The Remains of the Trade: The U.S.–China Trade War and its Aftermath*

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Abstract

We study how the U.S.–China trade war has reshaped global trade patterns, creating significant spillovers to third countries. Using recent tariff policy changes and monthly international trade flow data, we document a redirection of Chinese exports away from the U.S. market and toward third countries. To interpret the impact of these reallocations on third countries, we introduce a taxonomy that separates four exposure margins – export competition, import competition, consumer gains, and sourcing gains – and construct theoretically-derived indices that map countries into these channels. Recent work often proxies such exposure with trade-basket similarity. We show why this can be problematic: similarity measures are symmetric and omit the size of product-specific shocks, Chinese market penetration, substitution elasticities, and incidence weights. Our model-based indices therefore generate country rankings that differ substantially from conventional similarity measures.

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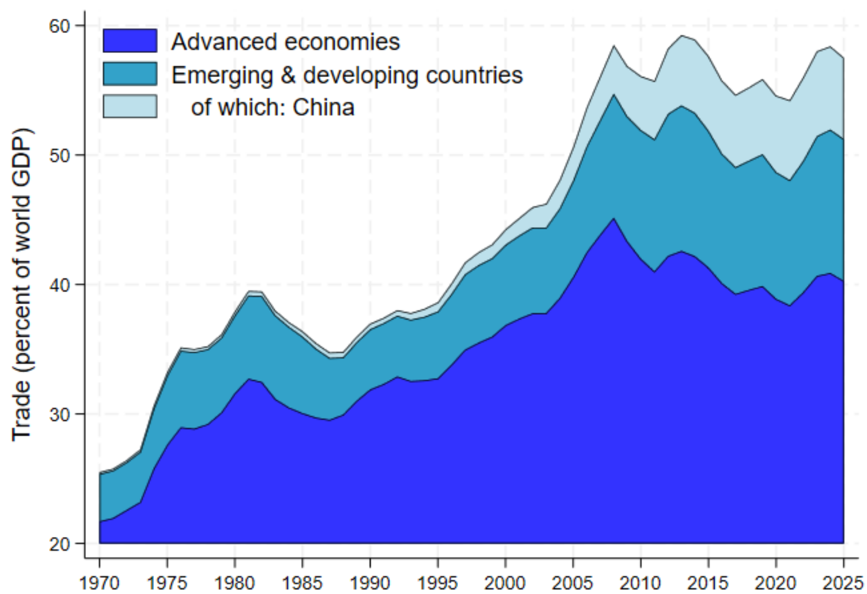
1 Introduction

Talk of 'deglobalization' has become a fixture of policy debates since the mid-2010s, and it has intensified in the wake of the U.S.–China trade war and the COVID-19 shock. Yet, as many authors have emphasized (Antràs, 2021; Goldberg and Reed, 2023), there is little systematic evidence that, at the global level, international trade has become a declining share of world consumption or income. Figure 1 plots the ratio of world trade (exports plus imports) over world GDP in the period 1970-2025. It is true that after having grown enormously during the late 1980s, 1990s and early 2000s, this ratio has remained flat since the Great Financial Crisis (GFC). Nevertheless, the world is not deglobalizing; it has just ceased to globalize *more*.

Figure 1: World Trade Over World GDP (1970-2025)

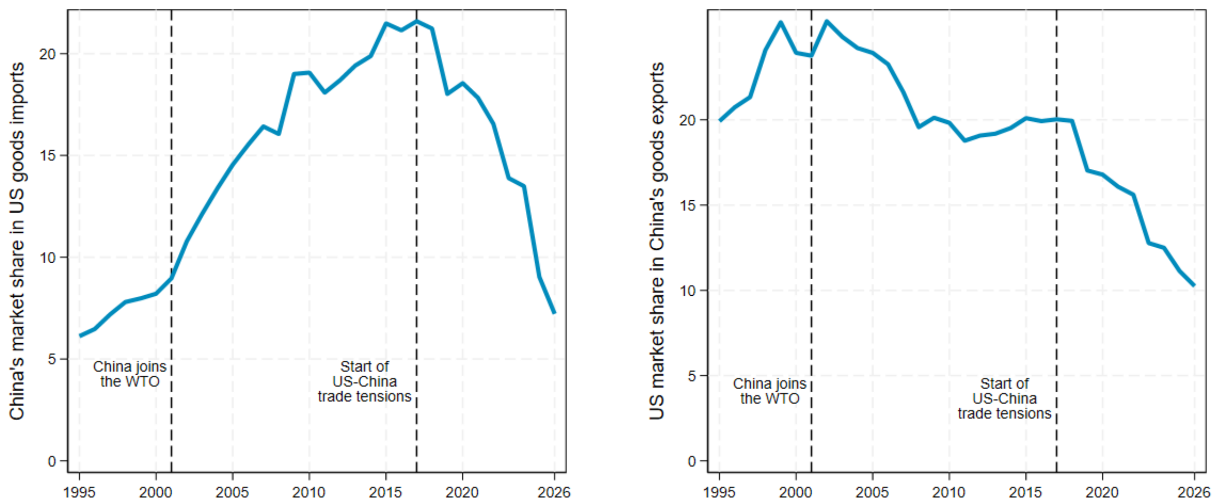


Notes: The figure plots world trade as a percentage of GDP for the period 1970-2025. It decomposes world trade between advanced economies, China, and emerging and developing countries (ex. China). For each region, trade is scaled by world GDP and taken as a backward-looking 3-year moving average.
Sources: World Bank's World Development Indicators.

At the same time, the recent stability in the world trade-to-GDP ratio masks a notable reshuffling of cross-border linkages. As Figure 1 shows, the contribution of advanced economies to global trade has declined since the GFC, while emerging and developing countries, particularly China, have assumed a larger role. Even more notably, direct trade flows between the U.S. and China have tumbled in recent years. As illustrated in the left panel of Figure 2, the share of U.S. imports accounted for by China has fallen drastically from 22% in 2017 to about 8%

in 2026, a level not recorded since China entered the WTO in 2001. Similarly, China's share of exports destined to the U.S. market has fallen from around 20% in 2017 to about 10% in 2026. Given the sheer size of Chinese exports ($3.77 trillion in 2025), this entails a redirection of Chinese exports from the U.S. market to other markets comparable in size to the GDP of certain high-income economies such as Chile, Portugal or Greece.

Figure 2: U.S.–China Decoupling



(a) China's market share in U.S. imports **(b)** U.S. market share in China's exports

Notes: Panel (a) plots the share of total U.S. goods imports from China, from the U.S. Census Bureau. Panel (b) plots the share of China's total goods exports to the U.S. The series is from the CEPII-BACI dataset until 2024 and from TDM for 2025 and 2026. For both panels, data for 2026 refer to January and February.

Sources: U.S. Census Bureau, CEPII-BACI dataset (Gaulier and Zignago, 2010), and Trade Data Monitor (TDM).

Seen in this light, the key question raised by recent events is not whether globalization is ending, but how trade and production relationships are being reorganized across countries, regions and geopolitical blocs, especially since the onset of the U.S.–China trade war. The defining feature of the post-2018 period is not an indiscriminate retreat from trade, but a 'Great Reallocation' (Alfaro and Chor, 2023) of trade flows across partners and products. Much as in Kazuo Ishiguro's *The Remains of the Day*, the drama here lies less in rupture than in reorganization: continuity in the aggregate, but a profound reshuffling in who trades what with whom, and on what terms.

In this paper, we make four contributions that speak to this post-2018 reorganization. First, we offer a new assessment of the U.S.–China trade war, shedding light on how it has evolved in recent months, especially since April 2, 2025, a date referred to as "Liberation Day," when the United States announced higher tariffs on a broad set of trading partners. Drawing on up-to-date tariff information and monthly trade data, we document the latest changes in trade policy and the associated reallocation of Chinese exports away from the United States and toward third countries.

Second, we provide a unified taxonomy of the principal channels through which this reallocation affects third countries. We distinguish competition faced by a country's exporters in foreign markets, competition faced by its domestic producers, gains accruing to consumers from cheaper consumer-good imports, and gains accruing to firms from cheaper intermediate inputs. These channels depend on different economic objects and therefore need not identify the same countries or products as being most exposed.

Third, we show why commonly-used export- and import-similarity indices can provide a misleading guide to the incidence of a Chinese export shock. Such indices are useful descriptions of trade-basket resemblance, but they are not derived from the response of quantities, revenues, or welfare to a supply shock. Instead, we derive theory-consistent alternatives and show that the resulting country exposures differ markedly from those generated by similarity alone.

Finally, rather than treating our theoretically-motivated indices of exposure as black-box summary statistics, we decompose them into their constituent parts. More specifically, we show how each index combines a product-level change in Chinese export prices with the country-specific incidence of that change across destinations, sectors, and input-output linkages.

Although our empirical application derives the product-level price change from the U.S.–China tariff conflict, this separation between the underlying shock and its incidence makes the framework more general. The same country-specific weights could be combined with product-level price or supply shocks generated by other forces, such as Chinese industrial policy, productivity growth, exchange-rate movements, or changes in Chinese domestic demand. In such applications, the set of exposed economies need not be restricted to countries caught in the middle of the U.S.–China conflict.

Our starting point is the influential work of Alfaro and Chor (2023) documenting systematic changes in U.S. sourcing patterns in recent years, involving a reduction in direct exposure to China and rising shares for alternative suppliers. In section 2, we document some novel aspects of this reallocation with a specific focus on the implications of the U.S.–China trade war in terms of (i) a reallocation of U.S. import sources; (ii) a reorientation of Chinese export destinations; and (iii) broader shifts in global trade patterns. Our analysis also shows that the pace of reallocation has accelerated since the beginning of the second Trump administration and especially since Liberation Day, arguably because that day's announcements were interpreted as a permanent shock to the U.S.–China trade relationship. Conversely, we find less evidence that other countries facing higher tariffs after Liberation Day saw their exports to the U.S. significantly reduced, likely because those other tariffs were surrounded by reversals and uncertainty. The sharp reduction of Chinese exports to the U.S. was mirrored by sizable increases in Chinese exports to other markets, which generated an intensification of competitive pressures in third markets where China and other exporters compete head-to-head.

Section 3 turns to a more systematic empirical exploration of the implications of the U.S.–China trade war for the countries 'caught in the middle'. We develop a practical taxonomy to measure third-country exposure to U.S.–China decoupling along four (non-mutually-exclusive) channels: (i) *export competition*, whereby China redirects sales from the U.S. toward third destinations and erodes other exporters' market shares; (ii) *import competition*, whereby redirected Chinese goods raise import penetration and competitive pressure in domestic markets; (iii) *consumer gains*, whereby cheaper imported goods from China reduce prices for consumers in destination markets; and (iv) *sourcing gains*, whereby cheaper Chinese intermediates reduce input costs and strengthen downstream competitiveness.

We operationalize these four channels with transparent, theoretically-grounded exposure indices and compare them with conventional export- and import-similarity measures (cf. Finger and Kreinin, 1979). Similarity indices provide useful descriptions of trade-basket resemblance, but they are not derived from the response of quantities, revenues, or welfare to a supply shock. In particular, they are symmetric, assign no role to the magnitude of the product-specific Chinese shock, and omit Chinese market penetration, substitution elasticities, and the expenditure, production, and input-output weights that govern incidence. Our theory-consistent indices incorporate these objects and produce materially different assessments of country exposure: the cross- country correlation between export similarity and export competition is only 0.493, while that between import similarity and import competition is actually negative, but relatively weak.

The implied magnitudes of our exposure indices are also economically meaningful. For several of the world's twenty largest economies, the export-competition index predicts export declines of between 0.4 and 0.9 percent; among the most exposed economies, the import competition index implies declines in domestic sales of more than 3 percent, while consumer and sourcing gains exceed one percent for some countries. Because these channels are not mutually exclusive, our framework allows countries to be exposed along several margins simultaneously, thereby replacing a single notion of 'exposure' with a multidimensional characterization of how U.S.–China decoupling is likely to affect each economy.

Finally, in section 4, we open the black box of our exposure indices by examining both the common product-level shock and the country-specific weights that govern its incidence. We first compare a transparent measure of Chinese exporters' initial dependence on the U.S. market with the model-implied decline in Chinese f.o.b. prices, and assess whether the products identified as more exposed exhibit the reallocation predicted by the model. Products initially more dependent on the U.S. market subsequently experienced faster growth in Chinese exports to non-U.S. destinations and sharper contractions in Chinese exports to the United States. We then decompose each country-level index into its product-level contributions, identifying the sectors responsible for measured exposure and showing whether that exposure is broad-based or concentrated in a small number of products. These exercises clarify how the same Chinese supply shock can translate, through different country-specific incidence weights, into export losses, domestic import competition, consumer gains, or sourcing gains.

Our paper relates to several strands of work. First, it speaks to the debate on 'deglobalization' and geoeconomic fragmentation, which emphasizes that global integration has not reversed uniformly but is increasingly shaped by security concerns and policy-driven shifts in the organization of trade (Antràs, 2021; Goldberg and Reed, 2023; Aiyar et al., eds, 2023). Second, it connects to the evidence on the 'great reallocation' in U.S. sourcing and global supply chains following the U.S.–China tariff war (Alfaro and Chor, 2023, 2026), including work highlighting reallocation, rerouting, and 'exports in disguise' through third countries (Fajgelbaum et al., 2024; Iyoha et al., 2025; Gopinath et al., 2025; Schulze and Xin, 2025). Third, it complements quantitative assessments of the incidence and welfare consequences of recent U.S. tariff actions and retaliation (Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021; Flaaen et al., 2020), and uses up-to-date tariff information to situate the post-2018 policy regime (Bown, 2025).

