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Makram Khalil, Pierre M. Rouillard, Felix Strobel

Import tariff transmission in a production network

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Abstract

We find that whether US import tariffs have supply-side effects or demand-side effects on US manufacturing sectors depends on where the affected sectors are located in the US production network. Using local projections in a panel of US manufacturing sectors, we find that US import tariffs —including the 2018-19 tariff hikes— led to sectoral output contractions via two different channels: (1) Tariff increases act as negative supply shifters for sectors that use goods from tariff-facing sectors as input in production and thus face rising input costs. (2) Tariff increases act as negative demand shifters for sectors whose customer sectors suffer negative supply side effects due to tariffs and reduce their production. We show that these results are consistent with a stylized production network model featuring complementarities in production. Overall, our finding suggests that tariffs markedly reduce US manufacturing production and that the role of input–output linkages is key for understanding the transmission of import tariff shocks to output and producer prices.

Keywords: Trade policy, sectoral production and prices, input-output tables, United States.
JEL classification: E23, E32, F13.

Non technical summary

Recent debates highlight the importance of production networks in the transmission of macroeconomic shocks. This also applies to the consequences of trade shocks, particularly as import tariffs have become a cornerstone of US trade policy in recent years. Yet empirical evidence on the transmission of trade shocks through the domestic input-output network remains scarce. This paper examines the short-run effects of US import tariffs on US manufacturing industries, with a focus on how these tariffs affect production and pricing through input-output relationships in the production network. Our sample consists of a panel of US manufacturing industries for the period January 2004–January 2020.

We find that the transmission of tariffs through the domestic production network occurs through two channels. The first is the backward exposure channel, through which tariffs affect industries that depend on imported goods as inputs for their production processes. When tariffs increase, these industries face higher production costs, which lead to higher producer prices and a decline in production. The second channel is the forward exposure channel, through which tariffs affect industries whose customer sectors are negatively affected by tariff hikes: when sectors experience higher input costs and reduce their production, their suppliers face a decline in demand for their own goods, resulting in lower production and reduced producer prices. We show that these results are consistent with a stylized production network model featuring complementarities in production.

Overall, we find that US import tariffs significantly reduce manufacturing production. Although tariffs are often implemented with the intention of protecting domestic industries, at least at business-cycle frequency, their negative consequences through the production network appear to outweigh the intended benefits. Interestingly, the demand-side repercussions for sectors via their forward linkages, caused by reduced production in their customers' industries, partially counterbalance the inflationary effects of tariffs. These dynamics underscore the importance of understanding the role of input-output linkages in shaping the macroeconomic impact of trade policies.

1 Introduction

The macroeconomic literature has highlighted the importance of sectoral input–output linkages in the transmission of sectoral and aggregate shocks (e.g. Carvalho and Tahbaz-Salehi 2019). More recently, it turned to the question of the transmission of trade shocks.[1] This comes as import tariffs have become a cornerstone of US trade policy in recent years.[2] Yet, the empirical evidence on the transmission of trade shocks through the domestic input–output network has been scarce. This raises the question of how, and through which channels, import tariffs affect price and output dynamics of US industries.

Ex ante, higher import tariffs on a given good may have supply-side effects for some US sectors and demand-side effects for others, depending on the location of the good and the sector in the domestic production network. Import tariffs typically aim at protecting the local industry from foreign competition, potentially raising the demand for goods produced in the protected sectors. In the domestic production network, suppliers to customers in protected industries may also benefit from that rise in demand from those customers. At the same time, tariffs imposed on imported intermediate goods raise input costs in sectors that use these goods as input in their production. Importantly, such supply-type repercussions may amplify output losses via the domestic production network. If, for instance, car engines face increased import tariffs, cars will likely become more expensive as well, because car production requires engines as intermediate inputs. This dampens the demand for cars. Moreover, other US sectors that supply inputs to US car production —such as, e.g., electronics— will face a lower demand for their products as their customers in the car industry reduce their production due to the tariff increase. We aim to assess the relevance of these intertwined channels empirically.

To disentangle the effects of import tariffs on US industries, we use US input–output data and construct measures of the industries' potential tariff exposures via linkages in the production network. Specifically, we utilize a panel of 71 US manufacturing industries with data spanning from January 2004 to January 2020 to compute measures of backward and forward exposure in the domestic production network.

[1] See, e.g., Caliendo and Parro (2015); Caliendo et al. (2021); Bachmann et al. (2022); Baqaee and Farhi (2024).

[2] The first Trump administration increased import tariffs markedly in 2018 and 2019. Over the course of these years, average import tariffs jumped by close to 2pp. In his second term, President Trump enacted additional and far more dramatic import tariff hikes.

To construct sector-specific tariff shocks, we use tariff information on US imports at the HS-10 product level that we aggregate at the sectoral level. The interaction of the tariff shocks with backward and forward linkages of a specific industry to other industries allows us to trace the transmission of sector-specific tariff shocks within a production network. In addition, we can separate the direct (i.e. horizontal) effect of import tariffs within an industry. Notably, our approach is designed to study short-run dynamic responses to import tariff hikes.

We find that tariff increases are transmitted through industries' backward exposure to imported inputs as negative supply shifters. By raising input costs, tariffs increase producer prices and reduce output. In addition, our results suggest that the direct effect of a sector-specific tariff shock, which is the estimated effect of an import tariff that hits the sector's own products, also acts like a supply-type shock. This owes to the fact that at the level of sectoral aggregation in which we conduct our analysis, input–output tables reveal strong intra-industry linkages with most sectors being their own key supplier. Finally, our analysis provides evidence that tariff hikes have negative demand effects for sectors whose customers experience the tariff increase as a negative supply shifter and reduce their demand for the industries goods. Consequently, the industry's output and producer prices both decline. Overall, we find that US import tariffs markedly reduce production of US manufacturing sectors. Though the aim of tariffs often is to protect local industries, we find no evidence of such a protective effect.

Notably, while via all channels we find negative effects on production, the sign of the sectoral producer price response depends on the channels, via which the sector is exposed to tariff shocks. Producer prices go up in sectors that use goods from tariff-facing sectors as input in production and thus face rising input costs. Producer prices decline in sectors whose customer sectors are negatively hit on their supply side by tariff shocks and reduce their production.

We decompose the effects of tariffs into components associated with backward and forward linkages within sectors and between sectors. Though intra-sector linkages are strong, with firms in the same sectors often being each others key suppliers and customers, our results are driven by the transmission of shocks between sectors in the production network.

Our results speak to theoretical contributions emphasizing the role of complementarities in the input–output network. In particular, Guerrieri et al. (2022) show in a New Keynesian model that within production networks, a macroeconomic shock that affects one sector negatively on the supply-side can lower demand in other sectors. They refer to this as "demand chain" amplification of supply shocks.[3] Our finding of the effect of the forward tariff exposure channel presents novel evidence confirming their theoretical insights. Moreover, we provide evidence for the amplification of supply-type trade shocks in input–output networks (e.g. Baqaee and Farhi 2024).

We rationalize our empirical findings in a stylized production network model featuring complementarities in production as well as tariff shocks that —building on the equivalence result in Werning et al. (2025)— act as cost-push shocks for a set of upstream firms. Within this simple model, we illustrate how a tariff shock that hits a specific industry A, which supplies input goods to a downstream sector, raises the input costs of this sector. Thus for the downstream sector, the shock has negative supply-side effects, analogous to our empirical effect of tariff shocks via industries' backward exposure. At the same time, because the downstream industry reduces its production, the same sector-specific shock that hits industry A, has negative demand effects for another upstream industry B, which supplies other input goods to the downstream industry. The negative demand effects on industry B illustrate the forward exposure of that industry to the tariff shock.

Related literature

We are not the first to empirically analyze the effects of US import tariffs on manufacturing output and prices of US industries. Closest to our investigation is the analysis by Flaaen and Pierce (2025). Using a difference-in-difference approach they investigate the effects of the 2018–2019 tariffs via the backward exposure (rising input cost) channel, a protection channel and retaliatory tariffs. In line with these findings, we confirm that US import tariffs markedly raise producer prices of industries via the backward exposure channel. In contrast to our finding, they do not find a decline in output. Importantly, we add to their study by highlighting the role of forward exposure in the US production network for the transmission of tariff shocks. Barattieri and Cacciatore (2023) study the dynamic employment effects of temporary trade barriers on protected industries and via vertical production linkages to downstream industries. They find evidence for marked employment declines in downstream industries that correspond to large input price hikes. Again, we add to this paper by analyzing the effect of import tariff shocks not only

[3] Guerrieri et al. (2022) show that in the presence of the "demand chain" channel, the likelihood for a Keynesian demand amplification of supply shock increases.

on the downstream industries, but also on industries that are upstream of the affected industries as well. These industries are exposed to the tariff shocks also via their forward linkages to their customer sectors, whose goods are subject to tariffs. This allows us to characterize supply- and demand-type patterns arising from tariff shocks.[4] The notion that industry-specific shocks may propagate as supply-side disturbances to downstream industries and as demand-side disturbances to upstream industries is confirmed by Barattieri et al. (2023) in the context of sector-specific government purchases, and, more recently, by Cacciatore and Candian (2025), in the context of sector-specific uncertainty shocks.

In the theoretical macroeconomic literature, the role of input–output linkages for the transmission of trade shocks has gained much attention in recent years. Caliendo and Parro (2015); Caliendo et al. (2021) as well as Baqaee and Farhi (2019) employ static multi-sector models and highlight the importance of input–output linkages and sectoral heterogeneity for the correct assessment of trade shocks on trade, output and welfare. Kalemli-Ozcan et al. (2025) build a dynamic multi-sector model to focus on macroeconomic predictions. Our empirical results corroborate insight that the effect of tariff rate shocks on industries differ, depending on the goods that are subject to tariffs and the location of the industry in the production network. Our analysis thereby focuses on the transmission of the domestic production network, while we abstract from possible connections of domestic sectors due to linkages in the foreign production networks. In a complementary paper to ours, Antonova et al. (2025) study a multi-sector model and present evidence, highlighting that whether a tariff shock is recessionary or expansionary depends on whether it mainly hits upstream or downstream industries. While the paper also stresses the importance of production network channels, Antonova et al. (2025) do not explore the role of demand amplification of import tariffs as supply side disturbances.

Finally, we contribute to the literature studying the implications of (US) trade policy shocks for the domestic economy (see, inter alia, Amiti et al. 2019; Furceri et al. 2019; Lindé and Pescatori 2019; Jacquinot et al. 2022; Khalil and Strobel 2024; Auray et al. 2025; Auclert et al. 2025; Werning et al. 2025 and Känzig and Den Besten 2025). We add to these papers by focusing on the role of the domestic production network in the transmission of trade policy shocks.

We proceed as follows: Section 2 presents the data and the data treatment. Section 3 discusses

[4]Moreover, our evidence concerns the role of import tariffs instead of trade barriers and output responses instead of employment.

the construction of the tariff exposure measures. Section 4 lays out our econometric approach. Our main results are discussed in Section 5. In Section 6, we decompose the effect of tariff shocks into the transmission via inter-industrial and intra-industrial linkages. In Section 7 we show that our empirical results are consistent with the predictions from a stylized production network model featuring complementarities in production. Section 8 concludes.

2 Data and concordance

We use data from January 2003 to January 2020 on US goods imports and import duties, sectoral industrial production and producer prices, as well as sectoral input–output tables. We retrieve monthly data on the dollar value of imports and calculated duties of US imports at the disaggregated HS-10 level from the US Census District-level reports. Monthly data on industrial production and producer prices of industries are sourced from the Federal Reserve and from the Bureau of Labor Statistics, respectively. Finally, we utilize yearly input–output tables from the Bureau of Economic Analysis (BEA) at the 71 industries $\times$ 73 commodities level. (See Appendix A for further details on the series and sources).

To facilitate the investigation of the tariff exposure of US industries, we map the HS-10 product groups that are covered by tariffs to NAICS industries at the 4-digit industry level (NAICS4) employing the concordance tables provided by Pierce and Schott (2012). In calculating industry-specific tariff rates we divide the sum of the calculated duties on HS-10 products associated with an industry by the sum of the import values of these HS-10 products. As NAICS codes are revised every five years, we concord NAICS4 industry codes from the full observation period into the 2022–NAICS4 classification, creating consistent industry-specific average tariff series for the full sample.[5] To allow for the construction of tariff exposure measures, which capture industries' exposure via their input and output linkages, we use input–output accounts at the 71 industry $\times$ 73 commodity level of the BEA classification. Specifically, we match the BEA industry dimension to NAICS4 industry codes by leveraging an update for the 2022 vintage of the Liao et al. (2020) NAICS–BEA concordance. Further details on the different concordance processes are outlined in Appendix B.

Finally, our analysis focuses on industries of the Manufacturing sector (31–33) at the Industry

[5]Note that though our sample stops in 2020, the current input–output tables, industrial production, and producer price series all reflect the most recent classification vintage —which in all cases is 2022.

group aggregation level (NAICS4). In particular, we only include industries where import tariff rates are available, which effectively restricts our sample to a set of 71 NAICS4 manufacturing industries (Table C.1). Additionally, not all commodities in the input–output tables have matched import data (duties or import volumes), and thus effective tariff rates. The construction of tariff shocks is thus based on a set of 21 non-service commodities (Table C.2).

3 Constructing tariff rate shocks and input–output linkages

In the following sections, we outline how we construct tariff rates as well as how we measure backward and forward linkages in the US product network. Additional details are reported in Appendix C.

