slowed Down as Their Tariffs Rose



Notes: All series are relative to 2017. Coefficients for each year on the protection measure, scaled by its interquartile range, 1.9 percentage points. Panel A: the protection measure by year, with each 2018 action counted from the day it took effect; from 2020 on, it equals the protection measure. Panel B: log BLS TFP net of the least-squares trend of each industry over 1987–2017. Panel C: the same with the trend fitted over 2014–17. Bands are 90 percent confidence intervals from standard errors clustered by three-digit sector. Sample: 86 industries, 2013–2022.

the trend fitted over 2014–17 does not.[14]

With either trend, the decline in TFP does not reflect a simple reversion of growth rates to their mean. The more protected of the industries whose TFP rose fastest over 2012–17 were still below their long-run trend in 2017. By 2019, instead of catching up to their long-run trend, they had fallen further below it.

[14]I report the estimates with one industry left out at a time in Section B.5 of the Appendix.

C. Sensitivity of the Estimate

As shown in Panel A of Table 2, the size of the break is similar across measures of exposure to the tariffs. One alternative measure ignores the tariff rate and counts only the share of the home market that the tariffs covered. Another is the exact measure published by Flaaen and Pierce (2026), which serves as a check on my reconstruction. A further alternative is the average tariff increase on the imports of an industry. Finally, I consider the change from 2017 to 2019 in the statutory output tariff, a simple average of the tariff schedule across the products of an industry. Because it does not weight products by imports, the estimate with this measure does not depend on the import weights from which the other measures are built.[15] With every measure, the difference in TFP between industries at the 75th and 25th percentiles is statistically significant at the 5 percent level. It ranges from about 1.3 to 2 percent.

With the statutory tariff, the effect per point is smaller than with the protection measure, but the statutory tariff differs more across industries. Industries at the 75th and 25th percentiles of the change in the statutory tariff are about 7.5 percentage points apart, against about 2 percentage points of protection. Between those two industries, the difference in TFP is a little under 2 percent, similar to the difference with the protection measure.

Moving to Panel B of Table 2, I find that the break is also robust to the weighting of industries, the set of controls, and the treatment of extreme values. I change one choice at a time. I weight industries equally in place of value added. I keep only the two trade-share controls. I cap the trade shares at their 95th percentiles. The difference in TFP remains statistically significant, at the 10 percent level with equal weights and at the 5 percent level with the other two choices. With equal weights it is smaller, about 1 percent, and with the other two choices it lies between 1.6 and 2.1 percent.

I find no sign of a fall in capacity utilization along the one margin that I can measure, hours per worker. BLS computes TFP as output over measured inputs, with capital entering as a stock, so an industry that runs its plants below capacity records lower TFP with no change in its technology (Basu et al., 2006). Following Basu et al. (2006), I use hours per worker as a proxy for utilization, because firms adjust hours before they adjust headcount. Between industries at the 75th and 25th percentiles of protection, hours per worker were about 0.8 percent higher in 2019, relative to their long-run trends, a difference that is not statistically significant. Utilization can also vary through the workweek of capital and the effort of workers, which hours per worker capture only if firms move them together with hours. Accordingly, I cannot rule out a fall in utilization along those margins.[16]

[15] I document the construction of the statutory output tariff in Section A.5 of the Appendix and put its estimate on the scale of the protection measure in Section B.6.

[16] I report the estimates for hours per worker in Section B.7 of the Appendix.

Table 2: The Relative Decline in TFP by 2019 under Alternative Measures of Exposure and Designs

	Percent difference in TFP, 75th against 25th percentile	Coefficient
Panel A. Measure of exposure		
Protection measure (baseline)	−1.64	−0.87
		(0.33)
Share of the home market covered	−1.26	−0.17
		(0.06)
Measure published by Flaaen and Pierce	−1.82	−1.08
		(0.35)
Import-weighted tariff change	−2.01	−0.34
		(0.16)
Statutory output tariff	−1.88	−0.25
		(0.10)
Panel B. Baseline measure, one design choice changed		
Industries weighted equally	−0.93	−0.49
		(0.24)
Trade shares as the only controls	−2.10	−1.11
		(0.46)
Trade shares capped at the 95th percentile	−1.61	−0.85
		(0.31)

Notes: Each row reports the 2019 coefficient for one measure of exposure or one variant of the design. The first column scales it by the difference in the measure between the industries at its 75th and 25th percentiles. For the measure published by Flaaen and Pierce, each industry in one of their groups takes the value of its group. Standard errors of the coefficients, clustered by the 21 three-digit sectors, are in parentheses. Every regression includes the controls of equation (2) and weights industries by 2017 value added, except where Panel B says otherwise. Sample: 86 industries.

A control for the effects of the pandemic leaves the estimates for the years after 2019 nearly unchanged. In addition to the cyclical sensitivity of each industry, already in the specification, I add its reliance on semiconductors, because the pandemic disrupted the supply of semiconductors.[17] The estimates for those years remain too imprecise to show whether the decline lasts.

Output per hour, an alternative measure of productivity, shows the same break from its long-run trend. Between industries at the 75th and 25th percentiles of protection, output per hour is about 2.3 percent lower in 2019, relative to their long-run trends. The estimate is less precise than the one for TFP and is statistically significant only at the 10 percent level. Accordingly, I take output per hour as confirming the direction of the TFP result, and I do

[17] I report the estimates with this control in Section B.8 of the Appendix.

not use it as separate evidence on its size.

Breaks this large are uncommon in the earlier history of these industries. With the trend fitted over 2014–17, three of the 22 earlier two-year windows show a break at least as large. Two of them, over 2000–02 and 2001–03, coincide with the onset of the China shock, which hit the industries that imported most from China, the same industries that the tariffs of 2018 reached.[18]

D. Output Prices and Productivity

The estimated fall in the productivity of the more exposed industries depends on whether output is measured in revenues or in quantities. If the tariffs let the protected industries raise their prices, a measure built from revenues would mix a fall in quantities with a rise in prices and understate the decline in productivity. Accordingly, I estimate the response of the output price directly. In Table 3, I report the 2019 coefficient for three outcome measures: the output price, real output per hour, and TFP. Between industries at the 75th and 25th percentiles of protection, the output price is about 1.3 percent higher in 2019, relative to its long-run trend, a difference that is statistically significant at the 10 percent level. Real output per hour is about 2.3 percent lower, so output per hour measured in revenues would be only about 1 percent lower. Adão et al. (2026) test a general-equilibrium model in which technology is fixed against the 2017–19 changes in value added per worker, a revenue measure. A model with fixed technology can match an earnings measure that prices move, but the decline that I estimate appears in real output per hour and in TFP, from which prices are divided out. Panel B of the table reports the changes from 2017 to 2019 with no adjustment for the trend. That comparison would be valid only if the more and less exposed industries had otherwise grown at the same rate, and before the tariff war the more exposed industries were growing faster.

If anything, my estimate of the fall in the measured TFP of the more exposed industries understates the decline in their physical productivity. The output prices of the protected industries rose, as they would if protection relaxed competition and producers raised their markups. BLS deflates output product by product, which divides out the price of each product, but no deflator captures every price movement within a product category. Any price increase that remains in deflated output raises measured TFP in the protected industries. The decline in their physical productivity would then be larger than the decline in measured TFP that I estimate.

[18] I can make this comparison only with the trend fitted over 2014–17, because the trend fitted over every year before the tariff war includes the earlier windows. I report further comparisons with random assignments of exposure in Section B.7 of the Appendix.

Table 3: By 2019, Output Prices Rose and Productivity Fell in the More Exposed Industries

	Output price	Real output per hour	TFP
Panel A. The 2019 change net of the 1987–2017 trend of each industry			
Protection measure	0.70	−1.20	−0.87
	(0.36)	(0.64)	(0.33)
Panel B. The change from 2017 to 2019, with no adjustment for the trend			
Protection measure	0.46	−0.75	−0.42
	(0.30)	(0.54)	(0.32)
Industries	86	86	86

Notes: Regressions across industries of the indicated change in the log outcome measure on the protection measure, InputCost, Retaliation, and the five controls of equation (2), with industries weighted by 2017 value added. Standard errors, clustered by the 21 three-digit sectors, are in parentheses. The output price is the implicit deflator of BLS sectoral output, current-dollar output divided by real output. Real output per hour is the BLS labor-productivity index. TFP is the BLS index.