Closer to the main policy focus of our paper, a growing number of academic and policy analyses examine the spillovers generated by China's recent export expansion (Beltran et al., 2026; Copestake et al., 2026). This expansion predates the 2025 U.S. tariffs and continues a broader trend associated with a weak exchange rate, industrial policy, and subdued Chinese domestic demand. The latter is consistent with the "vent for surplus" mechanism emphasized by Almunia et al. (2021). Nevertheless, the scale of the April 2025 U.S. tariff changes created the potential for an additional reallocation of Chinese exports across destinations.[1]

A prominent approach to assessing which countries are vulnerable to China's export expansion relies on the similarity or overlap between their trade baskets and China's. For instance, de Soyres et al. (2026) explicitly calculate the Finger–Kreinin export similarity index and document a growing resemblance between China's export basket and those of advanced economies, particularly the Euro area. ECB staff similarly use the Finger–Kreinin index to examine which exporters were positioned to replace Chinese products in the U.S. market after the first round of tariffs (Gunnella et al., 2025), while Allione et al. (2025) and Aprigliano et al. (2026) document increasing export similarity between China and the major Euro-area economies.[2]

[1] While Emlinger et al. (2026) find little robust evidence of substantial trade deflection toward Europe through October 2025, extending the sample through December shows that diversion toward Europe was concentrated in a relatively small tail of highly exposed products, while a larger share of redirected Chinese exports appears to have been absorbed by emerging and developing economies (Schulte et al., 2026).

[2] Other contributions use related, though not identical, measures of trade overlap. Evenett and Legge (2025), for instance, calculate the share of each country's exports falling within China's largest 25 or 100 export product categories and interpret this overlap as an indicator of competitive exposure. Although their statistic is not the Finger–Kreinin index, it embodies a similar empirical logic: a country is treated as more exposed when

A complementary strand studies realized competition rather than inferring exposure from aggregate trade-basket resemblance. Chinese competition can constrain exports in third markets (Chowdhry et al., 2026), while simultaneously putting pressure on domestic producers, with developing economies particularly exposed to these effects (Chatterjee and Subramanian, 2026). At the same time, cheaper Chinese goods may benefit consumers and importing firms. Focusing on the euro area, Aprigliano et al. (2026) document the disinflationary effect of Chinese competition, alongside adverse effects on euro area producers, which reduce investment and lose market share abroad.

Taken together, this literature establishes both the growing importance of Chinese export competition and the appeal of trade-basket overlap as a simple diagnostic of vulnerability. One of the contributions of our paper is to show that similarity and economic exposure are not the same object. Similarity measures do not condition on the magnitude of the product-specific Chinese shock, the destinations in which competition occurs, China's penetration of those markets, substitution elasticities, or the expenditure, production, and input-output weights that govern incidence. Moreover, similarity alone cannot distinguish losses to exporters and domestic producers from gains to consumers and downstream firms. Our model-based indices isolate these channels and make explicit the economic weights required to translate a Chinese supply shock into country-level exposure.

The remainder of the paper is organized as follows. Section 2 documents the key empirical patterns of the Great Reallocation associated with U.S.–China decoupling. Section 3 proposes a taxonomy to characterize third-country spillovers. Section 4 opens the black box of the indices: it examines the product-level shock underlying the model, tests whether that shock predicts the observed reallocation of Chinese exports across destinations, and decomposes each country-level index into its principal product contributions. Section 5 concludes.

2 The U.S.–China Trade War and the Great Reallocation

The U.S.–China trade war has been one of the most significant economic events in recent times. Early U.S. trade actions included Section 201 safeguard tariffs on solar products and washing machines and Section 232 tariffs on steel and aluminum, but the dispute quickly broadened into large-scale, China-specific Section 301 tariffs. Over 2018–19, successive Section 301 rounds expanded from targeted product lists to cover most bilateral trade, pushing the trade-weighted average U.S. tariff on imports from China from a low pre-war baseline into double digits (see Figure 3, based on Bown, 2025). China followed suit and retaliated in a commensurate manner. The January 2020 "Phase One" agreement halted further escalation and reduced some tariff

a larger share of its export basket coincides with products in which China is a major exporter.

rates, but most duties remained in place and bilateral trade barriers stayed far above pre-2018 levels, with a trade-weighted average of roughly 20% in both countries.

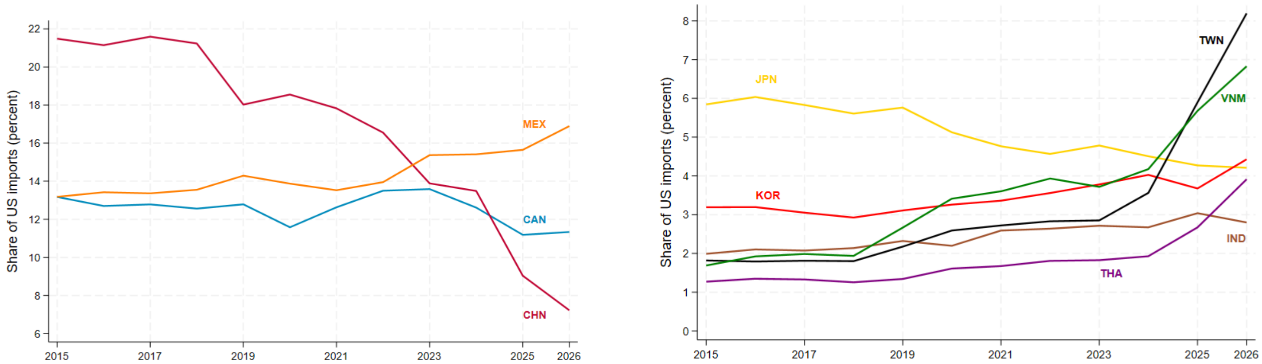
Figure 3: The U.S.–China Trade War: Trade-Weighted Average Tariffs 2016-2025

Notes: The series plot trade-weighted average applied tariffs. The solid blue line is the U.S. tariff on imports from China; the dashed red line is China's tariff on imports from the United States. The PIIE series begins in 2018; 2016-2017 are shown as a flat extension at the January 2018 level for display. The series excludes antidumping/countervailing duties.
Source: Bown (2025).

From 2021 through 2024, this tariff structure was largely maintained with only selective and sector-specific adjustments. In 2025, however, the conflict entered a much more volatile phase. A new wave of tariff actions associated with April 2, 2025 "Liberation Day" tariffs and related executive orders pushed effective tariff rates sharply higher (including brief peaks at triple-digit levels) before partial rollbacks, as seen in Figure 3 (Bown, 2025). On May 12, 2025, a joint U.S.–China statement issued after talks in Geneva committed the United States to remove many of the duties imposed in early April, but as of November of 2025, the trade-weighted average U.S. tariff on imports from China remained at 47.5% (see Figure 3, and Bown, 2025).[3] The scale and framing of the 2025 escalation were widely read as evidence that the U.S.–China relationship is being redefined on geopolitical grounds, making the shock appear long-lasting (or even permanent) rather than transitory. With that interpretation in mind, we now document how international trade flows have adjusted.

[3] The ratio of *collected* customs duties to U.S. imports from China has settled at a slightly lower level of around 40%, as reported by Mike Waugh's "Trade War Tracker" https://www.tradewartracker.com/.

Figure 4: The Great Reallocation: U.S. import shares (2015-2026)



(a) U.S. import shares for large exporters

(b) U.S. import shares for some smaller exporters

Notes: Shares are calculated as each partner's goods imports divided by total for all economies. Partner shares computed for China, Mexico, Canada, Japan, Vietnam, Taiwan Province of China, South Korea, India, and Thailand. Data for 2026 refer to the period January-April.

Sources: U.S. Census Bureau (`https://www.census.gov/foreign-trade/balance/index.html`).

The Great Reallocation

Against that backdrop, the central adjustment has been a reorganization of trade relationships – a 'Great Reallocation' of U.S. sourcing patterns – with broader implications for third countries. Figure 4 summarizes the evolution of U.S. import market shares across major partners from 2015 through April 2026 (the most recent month for which data is available). The dominant fact is an initially gradual but recently more pronounced decline in China's share. Overall, the Chinese share in U.S. imports fell from around 22 percent in 2017 to around 8 percent in 2026. This decline was mirrored by gains for a set of alternative suppliers, most prominently Vietnam, Mexico and Taiwan. Importantly, the timing of these gains is uneven: Vietnam's rise is relatively gradual, whereas Taiwan, Thailand and Mexico's gains are much more concentrated in the later years of the reallocation (2024–2026).

Much has been written about the slow initial decline in U.S. imports from China. The COVID-19 pandemic was certainly a contributor: although imports fell at the onset of the pandemic, they surged back within months as consumers shifted toward goods and e-commerce, helping propel a strong rebound in U.S. goods imports from China. Another key reason why the early tariff shock did not immediately translate into a one-for-one collapse of Chinese exports to the United States is that supply chains feature meaningful adjustment frictions. Antràs (2021) emphasized the importance of sunk costs in generating hysteresis in importing given the large policy uncertainty in the early 2020s, while Alfaro and Chor (2026) have recently shown that the reallocation away from China was slower in contract-intensive and relationship-sticky goods. In Appendix B.2, we provide evidence for a novel channel contributing to the gradual nature of the U.S.–China decoupling. More specifically, building on a measure of the duration of production developed by Antràs and Tubdenov (2025) – the so-called average period of production or $\mathcal{APP}$ – we show that reallocation of Chinese exports away from the U.S. was faster in products with a shorter $\mathcal{APP}$, while products with longer production cycles adjusted more slowly.

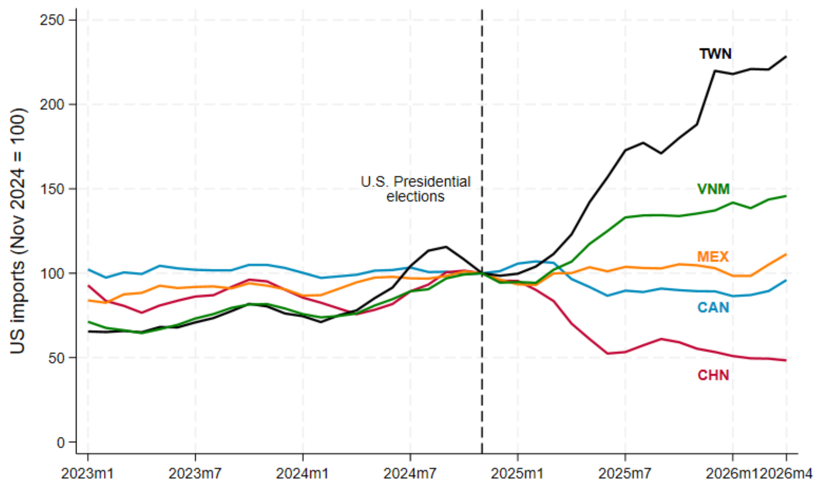
Trump 2.0 and Liberation Day

Returning to the more drastic reallocation observed since the start of President Trump's second administration, Figure 5 uses monthly data to zoom in on the impact on U.S. imports for selected trading partners during 2025. The figure illustrates the remarkable drop in U.S. imports from China coupled with a reallocation of those import flows to Taiwan, Vietnam and to a lesser extent Mexico. Imports from Canada fell during this period. Interestingly, Taiwan and Vietnam recorded strong growth in their exports to the U.S. despite facing announced Liberation Day tariff rates of 32 and 46 percent, respectively. Comparisons with Mexico and Canada are less straightforward because those countries remained subject to a separate tariff regime. Beyond these five trading partners, there does *not* seem to exist a strong systematic relationship between changes in U.S. imports and the tariff rates faced by partner countries. Figure 6, inspired by Figure 10 in Alfaro and Chor (2026), may be interpreted as suggesting that countries facing higher new tariff rates tended, on average, to see weaker growth in U.S. imports. With robust standard errors, however, the t-value of the negative coefficient drops from -3.91 to -0.87. Furthermore, this pattern is not robust: it is largely driven by China, and it fades when the relationship is estimated via ordinary least squares (rather than when weighting observations by import value, as in Alfaro and Chor, 2026).[4]

Liberation Day also led to a remarkable reorientation of Chinese exports. Figure 7 tracks China's exports to the United States relative to its exports to other destinations, normalized to November 2024. After the November 2024 election, Chinese exports to the U.S. declined sharply, while exports to Europe and to other Asian economies rose, suggesting a rapid diversion of Chinese sales away from the U.S. market and toward alternative destinations. This prospect has heightened anxiety in the recipient markets: in Europe, policymakers explicitly warned about trade diversion and moved to strengthen import-surveillance capacity to detect and respond to sudden surges, amid concerns about being "flooded" by redirected Chinese goods. In parts of Asia, similar fears about displacement and import surges have been reflected in a

[4] The legend in Figure 6 includes the regression results. The weighted least squares coefficient excluding China is actually positive, though not statistically significant. The ordinary least squares coefficient (including China) is also positive but essentially zero. We follow Alfaro and Chor (2026) in using the tariff rates announced on Liberation Day rather than those subsequently implemented, which were subject to exemptions, revisions, and delays.

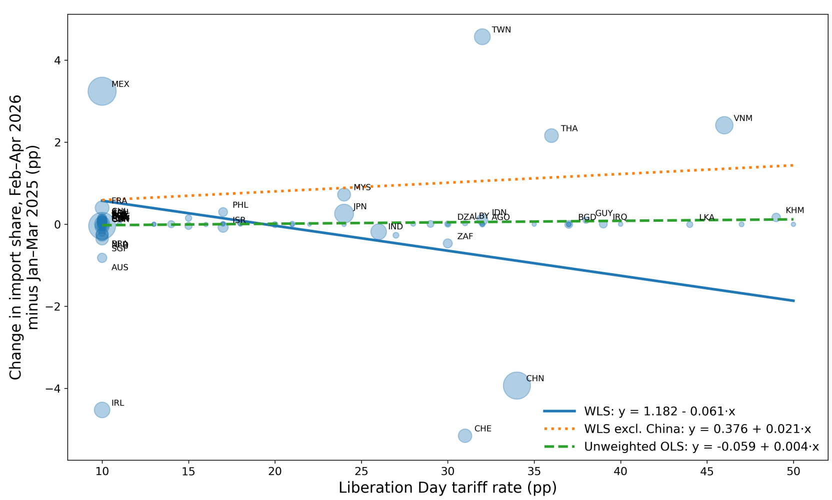
Figure 5: The Great Reallocation during Trump's Second Administration



Notes: Series show U.S. goods imports from each partner, indexed to Nov. 2024 = 100. Values are a 3-month backward moving average (month t equals the average of t-2, t-1, and t). Vertical dotted line marks Nov. 2024.