3.1 Tariff rate

The US administration sets the tariff rates at the disaggregated HS-10 product level. To calculate the tariff rate τ_j that is specific to the BEA commodity j at a higher aggregation level, we sum the import duties on all HS-10 products associated with the BEA commodity j and divide it by the sum of import values. That is, in our analysis we use an average effective tariff rate for each BEA commodity, that not only reflects changes in the tariff rate set by the administration, but also composition effects. Such composition effects arise, for instance, if US importers adjust their composition of imports within a commodity by importing different product varieties or sourcing goods from other supplying countries in the light of higher bilateral tariffs.[6,7]

[6] A potential limitation of constructing a measure of tariff shocks built on realized tariff changes is that the imposition of tariffs is rarely unexpected by market participants. Tariffs are often announced well in advance of their implementation, allowing firms time to anticipate the changes. As a result, firms may adjust their imports, production, or pricing strategies prior to the effective date, potentially distorting the observed impact of the shock. To account for any anticipation effects, in Appendix D, we run an exercise that evaluates the effect of tariffs on sector-specific production and prices in the periods leading up to the tariff's implementation. Our results suggest that the role of anticipation effects in the transmission of tariff shock through the production network is small. This is in line with the assessment by Amiti et al. (2020), who consider the U.S. application of tariffs during the 2018/2019 trade war with China a natural experiment for understanding the effects of tariffs. At the same time, it contrasts with the strong anticipation effects to import volumes in 2025 prior to the introduction of the "Liberation Day tariffs" by the US.

[7] By far the largest tariff rate changes in our sample take place in the trade war between the US and China in 2018 and 2019. In Appendix E, we show that our main results hold qualitatively, when we stop the sample in 2017.

3.2 Input channel - backward exposure measure

Industries are exposed to tariff changes through their input costs. Consider an unexpected rise in the import tariff rate on a commodity j. Industries that use product j in their production process then face a cost shock —the magnitude of which depends on the relative importance of that product in their production process (measured by its cost share from total inputs) and the import share in total supply. The measure for the backward exposure to tariffs formalizes this mechanism at the commodity level by decomposing the cost shock into these two components. For each input commodity, we capture how intensively an industry relies on that commodity and scale this exposure by the commodity's import penetration. More formally, for each commodity j that industry i uses, the backward exposure is defined as:

$$BW_{i,j,y} \equiv \frac{use_{i,j,y}}{M_{i,y} + CE_{i,y}} \times \frac{imp_{j,y}}{supply_{j,y}} = USE_{i,j,y} \times IM_{j,y}, \tag{1}$$

where $use_{i,j,y}$ is the cost of commodity j used by industry i as an intermediate input in year y. $M_{i,y}$ is the cost of the total intermediate use of inputs by industry i in year y, and $CE_{i,y}$ is the total compensation of employees paid within industry i in year y. $imp_{j,y}$ is the volume of imports of commodity j, and $supply_{j,y}$ denotes the total supply of commodity j (i.e., domestic supply plus imports). More compactly written, $USE_{i,j,y}$ represents industry i's use share of commodity j in its production process, and $IM_{j,y}$ is the import share of commodity j in its total supply.

Since the BEA Use tables do not allow us to directly identify industry-specific import shares of commodities, we instead scale $USE_{i,j,y}$ by the economy-wide import share of j to obtain a proxy for the backward exposure of industry i to tariffs on commodity j.

For an intuitive example consider the car industry: To the extent that it uses steel as an intermediate input in production, it is backward exposed to import tariffs on steel. The magnitude of the exposure depends on the cost share of steel in the production of the car industry and the economy-wide import share of steel (since the BEA's use tables do not allow pinning down the industry-specific import share of steel used by the car industry). The overall backward exposure of the car industry is then the sum of its backward exposures over all its intermediate inputs.[8]

[8] Similar backward exposure measures were used in in Flaaen and Pierce (2025) and used in Khalil and Weber (2022), Amiti et al. (2019), and Benguria and Saffie (2019). In the regressions, we use predetermined —but time-varying— exposure measurements to capture structural changes.

3.3 Output channel - forward exposure measure

In addition to the backward exposure measure, we introduce a second exposure measure that attempts to measure exposure to tariffs through industries' output linkages in the domestic production network.

The forward exposure measure captures how an industry is exposed to a tariff that affects its customers in other industries. Note, that in the US input–output tables, industries may produce more than one commodity. For instance, firms in the primary metal industry may also produce (though to a lesser extent) fabricated metals or even machinery or electrical appliances. An industry may have forward linkages to several customer industries —via all the commodities it produces and sells domestically. We define the forward exposure measure $FW_{i,j,x,y}$ for an industry i that domestically produces a commodity x and sells it to its customer industry j in year y.

Let the government raise the import tariff on the product(s) that industry j (e.g. the motor vehicle and parts industry) produces. This sector now ought to be protected by tariffs and if demand were to be redirected from foreign producers toward j, we could expect its demand for inputs to increase, including for x (e.g. steel). If such a protective channel were active, industry i (e.g. the steel industry) would benefit from the introduction of tariffs on goods produced by industry j through its product x's output linkage.

On the other hand, a tariff hike on the products that industry j produces can also lead to output contractions in sector j. At our level of aggregation, the input–output tables reveal strong intra-industry linkages: in many sectors, firms are important suppliers to other firms in the same sector. Thus, a tariff shock on imported products of the kind that is produced by industry j can affect industry j negatively. Consider, for example, the motor vehicle and parts industry. A tariff on imported car engines represents a tariff on a good associated with this industry. It may protect specific firms that produce mainly engines from outside competition. However, at the same time, it increases costs for firms within that sector that use engines as an input for producing cars. If the car producers reduce their production, that in turn may trigger a reduction of production by manufacturers of transmissions, brakes or tires —all within the motor vehicle and parts industry. In that scenario, this also reduces demand for products of suppliers from outside the motor vehicle industry (e.g., steel producers), who are exposed to these tariff changes via their forward linkages.

We use the BEA Make and Use tables to construct the forward exposure measure. These tables do not contain information on what share of an industry i's production of commodity x is used by industry j. Thus, we cannot straightforwardly identify the direct linkage between an industry that domestically produces a commodity, and another industry that sources such intermediate input from the former. Indeed, we only have the total dollar value of commodity x supplied by industry i, and the total dollar value of commodity x used by j as an intermediate input. We therefore proxy the direct linkage from i to j —through x— by using the dollar value of industry i's total supply of commodity x, as obtained from the Make tables, and the total domestic use of each industry of the good x, as obtained from the Use tables. The forward linkage between industry i and industry j through commodity x thus reads

$$FW_{i,j,x,y} \equiv \underbrace{\frac{supply_{i,x,y}}{supply_{x,y}}}_{\substack{\text{commodity } x \\ \text{supply share} \\ \text{from industry } i}} \times \underbrace{USE_{j,x,y} \times (1 - IM_{x,y}),}_{\substack{\text{industry } j\text{'s domestic} \\ \text{demand of commodity } x}} \tag{2}$$

where $USE_{j,x,y} \times (1 - IM_{x,y})$ approximates the share of commodity x that industry j sources domestically. Multiplying it with the domestic supply share of industry i in the production of commodity x yields a proxy for the domestic sourcing of this commodity by industry j that is supplied by i. To obtain a total linkage between the two industries we compute a weighted average of all commodity-specific linkages:

$$FW_{i,j,y} \equiv \sum_{x} w_{i,x,y} \times FW_{i,j,x,y}, \tag{3}$$

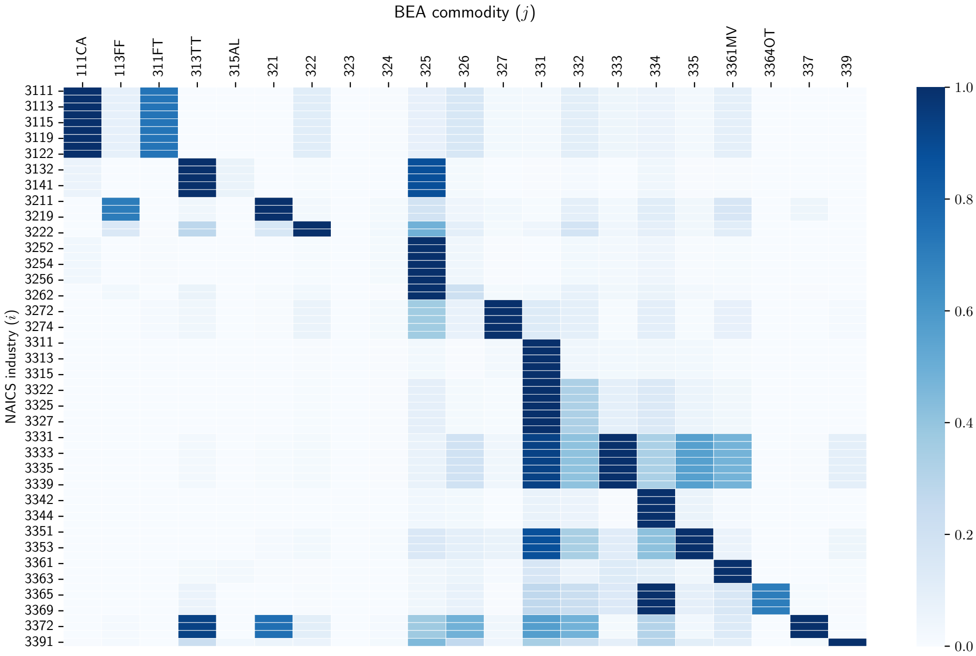
where the weight $w_{i,x,y}$ is given by commodity x's relative importance in industry i's total output, i.e. $w_{i,x,y} = \frac{supply_{i,x,y}}{supply_{i,y}}$.

3.4 Input–Output linkages in 2017

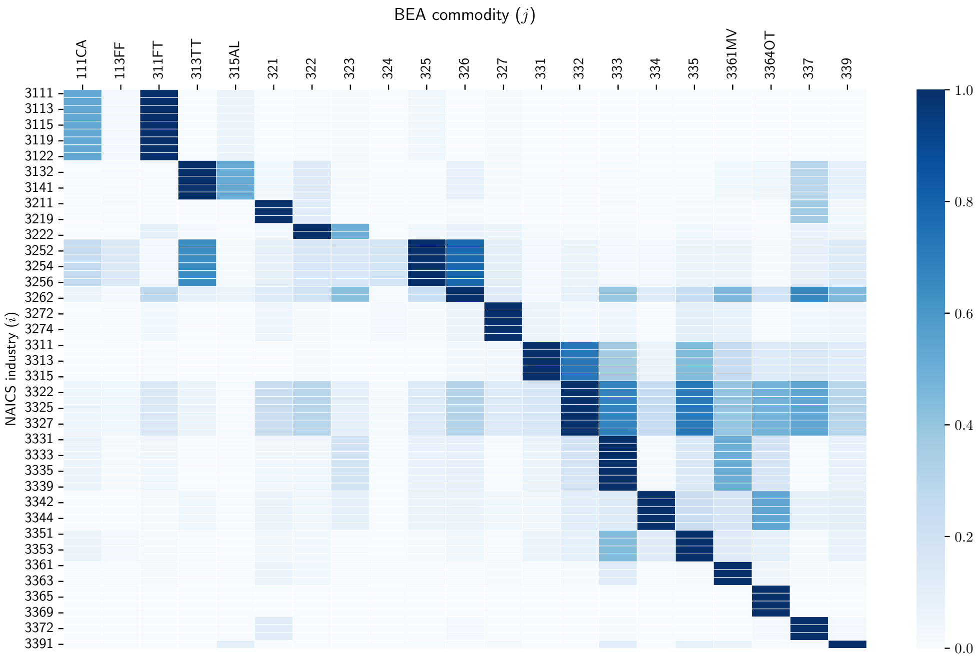
Figure 1 shows, for the year 2017, the distribution of backward linkages and forward linkages in the US production network. The heatmaps depict backward and forward exposure normalized by row as $(\frac{BW_{i,j}}{\max_j BW_{i,j}})$ and $(\frac{FW_{i,j}}{\max_j FW_{i,j}})$. The darker the cells, the higher the exposure of industries to tariffs via input or output linkages. Importantly, most industries' overall exposures

Figure 1: Exposure of US manufacturing industries to tariffs via input–output linkages in 2017

(a) Backward linkages



(b) Forward linkages



Upper panel: Normalized backward exposure linkages of NAICS industries (y-axis) to BEA commodities (x-axis) in 2017. *Lower panel*: Normalized forward exposure linkages of NAICS industries (y-axis) to BEA commodities (x-axis) in 2017. Darker cells indicate a higher exposure of industries via production network linkages.

are concentrated in a few linkages. As it turns out, at the level of disaggregation in which we conduct our analysis, firms in a given industry tend to be important suppliers and customers to other firms in the same industry. Our baseline measures for backward and forward exposure contains both intra-industrial and inter-industrial linkages, but in Section 6 we show that our main results still hold when we abstract from the intra-industry linkages —i.e. we analyze tariff exposures solely incorporating inter-industry linkages.

4 Empirical strategy

We employ a panel local projection approach as in Jordà (2005) to estimate the dynamic effects of import tariff changes on industry-specific production and output prices in the US manufacturing sector, taking input–output linkages into account.