III. Discussion

The TFP of the more exposed industries broke from its relative trend in 2019, but I cannot identify the cause of the break with a comparison across industries. A tariff that dulls the competition from foreign rivals could slow productivity in the industries it shields. The break is no sharper, however, in the industries where import competition mattered more before the tariff war, so the evidence does not single out that channel.[19]

Persistence can be expected to depend on the source of the decline. If the tariffs lowered the physical technology of the protected industries, the decline could be long lasting. In the models of medium-term fluctuations of Comin and Gertler (2006), research and development and the adoption of new technologies respond to economic conditions. A shock that depresses activity, even one that is not technological, can leave productivity below its previous path for years. By contrast, if the decline reflected a cost of adjusting to the tariffs, it would be more likely to fade quickly. Suppose that each firm pays a fixed overhead cost to operate, as in Melitz (2003). Newly imposed tariffs can attract entrants into the protected sector. Each entrant pays the overhead, so the sector uses more inputs for the same output, and measured TFP falls. The decline ends once the number of firms stops increasing. I cannot exclude that the estimated decline reflects both sources, and the data cannot yet tell them apart.

A decline of this size bears on the welfare effects of the tariffs. The case for a unilateral tariff rests on an improvement in the terms of trade. The studies of the 2018–19 tariffs find

[19]I report the break by industry characteristics measured before the tariff war in Section B.9 of the Appendix.

that the improvement was modest and that foreign exporters did not lower their prices by much. Because assessments of this kind hold technology fixed, they leave out a decline in productivity, however long it lasts. Two quantities that my design does not identify govern how far it weighs: the level of the decline in manufacturing as a whole, as opposed to the gap between industries, and its persistence.

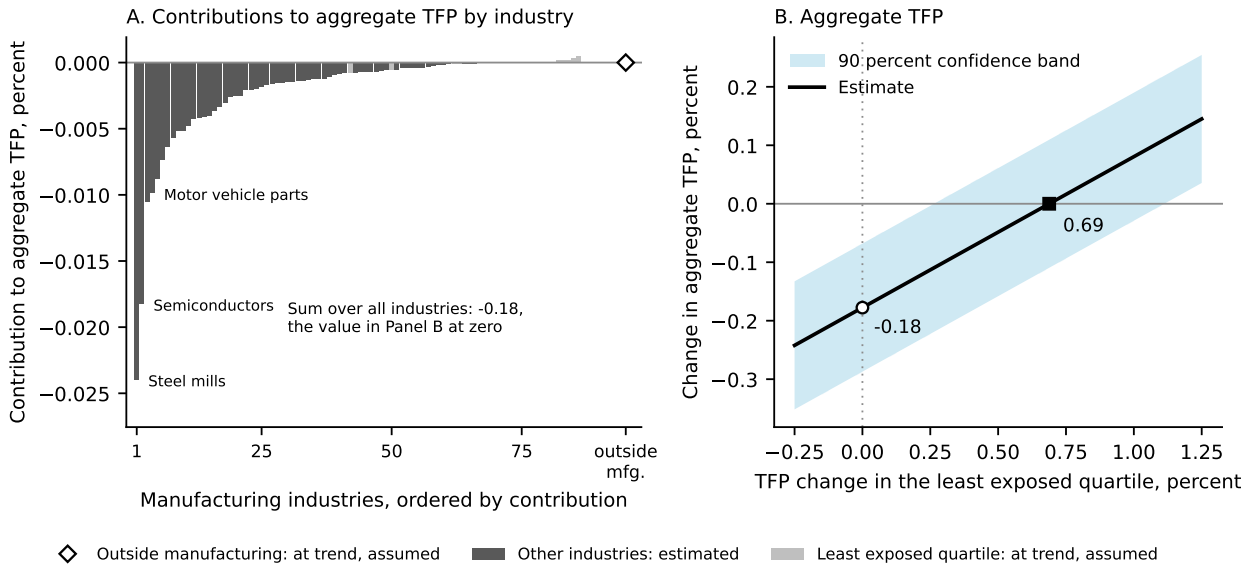
As shown in Figure 2, under two assumptions the estimated TFP gap across industries can also be read as a drop in aggregate TFP for the U.S. economy. I compare industries with one another, so a change that affected every industry alike would leave my estimate unchanged. To pin down the level, I assume that the least exposed quartile of the 86 manufacturing industries, where the added duty averaged 0.05 percent of the home market, kept its trend, and that the industries outside manufacturing kept theirs. I add up the changes in industry TFP, weighting each industry by its gross output relative to GDP, because BLS measures the TFP of each industry against its gross output. Under these two assumptions, the aggregate TFP drop in 2019 is about 0.2 percent. Panel A of the figure shows the TFP change that the assumptions assign to each industry, and Panel B the drop for alternative TFP changes in the least exposed quartile. Had the TFP of that quartile instead risen by about 0.7 percent, with the other industries keeping their estimated gaps to it, aggregate TFP would have been unchanged.

IV. Conclusion

After the U.S. tariff surge of 2018–19, the TFP of the industries that the tariffs shielded fell relative to that of the less exposed industries. Measured against long-run trends, TFP was about 1.6 percent lower by 2019 for the interquartile difference in exposure, and about 3 percent lower had the catch-up of the more exposed industries before the tariff war continued. The break appears with alternative measures of exposure and of productivity, breaks this large are uncommon in earlier years, and the estimates change little with controls for the business cycle and the pandemic.

A tariff increase is especially well suited to the study of how productivity responds to a change in policy. Measures of TFP can commingle changes in markups with changes in physical productivity, so a measured response to policy is often open to two readings. With a tariff increase, the direction of the change in markups is known. Protection lets the shielded industries exploit their market power and raise their markups. Higher markups are not just a theoretical possibility. I find evidence that output prices went up disproportionately in the industries that were more exposed to the tariffs, even after controlling for the higher cost of their imported inputs. A typical concern is that the price deflators used to construct TFP may miss part of that increase. All else equal, such a miss pushes measured TFP up. The

Figure 2: The Aggregate TFP Drop under Alternative Assumptions for the Least Exposed Manufacturing Industries



Notes: Changes by 2019 against the long-run trend of each industry. Panel A: the contribution of each of the 86 manufacturing industries to the change in aggregate TFP, its change in TFP times its 2017 gross output over GDP, sorted by size. The least exposed quartile and the industries outside manufacturing keep their trend by assumption; every other industry falls by the estimated decline for its additional exposure. The contributions sum to the value in Panel B at zero. Panel B: the change in aggregate TFP when the least exposed quartile changes by the amount on the horizontal axis and every other industry keeps its gap to it; the band reflects the sampling variation of the coefficient on the protection measure in equation (2), at the 90 percent level. Weights: 2017 sectoral output over GDP, BLS and BEA.

decline that I estimate in the TFP of the more exposed industries appears despite that push, which makes it all the more notable.

The decline bears on the welfare effects of tariffs. Assessments of the 2018–19 tariffs weigh the terms-of-trade gain against the costs to buyers while holding technology fixed, so they leave out the decline in TFP that I estimate. The same limitation applies beyond tariffs, to any assessment of a policy change in which productivity is taken as given. Within models in which productivity reacts to policy, the estimates can serve as a target for studying the fuller range of the effects of policy changes on welfare.

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Appendix

Appendix A documents the data:

A.1 an overview of the panel and the sources of every series;

A.2 the industry classification and its harmonization over time;

A.3 the protection measure and the two other channels, input costs and retaliation;

A.4 the productivity measures;

A.5 the statutory output tariff;

A.6 the regression weights and the cyclical control.