Source: U.S. Census Bureau (https://www.census.gov/foreign-trade/balance/index.html).

Figure 6: Liberation Day and Sources of U.S. Imports

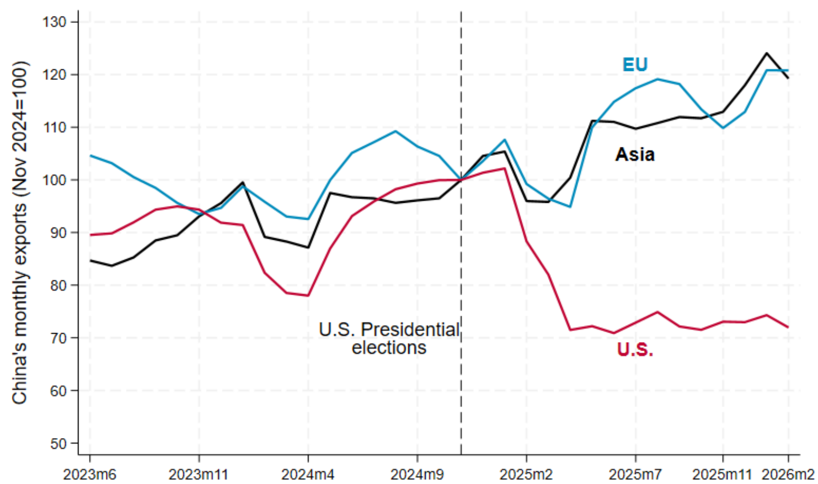


Notes: Each dot is a U.S. import partner. The y-axis is the change in the partner's share of total U.S. imports from February to April 2026 minus the same change from January to March of 2025. Dot size is proportional to the partner's 2023 total imports. Lines are linear fits: import-weighted (weights = 2023 imports), import-weighted excluding China, and unweighted OLS; none of the coefficients is significant at standard confidence levels when computing robust standard errors.

Source: U.S. Census Bureau import totals by partner; Liberation Day country tariff rates from the April 2, 2025 Executive Order, Annex I.

more defensive stance – e.g., new or extended anti-dumping actions against specific Chinese products – alongside broader public concern about the competitive pressure created by low-priced Chinese exports being redirected into regional markets. These concerns are not merely anecdotal. The European Commission created a dedicated import-surveillance tool in 2025 to monitor potentially harmful trade diversion, explicitly citing the risk that goods blocked by tariffs or other restrictions in one market could be redirected into the EU at disruptive scale.[5] Recent ECB evidence similarly documents strong Chinese export growth outside the U.S. in 2025, including to the euro area, ASEAN, Latin America, and Africa (Le Roux and Spital, 2026), while policy-oriented discussions of the "China shock 2.0" emphasize that the current episode combines export redirection with China's growing strength in higher-technology and intermediate-goods sectors.

Figure 7: The Reallocation of Chinese Exports during Trump's Second Administration



Notes: Exports are 3-month backward-looking moving averages. The vertical line is drawn in correspondence with the November 2024 U.S. presidential election. The Asia aggregate includes Bangladesh, Cambodia, Hong Kong SAR, India, Indonesia, Malaysia, Pakistan, the Philippines, Singapore, Sri Lanka, Taiwan Province of China, Thailand, and Vietnam. EU = European Union.
Sources: Trade Data Monitor.

Taking Stock

Taken together, Figures 5–7 suggest that Liberation Day may have been interpreted less as a temporary escalation and more as an inflection point toward deeper, sustained decoupling. While other countries were also hit with higher U.S. tariffs, those measures were surrounded by reversals and uncertainty, so it is unsurprising that we see no clean, systematic trade

[5] The trade diversion tool is accessible at: `https://policy.trade.ec.europa.eu/enforcement-and-protection/trade-defence/monitoring-trade-diversion_en`.

response. By contrast, the sharp curtailment of China's ability to sell into the U.S. market generated sizable spillovers elsewhere: Chinese exports were redirected into other destinations, and competitive pressures intensified in third markets where China and other exporters meet head-to-head. We next turn to a more systematic analysis of these spillover effects to third markets.

3 Caught in the Middle: Third-Country Spillovers from the U.S.–China Tariff War

When two giants fight, smaller economies are not simply flies on the wall, unaffected by the conflict. The new phase of the U.S.–China tariff war has indeed curtailed China's sales into the U.S. market but it has also altered the competitive environment faced by firms around the world. This section examines these third-country spillovers systematically.

A natural starting point is trade diversion in the narrow sense: third countries may gain U.S. market share as Chinese suppliers are displaced, or they may gain market share in China if U.S. sellers are displaced. The patterns since Liberation Day, however, offer limited support for this narrow diversion narrative. The cross-partner relationship between U.S. import growth and the new tariff schedule appears weak (Figure 6), and the relatively small scale of U.S. goods exports to China (compared with U.S. imports from China) implies that, for many countries, direct bilateral exposure to China through that channel is second-order. These observations motivate a different perspective in which the main action occurs in markets *other* than the U.S. itself.

Our emphasis is therefore on spillovers generated by China's impaired access to the U.S. market but realized in third markets. We decompose exposure into four conceptually distinct margins. First, *export competition*: as Chinese exporters redirect shipments, they displace other suppliers in shared destination markets. Second, *import competition*: redirected Chinese goods raise import penetration and competitive pressure in domestic markets. Third, *consumer gains*: those same redirected Chinese goods will tend to be sold at lower prices than the purchases they displace, which will reduce the price level for consumers in those import markets, and perhaps also increase the variety of goods available to them. Fourth, *sourcing gains*: lower-priced (or more readily available) Chinese intermediates can reduce input costs and expand downstream activity.

We next operationalize this taxonomy with tractable diagnostics and then use them to characterize which countries are most exposed along each margin. Before we dive into the specifics of our indices, we offer some broad observations applying to all these indices.

3.1 General Considerations

Our goal is to develop measures of the extent to which countries are exposed to an increase in Chinese exports to countries other than the U.S., resulting from the constrained ability of these same Chinese exporters to sell to the United States. At a very general level, it is clear that countries are more likely to face export competition from China if their export patterns are *similar* to those of China. At the same time, the other channels of exposure should be more salient when a country's reliance on imports from China is *large* and *similar* in structure to that of the U.S., since this would indicate that U.S. policies would divert relatively more Chinese exports toward that exposed country.

A common approach to capturing similarity in exports and imports follows from the influential work of Finger and Kreinin (1979). Let us review the basics of their index for the case of exports. Suppose that one is interested in assessing how similar is the export structure of two countries, i and j. By export structure, we mean a vector $\mathbf{X}_o = \{X_{o11}, ..., X_{odp}\}$ where X_{odp} refers to (origin) country o's exports of product p in (destination) market d. Finger and Kreinin (1979) proposed the following similarity index between the exports of country i and j when selling in destination market d:

$$ESI_{ijd} = \sum_{p \in \mathcal{P}} \min \left(\frac{X_{idp}}{\sum_{p' \in \mathcal{P}} X_{idp'}}, \frac{X_{jdp}}{\sum_{p' \in \mathcal{P}} X_{jdp'}} \right) \times 100. \tag{1}$$

To see how this measure captures export similarity, notice that if the countries i and j feature the same *share* of exports in all goods $p \in \mathcal{P}$, then $ESI_{ijd} = 100$ because the two countries are 100 percent similar in their export structure in that destination market d. Conversely, if there is *no* product p for which *both* countries feature positive exports in d, then their similarity is zero.[6]

The Finger and Kreinin (1979) index is an insightful index of export similarity, but it is much less clear that it constitutes a good index of export competition pressures. As pointed out by Jenkins (2008), the fact that the index ESI_{ijd} in equation (1) is symmetric is problematic: when interpreted as capturing competitive pressures, it would imply that China is as impacted by competition from Honduras as Honduras is impacted by competition from China. Furthermore, the index is also symmetric across products and thus does not take into account that competitive pressures might be felt more intensively in some products than others.

With that in mind, below we will develop alternative indices of exposure that are theoretically grounded, and we will compare them with the corresponding similarity measures. More specifically, in Appendix A, we develop a multi-product, multi-country Armington model:

[6] As shown by Sun and Ng (2000), the Finger and Kreinin (1979) index has good axiomatic properties, in the sense that it is invariant with respect to proportional sub-classifications.

in each destination market, expenditure on product p is allocated across exporter varieties according to a constant elasticity of substitution (CES) aggregator. A China-specific U.S. policy shock reduces Chinese exports to the U.S. and, via an upward sloping Chinese export supply schedule, this shock leads to lower prices in all other destinations. The model then traces the first-order implications of this shock on the exports of a given country j to all destination markets other than the U.S. and China. The model also clarifies why export or import similarity alone are insufficient for measuring exposure.

For the case of export competition, the first-order effect in a product-destination market depends jointly on the size of the Chinese supply shock in that product, Φ_p, the relevant substitution elasticity, China's initial share of the destination-product market, and the importance of that market for the affected exporter's revenues. The indices for the other three channels are analogous but require different incidence weights: domestic production for import competition, import expenditure for consumer gains, and input-output expenditure shares for sourcing gains. Conventional similarity indices focus on the similarity of export shares, but omit the product-level nature of the shock, do not allow for substitution patterns, and ignore the importance of China in the absorption of the destination market.

We construct all our exposure measures based on bilateral trade data in 2023 at the product level sourced from CEPII-BACI (Gaulier and Zignago, 2010). Some measures are available for 224 countries based on trade data for 5,380 6-digit HS code products. Nevertheless, some of our measures are constructed using a subset of 4,254 6-digit HS code products for which our product-level shock can be computed. When reporting country-level measures in the following tables and figures, we exclude countries with a population less than 200,000 in addition to Hong Kong and Macao, which are currently special administrative regions of China. Moreover, since indices require product-country elasticities which may be unavailable, we drop countries where our indices represent less than 25 percent of the underlying trade flows.[7] This leaves us with 110 countries. Additional details on index construction and data sources are in Appendix B, while values for additional countries and territories are provided on the paper's online platform.

3.2 Diagnosing Export Exposure

With this background in mind, we begin by proposing indices capturing the extent to which third countries may face increased export competition from China in countries other than the United States (and China) as a result of the inability of Chinese exporters to sell to the United States. We begin with the standard approach of producing measures of export similarity, but then propose our theoretically-grounded index of export competition.

[7] Due to incomplete product coverage, the indices should be interpreted as predicted changes for the subset of goods and countries where data is available. Additional details on product and country coverage are in Appendix B.

3.2.1 Export Similarity

To measure the export similarity between a given country j and China, we first aggregate the Finger and Kreinin (1979) export similarity index (ESI) across destination markets as follows:

$$ESI_j = 100 \times \sum_{d \in \mathcal{W}_-} \sum_{p \in \mathcal{P}} \min\left(\frac{X_{jdp}}{X_j}, \frac{X_{cdp}}{X_c}\right), \tag{2}$$

where c denotes China, X_{jdp} are country j's exports of product p in destination d (in some baseline year), $\mathcal{P}$ is the set of all products, $\mathcal{W}_-$ is the set of all countries in the world ($\mathcal{W}$) excluding the U.S. and China, and X_j and X_c are aggregate exports of j and China in all countries other than U.S. and China (in the baseline year). To avoid anticipation effects in the run-up of the U.S. presidential election, we choose 2023 as our baseline year.[8]

Table 1 lists the 20 economies that, according to export similarity at the product and destination levels (equation (2)), face the highest export exposure to China. The list is split largely between Asian and European economies, with Mexico the only economy from the Americas.

Table 1: Top 20 economies by Export Similarity (ESI_j)

Rank	Country	$\boldsymbol{ESI_j}$	Rank	Country	$\boldsymbol{ESI_j}$
1	Vietnam	31.38	11	Philippines	16.98
2	Taiwan	26.59	12	United Kingdom	16.87
3	South Korea	26.55	13	France	16.85
4	Japan	25.76	14	Singapore	16.61
5	Thailand	23.55	15	Poland	15.87
6	Germany	21.44	16	Netherlands	15.66
7	Italy	20.33	17	Turkey	15.12
8	Malaysia	20.27	18	Mexico	14.85
9	India	20.02	19	Hungary	14.56
10	Czechia	16.99	20	Spain	14.37

[8] We have also computed a variant of the export similarity index that instead aggregates across destinations as follows:

$$ESI_j = 100 \times \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} \min\left(\frac{X_{jdp}}{X_{jd}}, \frac{X_{cdp}}{X_{cd}}\right).$$

This amounts to an export-weighted average of the destination-specific export similarity indices with China. The correlation between this measure and the baseline one is 0.949. We also compute coarser indices of export similarity that only consider similarity in the types of products exported (regardless of where they are sold) and in the destination of sales (regardless of which goods are sold in those destinations). See Appendix B.4.1 for details. These three alternative indices of export similarity can be downloaded from our online platform.