The following specification is independently estimated for each horizon $h = 0, 1, \ldots, 14$ via ordinary least squares:

$$\begin{aligned}\mathcal{Y}_{i,t+h} = \alpha^{(h)} &+ \underbrace{\mu^{(h)} \Delta T_{i,t}}_{\substack{\text{Horizontal}\\ \text{channel}}} + \underbrace{\beta^{(h)} \mathbf{BW}_{i,y} \times \Delta \mathcal{T}^{Input}_{i,t}}_{\text{Input channel}} + \underbrace{\gamma^{(h)} \mathbf{FW}_{i,y} \times \Delta \mathcal{T}^{Output}_{i,t}}_{\text{Output channel}} \\ &\underbrace{+ \rho_1^{(h)} \mathbf{FW}_{i,y} + \rho_2^{(h)} \mathbf{BW}_{i,y} + \sum_{j=1}^{14} \boldsymbol{\theta}^{(h,j)\prime} \mathcal{Z}_{i,t-j} + f_i + \delta_t}_{\text{controls}} + \varepsilon^{(h)}_{i,t+h}\end{aligned} \tag{4}$$

where $\mathcal{Y}_{i,t}$ denotes for a NAICS4 industry i in month t, either the log of the producer price index, or the log of the index for industrial production. $\Delta T_{i,t}$ is the monthly tariff rate change in NAICS4 industry i, $\Delta \mathcal{T}^{Input}_{i,t}$ and $\Delta \mathcal{T}^{Output}_{i,t}$ are the weighted input and output tariff rate changes faced by industry i. Specifically, we construct the "Input tariff" and the "Output tariff" shock for sector i as:

$$\Delta \mathcal{T}^{Input}_{i,t} \equiv \sum_{j \in BEA} \frac{BW_{i,j,y-1}}{\mathbf{BW}_{i,y}} \times \Delta \tau_{j,t} \qquad \text{and} \qquad \Delta \mathcal{T}^{Output}_{i,t} \equiv \sum_{j \in BEA} \frac{FW_{i,j,y-1}}{\mathbf{FW}_{i,y}} \times \Delta \tau_{j,t}$$

where $\Delta \tau_{j,t}$ is the monthly effective tariff rate change on products of BEA sector j. $\mathbf{BW}_{i,y}$ and $\mathbf{FW}_{i,y}$ are the yearly (y) aggregate backward and forward exposures, which are defined as $\mathbf{BW}_{i,y} \equiv \sum_{j \in BEA} BW_{i,j,y-1}$ and $\mathbf{FW}_{i,y} \equiv \sum_{j \in BEA} FW_{i,j,y-1}$. The one-year lag $(y-1)$ ensures that the exposure measures entering our shock measures are pre-determined and do not contemporaneously react to current changes in tariff rates. Additionally, we control for the lags of the dependent variable and the past tariff changes (horizontal, input, output), to ensure that the estimated impulse responses reflect the effect of the contemporaneous tariff changes, rather than persistence in tariff rates or the dependent variable. These controls are collected in vector $\mathcal{Z}$. Further, the specification also includes industry fixed effects (f_i) to control for unobserved industry-specific heterogeneity, and time fixed effects (δ_t) to control for economy-wide shocks (e.g. the aggregate increase in tariffs), thus ensuring that we are isolating the effect of local —i.e. *industry-specific*— tariff shocks.[9]

The collection of estimated coefficients $\left(\hat{\mu}^{(h)}, \hat{\beta}^{(h)}, \hat{\gamma}^{(h)}\right)_{h=0}^{14}$ constitutes the impulse response functions (IRFs), i.e. the dynamic response of the dependent variable to the three tariff shocks.[10] Inference for the model parameters is conducted using Driscoll-Kraay standard errors, which account for spatial dependency, autocorrelation and heteroskedasticity. The estimation sample covers January 2004–January 2020. We do not extend the sample beyond the Covid-19 pandemic as the crisis that unfolded severely affected supply chains, trade links, and economic activity.[11]

5 Consequences of US import tariff hikes for US production

This section discusses our empirical results on the transmission of sector-specific tariff shocks through the industries' backward tariff exposure, the horizontal channel and the forward tariff exposure.

5.1 The effect of a tariff via the industry's backward linkages

We first find that, via the channel of backward exposure to imported inputs, tariff increases affecting suppliers are transmitted as supply-type disturbances (Figure 2). Previous studies show that US pre-tariff import prices did not change after the 2018-19 tariff hikes (see Amiti et

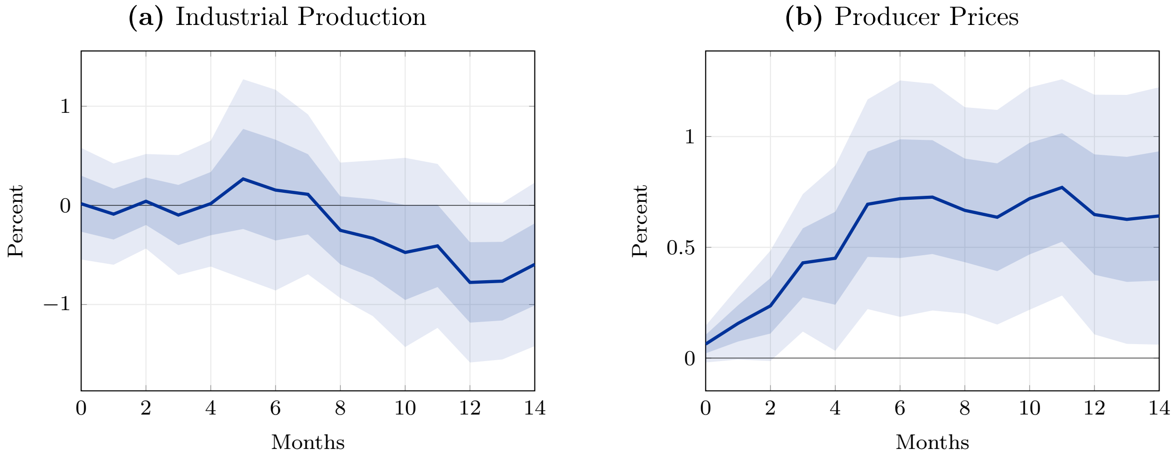
[9] The results are very similar, if we exclude time fixed effects and include a number of control variables instead, see Appendix F.

[10] Since we control for at least one lag of the outcome variable, the specification in level is equivalent to the long-difference, and the IRFs hence show cumulative responses. See Montiel Olea et al. (2025) for a complete overview.

[11] A similar stance is taken in Kuitunen (2026), where the transmission of US monetary policy shocks is channeled through trade linkages.

al. 2019; Fajgelbaum et al. 2020), leading to a near complete pass-through to importers. Thus, tariff hikes affecting industries via their input suppliers directly increase production costs.[12] Our results indicate that input tariff shocks raise average producer prices and lower production. Prices start climbing on impact until they reach 0.8% five months after a one-percentage-point (pp.) increase in the average input tariff rate. Thereafter prices stay at the new level. Production reacts only with a delay. It starts to contract after 8 months, eventually decreasing by around 0.8%. The sluggish output response may be due to firms depleting their input stocks before adjusting production.

Figure 2: The role of exposure to imported intermediates in the transmission of tariff shocks



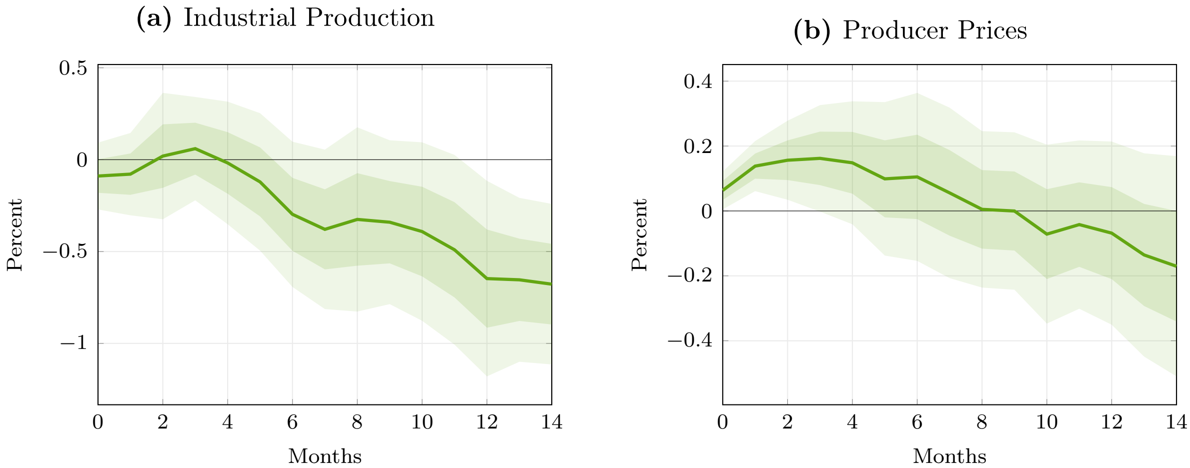
Notes: Cumulative response to a one percentage point local input tariff shock for the average industry. In scaling the effect, we set the aggregate backward linkage to 0.129 to match the average 2017 supply-chain state. Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

5.2 The effect of a tariff directly on the industry's goods

Figure 3 shows the effects of tariff hikes on goods produced in a specific sector, on output and prices of the same sector. We call this the direct or horizontal effect of tariffs. Interestingly, we find that direct tariff shocks also initially act as negative supply-side disturbances with producer prices increasing on impact and industrial production decreasing – again after a few months delay. After 10 months, the price response turns negative though not significantly so. At the same time, production keeps decreasing.

[12] In our baseline analysis, we account for the exposure to tariff hikes of *all* imported goods. The effects of Input tariffs look similar, if we only consider tariffs on products that are classified as intermediate good in the Broad Economic Categories by the UN (results available on demand).

Figure 3: The effects of direct tariff shocks



Notes: Cumulative response to a one percentage point local direct tariff shock for the average industry. Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

Thus, tariffs on imports of goods produced by the sector do not protect the sector. A possible explanation is that at the level of aggregation in which we conduct our analysis, US input–output tables reveal strong intra-industry linkages. That is, for firms in most sectors their own key suppliers and customers are located in the same sector (Figure 1). Thus, tariffs on imports intended to protect the production of some firms in this industry, also raise input costs for other firms within that industry. While protective effects may exist on a more disaggregated level, at the level of sectoral aggregation in which we conduct the analysis, the contractionary effects from higher input costs within a sector appear to be dominant.[13] This explains why the response via the horizontal channel is at least in the short-term similar to that via the backward channel, with negative effects on output and positive effects on prices.

Our result aligns with other findings in the literature on the dynamic implications of protectionist measures for the domestic economy (see Flaaen and Pierce 2025 and Barattieri and Cacciatore 2023), who do not find evidence for protective effects of import tariffs for domestic industry.

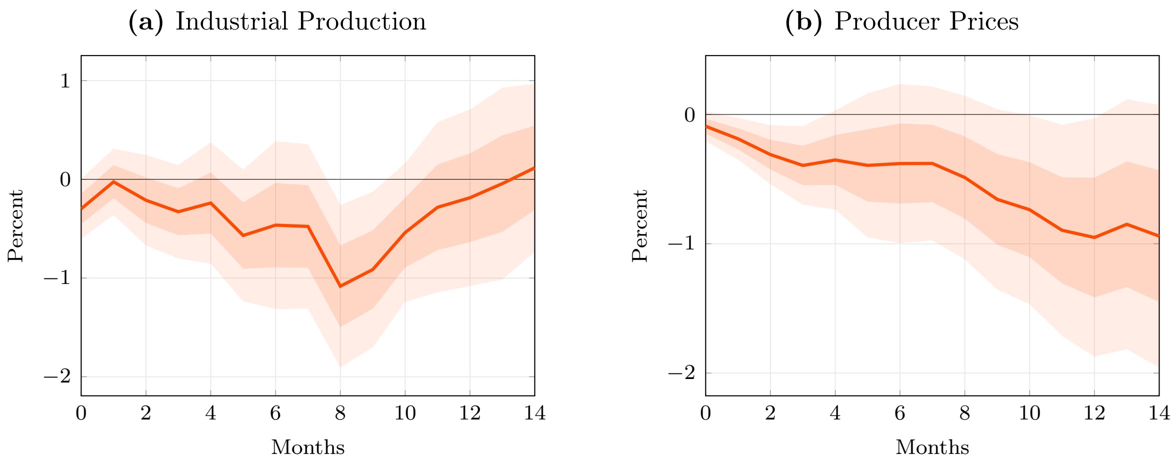
[13]There are other possible amplification forces of supply shocks that are not related to the production network. One such mechanism arises from firm entry and exit (see Bilbiie and Melitz 2022 and Khalil and Lewis 2024). Another possibility is that under oligopolistic competition, domestic firms respond to higher post-tariff prices of foreign competitors by raising their own prices – which consequently results in lower demand and output.

5.3 The effect of a tariff via the industry's forward linkages

As discussed in the previous section, sectors directly exposed to a tariff shock experience, on average, a supply-type disruption. This raises the question of how such disruptions propagate to industries that are linked to the shocked sectors through forward linkages, i.e. how output and producer prices respond in industries that supply goods to sectors affected by a tariff shock.

Figure 4 shows that tariff shocks in downstream customer sectors generate pronounced negative demand effects on supplying industries through forward linkages. Both the responses of output and prices are negative following an increase in the average tariff rate faced by its customer sectors. On average, a one percentage point increase in the output tariff rate leads to a 1% decline in the industry's own output, while producer prices likewise fall by up to about 1%. In other words, when customer sectors are hit by tariffs and reduce production, demand for the industry's own goods contracts as well.

Figure 4: The role of forward exposure to sectors that face higher tariffs



Notes: Cumulative response to a one percentage point local output tariff shock for the average industry. In scaling the effect, we set the aggregate forward linkage to 0.081 to match the average 2017 supply-chain state . Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

The contraction via the forward channel amplifies the overall production contraction in the economy, i.e. beyond the contraction in the initially affected sectors. Our empirical result thus aligns with recent theoretical contributions. Among others, Guerrieri et al. (2022) stress that a shock that reduces the supply in one sector can reduce output in other sectors due to "demand chain" effects, thereby amplifying the initial output contraction.

Notably, US manufacturing sectors for whom US import tariffs act as demand-side shocks via their forward linkages face negative price pressures. This counteracts the typically positive price pressures of import tariff hikes on producer and consumer prices. These findings highlight that the effect of import tariff shocks on producer prices depends crucially on where the tariff hits the domestic production network and, consequently, the relative weight of the transmission channels in shaping its impact.