Appendix B reports additional empirical results:

B.1 the estimates without removing the trend fitted before the tariff war;

B.2 all the coefficients of the baseline regression for 2018 and 2019;

B.3 a comparison of the estimate with other evidence on tariffs and productivity;

B.4 tests for breaks in the trend before the tariff war;

B.5 the estimate with one industry left out at a time;

B.6 the statutory tariff as the measure of exposure;

B.7 comparisons of the 2019 break with random assignments of exposure and with earlier years, and checks on the business cycle and on utilization;

B.8 controls for the pandemic years;

B.9 the break by industry characteristics before the tariff war.

A Data and Measurement

My estimates rest on a panel of manufacturing industries that combines three kinds of data: the tariffs that the United States raised in 2018, the trade of each industry, and its productivity. The industries are those of the North American Industry Classification System (NAICS), which is revised every five years, so I place every series on its 2012 version to make the data comparable over time and across sources. In this appendix I describe how I build that panel from public sources and how I check it against independent sources.

A.1 Overview

The panel is indexed by four-digit NAICS manufacturing industry j and year t and covers the 86 NAICS manufacturing industries of the BLS detailed-industry productivity accounts. For each industry I observe TFP and output per hour from BLS; the protection measure of equation (1) of the main text, the added duty of the 2018 actions on the 2017 imports of the industry as a share of the value of its home market; the input-cost and retaliation

measures; and the statutory output tariff, which I use as an alternative measure of exposure (Sections A.3 and A.5). I also use the value added of each industry in 2017 as its regression weight and a measure of its cyclical sensitivity as a control (Section A.6).

Table A1 lists the sources and coverage of every series.

A.2 Industry classification and harmonization

BLS publishes the productivity accounts on the 2012 NAICS basis for the whole period. The trade and tariff data carry the NAICS vintage of each year, and I convert them to the 2012 basis with the time-consistent concordance of Eckert et al. (2020), which assigns each six-digit code of an earlier vintage to codes of the 2012 vintage with weights that sum to one. I then sum the six-digit industries to the 86 four-digit industries of the panel. At the four-digit level of manufacturing, the 2012 and 2017 vintages coincide.

Table A1: Data sources and coverage

Series	Concept	Source	Coverage
Productivity			
Total factor productivity	Detailed-industry TFP index	BLS (U.S. Bureau of Labor Statistics, 2026)	1987–2023
Labor productivity, hours, employment and nominal output	Real sectoral output per hour; hours worked; employment; real and current-dollar sectoral output (also for the cyclical control)	BLS (U.S. Bureau of Labor Statistics, 2026)	1987–2025
Total factor productivity (cross-check)	Five-factor TFP index	NBER–CES (Becker et al., 2021)	1958–2016
Exposure to the tariffs			
Imports by product and origin	HS10 import values by country, for Protection and the import share	Schott (2025)	2016–2017
Exports by product	HS10 export values, for Protection and the export share	Schott (2018)	2016–2017
Shipments and value added	Value of shipments, for Protection and the import and export shares; value added, for the regression weights	NBER–CES (Becker et al., 2021)	2016–2017
Output tariff, statutory	Schedule rate (MFN + Sec. 232/301)	USITC DataWeb (U.S. International Trade Commission, 2025); Office of the United States Trade Representative (2018a,b,c, 2019); The White House (2018b)	2002–2023
Other channels and controls			
Retaliation, InputCost, imported share of input costs, capital per worker	Flaaen and Pierce's measures, rebuilt at four digits	Flaaen and Pierce (2024); BEA (U.S. Bureau of Economic Analysis, n.d.); NBER–CES (Becker et al., 2021)	2012, 2016–2017
Input–output weights	2012 benchmark detail use table	BEA (U.S. Bureau of Economic Analysis, n.d.)	2012 (fixed)

Notes: All series are at the four-digit NAICS level for the 86 manufacturing industries (NAICS 31–33) and are placed on a longitudinally consistent 2012 NAICS basis. The statutory rate is the most-favored-nation rate plus the Section 232 and 301 add-ons. The fixed BEA input–output weights enter the semiconductor-share control of Section B.8. I describe the construction in Sections A.3 to A.5.

A.3 The protection measure, input costs, and retaliation

I build the protection measure of equation (1) of the main text from public sources and turn to the replication package of Flaaen and Pierce (2024) only afterwards, to check the result; I compute retaliation and input costs by running the code of Flaaen and Pierce (2024), as I describe at the end of this section. The protection measure rests on the Census import and export records distributed by Schott (2025) and Schott (2018), on NBER–CES shipments (Becker et al., 2021), and on the Federal Register texts that define each 2018 action: the three Section 301 notices (Office of the United States Trade Representative, 2018a,b,c), the Section 232 proclamations (The White House, 2018b) and the Section 201 safeguards (The White House, 2018a). Where the sources leave a construction choice open and Flaaen and Pierce's choice is reasonable, I follow it, so that the comparison isolates the differences on which the legal texts settle the choice.

I take the products of the three Section 301 lists from the annexes of the Federal Register notices that set them (Office of the United States Trade Representative, 2018a,b,c). Reading those annexes yields 818, 279, and 5,745 eight-digit lines for Lists 1, 2, and 3, the counts that the notices themselves state. Section 301 applies to imports from China alone, whereas Sections 232 and 201 apply to all origins; like the code of Flaaen and Pierce (2024), I do not model the country exemptions, quotas, and product exclusions granted after the proclamations, so the protection measure is mildly overstated for the steel- and aluminum-producing industries. Two cases need a decision. For one of the eleven List 3 lines that the notice covers only in part, a line that the 2018 schedule split in two, I count as covered the share of its imports from China that went to its covered successor line. For the solar safeguard, I count the cells and modules, which have statistical lines of their own, and not the cells sold attached to generators and batteries, which the trade data do not separate from ordinary generators and batteries.

The protection measure is the product of two shares: the added duty on the imports of an industry as a share of those imports, and the import share of its home market. I measure both shares on 2017 data. For the first I use general imports at customs value, and for the import share, general imports, domestic exports, and shipments. The code of Flaaen and Pierce (2024) takes the import share from 2016 data instead. I keep 2016 for the import-share and export-share controls of equation (2) of the main text, as Flaaen and Pierce do. A dollar of imports covered by two actions counts once. One industry, audio and video equipment (NAICS 3343), reports domestic exports above its 2016 shipments, so its export share exceeds one; absorption is positive for every industry in both 2016 and 2017, so the protection measure is defined throughout. NAICS codes come from the Census records, and coating, engraving, and heat treating (NAICS 3328), which records no imports and has

no tariff lines, enters with a zero protection measure and a zero value of Retaliation_j, as in the data of Flaaen and Pierce (2024); I set its 2017–19 change in the statutory tariff to zero, which matches their rate-weighted protection measure of zero for it.

My protection measure is close to the one of Flaaen and Pierce, which I compute by running their code up to the step that builds the exposure measures. For this comparison alone I rebuild the measure with the import share of 2016, as in their code, and pool the three leather industries, as their code does at that step. On the 83 industries that the two constructions then share, with NAICS 3328, which imports nothing, left out, the import share of absorption agrees in every industry, and the protection measure correlates at 0.997. The rebuild assigns \$268.5 billion of the \$2,022 billion of 2017 manufacturing imports to the 2018 actions, against \$262.5 billion in theirs. Each difference in covered imports is justified by the Federal Register text that defines the action involved. The differences concern a partly covered List 3 line, List 3 and steel lines missing from their list files, solar-safeguard lines matched in full, and imports under two actions counted twice. Together these differences account for the whole gap in covered imports, with nothing left unexplained.