3.2.2 An Export Competition Index

We next turn to our theoretically-grounded index of export competition. We omit all the technical details in the main text, but the expressions below are derived from the Armington model in Appendix A. The percentage response of country j's exports is shaped by three key empirical objects.

a) Size of product-level shock. A first consideration is the size of the U.S.–China tariff shock for different products p. More specifically, we seek to measure by how much one would expect free-on-board (f.o.b.) Chinese prices to fall in third markets as a result of the tariffs set by the U.S. on China, and we denote that Chinese price decline by Φ_p. For uniform U.S. tariff changes and uniform demand and supply elasticities across sectors, the *relative* size of the shock across sectors turns out to be governed solely by the share of overall Chinese production of good p that was shipped to the U.S. (relative to other destinations) in the baseline year, or

$$\phi_p = \frac{Q_{cup}}{\sum_{d \in \mathcal{W}-\{c\}} Q_{cdp}}. \tag{3}$$

Intuitively, the larger is the share of Chinese output that was sold in the U.S., the larger will be the amount of exports that will need to be redirected to other markets, and with an upward sloping Chinese export supply, the larger will be the necessary price decline in other markets. In our empirical implementation, we proxy ϕ_p with the share of Chinese exports of product p destined to the U.S. market in 2023 (or $\phi_p = X_{cup}/\sum_{d \in \mathcal{W}-\{c\}} X_{cdp}$). In doing so, we are motivated by concerns about the reliability of the quantity information (in metric tons) in the CEPII-BACI dataset, especially when dealing with data aggregated at an HS6 industry level. Having said this, and as reported in Appendix Table B.4, the correlation between our value-based proxy for ϕ_p and a quantity-based one is very high (0.862), and their rank correlation is even higher (0.939).

As the model in Appendix A shows, with variation across products in tariff changes and demand and supply elasticities, the formula for the product-level price shock includes additional terms. More specifically, the implied decline in the Chinese f.o.b. price of good p in other destinations is given by

$$\Phi_p = -d \log p_{cp} = \phi_{cup} \times \frac{\varepsilon_{cup}}{\bar{\varepsilon}_{cp} + \eta_{cp}} \times \Delta \log (1 + \tau_{cup}). \tag{4}$$

In this expression, ε_{cup} is the U.S. demand elasticity for Chinese product p, $\bar{\varepsilon}_{cp}$ is the average import-demand elasticity faced by China across export markets, η_{cp} is the elasticity of supply of Chinese exports of good p, and $\Delta \log (1 + \tau_{cup})$ is the change in U.S. tariffs on imports from China of good p.

We construct a proxy for Φ_p based on our proxy for ϕ_p, on demand and supply elasticities from Soderbery (2018), and on tariff changes from the Global Tariff Database in Rodríguez-Clare et al. (2026) (based on the methodology developed in Teti, 2024). The details are in Appendix B. The correlation between Φ_p and ϕ_p is very high (0.831), suggesting that most of the variation in the shock is coming from the transparent and observable Chinese share of exports destined to the U.S., rather than the more debatable elasticity estimates or from variation in the change in tariffs across products. Indeed, taking logs of equation (4), we decompose the variance of $\log \Phi_p$ across products with positive shocks by computing the covariance of each of its three additive components with $\log \Phi_p$, divided by the variance of $\log \Phi_p$. The export share ϕ_p accounts for 78.4% of this variation, the elasticity term for 18.9%, and tariff changes for the remaining 2.6%.[9] We will provide more details on the product-level shock in Section 4.1.

It is worth stressing the broader applicability of our methodology for constructing exposure indices. The key product-level object is the change in Chinese export prices Φ_p, rather than the particular shock that generates it. In our application, higher U.S. tariffs reduce demand for Chinese exports and induce Chinese producers to move down their upward-sloping export-supply schedules. In other applications, a similar decline in Chinese export prices could instead result from an outward shift in supply – for instance, because of industrial subsidies or productivity growth – or from other contractions in demand for Chinese goods, including weaker Chinese domestic demand. Given an appropriate product-level estimate or proxy for the resulting price change Φ_p, the remainder of our analysis would apply with little modification.

b) Incidence of product-level shock in destination market d. The second key variable shaping exposure is the extent to which Chinese exports of good p diverted to a given destination d will crowd out other sellers of good p in that market. Our Armington-CES model indicates that this force can be approximated (up to a first order) by the share of expenditure in country d that is accounted for by Chinese exports, or

$$\chi_{cdp} = \frac{X_{cdp}}{\sum_{o \in \mathcal{W}} X_{odp}}. \tag{5}$$

The term χ_{cdp} captures the incidence of the shock in destination market d. Intuitively, a fall in the price of Chinese exports of product p generates larger competitive pressure in markets where China is already an important supplier of that product. If China accounts for only a negligible share of purchases of product p in destination d, then even a sizable fall in the Chinese price

[9] We compute tariff changes from January 2025 (before Trump's second inauguration) to September 2025. Later, we will consider robustness to a 'long' variant with export shares computed from 2017 data and tariff differences from January 2018 to September 2025. This has little bearing on the broad conclusion: in the long variant, ϕ_p accounts for about 79.6% of the variation in Φ_p, the elasticity term accounts for about 20.3%, and tariff changes account for only 0.04%.

has little first-order effect on the revenues of other exporters in that market. By contrast, when χ_{cdp} is large, Chinese exporters are already close competitors in that product–destination cell, so a reduction in their relative price produces a larger displacement of other suppliers.

c) Relevance of the shock for origin country o**.** Finally, the effect of this destination-product shock on the origin country o depends on how important that same destination-product cell is for country o's own exports. For a given destination d, define

$$s_{odp} = \frac{X_{odp}}{X_{od}}, \tag{6}$$

where $X_{od} = \sum_{p \in \mathcal{P}} X_{odp}$. Thus, s_{odp} is the share of country o's exports to destination d accounted for by product p. This term captures the relevance of the shock for the origin country: even if Chinese competition in product p is intense in destination d, country o is exposed only to the extent that it also sells product p in that destination. Conversely, if product p represents a large share of o's exports to d, then displacement in that product–destination cell has a larger effect on o's exports to that market.

The Export Competition Index. Aggregating across destinations – weighting each destination by its importance in country j's overall export basket – we show in Appendix A that the predicted percentage decline in country j's exports resulting from the U.S.–China trade shock is given by

$$\boldsymbol{ECI}_j = 100 \times \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} (\sigma_{dp} - 1) \times s_{jdp} \times \chi_{cdp} \times \Phi_p, \tag{7}$$

where remember that $\mathcal{W}_-$ is the set of all countries in the world excluding the U.S. and China. The index therefore combines three forces: the size of the China price shock in product p, Φ_p; the intensity of Chinese competition in destination market d, χ_{cdp}; and the importance of that product for origin country j's exports to destination d in country j's total exports.

The term $(\sigma_{dp} - 1)$ appears in equation (7) because export competition works through substitution across country-of-origin varieties within a destination–product market. More specifically, a U.S. tariff reduces Chinese export demand in the U.S.; with upward-sloping Chinese export supply, this lowers the Chinese f.o.b. price and therefore the delivered price of Chinese varieties in third markets. The revenue loss for other exporters then depends on how strongly buyers in destination d substitute toward the now-cheaper Chinese variety. When the elasticity of substitution is high, a given fall in China's relative price induces a larger reallocation of expenditure away from other origins and toward China. When demand is less elastic, the same price change generates less displacement. This is why the model weights the

China price shock by the demand elasticity term.

There are three main differences between the export competition index in equation (7) and the Finger-Kreinin similarity index in equation (2). First, although our index includes information on both country j's export shares s_{jdp} and China's market shares χ_{cdp}, these shares are conceptually different from each other. In particular, for China what matters is the relative importance of Chinese exports in total absorption of good p in destination d, rather than how important those Chinese exports are relative to overall Chinese exports (including exports of other goods and to other destinations). Second, the model indicates that exposure is proportional to the product of these shares χ_{cdp} and s_{jdp} rather than the minimum of the two, as in the similarity measure (2). Third, equation (7) also captures the fact that the shock may be more disproportionately felt in some sectors or products than others, and it shows that this heterogeneity is crucially shaped by the share of Chinese exports of good p that were destined to the U.S. market relative to other markets in the baseline year (see equation (4)).

We compute our export competition index with the same data used to compute the Finger-Kreinin export similarity index in (2). Because we do not have data on domestic production disaggregated at the HS6 product level, the denominator of χ_{cdp} in equation (5) does not include country d's domestic sales of product p.[10] When focusing on exposure of specific countries for which domestic sales data is available at a disaggregated level, researchers can easily compute an adjusted χ_{cdp}.

Table 2 reports the top 20 economies by the export competition index vis à vis China ($\boldsymbol{ECI}_j$). Remember that the magnitudes in the table correspond to the estimated percentage declines of these countries' exports due to increased Chinese competition. The ranking is headed by a set of relatively small and specialized economies (Armenia, Kyrgyzstan), but some notable medium-sized exporters, such as Vietnam, Hungary, Thailand or Mexico also emerge among the most exposed economies.

Relative to the export similarity in Table 1, the composition shifts markedly away from large diversified manufacturing exporters (especially large European economies) and toward smaller economies. There is substantial overlap, however: Vietnam ranks near the top in both tables, while ten other economies also appear in both lists. Importantly, our index still predicts non-negligible drops in exports even for large economies. For instance, several of the top 20 largest economies in the world are predicted to see their exports drop by between 0.4% and 0.9% (see our online platform for more details).

The differences between ESI_j and $\boldsymbol{ECI}_j$ stem from the fact that the two measures capture different objects. ESI_j is an *overlap* index: it is high when a country's export shares across

[10] For similar reasons, Chinese domestic sales are not included in the denominator of ϕ_p in equation (3), although this is not necessarily an issue if one interprets the Chinese export supply elasticity to be determined independently of Chinese domestic supply (see Appendix A).

Table 2: Top 20 economies by Export Competition Index ($\boldsymbol{ECI}_j$)

Rank	Country	$\boldsymbol{ECI}_j$	Rank	Country	$\boldsymbol{ECI}_j$
1	Armenia	2.46	11	India	0.92
2	Kyrgyzstan	2.31	12	Poland	0.92
3	Vietnam	2.26	13	South Korea	0.91
4	Cambodia	1.56	14	Slovakia	0.82
5	Bangladesh	1.28	15	Madagascar	0.82
6	Hungary	1.19	16	Japan	0.80
7	Czechia	1.07	17	Turkey	0.79
8	Sri Lanka	1.00	18	Philippines	0.79
9	Thailand	0.93	19	Fiji	0.77
10	Mexico	0.92	20	Tunisia	0.76

product–destination cells look similar to China's. This naturally elevates large, diversified exporters that "look like China" in terms of what they sell and where they sell it. By contrast, $\boldsymbol{ECI}_j$ is an *exposure-to-competition* measure: it loads heavily on where the country actually sells and how intense Chinese competition is in those markets. In particular, a country can have a high $\boldsymbol{ECI}_j$ if it is specialized in products and destinations where China has high baseline penetration in absorption (i.e., China sells a lot in those destination markets), even if the country's overall export structure is not especially similar to China's. This mechanism is especially relevant for smaller economies: because their exports are often concentrated in a narrow set of product–destination cells, they can be disproportionately affected by a China shock precisely when those cells coincide with markets in which China is a major supplier. Importantly, this can occur even when those product–destination cells are not large in the aggregate composition of Chinese exports. Panel (a) of Figure 8 plots our export competition index ($\boldsymbol{ECI}$) against the export similarity index (ESI). Despite the differences flagged above, the two indices feature a positive correlation of 0.493.[11]

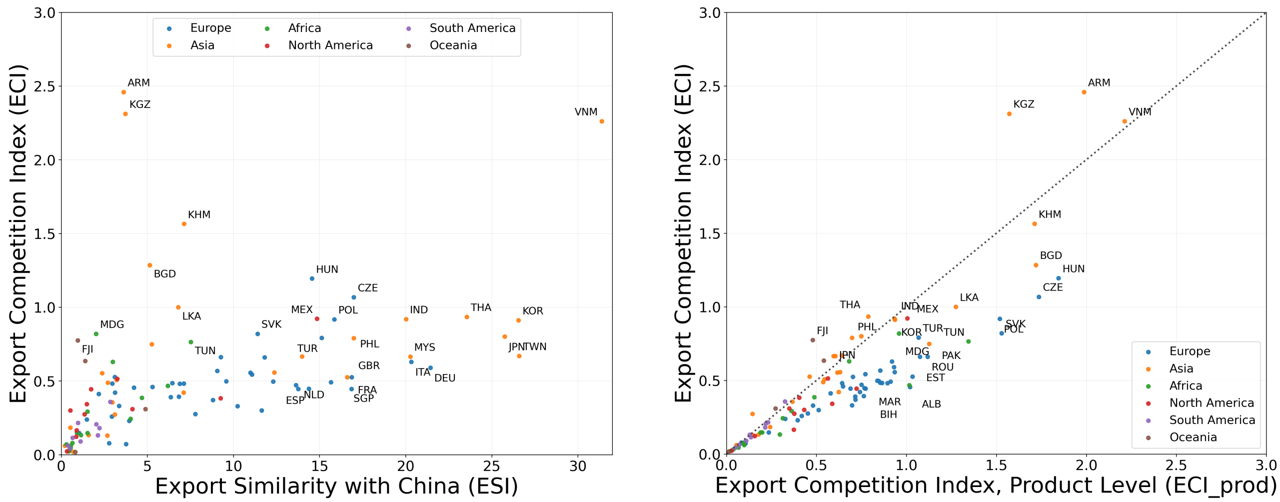
In addition to the baseline index in equation (7), we also compute a coarser version of our export competition index at the product level (aggregating the data first across destinations), which is given by

$$\boldsymbol{ECI}_j^{prod} = 100 \times \sum_{p \in \mathcal{P}} (\tilde{\sigma}_{jp} - 1) \times \frac{\sum_{d \in \mathcal{W}_-} X_{jdp}}{X_j} \times \frac{\sum_{d \in \mathcal{W}_-} X_{cdp}}{\sum_{o \in \mathcal{W}} \sum_{d \in \mathcal{W}_-} X_{odp}} \times \Phi_p, \tag{8}$$

where $\tilde{\sigma}_{jp}$ is the (export-weighted) average demand elasticity for good p *faced* by country j in

[11] In Appendix Tables B.6 and B.7, we report the bilateral (Pearson) and rank (Spearman) correlation between all our baseline indices.