6 Disentangling inter-industry and intra-industry linkages

To see whether our findings are driven by the strong intra-industry linkages or whether they reflect a genuine inter-sectoral transmission in the production network, we modify the local projection setup and decompose backward and forward channels into intra- and inter-industry components.[14] We then estimate the following h panel local projections to isolate their distinct contributions to the transmission channels:

$$
\begin{aligned}
\mathcal{Y}_{i,t+h} = \alpha^{(h)} + \mu^{(h)} \Delta T_{i,t} &+ \underbrace{\beta^{(h)}_{intra}\, BW_{i,\mathbf{i},y-1} \times \Delta\tau_{\mathbf{i},t} + \gamma^{(h)}_{intra}\, FW_{i,\mathbf{i},y-1} \times \Delta\tau_{\mathbf{i},t}}_{\text{Intra-industry}} \\
&+ \underbrace{\beta^{(h)}_{inter}\, \widetilde{\mathbf{BW}}_{i,y} \times \Delta\widetilde{\mathcal{T}}^{Input}_{i,t} + \gamma^{(h)}_{inter}\, \widetilde{\mathbf{FW}}_{i,y} \times \Delta\widetilde{\mathcal{T}}^{Output}_{i,t}}_{\text{Inter-industry}} \\
&+ \rho^{(h)}_1 \mathbf{FW}_{i,y} + \rho^{(h)}_2 \mathbf{BW}_{i,y} + \sum_{j=1}^{14} \boldsymbol{\theta}^{(h,j)\prime} \mathcal{Z}_{i,t-j} + f_i + \delta_t + \varepsilon^{(h)}_{i,t+h}
\end{aligned}
\tag{5}
$$

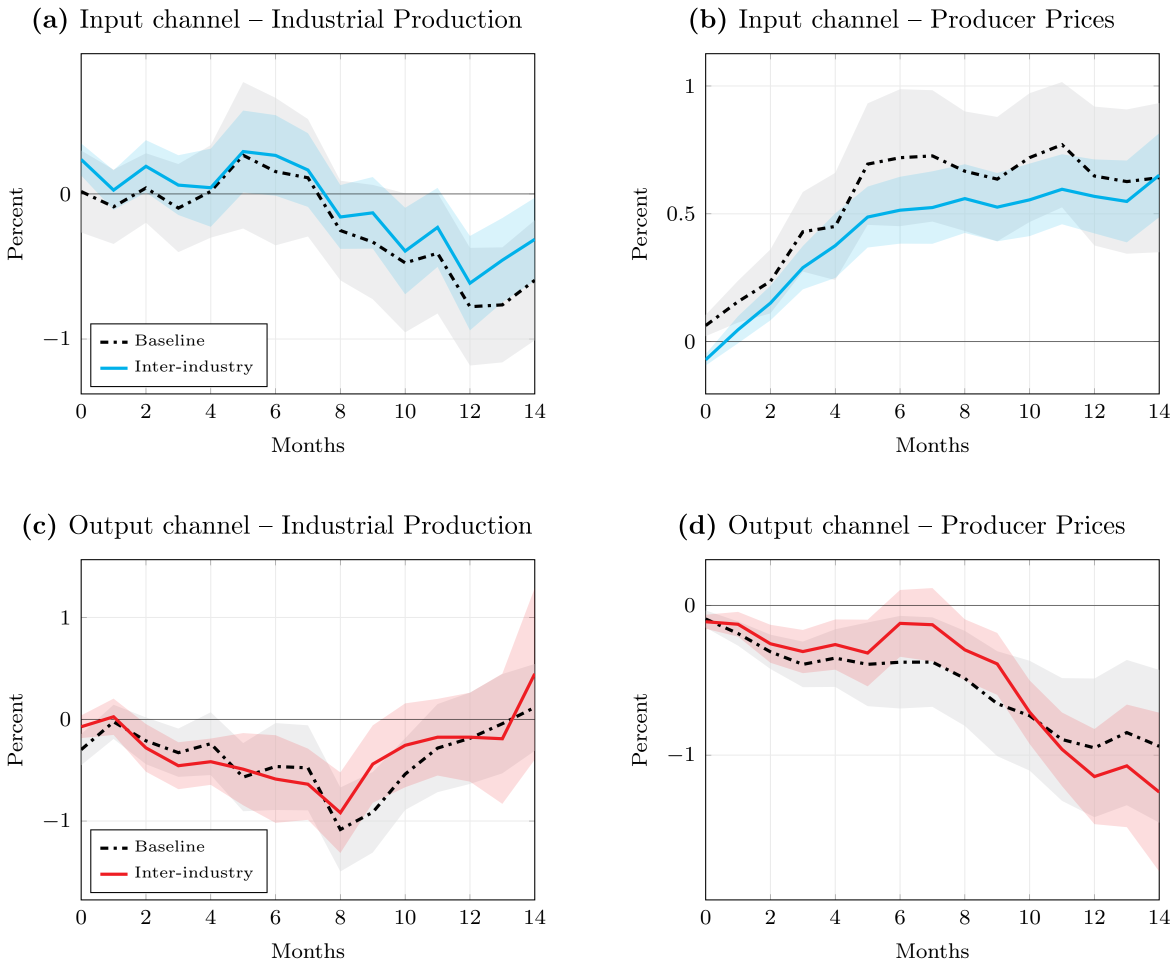
where $\widetilde{\mathbf{BW}}_{i,y} = \sum_{j \neq \mathbf{i}} BW_{i,j,y-1}$ is the aggregate backward tariff exposure measure excluding the link of the industry i to itself and $\widetilde{\mathbf{FW}}_{i,y} = \sum_{j \neq \mathbf{i}} FW_{i,j,y-1}$ is the analogue forward exposure measure. $\widetilde{\mathcal{T}}^{Input}_{i,t} = \sum_{j \neq \mathbf{i}} \frac{BW_{i,j,y-1}}{\widetilde{\mathbf{BW}}_{i,y}} \times \Delta\tau_{j,t}$, and $\widetilde{\mathcal{T}}^{Output}_{i,t} = \sum_{j \neq \mathbf{i}} \frac{FW_{i,j,y-1}}{\widetilde{\mathbf{FW}}_{i,y}} \times \Delta\tau_{j,t}$ are the corresponding tariff rate measures.

Though intra-industry linkages have a high weight in the backward and forward exposure measures, Figure 5 shows that the effects of tariff shocks via the backward and forward linkages are primarily driven by inter-industry linkages. For both the input and the output channel, the

[14] The average value of the backward exposure measure in our sample is 0.129 – 0.078 of this reflects an inter-industry exposure, 0.054 reflects an intra-sectoral exposure. The average value of the forward exposure measure in our sample is 0.077 – 0.046 of this reflects an inter-industry exposure, 0.031 reflects an intra-sectoral exposure.

responses of sectoral production and prices via inter-industry linkages are virtually the same as the responses measured using the full backward and forward exposure measures. This evidence corroborates that the role of input–output linkages is key for understanding the transmission of import tariff shocks within the US manufacturing sector.

Figure 5: Transmission of tariff increases through **inter-industry linkages**



Notes: Cumulative response to a one percentage point local tariff shock for the average industry. In scaling the effect, we set the inter-industry and aggregate backward linkages to 0.074 and 0.129 and the inter-industry and aggregate forward linkages to 0.048 and 0.081 to match the average 2017 supply-chain states. Shaded areas show the 68% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

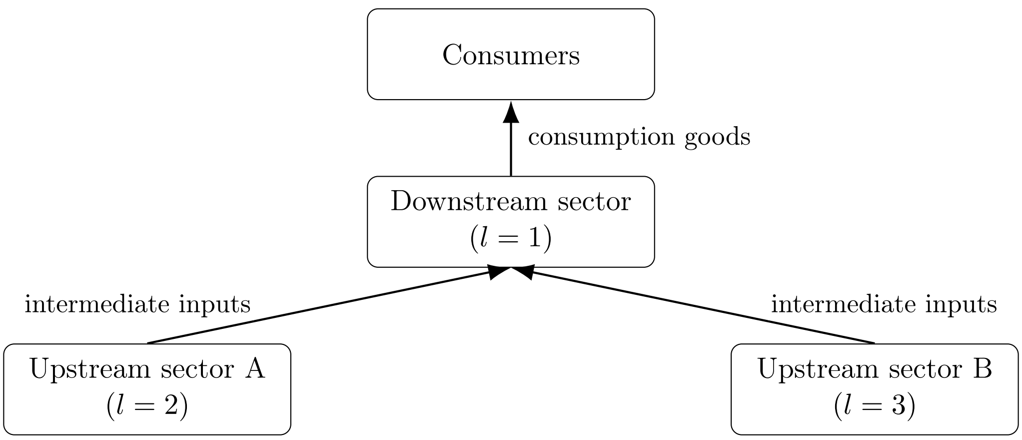
7 Inspecting the mechanism in a stylized production network model

Our empirical findings suggest that the effects of tariff shocks on sectoral outcomes depend on a sector's tariff exposure arising from its position in the domestic production network. To illustrate the mechanism behind these findings, we use a stylized three-sector New Keynesian model with input–output linkages.

We build on the equivalence result of Werning et al. (2025), who show that tariff shocks can be modeled as cost-push shocks in a closed economy model. In contrast to their setting, we consider three sectors: Downstream, Upstream A and Upstream B.

To isolate the mechanism of interest -— namely, demand-chain amplification of tariff shocks through the forward linkages of upstream sectors -— we assume a simple input–output structure: Downstream sources intermediate inputs only from Upstream A and Upstream B to produce consumption goods. Upstream A and Upstream B supply the downstream sector with intermediate goods and do not source from other sectors (see Figure 6). We then study the case of a tariff shock in 'Upstream A'. This allows us to relate the model predictions to our empirical specification by studying the effects of tariffs on Downstream (backward exposed to tariffs) and 'Upstream B' (forward exposed to tariffs via Downstream). We assume complementarities in the domestic production network and imperfect inter-sectoral labor mobility, as in production network models used to rationalize empirical patterns, such as Cacciatore and Candian (2025).

Figure 6: Stylized production network model



7.1 Model

We build on a nested version of the production network model developed by Burgert et al. (2025b).[15] In what follows, we focus on the model features most relevant for our mechanism.

7.2 Production

There are three sectors indexed by $l = 1, 2, 3$; i.e. Downstream (l=1), Upstream A (l=2) and Upstream B (l=3). In each sector, a continuum of firms produce goods under monopolistic competition.

Production network Gross output $y_{l,t}$ combines labor $n_{l,t}$ and intermediate inputs $x_{l,t}$:

$$y_{l,t} = a_{l,t} \left[\omega_{y,l}^{1/\phi} \, n_{l,t}^{(\phi-1)/\phi} + (1 - \omega_{y,l})^{1/\phi} \, x_{l,t}^{(\phi-1)/\phi} \right]^{\phi/(\phi-1)}, \tag{6}$$

with ϕ governing the substitutability between labor and intermediate input usage and $a_{l,t}$ total factor productivity. Parameter $\omega_{y,l}$ governs the sector-specific weight of own labor in production.

Intermediate goods in sector l are assembled via a CES production function combining intermediate inputs from each sector:

$$x_{l,t} = \left[\sum_{k=1}^{3} \omega_{k,l}^{1/\psi} \, x_{k,l,t}^{(\psi-1)/\psi} \right]^{\psi/(\psi-1)}, \tag{7}$$

where $x_{k,l,t}$ is the input from sector k used by sector l, ψ is the elasticity of substitution across intermediate goods from each sector, and $\omega_{k,l}$ determines the weight of each sector k in the input bundle of sector l.

We assume a price setting relationship that gives rise to a standard New Keynesian Phillips Curve as firms reset prices with probability $1 - \theta_{p,l}$.

[15] See also Burgert et al. (2025a) who use the model to assess the quantitative macroeconomic implication of US import tariffs without a focus on sector location within a production network. Our model is a nested version of the model in Burgert et al. (2025b) as we consider limit cases of their calibration to switch off channels in the rich model structure such as capital accumulation and nominal price rigidity to focus on our channel of interest. We explore richer versions of the model and find results that qualitatively align with the stylized model.

Tariff shocks: In the simulations below, we incorporate tariff shocks as cost-push shocks. That is, in the linearized Phillips curve, we include a sectoral tariff shock $\tau_{l,t}$ such that

$$\pi_{l,t} = \beta\,\mathbb{E}_t\widehat{\pi}_{l,t+1} + \kappa_l\,\widehat{mc}_{l,t} + \kappa_l\tau_{l,t}, \tag{8}$$

where $\widehat{\pi}_{l,t}$ is producer price inflation, $\widehat{mc}_{l,t}$ are marginal costs, $\kappa_l = \frac{(1-\theta_l^p)(1-\beta\theta_l^p)}{\theta_l^p}$ and $\tau_{l,t} = \rho_l^\tau\tau_{l,t-1} + \varepsilon_{l,t}^\tau$, where ρ_l^τ governs the persistence of the tariff shock and $\varepsilon_{l,t}^\tau \sim \mathcal{N}(0,1)$. We assume that any tariff revenue generated by the shock is rebated lump-sum to the representative household and is therefore non-distortionary. Hence, we abstract from separate fiscal effects of tariff revenues and focus on the production-network transmission mechanism.

7.3 Households

A representative household maximizes expected utility:

$$\mathbb{E}_0\sum_{t=0}^{\infty}\beta^t\left[\log(C_t - hC_{t-1}) - \frac{A_N}{1+\nu}N_t^{1+\nu}\right], \tag{9}$$

where C_t is aggregate consumption and N_t is total labor supply. Parameter β is the discount factor, h governs the degree of habit in consumption and ν denotes the inverse of the Frisch elasticity of labor supply, and A_N scales the disutility of labor.