Let Ω^* and a^*_{pc} denote the pairs hit by foreign retaliation and the rates it added, s_{cj} the share of commodity c in the costs of industry j (intermediate inputs and labor compensation) in the BEA 2012 detail Use table (U.S. Bureau of Economic Analysis, n.d.), and m_c the share of imports in the domestic absorption of commodity c in 2016. Then

$$\text{(A1)} \qquad \text{Retaliation}_j = \sum_{pc\in\Omega^*} a^*_{pc}\frac{X_{j,pc}}{X_j}\cdot\frac{X_j}{Q_j}, \qquad \text{InputCost}_j = \sum_c s_{cj}\, m_c \sum_{pc\in\Omega} a_{pc}\frac{M_{c,pc}}{M_c}.$$

I rebuild every measure of Flaaen and Pierce (2026) at the four-digit level by running the steps of their code without the step that combines industries into groups. The measures are their retaliation and input-cost channels, the share of input costs coming from imported goods, $\sum_c s_{cj}\, m_c$, and capital per worker. Capital per worker is measured in 2016, the last year for which the NBER–CES database reports the capital stock. Run with their groups, my code reproduces the values their code saves, with a largest difference of 5×10^{-7}. Two limitations remain, both in the source data. The detailed input-output table records apparel (NAICS 315) and leather (NAICS 316) only at three digits, so their four-digit industries share one input-cost share. The export file of Flaaen and Pierce (2024) records the three leather industries together, so they share one measure of retaliation. The leather industries are separate in the import data of Schott (2025), where the protection measure differs sharply among them. Other leather goods (NAICS 3169) had 49 percent of their home market newly covered in 2018, and footwear (NAICS 3162) none.

I depart from their code in three respects. For InputCost_j, I take the products covered

by each action from the Federal Register lists, as for the protection measure. I count the Section 201 safeguards on solar cells and washers among the duties on input commodities, as their protection measure does, although their code leaves them out of the input side. I keep the import share of absorption of each input commodity between zero and one; in their data it falls outside that range for several commodities, chief among them scrap, which makes the imported share of input costs negative for the primary-metal industries. Apart from these departures, I keep their lists of the products that other countries targeted, which enter Retaliation_j in equation (A1).

A.4 Productivity measures

I use two independently constructed panels of TFP at the four-digit NAICS level.

The primary measure is the BLS detailed-industry TFP. The Bureau of Labor Statistics publishes TFP indexes (sectoral output over a Törnqvist index of combined capital, labor, energy, and intermediate inputs) for detailed manufacturing industries (U.S. Bureau of Labor Statistics, 2026). These industries define the cross-section of the panel. Coverage is 1987–2023. I end the estimates in 2022, because the estimates for the years after 2019 are already too imprecise to show whether the decline lasts.

As a cross-check, I use the NBER–CES Manufacturing Industry Database (Becker et al., 2021) on the 2012 NAICS basis. It covers 364 six-digit industries, with dollar magnitudes for 1958–2018 and an independent five-factor TFP index through 2016. I sum the dollar magnitudes to four digits and take the shipments-weighted mean of the six-digit TFP index as the four-digit one. Because both TFP series are within-industry indexes with different base years, I compare them on the within-industry variation, removing the mean of each industry. The BLS and NBER–CES log-TFP series correlate at 0.77 over the 2,580 overlapping industry-years. This correlation supports the BLS series as the primary measure.

A.5 The statutory output tariff

The statutory rate is the legal schedule rate, set line by line, so it must be averaged across the tariff lines of each industry.

The statutory output tariff is the Column 1 (NTR, most-favored-nation) rate of the Harmonized Tariff Schedule plus the 2018–19 Section 232 and Section 301 additional duties. The Column 1 rate is ad valorem or, for a specific, compound, or formula duty, its ad valorem equivalent. China has paid Column 1 rates since 1980, and the Section 301 add-ons apply to Chinese goods alone, so from 2018 the statutory rate is the schedule rate facing Chinese-origin goods.

For industry j in year t,

$$\tau^{O}_{jt} \;=\; \frac{\sum_{\ell \in L_{jt}} \kappa_{\ell j} \left(m_{\ell t} + a^{232}_{\ell t} + a^{301}_{\ell t} \right)}{\sum_{\ell \in L_{jt}} \kappa_{\ell j}}, \tag{A2}$$

where τ^{O}_{jt} is the statutory output tariff of industry j in year t, in percent; ℓ indexes tariff lines and L_{jt} is the set of eight-digit lines of the schedule of year t that map to industry j and carry a Column 1 rate that year, one set for all three components; $m_{\ell t}$ is the Column 1 rate of line ℓ in year t, in ad valorem terms; $a^{232}_{\ell t}$ and $a^{301}_{\ell t}$ are the Section 232 and Section 301 add-ons on that line in force that year, zero before 2018 and weighted within the year an action takes effect by the days it applies; and $\kappa_{\ell j}$ is the share of line ℓ assigned to industry j, which equals one when the line maps to a single industry.

Defining the rate as the Column 1 rate plus the two add-ons leaves every other trade barrier outside it. The measure omits the 2002 and 2018 Section 201 safeguards, the derivative steel and aluminum products added to the Section 232 action in February 2020, and antidumping and countervailing duties, and it does not net out exclusions granted to individual importers. The two measures of exposure differ in the actions that they cover. The protection measure includes the 2018 safeguards and leaves out List 4A of the Section 301 tariffs, which took effect in September 2019. The statutory output tariff does the reverse. The derivative products arrive after the 2017–19 changes that I use, so they move only the level of the series; exclusions are granted to individual importers, whereas τ^{O} is the rate a covered line carries. The Column 2 rate is no part of τ^{O}. An origin-weighted alternative exists in the coverage shares of Flaaen and Pierce (2026), which I use as a measure of exposure in Section II.C of the main text.

I average the line rates within an industry with the simple mean, the construction of Pierce and Schott (2016, page 1638), so that a line gets no less weight because its tariff discourages imports of it. The schedule rates come from the annual tariff files of the USITC DataWeb (U.S. International Trade Commission, 2025) for 2002–2023. A specific, compound, or formula duty enters at its ad valorem equivalent, computed from unit import values as in Feenstra et al. (2002), with the unit values held at 2017 so that a change in τ^{O} reflects a change in the schedule. The Section 232 add-on follows the product ranges of The White House (2018b), and the Section 301 add-ons follow the lists of the Federal Register notices, the same source as the protection measure, with List 4A from the notice of 2019 (Office of the United States Trade Representative, 2019). With the unit values of each year, my method reproduces the equivalents that DataWeb publishes for 2002 to a median difference of 0.05 percentage points.

A.6 Weights and the cyclical control

I weight industries by their value added in 2017 and control for the sensitivity of their TFP to the business cycle, both built from data outside the trade records. The weight of each industry is its value added in 2017, the last year before the tariffs, from the NBER–CES database (Becker et al., 2021) on the 2012 NAICS basis, with the value added of six-digit industries summed to four digits.

The cyclical sensitivity of an industry is the slope of a regression of its annual TFP growth on the growth of real sectoral output in all other manufacturing industries, over the annual changes from 1988 to 2017, the years over which the baseline trend is fitted. The growth of output outside the industry averages the growth rates of the other industries, each weighted by its nominal sectoral output in the previous year, from BLS. Leaving the industry out keeps its own output from entering the right side of the regression. In the earlier windows of Section B.7, I estimate the slope only on the annual changes up to the base year of each window, so that no year of the window enters it.

B Additional Empirical Results

This appendix collects results that support the main text, in the order in which the paper draws on them.

B.1 The estimates without detrending (Section I.C)

In this section I estimate equation (2) of the main text, the relation between TFP and the protection measure year by year, without removing the trend that each industry followed before the tariff war. Comparing raw changes across industries is valid only if the more and less protected industries would otherwise have grown at the same rate. The estimates for the years before the tariffs test that premise directly, and it fails. I report the coefficients in Table B1. Flaaen and Pierce (2026) show the corresponding estimates for their outcome measures in their Figure 3. Each coefficient for a year before 2017 is the difference across industries in TFP growth from that year to 2017, with the sign reversed. The coefficients for 2013, 2014, and 2015 are negative and statistically significant, so over those years the TFP of the more exposed industries grew faster than that of the other industries. After 2017, no coefficient on the protection measure is statistically distinguishable from zero. In 2019 the coefficient is -0.42, with a standard error of 0.32. Measured against the long-run trend of each industry, as in Table 1 of the main text, the same history shows a decline, because the trend of the more exposed industries kept rising while their TFP flattened. Accordingly, the

estimate in the main text measures the growth that the more exposed industries lost relative to their own trend. Without detrending, one would miss that loss and take the end of their catch-up for no change at all.