Figure 8: Export Competition Index: Comparisons



(a) $\boldsymbol{ECI}_j$ versus ESI_j (b) $\boldsymbol{ECI}_j$ versus $\boldsymbol{ECI}_j^{prod}$

its various destinations of exports. This alternative index retains the structure of our preferred, theoretically-grounded index, but it better captures situations in which a large enough shock (e.g., Liberation Day) may lead to large increases in Chinese exports to destinations in which it sold relatively less in the baseline year, something that is inconsistent with the effects of a first-order shock in our model.

Panel (b) of Figure 8 plots this alternative export competition index against our baseline one.[12] The correlation between the two indices is high (0.882), but there are some notable differences. In particular, Bangladesh and many European economies, especially Eastern European ones (Hungary, Czechia, Poland, and Slovakia) appear disproportionately more exposed. These results are in line with those obtained under the coarser product-level variant of our export similarity measure developed in Appendix B.4.1 (see panel (a) of Appendix Figure B.2).

We also explore the robustness of our export competition index to the use of a more 'basic' measure of the price shock which removes all the elasticity terms and can thus be computed with *only* international trade data, and to a 'long' variant using market shares computed from 2017 data and tariff differences from January 2018 to September 2025. We label these variants as $\boldsymbol{ECI}^{basic}$ and $\boldsymbol{ECI}^{long}$, and we report them on our online platform.[13] The correlation between $\boldsymbol{ECI}$ and $\boldsymbol{ECI}^{basic}$ is 0.974, while that between $\boldsymbol{ECI}$ and $\boldsymbol{ECI}^{long}$ is 0.963. This provides some assurance that the reliability of our indices does not depend on the accuracy of demand and supply elasticity estimates or on the horizon over which trade barriers are computed.[14]

[12] This alternative index can also be downloaded from our online platform.

[13] In particular, $\boldsymbol{ECI}_j^{basic} = 100 \times \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} \times s_{jdp} \times \chi_{cdp} \times \phi_p$.

[14] In Appendix Tables B.8 and B.9, we report analogous bilateral (Pearson) and rank (Spearman) correlation

3.3 Diagnosing Import Exposure

Bystanders of the current U.S.–China trade war may view the constraints faced by Chinese exporters in selling to the United States not only as a competitive threat in export markets, but also as a competitive threat in their *own* market. This reflects a more standard import competition shock, which in this case is triggered by developments in the United States, not China. Of course, the flip side of these import competition forces is the fact that cheaper Chinese imports will reduce the prices faced by consumers, which is a positive aspect of that trade deflection. For this type of import threats or opportunities, neither export similarity between a given country j and China nor our export competition index are particularly informative.

Import Similarity

We begin by exploring an index of the similarity between the products that both country j and the U.S. import from China in a baseline year. The idea is that if a given country j imports the same types of goods from China as the U.S., it is more likely that the U.S.–China trade war will result in a surge of Chinese exports to that market j. More specifically, we define this import similarity index (ISI) as

$$ISI_j = 100 \times \sum_{p \in \mathcal{P}} \min \left\{ \frac{X_{cjp}}{X_{cj}}, \frac{X_{cup}}{X_{cu}} \right\}, \tag{9}$$

where X_{cjp} are country j's imports of good p from China, X_{cup} are U.S. imports of good p from China, and X_{cj} and X_{cu}, are aggregate imports from China of country j and of the U.S., respectively. We again use 2023 as the reference year for all these flows.[15]

Table 3 lists the 20 economies that, according to the import similarity index in equation (9), may face the highest import exposure because they import from China the type of goods the U.S. imported from China in the baseline year. This list is quite different from that in Table 1 and is dominated by European countries; outside Europe, the top 20 also includes Canada, New Zealand, Japan, and Israel.

An Import Competition Index

The import similarity measures are informative, but they have at least two limitations. First, they are at best measures of 'exposure', so it is hard to disentangle whether they capture import

for our other three main indices of exposure.

[15] As a robustness, in Appendix B.4.2 we compute two alternative measures of import similarity which account for the possibility that: 1) a surge of imports into country j may be driven by an excess supply of products that China was *not* exporting to country j, and 2) Chinese exporters redirect (or "dump") into third-country markets products with limited exports to the United States in the benchmark year, such as electric vehicles (EVs).

Table 3: Top 20 economies by Import Similarity (ISI_j)

Rank	Country	$\boldsymbol{ISI}_j$	Rank	Country	$\boldsymbol{ISI}_j$
1	Canada	72.79	11	Switzerland	58.24
2	United Kingdom	68.46	12	Spain	58.03
3	France	67.51	13	Netherlands	57.84
4	Germany	64.28	14	Estonia	57.10
5	Japan	64.10	15	Italy	56.98
6	Poland	63.73	16	Czechia	56.34
7	Austria	61.09	17	Sweden	55.33
8	Norway	59.57	18	Slovakia	54.17
9	Finland	59.03	19	Moldova	53.76
10	New Zealand	58.83	20	Israel	52.81

competition forces – which reduce the sales and employment of domestic firms – or they reflect potential consumer gains derived from access to cheaper imported goods. Second, as with the Finger-Kreinin export similarity index, these indices are not theoretically grounded, so it is not clear that the import shares in equation (9), as well as the min operator in the index, are the relevant objects for assessing import competition threats or cheaper import opportunities. In Appendix A, we use our Armington-CES model to shed light on these issues.

We begin by constructing an index of *import competition*. In particular, we seek a measure of the extent to which the increased Chinese exports diverted into a market j will reduce the size of the domestic, import-competing sector in that country j. Naturally, there is a clear connection between this question and our derivations above related to how Chinese exports were crowding out third-market exporters in export markets. In this case, the destination market under study coincides with the 'origin' country j under consideration, and the relevant reduced sales X_{jjp} correspond to domestic sales of good p by producers in j, which we simply denote by S_{jp}. The resulting import competition index corresponds to the percentage decline in domestic sales caused by the U.S.–China trade conflict, and is given by:

$$\boldsymbol{ICI}_j = 100 \times \sum_{p \in \mathcal{P}} (\sigma_{jp} - 1) \times s_{jp} \times \chi_{cjp} \times \Phi_p, \tag{10}$$

where $s_{jp} = S_{jp} / \sum_{p' \in \mathcal{P}} S_{jp'}$ is the share of domestic sales accounted for by sector p domestic producers.

The intuition for this expression is analogous to that behind our export competition index. The terms Φ_p and χ_{cjp} reflect the relative size of the shock in product p, and how it will be felt in country j, given how much that country relies on Chinese imports of good p in the baseline year. Import growth of product p will be higher when the product $\Phi_p \times \chi_{cjp}$ is larger. The term s_{jp} then captures how this import surge will affect domestic sales, and corresponds to the relative size of sector p in the overall domestic sales in country j. The predicted import growth may be large, but if there are no (or close to no) domestic producers of that good, the resulting decline in domestic sales will be negligible and does not pose a significant threat for the country.

A difficulty in implementing the import competition index in (10) is that it requires information on domestic sales at the product level, which are not readily available to researchers, at least in unified datasets covering many countries. With that in mind, we compute $\boldsymbol{ICI}_j$ proxying the domestic share $s_{jp} = S_{jp} / \sum_{p' \in \mathcal{P}} S_{jp'}$ with the share of overall exports of country j that are accounted for by exports of good p, or

$$s_{jp} \simeq s_{jp}^X = \frac{\sum_{d \in \mathcal{W}} X_{jdp}}{\sum_{d \in \mathcal{W}} \sum_{p' \in \mathcal{P}} X_{jdp'}}. \tag{11}$$

The idea is that countries will tend to feature higher exports in sectors that are disproportionately large in the industrial structure of a country, and vice versa. Naturally, variation in the tradability of different products introduces noise in our proxy, so our results below should be treated with a grain of salt. Researchers interested in assessing import competition pressures in specific countries should definitely use those product-level domestic sales when that data is available. For similar data limitation issues, and as in the export competition index, we continue to approximate χ_{cjp} with the share of China in country j's imports of good p.

We compute our import competition index $\boldsymbol{ICI}_j$ in equation (10) for all 110 countries in our sample for the year 2023. Table 4 ranks countries by this index. Vietnam and Cambodia head the ranking, with index values of 3.44 and 3.03, followed by Pakistan and Madagascar. Asian economies account for most of the top 20, including large manufacturing economies such as Japan, India, and South Korea. The list also includes Madagascar and Ethiopia in Africa; Poland and Czechia in the European Union; and Mexico and the Dominican Republic in the Americas. This pattern is consistent with $\boldsymbol{ICI}$ being an exposure-to-competition measure: it is high when (i) Chinese import penetration is large in the products affected by the shock and (ii) those products represent a meaningful share of the destination country's domestic, import-competing sales. In section 4.3, we open the black box of the index by decomposing it into product-level contributions and identifying the sectors through which each country is predicted to experience increased competition.

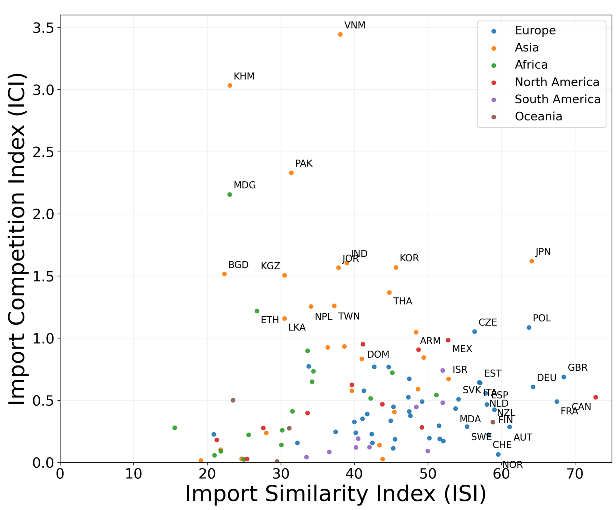
The ranking in Table 4 differs sharply from that of the import similarity index (ISI), which is an overlap measure based on the composition of a country's imports (typically relative to the set of goods the U.S. imported from China in the baseline year). By contrast, $\boldsymbol{ICI}$ is designed to capture the *incidence on domestic producers*: it weights product-level import pressure by the importance of each sector in domestic sales. As a result, countries can have high $\boldsymbol{ICI}$

Table 4: Top 20 economies by Import Competition Index ($\boldsymbol{ICI}_j$)

Rank	Country	$\boldsymbol{ICI}_j$	Rank	Country	$\boldsymbol{ICI}_j$
1	Vietnam	3.44	11	Thailand	1.37
2	Cambodia	3.03	12	Taiwan	1.26
3	Pakistan	2.33	13	Nepal	1.26
4	Madagascar	2.16	14	Ethiopia	1.22
5	Japan	1.62	15	Sri Lanka	1.16
6	India	1.61	16	Poland	1.09
7	South Korea	1.57	17	Czechia	1.05
8	Jordan	1.57	18	Armenia	1.05
9	Bangladesh	1.52	19	Mexico	0.98
10	Kyrgyzstan	1.51	20	Dominican Republic	0.95

even if they are not particularly similar to the U.S. in what they import from China; what matters is that domestic producers are concentrated in sectors where Chinese import pressure rises. Consistent with the different objects being measured, the overlap between the top-20 lists for $\boldsymbol{ICI}$ and ISI is limited: only Czechia, Japan, and Poland appear in both. Across the 110 economies in our baseline sample, the correlation between import competition ($\boldsymbol{ICI}$) and import similarity (ISI) is actually negative, though close to zero (-0.039). This weak relationship is made evident in Figure 9.

Figure 9: Import Similarity and the Import Competition Index



(a) $\boldsymbol{ICI}_j$ versus ISI_j

A Consumer Gains Index

As shown above, the Armington-CES model can be used to assess the implications of the U.S.–China trade war for firm sales. Interestingly, it can also be employed to evaluate its consequences for consumer prices. In Appendix A, we show that the percentage decline in import prices in a given market j can be approximated, up to a first order, with the following expression

$$\boldsymbol{CGI}_j = 100 \times \sum_{p \in \mathcal{P}} s^M_{jp} \times \chi^M_{cjp} \times \Phi_p, \tag{12}$$

where Φ_p is identical to that in the expressions for $\boldsymbol{ECI}_j$ and $\boldsymbol{ICI}_j$ in equations (7) and (10), and where χ^M_{cjp} is the Chinese share in total imports of good p in country j (which was already our proxy for χ_{cjp} when empirically implementing our export and import competition indices). The term s^M_{jp} in the above equation for $\boldsymbol{CGI}_j$ is the share of country j's imports accounted for by sector p. Intuitively, up to scalars, the predicted price decline of imports of good p is proportional to the surge in imports of that good (which is captured by the product $\Phi_p \times \chi^M_{cjp}$), and then the spending shares that are relevant to compute the aggregate consumer gains associated with those lower import prices are the import shares s^M_{jp}.

Table 5 ranks countries by the predicted import-price decline from a China-specific supply shock, $\boldsymbol{CGI}_j$. To reiterate, this measure mechanically puts weight on (i) how large China is in a country's import basket in the affected products (χ^M_{cjp}) and (ii) how important those products are in the country's overall import spending (s^M_{jp}).