Labor supply Total labor supply is a CES aggregate of sectoral labor inputs:

$$N_t = \left[\sum_{l=1}^{3}\omega_{n,l}^{-1/\xi}\,n_{l,t}^{(\xi+1)/\xi}\right]^{\xi/(\xi+1)}, \tag{10}$$

where $\omega_{n,l} \geq 0$ captures the relative disutility associated with supplying labor to sector l. This specification gives rise to imperfect labor mobility across sectors with ξ denoting the elasticity of labor supply across sectors. Each labor bundle $n_{l,t}$ consists of a continuum of labor inputs sourced within sector l that are substitutable with elasticity ϕ_w.[16]

[16] We inherit the assumption of differentiated labor inputs from Burgert et al. (2025b). We retain differentiated labor inputs to preserve imperfect labor mobility across sectors, but abstract from wage stickiness.

7.4 Closing the model

Monetary policy The central bank sets the nominal interest rate R_t according to a Taylor-type rule:

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\rho_r} \Pi_t^{\varphi_\pi(1-\rho_r)}, \tag{11}$$

where Π_t is gross consumer price inflation and $\bar{R}$ the steady-state nominal interest rate. ρ_r denotes the degree of interest rate smoothing.

7.5 Calibration

$\omega_{n,l}$ are set such that each of the three sectors contributes equally to employment. The share of intermediate goods in total output is set to 0.6 – roughly the corresponding measure in US manufacturing from 2022 input–output tables. We assume that Upstream A and Upstream B do not use intermediate inputs from any other sector while Downstream sources intermediate goods from Upstream A and Upstream B in equal proportions. To simplify, we also assume that there is no capital used in production.[17]

To highlight the mechanism, we assume fully flexible prices ($\theta_{p,l} \to 0$) and that labor supply is very elastic in the short run ($\nu \to 0$). At the same time, intermediates are used in the Downstream sector in a Leontief fashion ($\psi \to 0$).

The household discount factor is set to $\beta = 0.99$. The parameters for habit formation and interest rate smoothing are set to $h = 0.7$ and $\rho_r = 0.7$. The elasticities of substitution of labor inputs sourced across and within sectors are both set to one ($\xi = 1$ and $\phi_w = 1$). The Taylor inflation coefficient is $\varphi_\pi = 1.5$. The elasticity between labor and intermediate inputs is set to $\phi = 0.5$, and A_N is set to 11.3 to satisfy the steady state equation.

7.6 Theoretical results

We simulate a tariff shock in the sector Upstream A.[18] To focus on the responses of the other two sectors, we simulate a tariff shock that raises producer prices in Upstream A by 1 percent on

[17] The qualitative predictions remain the same if we allow for capital in the production function and nominal price rigidity.
[18] The simulation builds on a linearized version of the model.

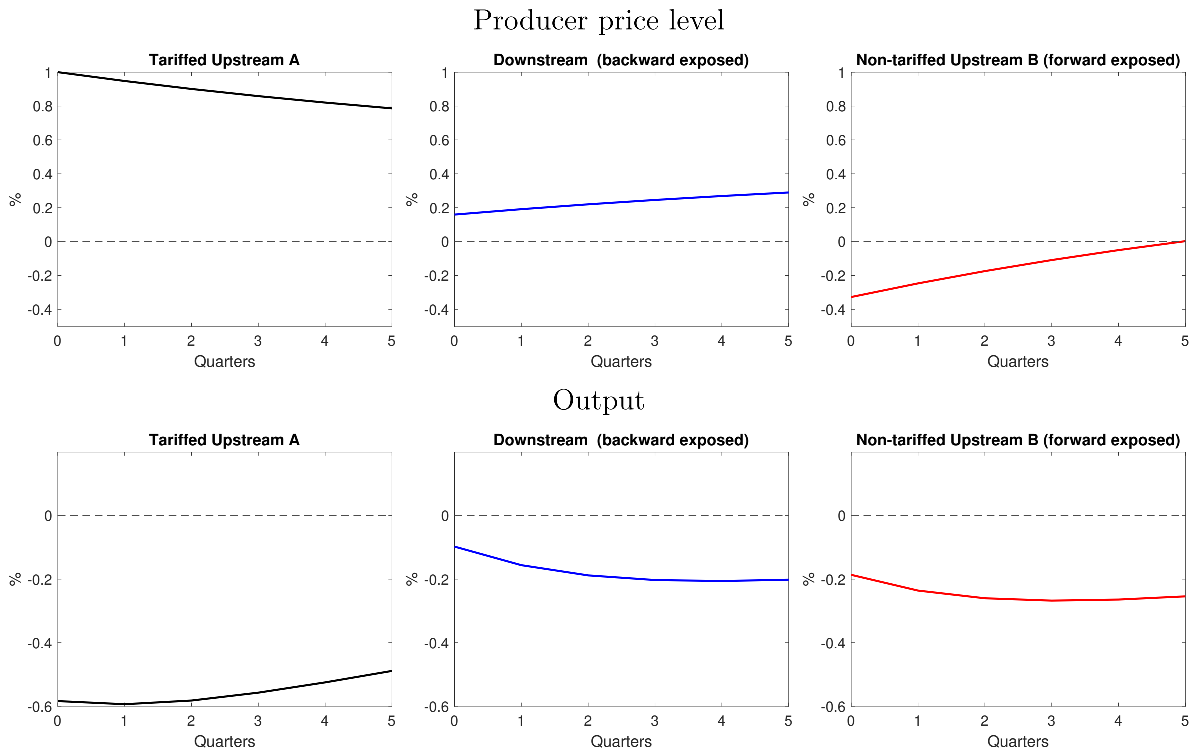


Figure 7: Transmission of sectoral tariff shocks (in Upstream A) through the production network. The shock is normalized to affect producer prices in Upstream A by 1 % on impact. Prices denote the cumulated inflation response.

impact.[19] Figure 7 shows the results. The tariff shock in Upstream A raises the cost of intermediate inputs for Downstream, thereby having negative supply-type repercussions: Downstream producer prices increase while Downstream output falls. This corresponds qualitatively to our estimated effect of empirical tariff shocks via the backward exposure channel.

Notably, the contraction in downstream activity reduces input demand more broadly, generating a secondary contractionary effect. This becomes evident when considering dynamics in Upstream B: Even though Upstream B is not directly hit by the tariff, it experiences a negative demand-type spillover through weakened demand of its customers in the Downstream sector, leading to lower output and declining producer prices in Upstream B. Overall, the results highlight how sector-specific tariff increases can propagate through input–output linkages, first as cost-push shocks in tariff-exposed input suppliers and downstream users, and then as demand-driven contractions in upstream sectors connected through downstream production networks. This theoretical mechanism is consistent with our empirical findings.

[19] The autocorrelation of the tariff shock process is set to 0.9. We refrain from a deeper inspection of tariff pass-through within Upstream A to focus on the consequences of production network linkages.

8 Conclusion

Input–output linkages are crucial for understanding the transmission of import tariff shocks. We find that tariff rate increases reduce industry-specific production through backward and forward channels arising in a domestic production network. However, the response of an industry's producer price depends on which channel dominates the transmission of the tariff increase.

For aggregate output and prices, our results suggest that backward and forward linkages amplify the contraction of production due to tariff increases. At the same time, the negative demand-type repercussion of tariff shocks for some sectors in the domestic production network ought to dampen aggregate price increases. The findings align with recent theoretical literature on shock transmission in production networks. Thus, our results are likely relevant for other supply-type shocks such as supply chain disruptions or energy price shocks.

References

Amiti, Mary, Stephen J. Redding, and David E. Weinstein, "The Impact of the 2018 Tariffs on Prices and Welfare," *Journal of Economic Perspectives*, 2019, *33* (4), 187–210.

_ , _ , **and** _ , "Who's Paying for the US Tariffs? A Longer-Term Perspective," *AEA Papers and Proceedings*, May 2020, *110*, 541–46.

Antonova, Anastasiia, Luis Huxel, Mykhailo Matvieiev, and Gernot J. Müller, "The Propagation of Tariff Shocks via Production Networks," CESifo Working Paper Series 11917, CESifo 2025.

Auclert, Adrien, Matthew Rognlie, and Ludwig Straub, "The Macroeconomics of Tariff Shocks," Working Paper 33726, National Bureau of Economic Research April 2025.

Auray, Stéphane, Michael B. Devereux, and Aurélien Eyquem, "Tariffs and Retaliation: A Brief Macroeconomic Analysis," Working Paper 33739, National Bureau of Economic Research, Cambridge, MA 2025.

Bachmann, Ruediger, David Baqaee, Christian Bayer, Moritz Kuhn, Andreas Löschel, Benjamin Moll, Andreas Peichl, Karen Pittel, and Moritz Schularick, "What if? The Economic Effects for Germany of a Stop of Energy Imports from Russia," ECONtribute Policy Brief Series 028, University of Bonn and University of Cologne, Germany 2022.

Baqaee, David Rezza and Emmanuel Farhi, "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem," *Econometrica*, 2019, *87* (4), 1155–1203.

_ **and** _ , "Networks, Barriers, and Trade," *Econometrica*, 2024, *92* (2), 505–541.

Barattieri, Alessandro and Matteo Cacciatore, "Self-Harming Trade Policy? Protectionism and Production Networks," *American Economic Journal: Macroeconomics*, April 2023, *15* (2), 97–128.

_ , _ , **and Nora Traum**, "Estimating the Effects of Government Spending Through the Production Network," Working Paper 31680, National Bureau of Economic Research September

2023.

Benguria, Felipe and Felipe Saffie, "Dissecting the Impact of the 2018-2019 Trade War on U.S. Exports," *SSRN*, 2019.

Bilbiie, Florin Ovidiu and Marc J Melitz, "Aggregate-Demand Amplification of Supply Disruptions: The Entry-Exit Multiplier," Working Paper, University of Cambridge October 2022.

Burgert, Matthias, Benoit Mojon, Daniel Rees, Matthias Rottner, and Hongyan Zhao, "A multi-sector assessment of the macroeconomic effects of tariffs," *BIS Quarterly Review*, 2025.

_ , Giulio Cornelli, Burcu Erik, Benoit Mojon, Daniel Rees, and Matthias Rottner, "The BIS multisector model: a multi-country environment for macroeconomic analysis," BIS Working Papers 1297, Bank for International Settlements 2025.

Cacciatore, Matteo and Giacomo Candian, "Uncertainty through the Production Network: Sectoral Origins and Macroeconomic Implications,," Technical Report, Unpublished Manuscript, HEC Montreal 2025.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 2015, *82* (1 (290)), 1–44.

_ , Luca David Opromolla, Fernando Parro, and Alessandro Sforza, "Goods and Factor Market Integration: A Quantitative Assessment of the EU Enlargement," *Journal of Political Economy*, 2021, *129* (12), 3491–3545.

Carvalho, V. M. and A. Tahbaz-Salehi, ""Production Networks: A Primer"," *Annual Review of Economics*, 2019, *11*, 635–663.

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

Flaaen, Aaron and Justin R. Pierce, “"Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector",” *Review of Economics and Statistics (forthcoming)*, 2025.

Furceri, Davide, Swarnali A Hannan, Jonathan David Ostry, and Andrew K Rose, “Macroeconomic Consequences of Tariffs,” IMF Working Papers 2019/009, International Monetary Fund 2019.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning, “Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?,” *American Economic Review*, May 2022, *112* (5), 1437–74.

Jacquinot, Pascal, Matija Lozej, and Massimiliano Pisani, “Macroeconomic effects of tariffs shocks: The role of the effective lower bound and the labour market,” *Journal of International Money and Finance*, 2022, *120*, 102528.

Jordà, Oscar, “Estimation and Inference of Impulse Responses by Local Projections,” *American Economic Review*, 2005, *95* (1), 161–182.

Kalemli-Ozcan, Şebnem, Cem Soylu, and Mehmet Yildirim, “Global Networks, Monetary Policy and Trade,” Working Paper 33686, National Bureau of Economic Research, Cambridge, MA 2025.

Känzig, Diego R. and Tamar Den Besten, “The Macroeconomic Effects of Tariffs: Evidence From U.S. Historical Data,” December 2025. SSRN Working Paper.

Khalil, Makram and Felix Strobel, “US trade policy and the US dollar,” *Journal of International Economics*, 2024, *151*, 103970.

_ **and Marc-Daniel Weber**, “"Chinese supply chain shocks",” *Deutsche Bundesbank Discussion Paper*, 2022, *44*.

_ **and Vivien Lewis**, “Product turnover and endogenous price flexibility in uncertain times,” CEPR Discussion Paper No. 18941 2024.

Kuitunen, Laura, “The International Transmission of the Fed Information Effects: Evidence from Europe,” *Job Market Paper*, 2026.

Liao, Steven, In Song Kim, Sayumi Miyano, and Feng Zhu, “"concordance: Product Concordance",” *R package version 2.0.0*, 2020.

Lindé, Jesper and Andrea Pescatori, “The macroeconomic effects of trade tariffs: Revisiting the Lerner symmetry result,” *Journal of International Money and Finance*, 2019, *95*, 52–69.

Montiel Olea, José Luis, Mikkel Plagborg-Møller, Eric Qian, and Christian K. Wolf, “Local Projections or VARs? A Primer for Macroeconomists,” *arxiv*, 2025.

Pierce, Justin R. and Peter K. Schott, “"A concordance between ten-digit U.S. Harmonized System codes and SIC/NAICS product classes and industries",” *Board of Governors of the Federal Reserve System (U.S.)*, 2012.

Werning, Iván, Guido Lorenzoni, and Veronica Guerrieri, “Tariffs as Cost-Push Shocks: Implications for Optimal Monetary Policy,” Working Paper 33772, National Bureau of Economic Research May 2025.

Appendix

A Data sources

We start by further describing the data sources and associated measures in Section 2. All data come from publicly available resources.