Table B1: Protection and TFP by year without removing the trend before the tariff war

	Log TFP, not detrended		
	Protection measure	InputCost	Retaliation
2013	-1.46	1.62	0.52
	(0.42)	(2.38)	(2.62)
2014	-1.83	2.86	0.74
	(0.37)	(2.80)	(1.40)
2015	-1.04	-1.23	-0.36
	(0.39)	(1.77)	(1.29)
2016	-0.16	-2.96	1.33
	(0.37)	(1.53)	(1.00)
2017		0 (base year)	
2018	-0.14	-0.47	-1.07
	(0.19)	(0.41)	(0.77)
2019	-0.42	-1.08	-2.18
	(0.32)	(0.93)	(1.58)
2020	0.59	-2.83	0.80
	(0.61)	(1.35)	(2.00)
2021	-0.42	-3.19	-6.42
	(0.82)	(1.79)	(2.34)
2022	-0.95	-4.05	-2.63
	(1.19)	(3.91)	(3.79)
Observations		860	

Notes: Coefficients for each year from equation (2) of the main text, estimated on log BLS TFP with no trend removed, relative to 2017. The regression includes InputCost, Retaliation, and the five controls, each interacted with year dummies, and industry and year fixed effects, with industries weighted by 2017 value added. Standard errors, clustered by the 21 three-digit sectors, are in parentheses. Sample: 86 industries, 2013–2022.

B.2 All the coefficients of the baseline regression (Section II)

Among the three measures of exposure to the tariffs, only the protection measure shows a clear relation with TFP. In Table B2, I report every coefficient of the baseline regression for 2018 and 2019. Because the regressors are on different scales, I also report the difference in TFP that each coefficient implies between industries at the 75th and 25th percentiles of the regressor, with the other regressors held fixed. The coefficients on InputCost and Retaliation are negative in both years and not statistically significant. In 2019, the industries more exposed to retaliation had lower TFP, the direction that Flaaen and Pierce (2026) find for employment and output, but I cannot distinguish that difference from zero.

Among the controls, the two trade shares account for the largest differences in 2019, and

I read them together. Industries that import much also export much, so for an industry with high shares of both, the two differences largely cancel. Together the two coefficients pick out the contrast between the industries that compete with imports at home and the industries that sell abroad. In 2019, TFP was lower against trend where the export share was higher and higher where the import share was higher. A strong dollar or weak foreign demand would produce such a pattern, and shocks of that kind are the reason for including the two shares. In 2018, neither is statistically significant. The other three controls, the share of imported inputs in costs, capital per worker, and the cyclical sensitivity, imply smaller differences that are not statistically significant at the 5 percent level in either year.

For convenience, I repeat equation (2) of the main text:

$$\begin{aligned}\tilde{y}_{jt} \;&= b_t^P \,\text{Protection}_j \;+\; b_t^I \,\text{InputCost}_j \;+\; b_t^R \,\text{Retaliation}_j \\ &\quad +\; b_t^M \,\text{ImpShare}_j \;+\; b_t^X \,\text{ExpShare}_j \;+\; b_t^C \,\text{ICShare}_j \;+\; b_t^K \ln(K/L)_j \\ &\quad +\; b_t^B \,\text{Cycle}_j \;+\; c_j \;+\; d_t \;+\; e_{jt}.\end{aligned} \tag{2}$$

Table B2: All the coefficients of the baseline regression, 2018 and 2019

	2018			2019		
	Coefficient	s.e.	Percent difference in TFP, 75th against 25th percentile	Coefficient	s.e.	Percent difference in TFP, 75th against 25th percentile
Protection measure	-0.36	0.20	-0.68	-0.87	0.33	-1.64
InputCost	-0.14	0.60	-0.09	-0.43	1.77	-0.28
Retaliation	-1.30	1.03	-0.40	-2.64	2.21	-0.81
ImpShare	0.00	0.03	0.14	0.12	0.06	4.58
ExpShare	0.02	0.03	0.31	-0.18	0.08	-3.72
ICShare	0.02	0.04	0.14	0.05	0.09	0.34
$\ln(K/L)$	-0.01	0.00	-0.72	0.00	0.01	0.15
Cycle	0.00	0.02	0.12	-0.02	0.03	-0.96

Notes: Coefficients for 2018 and 2019 from equation (2) of the main text, relative to 2017, with log BLS TFP net of the least-squares trend of each industry over 1987–2017 as the outcome. The first row repeats Table 1 of the main text. The third column for each year multiplies the coefficient by the difference in the regressor between the industries at its 75th and 25th percentiles. The regression includes industry and year fixed effects, with industries weighted by 2017 value added. Standard errors, clustered by the 21 three-digit sectors, are in the columns headed s.e. Sample: 86 industries, 2013–2022.

B.3 The estimate against other evidence on tariffs and productivity (Section II)

Per point of tariff, my estimate lies between the two earlier estimates with which I can compare it. In both studies, the authors measure the productivity effects of trade policy in

a form comparable with mine. The first is Pierce (2011), who sets U.S. plants in products granted antidumping duties against plants in products whose petitions failed, in the Census of Manufactures for 1987, 1992, and 1997. For the plants that report output in physical units, he measures physical TFP as in Foster et al. (2008). The coefficient on the interaction of the post-duty period with the effective antidumping duty implies a change in physical TFP of −3.12 percent per percentage point of duty (his Table 7, column 3). In the same plants, his revenue productivity, which he computes by deflating revenue with industry price indexes, barely moves, at −0.05 percent per point, and is not significant (his Table 6, column 7). His post-duty indicator equals one in every census year after the final determination of the investigation, and the determinations fall between 1988 and 1996, so his estimate averages over the first one to nine years after the duty. Pierce warns that "it would be inappropriate based on these results to claim that antidumping duties, in general, decrease plant-level physical productivity," because plants that report quantities may differ from those that do not (page 229).

The second study is Bernard et al. (2006), who regress the average annual growth of five-factor industry TFP from the NBER–CES database over the five years after a census year on the annualized change in trade costs, the ad valorem duty plus freight and insurance, over the five years before it, for U.S. manufacturing industries. Their coefficients are −0.152 without and −0.190 with two-digit industry fixed effects (their Table 2). They state both variables in percentage points per year: the change in trade costs as the change in the ad valorem rate over five years, divided by five (page 922), and TFP growth as an average annual percent change (page 924). Accordingly, a cut of one percentage point in trade costs spread over five years raises industry TFP by 0.152 to 0.190 percent over the following five years, a horizon of up to ten years from the start of the cut.

My estimate is −0.25 percent per point of the statutory output tariff, as reported in Table 2 of the main text. It is the change from 2017 to 2019 relative to the long-run trend of each industry, so it measures the gap within two years of the tariffs imposed in 2018. Per point, the physical TFP of the plants of Pierce (2011) falls by more, and the industry TFP of Bernard et al. (2006) rises by less after a cut in trade costs. The three estimates differ in horizon. Mine covers two years, and the horizon of Bernard et al. reaches ten. They also differ in what they measure. I measure exposure across whole industries and TFP from BLS deflators, as Bernard et al. do with the NBER–CES database, while Pierce measures plants in narrowly defined products. Accordingly, I conclude only that my estimate lies within the range of the earlier evidence.