Table 5: Top 20 economies by Consumer Gains Index ($\boldsymbol{CGI}_j$)

Rank	Country	$\boldsymbol{CGI}_j$	Rank	Country	$\boldsymbol{CGI}_j$
1	Kyrgyzstan	1.57	11	Japan	0.82
2	Russia	1.20	12	Ghana	0.80
3	Paraguay	1.09	13	Peru	0.75
4	Venezuela	1.04	14	Chile	0.74
5	United Arab Emirates	0.92	15	Vietnam	0.73
6	South Africa	0.91	16	Cameroon	0.71
7	Iran	0.91	17	South Korea	0.67
8	New Zealand	0.87	18	Thailand	0.65
9	Belarus	0.85	19	Indonesia	0.64
10	Kazakhstan	0.84	20	Colombia	0.63

Compared with Table 4, which captures producer-side exposure, Table 5 tilts toward economies whose import expenditure is concentrated in products for which China is an important supplier and the predicted Chinese supply shock is large. Kyrgyzstan ranks first, followed by Russia, Paraguay, Venezuela, and the United Arab Emirates. The top 20 includes several relatively small or import-dependent economies, but also larger economies such as Japan, South Korea, Russia, Vietnam, and Indonesia. The overlap with the top-20 $\boldsymbol{ICI}$ ranking is limited to five economies: Japan, Kyrgyzstan, South Korea, Thailand, and Vietnam. This limited overlap is consistent with the theory: consumer price gains are governed by import-expenditure weights, whereas producer pressures depend on the importance of the affected sectors in domestic, import-competing sales.

When interpreting the consumer gains index, two caveats are important. First, $\boldsymbol{CGI}$ aggregates over *all* imported products. In this respect, it conflates the effect that cheaper Chinese imports of final products can have on consumer prices, with that of cheaper intermediate inputs on domestic firms. In Appendix B.4.3 we discuss two alternative versions of the consumer gains index: one focusing on final goods only, and one on intermediates.[16] Second, the magnitudes in Table 5 should be interpreted cautiously. The index is expressed as an approximate percentage decline in the price of imported goods, holding fixed pass-through and distribution margins, not as a change in the overall consumer price index. As a result, even when the estimated import-price decline is economically meaningful, its implications for household welfare depend on how much of the price decline is passed through to consumers and on the importance of the affected imported goods in final consumption.

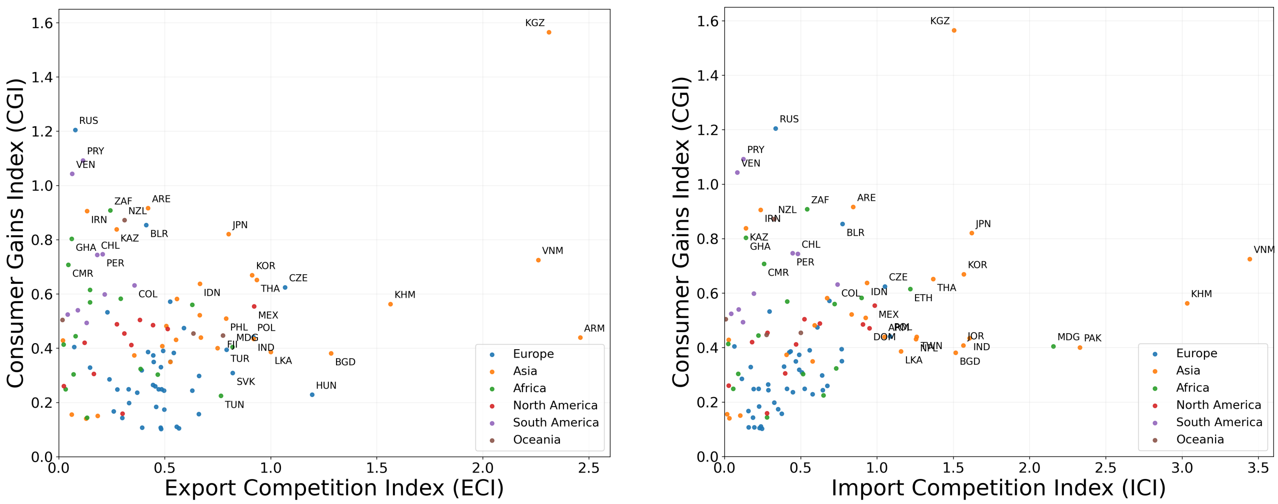
In Figure 10, we compare our consumer gains index $\boldsymbol{CGI}_j$ with our export competition index $\boldsymbol{ECI}_j$ (panel (a)) and with our import competition index $\boldsymbol{ICI}_j$ (panel (b)). Across the 110 such economies for which all three indices are observed, the correlations between $\boldsymbol{CGI}_j$ and both $\boldsymbol{ECI}_j$ and $\boldsymbol{ICI}_j$ are positive but weak, and in fact, the Spearman rank correlation between $\boldsymbol{CGI}_j$ and $\boldsymbol{ECI}_j$ is marginally negative (all bilateral Pearson and Spearman correlations are reported in Appendix Tables B.6 and B.7). This reinforces the view that our indices capture distinct and independently interesting margins of exposure to the current U.S.–China trade war.

3.4 Diagnosing Sourcing Exposure

An interesting feature of the current U.S.–China trade war is that the excess Chinese supply displaced from the U.S. market is not just concentrated in relatively downstream consumption goods. A substantial share of the affected products are *intermediate inputs* – parts, components, and materials used by firms in subsequent stages of production (cf., Bown and Zhang, 2019). When Chinese exports of such inputs are redirected toward third markets, the resulting shock

[16] Given that computing the $\boldsymbol{CGI}$ for final goods requires additional data which are not available for all HS6 products and since this measure is highly correlated (0.903) with that of equation (12), in our baseline we rely on the $\boldsymbol{CGI}$ measure, implicitly assuming that it captures the effects on consumer prices.

Figure 10: Consumer Gains Index versus Export Competition and Import Competition Indices



(a) $\boldsymbol{CGI_j}$ versus $\boldsymbol{ECI_j}$

(b) $\boldsymbol{CGI_j}$ versus $\boldsymbol{ICI_j}$

has a fundamentally different interpretation than in the case of final goods: it may intensify import competition for domestic input producers, but it can also relax sourcing constraints and reduce costs for domestic downstream users of those inputs, thereby strengthening their competitiveness.

It is straightforward to develop a version of our import competition index in equation (10) that restricts attention to intermediate inputs (see Appendix A.2). Here, we focus on developing an index of the sourcing gains associated with cheaper Chinese intermediate inputs. This is not simply a version of our consumer gains index restricted to intermediate inputs (as plotted in panel (b) of Appendix Figure B.4) because properly accounting for sourcing gains requires the use of information on input-output links between sectors.

A Sourcing Gains Index

To account for the gains from cheaper inputs, we develop a variant of our Armington-CES model that incorporates input-output links. In particular, production of each good p now uses inputs of product-type z with a cost share a_{pz}. Cheaper intermediate inputs generate heterogeneous effects on downstream sectors depending on the drop in prices of the particular inputs that each downstream sector uses. To aggregate these effects, we trace the implications of these lower costs for a country's exports to all destinations (other than the U.S. and China). In Appendix A, we show that the (first-order) percentage response of country j's exports to cheaper Chinese intermediate inputs is given by:

$$\boldsymbol{SGI}_j = 100 \times \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} (\varepsilon_{jdp} - 1) \times s_{jdp} \times \sum_{z \in \mathcal{P}^I} a_{pz} \times \chi^M_{cjz} \times \Phi_z. \tag{13}$$

where Φ_z and χ^M_{cjz} are the product-level price shock and China's share in country j's imports of input z, respectively, and where a_{pz} are IO weights mapping output p into its intermediate input requirements. In the absence of a harmonized IO table at the HS level, we use binary input-output connections provided by Fetzer et al. (2024) (see Appendix B for more details).

Our index should be interpreted as a direct, first-round exposure measure. More precisely, $\boldsymbol{SGI}$ captures the direct cost-side benefit from lower Chinese input prices, holding input shares, technology, wages, and non-Chinese input prices fixed. Furthermore, we do not solve for the full vector of induced price changes among non-Chinese producers. A richer input-output model would propagate the sourcing shock through a Leontief inverse, but our $\boldsymbol{SGI}$ is intentionally the more transparent direct-input component of that broader object.

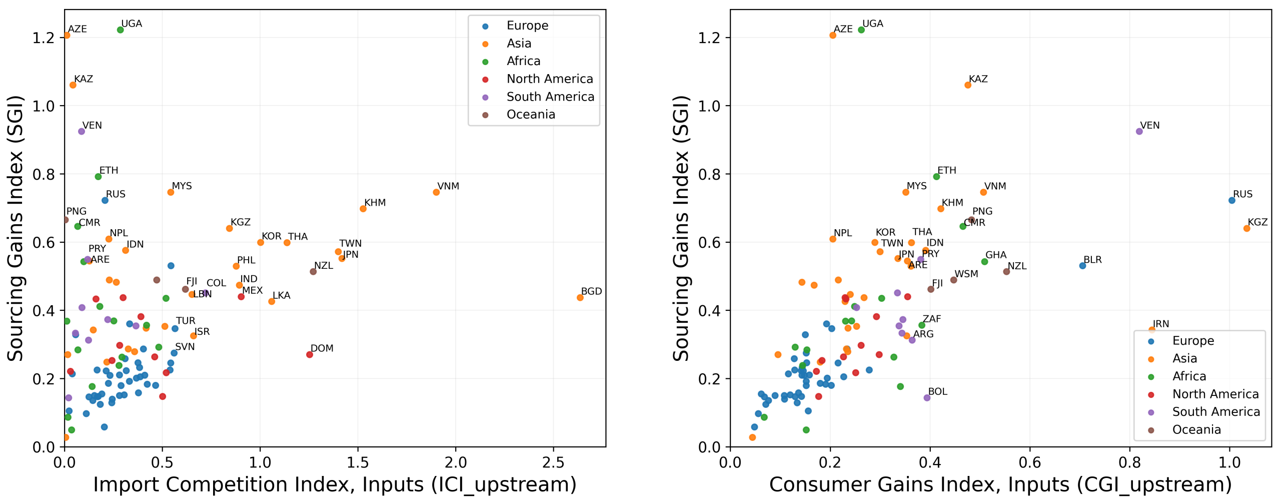
Table 6 reports the 20 economies with the highest sourcing gains index ($\boldsymbol{SGI}_j$). Uganda and Azerbaijan head the ranking, followed by Kazakhstan and Venezuela. The top 20 is geographically diverse, encompassing economies in Asia and Europe, Africa, Latin America, and the South Pacific. It includes several large or highly integrated manufacturing economies, such as Russia, Malaysia, Indonesia, Vietnam, Japan, and South Korea, as well as smaller economies such as Papua New Guinea. This composition reflects the fact that sourcing gains depend not only on direct reliance on Chinese intermediate inputs, but also on whether the affected inputs are important to the downstream sectors in which each country produces and exports.

Table 6: Top 20 economies by $\boldsymbol{SGI}_j$

Rank	Country	$\boldsymbol{SGI}_j$	Rank	Country	$\boldsymbol{SGI}_j$
1	Uganda	1.22	11	Cameroon	0.65
2	Azerbaijan	1.21	12	Kyrgyzstan	0.64
3	Kazakhstan	1.06	13	Nepal	0.61
4	Venezuela	0.92	14	South Korea	0.60
5	Ethiopia	0.79	15	Thailand	0.60
6	Malaysia	0.75	16	Indonesia	0.58
7	Vietnam	0.75	17	Taiwan	0.57
8	Russia	0.72	18	Japan	0.55
9	Cambodia	0.70	19	Paraguay	0.55
10	Papua New Guinea	0.67	20	United Arab Emirates	0.54

Figure 11 compares the sourcing-gains index with two alternative input-side exposure measures across the 110 economies. Panel (a) shows a positive but weak correlation (0.233) between $\boldsymbol{SGI}_j$ and a version of import competition index computed for intermediate inputs ($\boldsymbol{ICI}^{upstream}$, see Appendix A.2). Panel (b) shows a considerably stronger positive relationship between $\boldsymbol{SGI}_j$ and the upstream version of the consumer gains index ($\boldsymbol{CGI}^{upstream}$, see Appendix B.4.3), as the correlation between the two measures is 0.586. Sourcing gains are therefore much more closely aligned with the input-price-gain channel than with import-competition pressures. Nevertheless, the relationship is not mechanical because the effect of cheaper Chinese intermediates also depends on countries' input-output linkages and downstream production structures.

Figure 11: The Sourcing Gains Index versus the $\boldsymbol{ICI}$ and $\boldsymbol{CGI}$ for inputs



(a) $\boldsymbol{SGI}_j$ versus $\boldsymbol{ICI}^{upstream}$ (b) $\boldsymbol{SGI}_j$ versus $\boldsymbol{CGI}^{upstream}$

3.5 Taking Stock

The indices developed above capture four distinct channels through which the reallocation of Chinese exports may affect third countries. Because these channels are not mutually exclusive, there is no single notion of exposure to the U.S.-China trade war. For instance, countries may simultaneously face stronger competition from Chinese exports while benefiting from lower import prices or cheaper intermediate inputs.

Tables B.6 and B.7 shed light on the relationship among the four margins. The two competition measures are strongly correlated across countries, suggesting that economies facing greater export competition from China also tend to be more exposed to import competition in their domestic markets. Likewise, consumer gains and sourcing gains are closely related, indicating that countries benefiting from cheaper Chinese imports often also benefit from lower input costs.

In contrast, the relationship between competitive pressures and gains is considerably weaker: countries that are highly exposed to export or import competition are not necessarily those that benefit the most from lower import prices or cheaper inputs. This reflects the fact that the four indices weight the same underlying product-level shock differently, depending on countries' export patterns, import structures, and production linkages. As a result, economies can be exposed along multiple margins at once, experiencing both competitive pressures and gains from the same reallocation of Chinese exports.