Import data at the product level — HS classification: The Harmonized System (HS) is an international commodity classification developed by the World Customs Organization (WCO) to classify international trade. The baseline WCO classification extends to six digits (HS6), which is common across countries and revised only by the WCO every five years, generating successive HS versions (2002–HS, 2007–HS, ..., 2022–HS). Countries may further subdivide HS6 categories at their own discretion. In the United States, the International Trade Commission (ITC) maintains a 10-digit extension (HS10). We use data on imports from the US Census Harmonized System at monthly frequency and at the most disaggregated level (HS10): (i) Customs Value in US$ i.e. "The value of goods imported as appraised by U.S. Customs and Border Protection. Excludes freight and duties"; (ii) Calculated duty in US$.[20]

Industrial production: The Federal Reserve System provides Industrial Production (IP) series. These series are identified by IP codes, and related codes of the North American Industry Classification System (NAICS) are also provided. The *related NAICS industries* associated with IP codes have several features worth noting.

First, depending on the level of aggregation of the IP industry, an IP code may be linked to a NAICS code ranging from NAICS3 (more aggregated) to NAICS6 (more disaggregated). For example, the IP series for "Oil and gas extraction" (G211) is linked to NAICS3 code 211, whereas "Crude Oil alone" (G21112) is linked to NAICS6 code 21112. Second, some IP codes are linked only to *part of* a NAICS industry. For example, "Natural gas" (N21113G) and "Natural gas liquid extraction" (G21113PQ) are both associated with the related NAICS code "211130pt.", where pt. stands for *part of*. We exclude these IP codes because the indication *part of*, without any proportion or weight, makes it impossible to allocate data for that NAICS industry across the corresponding IP-labeled industries. Lastly, some IP codes correspond to aggregates of multiple

[20] https://usatrade.census.gov/

NAICS codes. For example, the industry "Hydroelectric, renewables, and other," with IP code G221111A4T8, is linked to "NAICS 221111,4–8," where 4–8 refers to digits 4 to 8. This series therefore aggregates the industrial production of NAICS6 industries 221111, 221114, 221115, 221116, 221117, and 221118. We also exclude these series, since data may be unavailable for some underlying subcodes, and we prefer to base the analysis on simple industry levels rather than on mixes of industries and aggregates.

Producer price index: Monthly producer price indices are produced by the Bureau of Labor Statistics (BLS) covering a broad range of industries, including mining, manufacturing, agriculture, utilities, construction, retail, transportation, and other services.

Input-output tables — BEA classification: The Input-Output (IO) Accounts are released by the Bureau of Economic Analysis (BEA). *Supply tables* report the domestic production of commodities by industry and provide broad import volumes for these commodities. *Use tables* show each industry's use of different commodities as intermediate inputs, including compensation of employees. The BEA uses its own classification, derived from NAICS, to define *both* commodities and industries. A key feature of the IO tables is that industries and commodities are identified by the same codes. We refer to this system simply as the BEA classification. The BEA publishes IO tables annually at the "71 industries × 73 commodities" level and every five years at the "402 industries × 402 commodities" level.

B Concordance between HS, NAICS, and BEA classifications

Matching data from sources that employ different classification schemes requires a number of concordance tasks.

HS10 and 20xx–NAICS6 concordance: We use the Pierce and Schott (2012) concordance between U.S. HS10 codes and NAICS6 codes.[21] Because NAICS codes are revised every five years, the concordance also operates in five-year blocks. As a result, the first stage of processing import data yields a range of NAICS codes from different vintages, including vintages older than 2022, which is the classification used for other series such as IP and PPI. This feature of the

[21] Here, "20xx–NAICS" refers to any NAICS vintage among 2002, 2007, 2012, 2017, or 2022. Concordances are available at: `https://sompks4.github.io/sub_data.html`.

HS10–NAICS6 concordance complicates the construction of consistent customs values and duties series at the 2022–NAICS level over the full sample. To illustrate, consider a code introduced in the 2012 NAICS revision and renamed in the 2017 revision. In the Pierce and Schott (2012) concordance, HS codes are linked to that NAICS code only from January 2013 to December 2017. Accordingly, when HS-level import data are translated into NAICS-level data, imports under that code appear only over that period rather than throughout the full sample. For example, the NAICS6 codes 211120, "Crude Petroleum Extraction," and 211130, "Natural Gas Extraction," were introduced in the 2017 NAICS revision and therefore appear in the import data only from January 2018 onward.

It is also worth noting that, as of early 2026, the latest available HS–NAICS concordance covered codes only through 2021, that is, up to the 2022 NAICS revision.[22] To extend the sample beyond 2021, one possible approach would be to apply the latest Pierce and Schott (2012) concordance to subsequent years and assess the number of unmatched HS codes. However, because our baseline analysis ends in January 2020 to avoid pandemic-related distortions, this limitation is largely immaterial for the baseline results.

20xx–NAICS to 2022–NAICS: After each NAICS revision, the US Census provides concordance tables between old and revised codes that helps tracking changes. The nature of these changes are either a code name revision, a code split or codes merging. For instance, in the 2007 revision the NAICS6 code 111998 "All Other Miscellaneous Crop Farming" is split between NAICS6 111998 "All Other Miscellaneous Crop Farming" and NAICS6 112519 "Other Aquaculture". This example of a splitting code shows that despite the 2002–NAICS6 code 111998 still appearing after the 2007 revision, its underlying composition has nonetheless changed. Utilizing all concordance files provided by the US Census, we provide Stata routines to match any 20xx–NAICS6 code to its 2022 equivalent(s).[23] The emphasis here being on equivalent***s*** as a code can be split in revisions, and we will then associate all subsequent codes to the former. As our analysis is not conducted at such disaggregated level, we also make use of concordances for higher aggregation orders —and in particular NAICS4.

[22] See Prof. Liao's comment under the *concordance* project: https://github.com/insongkim/concordance/issues/20.

[23] See the replication package.

NAICS and BEA industry concordance: Liao et al. (2020) provide a set of utilities for matching products labeled in different international trade classification systems.[24] This includes the concordance between the 2012 edition of the NAICS and BEA industry classifications. Specifically, it matches any 2012–NAICS6 code to one or more of the 412 disaggregated BEA industries (2012 edition). We take their initial concordance as foundation for the work developed of this subsection. Our use case for the NAICS–BEA concordance is twofold. One the one hand, we translate import data identified via NAICS codes to BEA codes, effectively linking imports to the "Commodities" section of the Input-Output tables. This requires NAICS→BEA matches. On the other hand, we concord the "Industry" section from BEA codes to NAICS codes in order to use Producer Prices and Output series. Conversly, this requires BEA→NAICS matches.

We first update the "2012–NAICS6 & 2012–BEA412" concordance to a 2022 version, i.e. "2022–NAICS & 2022–BEA". To do so, we revise both sides of the concordance by translating the NAICS and BEA classifications to their most up to date vintage. Updating the NAICS6 codes from the 2012 edition to the 2022 edition is straightforward using the processed Census concordance files. Going back on the presentation of the BEA classification from Appendix A, we note that the effects of the revisions to the BEA codes between 2012 and 2012 were to collapse the most disaggregated level from 412 industries down to 406 industries.[25] Finally, we obtain an updated "2022–NAICS6 & 2022–BEA406" concordance. However, with the yearly input-output tables only using a more aggregated view —namely the second tier of the BEA classification with 73 codes— the obtained "2022–NAICS6 & 2022–BEA406" concordance needs to go up the BEA classification tiers for our purposes. To that end, we make use of the detailed table from the appendix of the 2018 comprehensive update of the Input-Output tables that reads a complete breakdown of the BEA classification from the 23 sectors down to the most detailed 406 industries.[26] It is then straightforward to obtain from the "2022–NAICS6 & 2022–BEA406" concordance the "2022–NAICS6 & 2022–BEA73" concordances.

However, since trade data over the sample is also denominated in other NAICS vintages, we go a step further and extend the "2022–NAICS6 & 2022–BEA406" concordance to match any NAICS6 code of other versions (2002, 2007, 2012, and 2017), to at least one 2022-BEA406 industry code. For that purpose, we follow a simple twos-step procedure: We first match each 20xx–NAICS6

[24] We are grateful to the authors for making open-source their R package *concordance*

[25] See —with the vintage available as of early 2026— the BEA Input-Output tables at the "Detail" level.

[26] See `https://apps.bea.gov/scb/issues/2018/08-august/pdf/0818-industry-tables.pdf`

code to possibly more than one 2022–NAICS6 using the Stata routines we built from Census files. We then leverage the Liao et al. (2020) NAICS–BEA concordance —updated with 2022–BEA codes— to convert the obtained 2012–NAICS6 code(s) to their 2022–BEA406 equivalent(s). In fine, we also derive "20xx–NAICS6 & 2022–BEA73" concordances by going up the aggregation level of the matched 2022–BEA406 codes.

Lastly, we convert the "Industry" level of the BEA Input-Output tables to NAICS equivalents in order to use Industrial Production and Producer Prices series. To that end, by going up the aggregation level —but this time for the NAICS classification— we derive "20xx–NAICS4 & 2022–BEA73" concordances.

We provide additional details on the output of this procedure.

- In the original work of Liao et al. (2020), the 2012–NAICS6 codes are only effectively matched to 392 out of the 412 different 2012–BEA codes.
  → Thus, not all 412 2012–BEA codes have (at least) one 2012–NAICS6 equivalent. Since the revision of BEA codes from the 2012 to the 2022 edition does not coincidentally solve this issue, then neither will all of the 406 2022-BEA codes.

- Specifically, out of the 406 BEA codes from the 2022 edition, only 389 are matched to a least one 20xx–NAICS6 code.
  → Despite this gap we still refer to any of the obtained concordances as "20xx–NAICS6 & 2022–BEA406".

- Additionally, the 389 matched BEA codes only cover 67 out of the 73 2022–BEA codes from the second tier of the BEA classification.
  → We can already see that bits of the data from the 71×73 Use/Make tables will not be accounted for when translating the BEA industries codes to NAICS4 equivalents.

It is important to mention that the latter concordances are *many-to-many* and not *one-to-many* (neither *one-to-one*); or in other words, one NAICS6 code can be matched to more than one BEA406 code, and vice versa. In this regard, we note that this is mostly a one-way situation as while most BEA codes are matched with more than one NAICS, it is much more limited in the other way.[27] Still, this feature will force us to make assumptions when computing the exposure

[27] Note that this is true for both NAICS6–BEA406 and NAICS4–BEA73 concordances.

measures, particularly during the concordance process of BEA labeled data to NAICS6 done in Appendix C.

C Construction of the input–output exposure measures

The PPIs are widely available at the most disaggregated NAICS6 level. However, this is not necessarily true for the industrial production series where the number of series available at this disaggregated level strongly shrinks. For the consistency of our results, we include in our sample only industries where both output and price series are available. Similarly to Flaaen and Pierce (2025), we conduct our analysis and subsequent regressions, at the four-digit NAICS industry level "Industry Group". The rationale is that it is the most disaggregated level where we manage to keep a consistent sample of industries for both output and price series.

Turning to the exposure measures, since all variables that are used in the definitions outlined in Sections 3.2–3.3 originate from the IO-tables, the industry and commodity levels are given by the BEA classification: 71 industries and 73 commodities. However, as we conduct the analysis at the NAICS4 level we specifically convert the industry dimension. The commodity dimension is kept at the BEA-level. Since we will be interacting the defined exposure measures with tariff changes, we also need to define tariff rates at the BEA commodity level. Hence, we need to convert data following two separate stages:

A. Computing tariff rates at the BEA-commodity level ($\tau_{j=BEA}$) from HS labeled import data

B. Deriving $USE_{i=NAICS,j=BEA}$ from $USE_{i=BEA,j=BEA}$ and $w_{i=NAICS,j=BEA}$ from $w_{i=BEA,j=BEA}$, respectively for the backward and forward exposure measures

A. Computing tariff rates at the BEA commodity level

We implement the following procedure:

1. **Process import data:** Convert import data labeled with the HS10 classification to 20xx-NAICS6 using the Pierce and Schott (2012) concordance by five-year blocks. Collapse matches at the 20xx–NAICS6 level. This step is common to the process of computing NAICS4-level tariff rates.

2. **Harmonize NAICS-level import data:** Convert obtained 20xx–NAICS6 codes to 2022–NAICS6. Recall that in addition to renaming and merging NAICS codes, revisions also include splitting codes. This is an issue for us here. Indeed, while our concordance files allow us to know which codes relate to which, we do not have any indication on how to split the derived 20xx–NAICS6 industry-level values from older to newer codes. In general this work is done by the Federal agencies during episodes of major revisions. For instance, the Bureau of Labour Statistics reconstructs Producer Prices series to reflect the underlying new structure of NAICS industries (which includes, reclassifying historical data and updating weights). In order not to duplicate dollar values, we make a naive assumption: for each 20xx-NAICS6 matched to more than one 2022–NAICS6, **evenly allocate** the considered variable (duty or import value) across 2022 code matches. Finally, we aggregate the resulting 2022–NAICS6 data up to 2022–NAICS4. This step is also common to the process of computing NAICS4-level tariff rates.

3. **Derive BEA-level import data from NAICS:** Convert the obtained 2022–NAICS4 level data to 2022–BEA73. As previously illustrated, a NAICS6 code might be matched to several BEA73 codes. We take the following stance: For each 20xx-NAICS6 where we have data from Step2, we count the number of BEA codes it will be matched with when using the "20xx–NAICS6 & 2022–BEA73 concordance" of Appendix B, and then **evenly allocate** the considered variable (duty or import value) for this NAICS6 between these associated BEA codes.[28] This is the assumption mentioned in the last paragraph of Appendix B, but note that such case is not prevalent. Finally, collapse data at the BEA level. Again we note that this does not mean that all BEA-level commodities will have import data and thus tariff rates. In fact, in our data set we end up with only 21 BEA manufactured commodities, reflecting the large structure of service-based commodities.