B.4 Breaks in the trend before the tariff war (Section II.B)

Allowing for a break in the relative trend of the more exposed industries before the tariff war leaves the 2019 TFP gap unchanged or larger. I search for breaks in that trend over 1987–2017 on the panel of the 86 industries, following Bai and Perron (1998, 2003). Each segment between breaks has its own intercept and trend for the protection measure and for each control of equation (2) of the main text, with industry and year effects, industries weighted by 2017 value added, and segments at least five years long. In Table B3, I report the break dates that minimize the sum of squared residuals for one, two, and three breaks. By the Bayesian information criterion, the preferred number of breaks is one, after 2005, and the trend of the protection measure is flatter after it. That date is the one at which a break in the trends of all the regressors fits the data best. The date at which the change in the intercept and trend of the protection measure alone is most significant is later, after 2012.

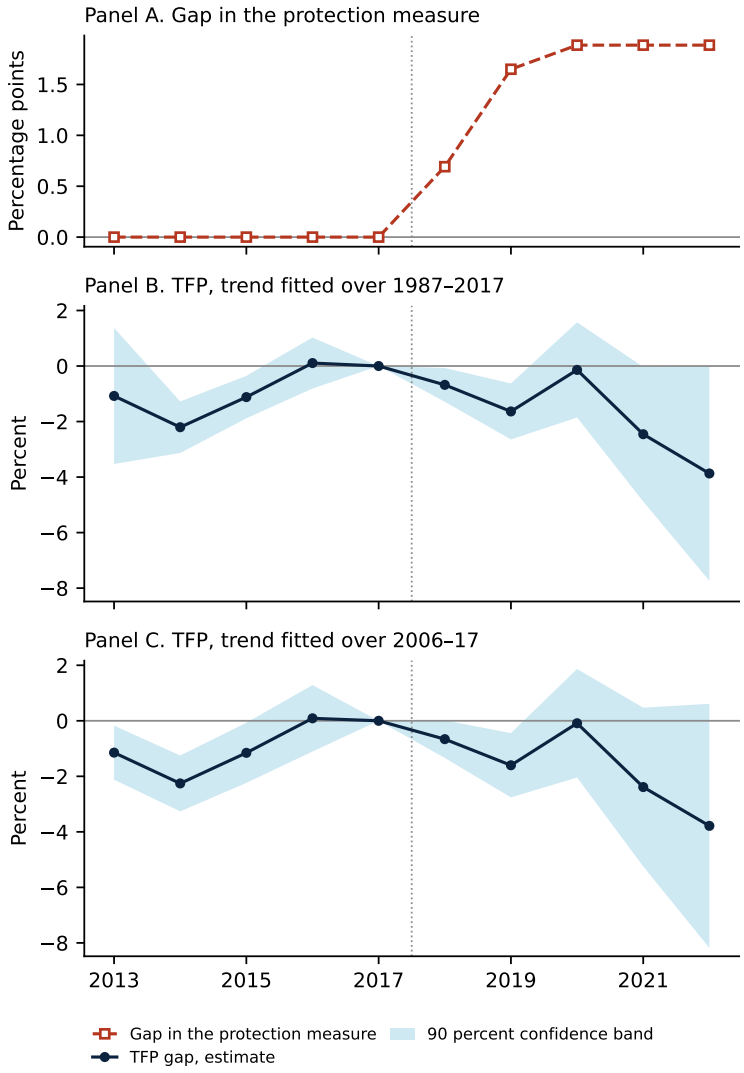
As shown in Figure B1, with the trend of each industry fitted over 2006–17, TFP is about 1.6 percent lower in 2019 at the interquartile difference in exposure, the same as in the baseline. With the trend fitted only on the years after 2012, the 2019 TFP gap is about 2.5 percent, closer to the version with the trend fitted over 2014–17. Accordingly, the baseline, which allows for no break in the trend, gives the more cautious of these estimates.

Table B3: Breaks in the trend of the protection measure before the tariff war, 1987–2017

Number of breaks	Breaks after	Trend of Protection by segment	BIC
0		0.42	-11010
1	2005	0.84, 0.40	-11195
2	1994, 2005	0.79, 0.54, 0.40	-11102
3	1993, 2000, 2006	0.70, 1.18, -0.30, 0.47	-10999

Notes: Log BLS TFP of the 86 industries, 1987–2017, with industry and year effects; each segment between breaks has its own intercept and trend for the protection measure and for each control of equation (2) of the main text; industries weighted by 2017 value added; segments at least five years long. For each number of breaks: the break dates that minimize the sum of squared residuals, the trend of the protection measure in each segment, in percent a year at its interquartile range, and the Bayesian information criterion.

Figure B1: Tariffs and TFP by the protection measure, with the trend fitted after the earlier break



Notes: All series are relative to 2017. Coefficients for each year on the protection measure from equation (2) of the main text, scaled by its interquartile range, 1.9 percentage points. Panel A: the protection measure by year, with each 2018 action counted from the day it took effect; from 2020 on, it equals the protection measure. Panel B: log BLS TFP net of the least-squares trend of each industry over 1987–2017. Panel C: the same with the trend fitted over 2006–2017, after the earlier break. Bands are 90 percent confidence intervals from standard errors clustered by three-digit sector. The dotted line marks the first 2018 tariffs. Sample: 86 industries, 2013–2022.

B.5 The estimate with one industry left out at a time (Section II.B)

The baseline estimate relies on the full set of industries for its statistical significance, whereas the estimate with the trend fitted over 2014–17 does not. I re-estimate the 2019 coefficient leaving out one industry at a time. With the baseline trend, the coefficient stays negative in all 86 regressions and statistically significant at the 5 percent level in 83 of them. The three exceptions are: iron and steel mills, semiconductors, and motor vehicles. The exclusion of motor vehicles still leaves the coefficient significant at the 10 percent level. The others do not.

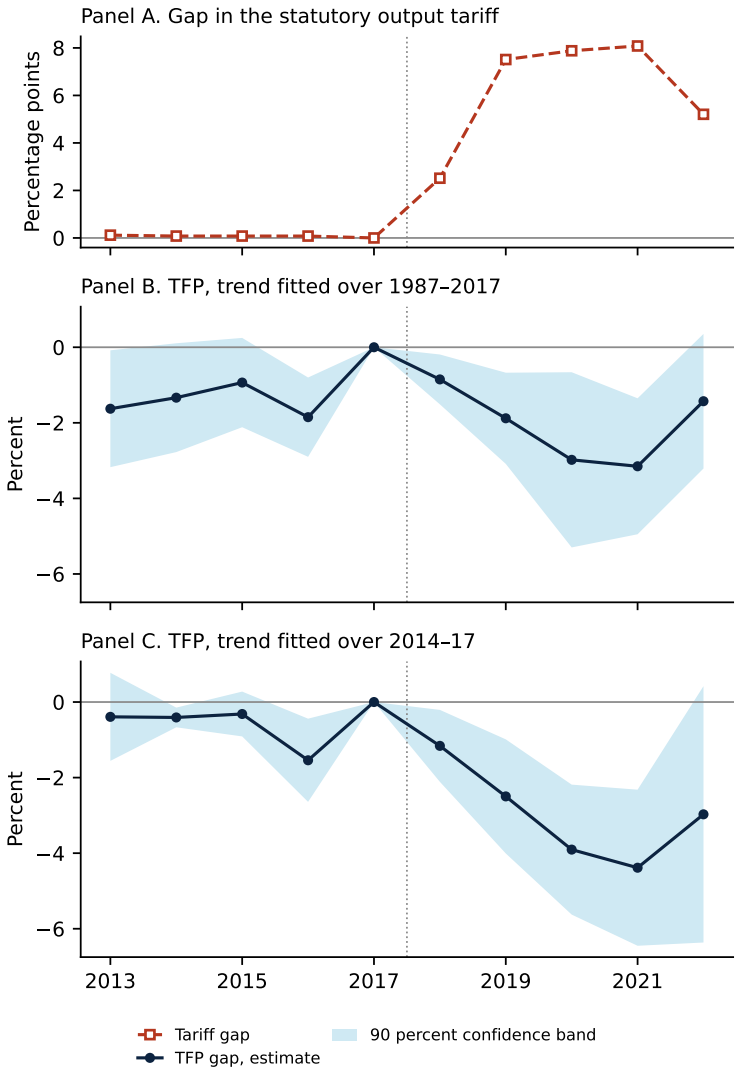
With the trend fitted over 2014–17, the coefficient is statistically significant in all 86 regressions.