The next section opens the black box of the indices and shows how these different exposure patterns arise from the interaction between a common product-level shock and country-specific incidence weights.

4 Opening the Black Box of the Indices

Section 3 summarized the exposure of countries to the reallocation of Chinese exports via four indices capturing export competition, import competition, consumer gains, and sourcing gains. The economic content of these indices rests on two building blocks: a common product-level shock measuring the decline in Chinese (f.o.b.) prices induced by the deterioration in access to the U.S. market, and country-specific weights governing where and through which margins that shock is felt. This section digs deeper into each of these layers. We first examine the product-level shock and compare the model-implied price decline, Φ_p, with the more transparent measure of initial U.S. exposure, ϕ_p. We then assess whether the products identified as more strongly affected display the reallocation of Chinese exports predicted by the model. Finally, we decompose the country-level indices into their product-level contributions, clarifying which products drive each country's measured exposure and why the same underlying shock can generate different combinations of competitive pressures and gains across countries.

4.1 The Product-Level Shock

Table 7 reports the twenty HS6 products with the highest values of ϕ_p in 2023, excluding special classification codes. Recall that ϕ_p is the share of China's exports of product p shipped to the United States in the baseline year. It therefore measures the dependence of Chinese exporters of product p on the U.S. market. The products are concentrated in a relatively narrow set of primary commodities and specialized inputs, including seafood and other animal products, ores and metals, chemical inputs, and selected nuclear and firearms-related products. High values of ϕ_p indicate that, for Chinese exporters of these goods, the U.S. market represents a particularly important destination. Exports of these products from China are therefore disproportionately oriented toward the United States.

Table 7: Top 20 HS6 Products by ϕ_p

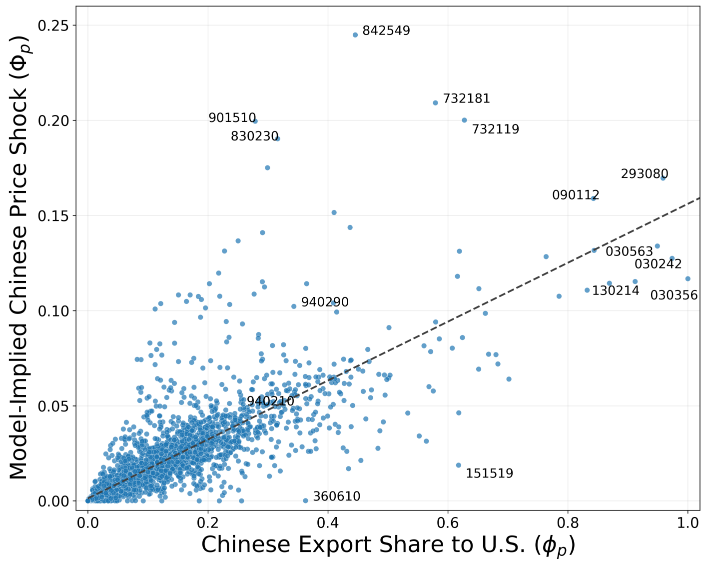
Rank	HS6	Description	ϕ_p
1	030356	Frozen cobia (*Rachycentron canadum*)	1.000
2	030242	Fresh or chilled anchovies (*Engraulis* spp.)	0.974
3	293080	Organo-sulphur compounds	0.959
4	030563	Salted anchovies, not dried or smoked	0.949
5	130214	Ephedra saps and extracts	0.912
6	030462	Frozen catfish fillets (*Pangasius* spp.)	0.869
7	030615	Frozen Norway lobsters (*Nephrops norvegicus*)	0.843
8	090112	Decaffeinated coffee, not roasted	0.843
9	842860	Teleferics, chair-lifts and ski-draglines	0.832
10	121292	Locust beans (carob), fresh, chilled, frozen or dried	0.785
11	300449	Medicaments containing alkaloids or derivatives	0.764
12	282540	Nickel oxides and hydroxides	0.702
13	630411	Knitted or crocheted bedspreads	0.683
14	901310	Telescopic sights and periscopes	0.680
15	720450	Remelting scrap ferrous ingots	0.668
16	680210	Small tiles and granules of natural stone	0.662
17	902229	Non-medical ionising radiation apparatus	0.652
18	441891	Bamboo builders' joinery and carpentry	0.651
19	732119	Solid-fuel cooking appliances and plate warmers	0.627
20	300660	Chemical contraceptive preparations	0.624

Notes: The table reports the 20 HS6 products with the highest values of ϕ_p, defined in equation (3). The sample of products is restricted to those where Φ_p, defined in equation (4), can be computed. Product descriptions are shortened from the HS6 nomenclature for readability.

Figure 12 compares this simple exposure measure ϕ_p with the model-implied Chinese price shock, Φ_p.[17] The comparison is based on the 4,254 HS6 products for which Φ_p can be computed. The two variables remain strongly related: the Pearson correlation is 0.831 and the rank correlation is 0.963. This is consistent with the variance decomposition mentioned in section 3.2.2, which indicated that most of the cross-product variation in the model-implied shock is driven by the transparent quantity component ϕ_p, rather than by the tariff and elasticity adjustments. Products well above the fitted relationship tend to combine moderate U.S. exposure with unusually large tariff changes or favorable elasticity terms. For example, HS 842549 ('non-hydraulic vehicle jacks and hoists') and HS 901510 ('rangefinders') have $\phi_p = 0.445$ and $\phi_p = 0.279$, but disproportionately large values $\Phi_p = 0.245$ and $\Phi_p = 0.200$, respectively; in both cases, the tariff-change term is particularly large, at $\Delta \log(1 + \tau_{cup}) = 0.824$. Similarly, HS 940290 ('medical or surgical furniture') lies well above the fitted line because its estimated U.S.

[17] Table B.5 reports the twenty HS6 products with the highest values of Φ_p, and decomposes it into its components as shown in equation (4).

Figure 12: The Basic versus Full Price Shock



Notes: Each dot represents an HS6 product for which both ϕ_p and Φ_p are observed. The dashed line is the OLS fitted relationship. Product labels identify selected high-exposure products and large positive or negative residuals. The sample contains 4,254 products; products with missing tariff or elasticity components needed to construct Φ_p are not shown.

demand elasticity is large relative to the average demand elasticity and Chinese export-supply elasticity entering the denominator of equation (4). Conversely, HS 151519 ('refined linseed oil') and HS 360610 ('lighter-refill fuel in small containers') have relatively high U.S. export shares, $\phi_p = 0.618$ and $\phi_p = 0.363$, but much smaller model-implied shocks, $\Phi_p = 0.019$ and $\Phi_p = 0.0001$, because their estimated Chinese export-supply elasticities are very large. In sum, ϕ_p captures the broad ranking of product exposure, while Φ_p refines it by incorporating differential tariff changes and product-specific demand and supply elasticities.

4.2 Product-Level Shocks and Chinese Export Reallocation

We now explore whether these ex ante measures of the product-level shock line up with the observed reallocation of Chinese exports across destinations. We focus on changes in cumulated Chinese exports between the twelve-month period April 2023 to March 2024 (the 'pre-period') and the twelve-month period April 2025 to March 2026 (the 'post-period'), both obtained from Trade Data Monitor. This choice is motivated by the fact that full-year 2026 data are not yet available, and the fact that the period April 2024 to March 2025 may already reflect anticipatory responses, especially after President Trump's reelection in November of 2024.

Admittedly, the exercise below is descriptive rather than causal in nature: product-level trade growth between 2023-24 and 2025-26, especially at the destination level, reflects many shocks other than U.S. trade policy. Nevertheless, the mechanism underlying our indices has a clear cross-product implication. Products subject to a larger deterioration in U.S. market access should experience a larger decline in the Chinese f.o.b. price and, in turn, a stronger expansion of Chinese exports outside the United States. We therefore begin with this third-market implication, which is the one most directly connected to the country-level exposure indices developed in Section 3. We then turn to the complementary question of whether the same products experienced larger contractions in the U.S. market.[18]

Chinese exports to the rest of the world. Consider a destination d other than the U.S. ($d \neq u$). Because U.S. tariffs do not directly affect the price paid by buyers in destination d, the change in the delivered price of the Chinese variety is simply the change in its f.o.b. price. Recalling that $\Phi_p \equiv -\Delta \log p_{cp}$ denotes the decline in the Chinese f.o.b. price, the Armington-CES model implies (see Appendix A.5)

$$\Delta \log X_{cdp} = (\varepsilon_{cdp} - 1) \times \Phi_p, \tag{14}$$

where ε_{cdp} is demand elasticity faced by China in destination d.

The model therefore predicts a positive relationship between the growth of Chinese exports to destinations other than the U.S. and the product-level price decline Φ_p, with the effect mediated by the demand elasticity term $\varepsilon_{cdp} - 1$. We test this prediction at the HS6 product–destination level using three proxies for the term $(\varepsilon_{cdp} - 1) \times \Phi_p$. We first consider a case in which all demand and supply elasticities are common across countries and products, and in which U.S. trade barriers vis à vis China are uniform across products, so that variation in the independent variable reduces to ϕ_p, i.e., the share of Chinese exports of product p shipped to the United States in the baseline year. This is a transparent exposure measure that has the benefit of not relying on potentially problematic estimates of demand and supply elasticities, or noisy proxies for effective trade barriers. Next, we experiment with specifications in which ϕ_p is replaced with Φ_p, which is the model-implied decline in the Chinese f.o.b. price and which incorporates the product-specific tariff change and the demand and supply elasticities entering equation (4). Finally, we interact Φ_p with proxies for the destination- and product-specific demand elasticity term $\varepsilon_{cdp} - 1$.

Our destination-level specification allows us to control for destination fixed effects, thereby

[18] It may have seemed more natural to assess the model-implied price decline, Φ_p, with observed changes in Chinese export unit values. We do not do so because customs data report ratios of trade values to recorded quantities rather than constant-quality prices. Even within an HS6 product, changes in unit values may reflect changes in quality, product composition, destination mix, firms, contractual terms, or reporting units. These concerns are particularly relevant here because the U.S. trade shock may itself change the composition of Chinese exports across firms and destinations. Observed unit-value changes would therefore provide a potentially endogenous and noisy measure of the common f.o.b. price change featured in the model.

absorbing changes in aggregate import demand, exchange rates, and other destination-wide conditions between 2023 and 2025. It also permits the response to the common product-level price decline to vary with the destination-specific elasticity of demand faced by Chinese exporters. In some specifications, we will also incorporate two-digit HS (HS2) fixed effects. Throughout, standard errors are two-way clustered by HS6 product and destination.

It is worth emphasizing that our destination and product-specific design also carries important limitations. Product–destination trade growth may be particularly noisy for initially small flows. Furthermore, the log-change specification requires positive Chinese exports in both periods and consequently excludes entry and exit. To avoid our results being driven by volatile growth of low-volume product categories, our baseline estimates are weighted proportionally to the 2023 value of Chinese exports in each product–destination cell, or:

$$\omega_{dp} = \frac{X_{cdp,2023}}{\sum_p \sum_{d' \in \mathcal{W}_-} X_{cd'p,2023}}. \tag{15}$$

In Appendix B.5 (Table B.10), we also present results of unweighted regressions with our full sample, and also with restricted samples that apply winsorizing or remove particular product categories with especially small aggregate Chinese exports to non-U.S. destinations.

Table 8: Predicted price responses and Chinese export reallocation across destinations

	$\Delta \log X_{cdp}$					
	(1)	(2)	(3)	(4)	(5)	(6)
ϕ_p	1.280***	0.998***				
	(0.223)	(0.230)				
Φ_p			3.371***	2.115**		
			(0.810)	(0.968)		
$(\varepsilon_{cdp} - 1)\Phi_p$					1.715***	1.413**
					(0.501)	(0.557)
Destination fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
HS2 fixed effects	No	Yes	No	Yes	No	Yes
Observations	479,835	479,835	391,915	391,915	300,862	300,862
HS6 products	5,189	5,189	4,068	4,068	4,011	4,011
Destinations	191	191	191	191	163	163
R^2	0.071	0.128	0.079	0.124	0.089	0.137

Notes: The dependent variable is $\Delta \log X_{cdp}$ between the pre-period (April 2023 to March 2024) and the post-period (April 2025 to March 2026). The United States, Hong Kong, and Macao are excluded as destinations of Chinese exports. The regressions are weighted by each destination-product cell's 2023 Chinese export value. Standard errors are clustered by HS6 product and destination and reported in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8 presents our baseline results. Columns (1) and (2) regress bilateral export growth between the pre- and post-periods on the basic U.S. exposure measure ϕ_p. Regardless of whether HS2 fixed effects are included or not, the coefficient on ϕ_p is positive and statistically significant at the 1 percent level. Products for which the United States initially represented a larger share of Chinese exports therefore experienced faster subsequent export growth across their non-U.S. destinations. The results are also quantitatively meaningful: in column (1), a 10-percentage-point increase in U.S. exposure (say from 10% to 20%) is associated with 0.128 log points (or 13.7%) higher growth to a non-U.S. destination.

Columns (3) and (4) replace ϕ_p with the model-implied f.o.b. price decline Φ_p, but do not yet interact that price decline with destination-specific demand conditions. The estimated coefficient is 3.371 without HS2 fixed effects and remains statistically significant at the 1 percent level, while it drops to 2.115 and is significant at the 5 percent level with HS2 effects. It should be stressed that coefficients should not be compared mechanically with those in columns (1) and (2) involving ϕ_p, since the two shock measures are expressed on different scales. Their common implication, however, is that larger predicted Chinese price declines are associated with faster bilateral export growth outside the United States.