B. Input-Output tables with NAICS industry and BEA commodity dimensions

We implement the following procedure:

1. From the Make and Use tables of the BEA, match the industry dimension from BEA73 to NAICS4 using the 2022 concordance". As a vast majority of BEA codes are matched to

[28] The concordance procedures presented earlier make the conversion of all NAICS6 codes possible, but we underline that from the Pierce & Schott concordance of HS10 level data not all NAICS codes have associated import data.

more than one NAICS4 code, we follow the same approach as in the previous procedure: for each BEA industry, we count the number of NAICS codes it is matched with and then **evenly allocate** the considered variable (supply or use of j by i, where i is the dimension being converted) between matches.

2. Collapse the data at the NAICS4 level.

Table C.1: List of NAICS4 industries forming the sample.

PPI series	**IP** series	**BEA** match	NAICS4 industry description
3111	G3111	311FT	Animal food manufacturing
3112	G3112	311FT	Grain and oilseed milling
3113	G3113	311FT	Sugar and confectionery product manufacturing
3114	G3114	311FT	Fruit and vegetable preserving and specialty food manufacturing
3115	G3115	311FT	Dairy product manufacturing
3118	N3118	311FT	Bakeries and tortilla manufacturing
3119	G3119	311FT	Other food manufacturing
3121	G3121	311FT	Beverage manufacturing
3122	G3122	311FT	Tobacco manufacturing
3131	G3131	313TT	Fiber, yarn, and thread mills
3132	G3132	313TT	Fabric mills
3133	G3133	313TT	Textile and fabric finishing mills
3141	G3141	313TT	Textile furnishings mills
3149	G3149	313TT	Other textile product mills
3211	N3211	321	Sawmills and wood preservation
3212	G3212	321	Plywood and engineered wood product manufacturing
3219	G3219	321	Other wood product manufacturing
3221	G3221	322	Pulp, paper and paperboard mills
3222	G3222	322	Converted paper product manufacturing
3251	G3251	325	Basic chemical manufacturing
3252	G3252	325	Resin, synthetic rubber, and artificial, synthetic fiber, filaments manufacturing

Continued on next page

Table C.1: −*continued* **List of NAICS4 industries forming the sample**

PPI series	**IP** series	**BEA** match	NAICS4 industry description
3253	G3253	325	Pesticide, fertilizer, and other agricultural chemical manufacturing
3254	G3254	325	Pharmaceutical and medicine manufacturing
3255	G3255	325	Paint, coating and adhesive manufacturing
3256	G3256	325	Soap, cleaners, and toilet preparation manufacturing
3261	G3261	326	Plastics product manufacturing
3262	G3262	326	Rubber product manufacturing
3271	G3271	327	Clay product and refractory manufacturing
3272	G3272	327	Glass and glass product manufacturing
3273	G3273	327	Cement and concrete product manufacturing
3274	G3274	327	Lime and gypsum product manufacturing
3279	G3279	327	Other nonmetallic mineral products
3311	G3311A2	331	Iron and steel mills and ferroalloy manufacturing
3312	G3311A2	331	Steel product manufacturing from purchased steel
3313	G3313	331	Alumina and aluminum production and processing
3314	G3314	331	Nonferrous (excluding aluminium) production and processing
3315	G3315	331	Foundries
3321	N3321	332	Forging and stamping
3322	N3322	332	Cutlery and handtool manufacturing
3323	N3323	332	Architectural and structural metals manufacturing
3325	G3325	332	Hardware manufacturing
3326	N3326	332	Spring and wire product manufacturing

Continued on next page

Table C.1: –*continued* **List of NAICS4 industries forming the sample**

PPI series	**IP** series	**BEA** match	NAICS4 industry description
3327	G3327	332	Mach shops, turn prod, screw, nut, bolt manufacturing
3329	G3329	332	Other fabricated metal product manufacturing
3331	G3331	333	Agricultural, construction, and mining machinery manufacturing
3332	G3332	333	Industrial machinery manufacturing
3333	G3333A9	333	Commercial and service industry machinery manufacturing
3334	G3334	333	HVAC and commercial refrigeration equipment
3335	G3335	333	Metalworking machinery manufacturing
3336	G3336	333	Turbine and power transmission equipment manufacturing
3339	G3333A9	333	Other general purpose machinery manufacturing
3341	G3341	334	Computer and peripheral equipment manufacturing
3342	G3342	334	Communications equipment manufacturing
3343	G3343	334	Audio and video equipment manufacturing
3344	G3344	334	Semiconductor and other electronic component manufacturing
3345	G3345	334	Navigation, measuring, medical, control instruments manufacturing
3351	G3351	335	Electric lighting equipment manufacturing
3352	G3352	335	Household appliance manufacturing
3353	G3353	335	Electrical equipment manufacturing
3359	G3359	335	Other electrical equipment and component manufacturing
3361	G3361	3361MV	Motor vehicle manufacturing
3362	G3362	3361MV	Motor vehicle body and trailer manufacturing
3363	G3363	3361MV	Motor vehicle parts manufacturing

Continued on next page

Table C.1: −*continued* **List of NAICS4 industries forming the sample**

PPI series	**IP** series	**BEA** match	NAICS4 industry description
3364	G3364	3364OT	Aerospace product and parts manufacturing
3365	N3365	3364OT	Railroad rolling stock manufacturing
3366	G3366	3364OT	Ship and boat building
3369	N3369	3364OT	Other transportation equipment manufacturing
3371	N3371	337	Household and institutional furniture and kitchen cabinet manufacturing
3372	G3372A9	337	Office furniture (including fixtures) manufacturing
3379	G3372A9	337	Other furniture related product manufacturing
3391	N3391	339	Medical equipment and supplies manufacturing

Notes: PPI and IP series are matched based on NAICS4 coverage.

Table C.2: List BEA commodities included in the tariff shocks

BEA commodity	Description
111CA	Farms
113FF	Forestry, fishing, and related activities
311FT	Food and beverage and tobacco products
313TT	Textile mills and textile product mills
315AL	Apparel and leather and allied products
321	Wood products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
327	Nonmetallic mineral products
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
3361MV	Motor vehicles, bodies and trailers, and parts
3364OT	Other transportation equipment
337	Furniture and related products
339	Miscellaneous manufacturing

D Testing for anticipation effects

In our baseline analysis, we construct tariff shock measures based on realized changes of tariff rates. This may raise the concern that anticipation effects distort our results. Tariffs are typically announced in advance, giving firms time to adjust their imports, production and prices before tariffs take effect. Here, we extend our baseline analysis to evaluate industry-specific production and price effects not only after tariff changes, but also in preceding months.

The following specification is independently estimated for each horizon $h = -6, -5, \ldots, -1, 0, 1, \ldots, 14$ via ordinary least squares:

$$\begin{aligned} \mathcal{Y}_{i,t+h} = \alpha^{(h)} &+ \underbrace{\mu^{(h)} \Delta T_{i,t}}_{\substack{\text{Horizontal}\\ \text{channel}}} + \underbrace{\beta^{(h)}\, \mathbf{BW}_{i,y} \times \Delta \mathcal{T}^{Input}_{i,t}}_{\text{Input channel}} + \underbrace{\gamma^{(h)}\, \mathbf{FW}_{i,y} \times \Delta \mathcal{T}^{Output}_{i,t}}_{\text{Output channel}} \\ &+ \rho_1^{(h)} \mathbf{FW}_{i,y} + \rho_2^{(h)} \mathbf{BW}_{i,y} + \sum_{j=1}^{14} \boldsymbol{\theta}^{(h,j)\prime} \mathcal{Z}^{(h)}_{i,t-j} + f_i + \delta_t + \varepsilon^{(h)}_{i,t+h}, \end{aligned} \tag{D.1}$$

where the lag controls are defined as

$$\mathcal{Z}^{(h)}_{i,t-j} = \begin{cases} \mathcal{Z}_{i,t-j}, & \text{if } h \geq 0, \\ \mathcal{Z}_{i,t+h-j}, & \text{if } h < 0. \end{cases} \tag{D.2}$$

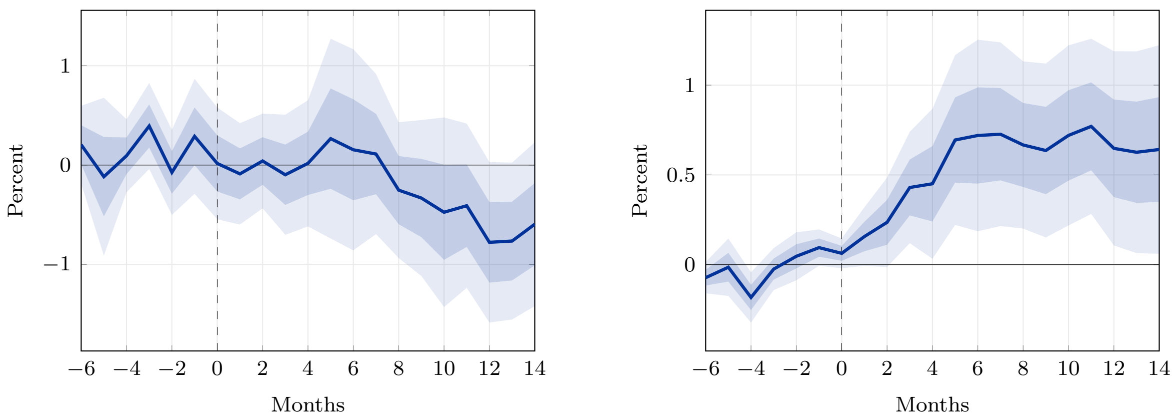
For the regressions for horizons $h < 0$, the dependent variable is $\mathcal{Y}_{i,t+h}$, that is, the outcome observed before the shock at time t. To avoid mechanically controlling for the dependent variable itself, the autoregressive controls are shifted back accordingly: instead of including the standard lags $\mathcal{Y}_{i,t-1}, \mathcal{Y}_{i,t-2}, \ldots,$ the specification includes only lags that are earlier than $\mathcal{Y}_{i,t+h}$. Thus, for a horizon such as $h = -3$, the regression explains $\mathcal{Y}_{i,t-3}$ using the shock dated at t, while controlling only for outcomes dated prior to $t-3$. This ensures that the negative-horizon coefficients provide a valid diagnostic for anticipation, while the nonnegative horizons retain the standard local-projection interpretation as post-shock dynamic responses.

Figures D.8 and D.9 show that, though there is some moderate movement of prices and production before industries are hit by tariffs via their backward exposure to tariffs on their inputs or via their forward exposure to tariffs that hit their customers, they are at a markedly lower amplitude than the changes in prices and production after tariffs become effective.

Figure D.10 shows that the same holds for industrial production in the case of direct tariff shocks on an industry. The exception is the price reaction of industries to direct tax shocks. In that case, prices start to increase two months before the tariff become effective. This implies that to some degree, firms can anticipate the coming of tariffs and adjust their prices in a forward-looking manner, when their own industry is directly affected. However our results imply that adjusting prices in a forward-looking manner may be more difficult for firms when they are not directly affected but indirectly via their backward and forward linkages in the production network.

Figure D.8: The role of exposure to imported intermediates in the transmission of tariff shocks

(a) Industrial Production **(b)** Producer Prices

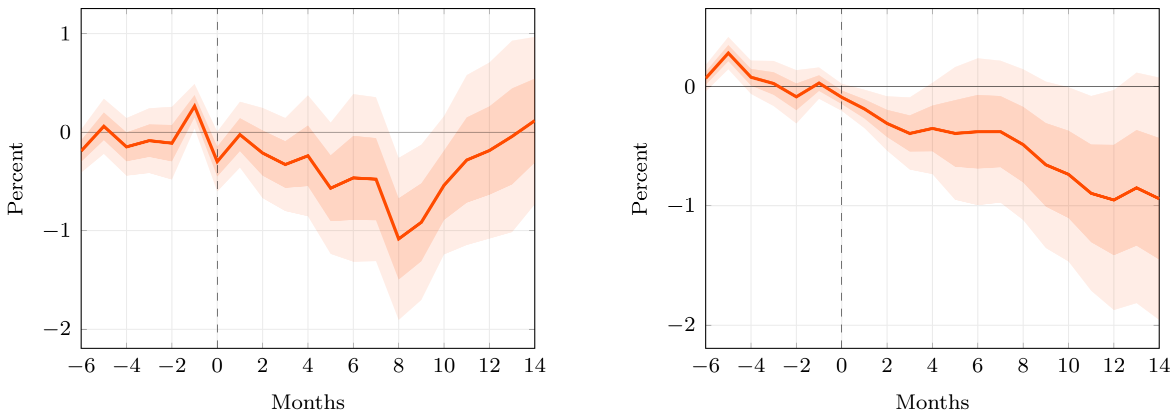


Notes: Cumulative response to a one percentage point local input tariff shock for the average industry. In scaling the effect, we set the aggregate backward linkage to 0.129 to match the average 2017 supply-chain state. The figure reports horizons from -6 to 14; negative horizons are pre-shock placebo coefficients. Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