B.6 The statutory rate as the measure of exposure, and the estimate in a common unit (Section II.C)

The statutory output tariff and the protection measure give 2019 TFP gaps of similar size. In this section I compare the two estimates. The two measures are in different units, so I compare industries at the 75th and 25th percentiles of each. The industry at the 25th percentile of the 2017–19 increase in the statutory tariff saw its tariff rise by 11.9 percentage points, and the industry at the 75th percentile by 19.4, a gap of 7.5 points. Between those two industries, TFP in 2019 is 1.9 percent lower at the 75th percentile than at the 25th, with a 90 percent confidence interval from 0.6 to 3.1 percent. With the protection measure, whose interquartile range is 1.9 percentage points of the home market, the gap is 1.6 percent, with a 90 percent confidence interval from 0.6 to 2.7 percent. In Figure B2, I plot the path for the statutory output tariff; the path for the protection measure is in Figure 1 of the main text.

Because the two measures single out different industries, their paths before the tariff war differ. The industries with the largest statutory increases are mostly in metals and heavy machinery, whose TFP fell in 2015–16, the years of the slump in commodity prices, and recovered in 2017. The coefficients on the statutory tariff for 2013–16 are all negative, and the one for 2016 is as large as the one for 2019 (Figure B2), so the estimate with the statutory measure depends on 2017 as the base year. Panel C of the figure fits the trend of each industry over 2014–17 instead. The coefficients for 2013–15 are then small, the dip in 2016 remains, and the gap in 2019 is larger than with the baseline trend. By contrast, the coefficient on the protection measure for 2016 is close to zero (Table 1 of the main text). Accordingly, I keep the protection measure as the baseline and use the statutory output tariff only as a check on the size of the estimate.

Figure B2: Tariffs and TFP by the change in the statutory output tariff, relative to 2017



Notes: All series are relative to 2017. Coefficients for each year on the change in the statutory output tariff over 2017–19 from equation (2) of the main text, scaled by its interquartile range, 7.5 percentage points, so the axes read as gaps between industries at its 75th and 25th percentiles. Panel A: the statutory output tariff, not detrended, as the outcome. Panel B: log BLS TFP net of the least-squares trend of each industry over 1987–2017. Panel C: the same with the trend fitted over 2014–17. Bands are 90 percent confidence intervals from standard errors clustered by three-digit sector. The dotted line marks the first 2018 tariffs. Sample: 86 industries, 2013–2022.

B.7 Chance, the business cycle, and utilization (Section II.C)

The 2019 break is rare across random assignments of exposure and uncommon in the earlier history of these industries. In this section I report those two comparisons, which I summarize in Section II.C of the main text, and a test of whether the business cycle accounts for the break. I collect the results in Table B4, whose first block uses the baseline trend and whose Panels A to D use the trend fitted over 2014–17. Both comparisons address the concern that the TFP of an industry fluctuates widely from year to year, so that a break of this size could be ordinary.

Table B4: The 2019 break against chance, the business cycle, and utilization

	Protection measure	s.e.
Baseline: trend fitted on 1987–2017, 2019		
Coefficient	-0.87	0.33
Random draws at least as large, per 1,000, across industries	16	
Random draws at least as large, per 1,000, within three-digit sectors	11	
Utilization: log hours per worker, coefficient	0.42	0.29
A. Trend fitted on 2014–17, 2019		
Coefficient	-1.70	0.38
B. Random assignments and earlier windows		
Random draws at least as large, per 1,000, across industries	1	
Random draws at least as large, per 1,000, within three-digit sectors	2	
Earlier windows with a break at least as large	3 of 22	
C. The role of cyclical sensitivity		
Without the cyclical sensitivity	-1.66	0.34
With the 2007–09 change in TFP	-1.66	0.37
D. Utilization: log hours per worker, trend fitted on 2014–17		
Coefficient	0.42	0.44
Interquartile effect, percent, by version of the protection measure:		
rebuilt, as above	0.80	0.84
Coverage share built from Flaaen and Pierce's data	0.20	0.80
Flaaen and Pierce's rate-weighted measure	0.16	0.89
rebuilt, the 69 industries that Flaaen and Pierce do not group	0.54	0.93
Industries / three-digit sectors	86 / 21	

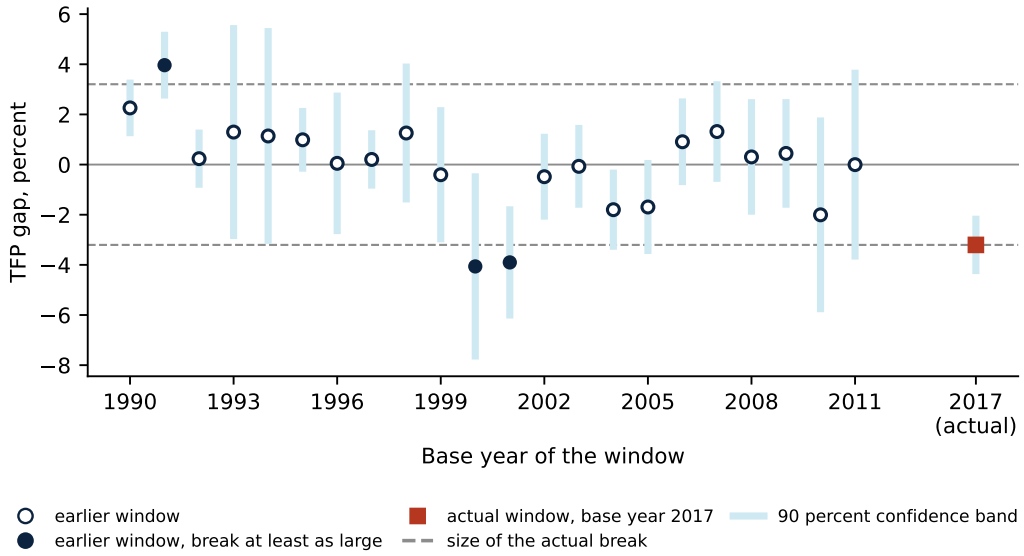
Notes: The 2019 coefficient on the protection measure, from the regression across industries of the change in log BLS TFP from 2017 to 2019, net of the least-squares trend of each industry, on the protection measure, InputCost, Retaliation, and the five controls, all measured before the tariff war, with industries weighted by 2017 value added. The trend is fitted over 1987–2017 in the baseline block and over 2014–17 in Panels A to D. Standard errors, clustered by the 21 three-digit sectors, are in the column headed s.e., which is blank for counts. Random draws re-assign the three exposure measures together, across industries or within three-digit sectors, 9,999 times; each row gives the draws per 1,000 with a coefficient at least as large in absolute value. The earlier windows use the same statistic around base years 1990–2011 on the 2017 exposures (Figure B3). Panel D and the utilization row: log hours per worker, BLS hours worked over employment, for the protection measure.

Random assignments of exposure rarely produce a break as large as the actual one. I re-assign the three exposure measures together across industries 9,999 times, keeping the

outcome, the controls, and the weight of each industry in place, and re-estimate the 2019 coefficient. As shown in the first block of Table B4, with the baseline trend a coefficient at least as large in absolute value appears in about 16 of every 1,000 draws. When I re-assign exposure only within three-digit sectors, which keeps the mix of exposures of each sector fixed, the count is about 11. In Panel B, with the trend fitted over 2014–17, the counts are lower, 1 and 2 in 1,000.

Breaks as large as the 2019 break are uncommon in earlier years. To check, I hold the 2017 exposure of each industry fixed and repeat the estimate around each earlier base year from 1990 to 2011, none of which involves a tariff war. I stop at base year 2011 because a later window would share years with the actual one, which uses 2014 through 2019. Because the baseline trend is fitted over those same years, I fit the trend in each window over its base year and the three years before it, as in the 2014–17 version. As shown in Figure B3, only three of the 22 earlier windows show a break as large as the one in 2019. One of them, in 1991, goes the other way. The other two, in 2000 and 2001, cover the onset of the China shock, which hit the same import-intensive industries that the tariffs of 2018 reached. Several earlier windows are also statistically significant, so I judge the 2019 break by its size relative to earlier years rather than by its significance alone.

Figure B3: The break around earlier base years



Notes: For base year b, the coefficient from the regression across the 86 industries of the change in log BLS TFP from b to $b+2$, net of the least-squares trend of each industry over $b-3$ to b, on the protection measure, InputCost, Retaliation, and the five controls, all measured before the tariff war, scaled by the interquartile range of the protection measure, 1.9 percentage points. Filled circles mark the earlier windows with a break at least as large in absolute value as the actual one; dashed lines mark the size of the actual break. Bands are 90 percent confidence intervals from standard errors clustered by three-digit sector. Every year used by an earlier window is before the 2018 tariffs.

The business cycle does not account for the break. Manufacturing output fell in 2019, so industries whose TFP moves strongly with the cycle could have fallen with it. The specification already controls for the cyclical sensitivity of each industry (Section I.C of the main text). In Panel C of Table B4, without that control, the 2019 coefficient with the 2014–17 trend is −1.66 against −1.70. With the change in TFP over 2007–09 as an added control, it is −1.66. Cyclical sensitivity is nearly unrelated to exposure across industries, correlating at 0.14 with the protection measure.

Hours per worker, the proxy for utilization of Basu et al. (2006), did not fall in the more exposed industries. As shown in the utilization row of the first block of Table B4, with the baseline trend the 2019 coefficient for log hours per worker is 0.42, with a standard error of 0.29. In Panel D, with the 2014–17 trend, it is 0.42, with a standard error of 0.44. The same panel reports the hours coefficient with each version of the protection measure, and it is positive with every one, including the two built from the replication data of Flaaen and Pierce (2024).

B.8 Controls for the pandemic years (Section II.C)

A control for the semiconductor shortage leaves the estimates for the years after 2019 nearly unchanged. In this section I check whether the pandemic distorts those estimates. The pandemic disrupted the supply of semiconductors in 2021–22, so industries that rely on chips could have lost ground for reasons unrelated to the tariffs. To account for this, I add to equation (2) of the main text the share of semiconductors and other electronic components (NAICS 3344) in the intermediate purchases of each industry in the 2012 input–output tables, interacted with every year dummy like the other controls. The share is fixed before the pandemic. It misses chips embedded in purchased parts. The cyclical sensitivity of each industry is already among the controls. As shown in Table B5, the semiconductor share leaves the path of the coefficients nearly unchanged. With it, the 2019 coefficient is −0.94, with a standard error of 0.36, against −0.87 without it, and the 2022 coefficient is −2.09, against −2.05. The coefficients before the tariff war move by less than one standard error. Accordingly, the decline after 2019 does not reflect the chip shortage, as far as this share measures it. Other features of the pandemic remain uncontrolled, which is why I measure the decline in relative TFP in 2019.

Table B5: Protection and TFP by year with controls for the pandemic

	Protection measure	
	(1) Baseline	(2) Semiconductor share
Before the tariffs		
2013	-0.57	-0.82
	(0.79)	(0.57)
2014	-1.17	-1.37
	(0.30)	(0.25)
2015	-0.59	-0.73
	(0.25)	(0.26)
2016	0.06	0.00
	(0.30)	(0.35)
After the tariffs		
2018	-0.36	-0.42
	(0.20)	(0.20)
2019	-0.87	-0.94
	(0.33)	(0.36)
2020	-0.07	-0.12
	(0.55)	(0.60)
2021	-1.30	-1.38
	(0.78)	(0.83)
2022	-2.05	-2.09
	(1.25)	(1.27)
Observations	860	860

Notes: Coefficients for each year on the protection measure from equation (2) of the main text, relative to 2017, as in Table 1 of the main text. Column 1 repeats that table. Column 2 adds the share of NAICS 3344 in the intermediate purchases of each industry (2012 input–output tables), interacted with every year dummy. Outcome, controls, weights, and fixed effects as in Table 1 of the main text. Standard errors, clustered by the 21 three-digit sectors, are in parentheses. Sample: 86 industries, 2013–2022.

B.9 The break by industry characteristics before the tariff war (Section III)

The break is no sharper where import competition mattered more before the tariff war. The exposure I measure is the coverage of the home market of an industry by the tariffs, so a competition channel would predict a sharper break in four kinds of industries: those whose imports came more from China, those where imports took a larger share of the home market, those where margins were thin, and those where Chinese competition had been rising. I test that prediction in the 2019 regression across industries of Table B4, with the baseline trend. I interact the protection measure with one characteristic at a time, each measured before the tariff war, either as an indicator for an above-median value or standardized. I also re-estimate the regression on each half of the sample. As reported in Table B6, I scale every estimate to the interquartile move in the protection measure.

Of the eight interactions with these four characteristics, two are statistically significant at the 10 percent level and none at the 5 percent level. The three measures of import competition carry the sign opposite to the one a competition channel predicts, so the break is, if anything, weaker where imports, and Chinese imports in particular, mattered more. The price–cost margin has the predicted sign, and its standardized interaction is significant at the 10 percent level, but its interaction with the above-median indicator is close to zero.

The break does vary with the TFP growth of the industry itself before the tariff war. It is concentrated in the industries that grew faster over 2012–17, and the interaction with the above-median indicator is significant for TFP growth over 2012–14 as well. Those years overlap the catch-up described in Section II.B of the main text, so I read the split as a description of the break, not a test of a channel. It does not reflect a return of fast-growing industries to their trend. Take the 27 industries above the median in both TFP growth over 2012–17 and protection. Weighted by value added, their TFP stood at -5.1 percent relative to its long-run trend in 2017 and at -10.9 percent in 2019. An industry returning to its trend would have moved toward it, and these moved further away.

In sum, I cannot attribute the 2019 decline in relative TFP to weaker competition with these data, and I leave the channel open.

Table B6: The 2019 break by industry characteristics before the tariff war

	Split at the median		Interaction	
Characteristic	Below	Above	Above-median indicator	Standardized
No interaction		-1.64		
		(0.61)		
China's share of imports, 2016–17	-1.34	-0.62	0.72	0.26
	(0.92)	(0.50)	(1.15)	(0.43)
Import share of absorption, 2016	-0.29	-0.07	1.68	0.35
	(1.65)	(0.89)	(1.76)	(1.13)
Price–cost margin, 2012–16	-1.76	-0.43	0.02	1.57
	(0.59)	(1.15)	(1.51)	(0.84)
Change in China's import share, 2007–16	-1.24	1.14	2.27	1.26
	(0.87)	(0.82)	(1.26)	(0.87)
TFP growth, 2012–14†	-0.04	-2.67	-2.35	-1.15
	(1.48)	(1.01)	(0.78)	(0.69)
TFP growth, 2012–17†	-0.17	-2.29	-3.55	-0.93
	(1.39)	(0.95)	(0.96)	(0.25)

Notes: The 2019 regression across industries of Table B4, with the trend fitted over 1987–2017, on the protection measure, InputCost, Retaliation, and the five controls, with industries weighted by 2017 value added. Coefficients are scaled by the interquartile range of the protection measure and multiplied by 100, so they read as the percent difference in TFP between industries at the 75th and 25th percentiles of exposure. Standard errors, clustered by the 21 three-digit sectors, are in parentheses. Split at the median: the regression re-estimated on the industries below and above the median of the characteristic. Interaction: the coefficient on the protection measure times an indicator for an above-median value, or times the standardized characteristic, with the characteristic itself as a control (the import share of absorption is already a control). The shares of China in imports are from Schott (2025); the price–cost margin is shipments less payroll and materials over shipments, from Becker et al. (2021). †These years overlap the catch-up before the tariff war.