Figure D.9: The role of forward exposure to sectors that face higher tariffs

(a) Industrial Production

(b) Producer Prices

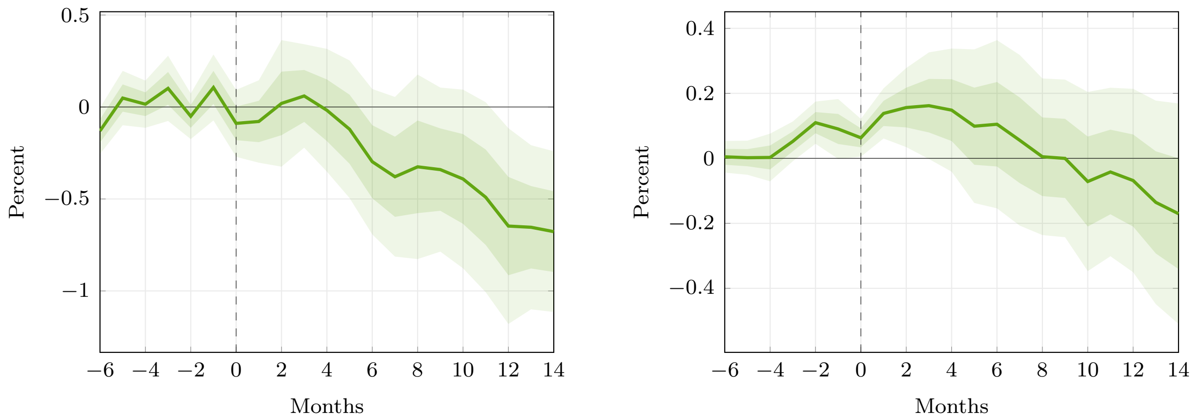


Notes: Cumulative response to a one percentage point local output tariff shock for the average industry. In scaling the effect, we set the aggregate forward linkage to 0.081 to match the average 2017 supply-chain state. The figure reports horizons from -6 to 14; negative horizons are pre-shock placebo coefficients. Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

Figure D.10: The effects of direct tariff shocks

(a) Industrial Production

(b) Producer Prices



Notes: Cumulative response to a one percentage point local direct tariff shock for the average industry. The figure reports horizons from -6 to 14; negative horizons are pre-shock placebo coefficients. Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

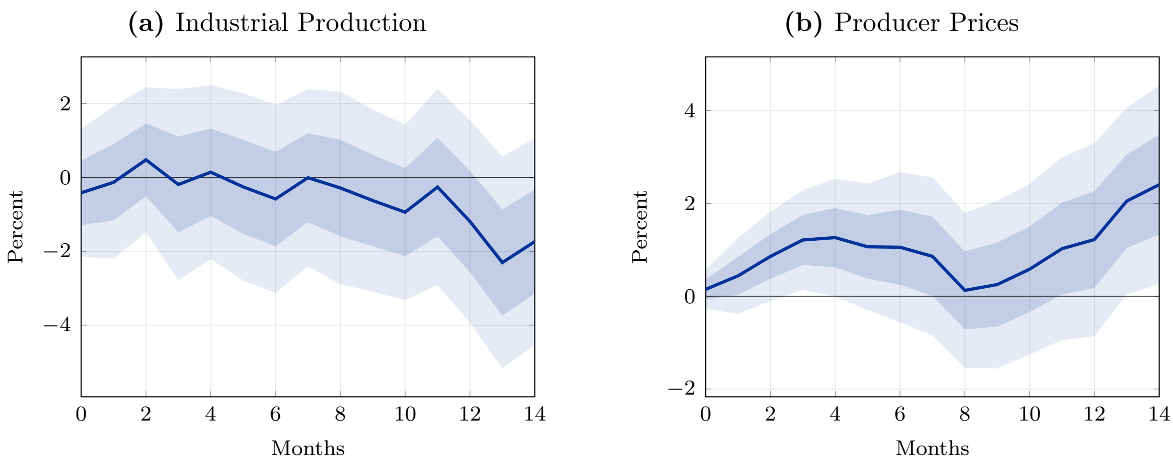
E Omitting the US-China trade war of 2018/2019

The 2018/2019 trade war between the US and China accounts for by far the largest tariff shocks in our sample. To understand the role of the trade war for our main results, we omit this episode from our sample, and cutoff the sample in December 2017.

Figures E.11 and E.12 show that the effects of tariff shocks via the input and via the output channel remain qualitatively similar, when we omit the US-Chinese trade war of President Trumps first term. We find that, in that sample, via the channel of backward exposure to imported inputs, tariff increases tend to lower production and raise producer prices in the affected industry. However, the effect on production is insignificant for the first year after the shock. Thereafter the negative effects are outside the 68% confidence interval. Also similar to our baseline result in the full sample, we find that industries whose customers are hit by tariff shocks suffer from a decline in demand with production and prices decreasing after the shock.

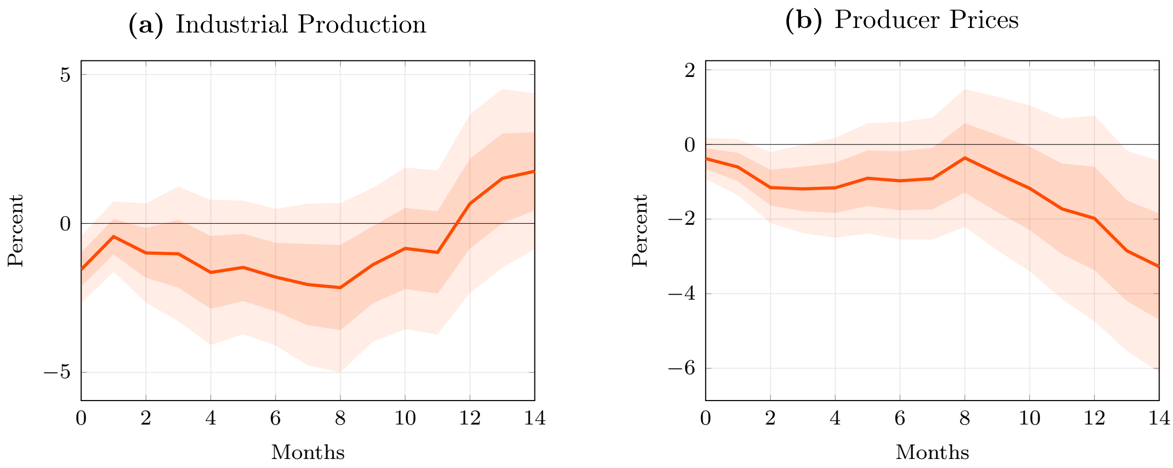
Thus, while the 2018/2019 trade war plays in important role in shaping our baseline results, the results also survive qualitatively, when we omit the trade war.

Figure E.11: The transmission of tariff shocks via the input channel in a sample that ends in 2017



Notes: Cumulative response to a one percentage point local input tariff shock for the average industry. In scaling the effect, we set the aggregate backward linkage to 0.129 to match the average 2017 supply-chain state. Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Dec.2017.

Figure E.12: The role of forward exposure to sectors that face higher tariffs in a sample that ends in 2017



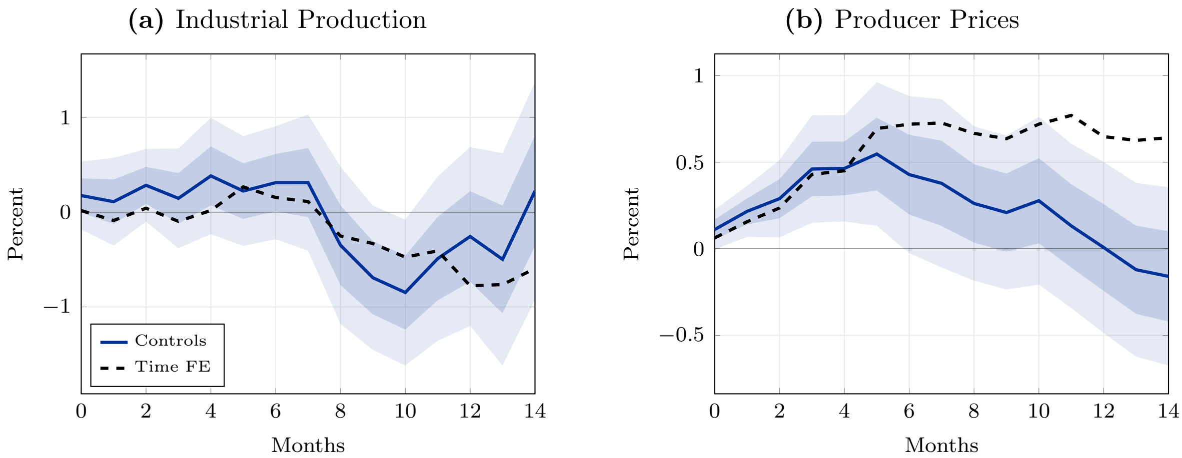
Notes: Cumulative response to a one percentage point local output tariff shock for the average industry. In scaling the effect, we set the aggregate forward linkage to 0.081 to match the average 2017 supply-chain state . Shaded areas show the 68% and 95% confidence bands using Driscoll-Kraay standard errors. Sample: 71 NAICS4 industries, Jan.2004–Dec.2017.

F Controls instead of time fixed effects

We replace time fixed effects in the baseline LP (4) with an additional set of controls comprised of lags 0–14 of:

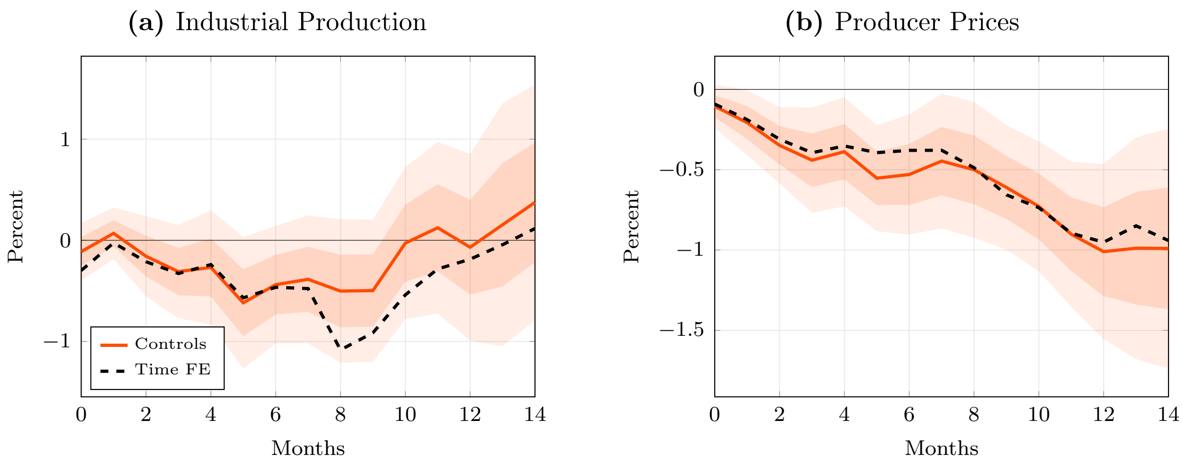
- Real GDP (in log)
- Federal Funds (effective) Rate
- Effective USD exchange rate (Wall Street Journal Dollar Index)
- S&P Goldman Sachs Brent Crude Index
- 10-year US government bond yields

Figure F.13: The role of exposure to imported intermediates in the transmission of tariff shocks



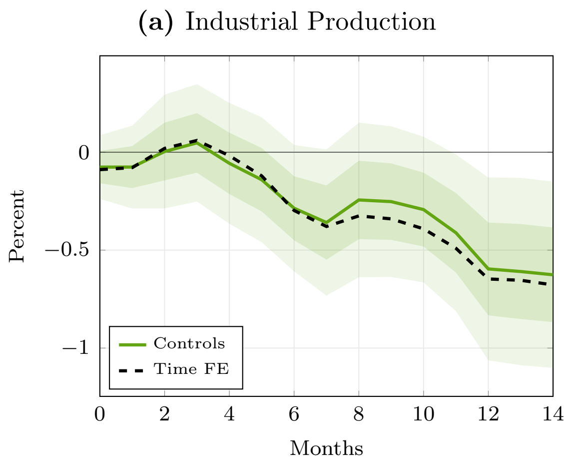
Notes: Cumulative response to a one percentage point local input tariff shock for the average industry. In scaling the effect, we set the aggregate backward linkage to 0.129 to match the average 2017 supply-chain state. Shaded areas show the 68% and 95% confidence bands using NAICS4 clustered standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

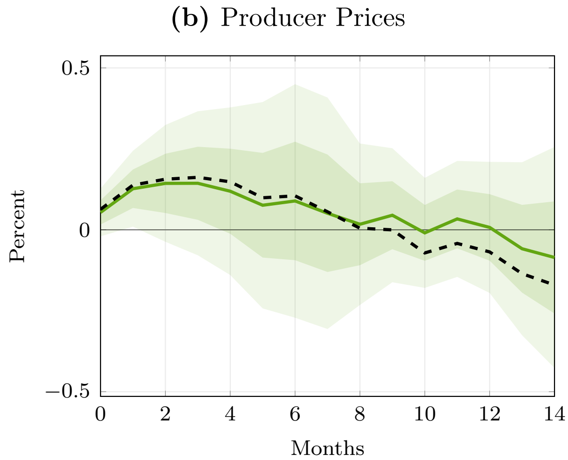
Figure F.14: The role of forward exposure to sectors that face higher tariffs



Notes: Cumulative response to a one percentage point local output tariff shock for the average industry. In scaling the effect, we set the aggregate forward linkage to 0.081 to match the average 2017 supply-chain state. Shaded areas show the 68% and 95% confidence bands using NAICS4 clustered standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

Figure F.15: The effects of direct tariff shocks





Notes: Cumulative response to a one percentage point local direct tariff shock for the average industry. Shaded areas show the 68% and 95% confidence bands using NAICS4 clustered standard errors. Sample: 71 NAICS4 industries, Jan.2004–Jan.2020.

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Makram Khalil
European Central Bank, Frankfurt am Main, Germany; Deutsche Bundesbank, Frankfurt am Main, Germany;
email: makram.khalil@bundesbank.de

Pierre M. Rouillard
European Central Bank, Frankfurt am Main, Germany; email: prd1@proton.me

Felix Strobel
Deutsche Bundesbank, Frankfurt am Main, Germany; email: felix.strobel@bundesbank.de

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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