Finally, in columns (5) and (6) we introduce the full destination-specific predictor, $(\varepsilon_{cdp} - 1) \times \Phi_p$. When only destination fixed effects are included in column (5), the coefficient is 1.715, significant at the 1% level. Adding HS2 fixed effects in column (6) reduces the estimate to 1.413, but preserves statistical significance at the 5 percent level. The positive coefficients are consistent with the model's prediction that a given Chinese price decline generates more export growth where residual demand is more elastic. Furthermore, although both estimates lie above the model's predicted value of 1, the hypothesis that the coefficient is indeed 1 cannot be rejected.[19]

In Appendix Table B.10, we examine various dimensions of robustness. First, winsorizing the dependent variable at its 2.5th and 97.5th percentiles modestly reduces the estimates while preserving their qualitative pattern. The baseline results therefore do not appear to be driven solely by extreme bilateral export-growth observations. Second, excluding products for which China's aggregate 2023 exports to the included non-U.S. destinations were no more than \$1 million leaves the estimates essentially unchanged. The positive relationship therefore does not appear to be generated by products with negligible exports outside the United States. The role of the weighting in equation (15) is more consequential. In unweighted regressions, the coefficients on ϕ_p and Φ_p remain positive and statistically significant but fall markedly, to 0.137 and 0.799, respectively, without HS2 fixed effects. The coefficient on the exact destination-

[19] In principle, the specification in columns (5) and (6) also allows one to include HS6 fixed effects. We do not favor this specification because, in this case, the effect is estimated off variation in destination- and product-specific demand elasticities, which may be estimated with substantial noise. Indeed, when running this specification, the coefficient on $(\varepsilon_{cdp} - 1) \times \Phi_p$ falls to 0.705 and is only statistically significant at the 10 percent level. This suggests that the baseline relationship is driven primarily by between-product variation, rather than the destination-specific elasticity channel.

specific predictor in column (5) falls to 0.795, though it remains statistically significant at the 1% level (the same is true when adding HS2 fixed effects). The last three robustness tests in Table B.10 have a much more muted impact on our estimates. We first explore an 'unmirrored' specification in which Chinese exports are measured using each destination's reported imports alone, rather than the baseline measure, which imputes missing imports with each country pair's reported exports, and uses weights equal to that unmirrored value. We then explore two alternative definitions of the pre- and post-periods. The alternate-pre specification replaces the pre-period with January 2023 to December 2023, holding the post-period fixed at April 2025 to March 2026, while the alternate-post specification replaces the post-period with December 2024 to November 2025, holding the pre-period fixed at April 2023 to March 2024. To reiterate, these three robustness tests deliver very similar results to our baseline ones.

Taken together, our results offer some support to the central product-level implication of our framework: Chinese exports expanded more rapidly outside the United States in products that were initially more exposed to the U.S. market. The evidence for the full elasticity-adjusted price shock points in the same direction, but is a bit weaker once comparisons are restricted to products within the same HS2 sector. Overall, we regard these regression results as evidence of a broad cross-product reallocation pattern, but we refrain from interpreting them as a causal estimate of the effect of U.S. tariffs on Chinese exports to third markets.

Chinese export contraction in the United States. The preceding results concern the destinations toward which Chinese exports were reallocated. A complementary question is whether the same product-level measures identify the sectors in which Chinese exports to the United States contracted the most. The mapping is less immediate on the U.S. side because the tariff is the primitive adverse shock, whereas the decline in the Chinese f.o.b. price is an equilibrium response that partly cushions the contraction in U.S. demand. More specifically, as shown in Appendix A.5, CES demand in the United States implies that f.o.b. Chinese exports to the U.S. ($\tilde{X}_{cup}$) satisfy:

$$\Delta \log \tilde{X}_{cup} = -\varepsilon_{cup} \Delta \log(1 + \tau_{cup}) + (\varepsilon_{cup} - 1)\Phi_p. \tag{16}$$

The first term is the direct contraction generated by the tariff, whereas the second captures the extent to which the endogenous decline in the Chinese f.o.b. price cushions that contraction.

We first take equation (16) directly to the data in Appendix Table B.11, using the log change in Chinese exports to the United States as the dependent variable, analogously to our specification in Table 8. The regressions are weighted by each product's 2023 China-to-U.S. export value, as in Table 8. Products with greater initial U.S. exposure experienced larger subsequent export contractions: the coefficient on ϕ_p is -1.481 in column (1) and remains at -1.474 after controlling for the observed tariff change in column (2), with both estimates statistically significant at the 10 percent level. Thus, a 10-percentage-point increase in initial U.S. exposure is associated with approximately 0.15 log points lower growth in Chinese exports to the United States. The coefficient on the model-implied price decline Φ_p is also negative: it is -5.979 in column (4) and -11.121 when the tariff change is included in column (5), although only the latter estimate is statistically significant at the 10 percent level.

These results may seem intuitive given our interpretation of Φ_p as an index of product-level exposure, but the negative estimated coefficients are actually inconsistent with equation (16). Conditional on the tariff shock, the model predicts that the endogenous decline in the Chinese f.o.b. price should cushion the contraction in U.S. demand, implying a *positive* coefficient on Φ_p (and on ϕ_p , in the simpler specification in which ϕ_p is used as a proxy for the price response). Instead, both variables continue to enter negatively after controlling for the tariff change. The tariff coefficient itself is -0.210 and statistically insignificant in column (2), while it is positive and statistically significant in column (5). This is again contrary to the model's direct tariff channel. The direct log-change test therefore fails to recover the signs predicted by the model.[20] One possible explanation is that statutory tariff changes are a noisy or imperfect proxy for changes in the effective trade barriers faced by individual products. Exemptions, enforcement, tariff avoidance, non-tariff measures, anticipation, and differences in implementation may all weaken the correspondence between measured tariffs and the economically relevant trade cost.

Motivated by this failure, we next examine the less demanding implication that products with greater U.S. exposure and larger model-implied shocks experienced greater reallocation *in levels*. To express the contraction in U.S. exports relative to China's aggregate pre-period exports of the product, define

$$Y_p \equiv \frac{\tilde{X}_{cup}^{post} - \tilde{X}_{cup}^{pre}}{\tilde{X}_{cp}^{pre}}.$$

Because $\tilde{X}_{cup}^{pre}/\tilde{X}_{cp}^{pre} \simeq \phi_p$, we obtain the approximation:

$$Y_p \simeq -\varepsilon_{cup} \times \phi_p \times \Delta \log(1+\tau_{cup}) + (\varepsilon_{cup} - 1) \times \phi_p \times \Phi_p. \tag{17}$$

Equation (17) predicts a negative coefficient on the direct tariff component, mediated by the product's initial U.S. export share, and a positive coefficient on the price-offset component. This motivates the alternative specification reported in Table 9. The baseline specifications weight each HS6 product by the value of China's exports of that product to the United States in 2023, but we will show that similar results apply in unweighted regressions.

Columns (1) and (2) of Table 9 begin with the basic U.S. exposure measure (ϕ_p). The

[20] Including interactions with demand elasticities, in columns (3) and (6), also fails to render the coefficients consistent with theory.

Table 9: Product-level exposure and changes in Chinese exports to the United States

	Dependent variable: $Y_p \equiv (\tilde{X}_{cup}^{post} - \tilde{X}_{cup}^{pre})/\tilde{X}_{cp}^{pre}$					
	(1)	(2)	(3)	(4)	(5)	(6)
ϕ_p	-0.446***	-0.503***				
	(0.070)	(0.070)				
$\phi_p \Delta \log(1+\tau_{cup})$			-0.874***	-0.869***		
			(0.281)	(0.302)		
$\varepsilon_{cup}\phi_p \Delta \log(1+\tau_{cup})$					-0.311	-0.338
					(0.221)	(0.216)
$(\varepsilon_{cup}-1)\phi_p \Phi_p$					0.496	0.270
					(1.218)	(0.974)
HS2 fixed effects	No	Yes	No	Yes	No	Yes
Observations	4,617	4,617	4,580	4,580	3,485	3,485
R^2	0.207	0.295	0.124	0.210	0.058	0.234

Notes: The dependent variable is $\Delta \tilde{X}_{cup}$ between the pre-period (April 2023 to March 2024) and the post-period (April 2025 to March 2026), normalized by total product-level Chinese exports $\tilde{X}_{cp}$ in the pre-period. The sample contains HS6 products with positive China-to-U.S. exports in 2023. Weights are equal to 2023 China-to-U.S. export values. Heteroskedasticity-robust standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

estimated coefficient is -0.446 without HS2 fixed effects and -0.503 with them. Both estimates are statistically significant at the 1 percent level. Thus, among products representing economically important U.S. trade flows, greater initial dependence on the U.S. market predicts a larger subsequent contraction in Chinese exports to that market.

Columns (3) and (4) incorporate the product-specific tariff change. The coefficient on $(\phi_p \Delta \log(1 + \tau_{cup}))$ is -0.874 without HS2 fixed effects and -0.869 with them, and both estimates are statistically significant at the 1 percent level. The near equality of the two estimates indicates that this relationship is not driven by broad differences across HS2 sectors.

Columns (5) and (6) implement the decomposition in equation (17). The direct tariff component enters negatively, while the price-offset component enters positively, as predicted by the model. With or without HS2 fixed effects, however, neither of the coefficients is statistically significant. The results therefore offer some support for the negative impact of trade barriers and initial shares of Chinese exports destined to the United States on Chinese export revenue in the United States, but there is much weaker evidence for the endogenous f.o.b. price decline cushioning part of that contraction.

Appendix Table B.12 examines the robustness of the Table 9 results. Winsorizing Y_p at its 2.5th and 97.5th percentiles modestly attenuates the estimates while leaving the qualitative pattern of the baseline results unchanged. Restricting the sample to products with more than \$1 million of 2023 China-to-U.S. exports likewise leaves the weighted estimates virtually unchanged, as small flows receive negligible weight in the baseline. The reduced-form exposure results are also robust to removing the weights: the coefficients on ϕ_p and on $\phi_p \Delta \log(1 + \tau_{cup})$ remain negative and highly statistically significant. The structural decomposition is less robust, however. In the unweighted specification, the direct tariff component remains negative and becomes statistically significant, but the estimated price-offset component turns negative and statistically significant, contrary to the model's prediction.

The remaining robustness exercises reinforce this distinction. Measuring Chinese exports using U.S.-reported imports alone produces estimates very close to the baseline, including a negative direct tariff component and a positive, though imprecisely estimated, price-offset component. The reduced-form exposure coefficients also remain negative and statistically significant under both alternative time windows. The structural price-offset term remains positive but imprecisely estimated under both alternative time windows. Its sign reversal in the unweighted specification nevertheless underscores the fragility of the evidence for this channel. Thus, the negative relationship between initial U.S. exposure and subsequent Chinese export performance in the United States is quite robust, whereas the evidence for the model's positive price-offset channel is considerably weaker.

Taken together, Table 9 provides robust evidence that products more exposed to the U.S. market, particularly when that exposure is scaled by the observed tariff change, experienced larger contractions in U.S. sales. The more structural decomposition provides only suggestive evidence for the mechanisms emphasized by the model: its baseline point estimates have the predicted signs, but neither component is precisely estimated and the positive price-offset coefficient is not robust across specifications. Together with the failure of observed tariff changes to deliver the predicted conditional signs in the direct log-change specification, these results support interpreting the exercise primarily as a qualitative check on whether the model aligns with broad cross-product patterns in the data, rather than as a causal or quantitative validation of the model.

4.3 Decomposing the Indices

The previous subsection showed that the product-level shock Φ_p has empirical content in explaining the reallocation of Chinese exports toward non-U.S. destinations. We now ask how this product-level variation maps into the country-level exposure indices developed in Section 3. In particular, each of our four indices is a weighted aggregate of the same product-level shocks, but the weights applied differ across exposure margins. As a result, the same underlying product-level shocks can imply export competition for one country, domestic import competition for another, consumer gains for a third, and sourcing gains for a fourth. This exercise may also prove useful for researchers and policy makers interested in opening the black box of our aggregated indices to better understand the sources of exposure.

We decompose each index into product-level contributions as follows. For each exposure margin $\boldsymbol{Z} \in \{\boldsymbol{ECI}, \boldsymbol{ICI}, \boldsymbol{CGI}, \boldsymbol{SGI}\}$, we write $\boldsymbol{Z}_j = \sum_{p \in \mathcal{P}} \boldsymbol{Z}_{jp}$, where $\boldsymbol{Z}_{jp}$ denotes the contribution of product p to country j's exposure through margin Z. For instance, for the export competition index, the product contribution aggregates internally over destination markets:

$$\boldsymbol{ECI}_{jp} = 100 \times \Phi_p \times \sum_{d \in \mathcal{W}^-} (\sigma_{dp} - 1)\, \chi_{cdp} \, \frac{X_{jdp}}{X_j}.$$

Thus, although export competition is conceptually determined in product–destination markets, the decomposition reported below aggregates those destination-specific terms to the HS6 product level. For the other three indices, the decomposition is also at the product level:

$$\boldsymbol{ICI}_j = \sum_{p \in \mathcal{P}} \boldsymbol{ICI}_{jp}, \qquad \boldsymbol{CGI}_j = \sum_{p \in \mathcal{P}} \boldsymbol{CGI}_{jp}, \qquad \boldsymbol{SGI}_j = \sum_{p \in \mathcal{P}} \boldsymbol{SGI}_{jp}.$$

The difference across these objects lies in the weights attached to Φ_p. The import competition index weights the shock by the importance of product p for domestic production and by the extent of Chinese penetration in that product. The consumer gains index weights the same shock by the importance of product p in the country's import basket. The sourcing gains index instead traces the effect of cheaper Chinese inputs through downstream production linkages.

For each index, we compute the product's share in the corresponding country-level exposure, or $\omega^Z_{jp} = 100 \times \boldsymbol{Z}_{jp}/\boldsymbol{Z}_j$. These shares sum to 100 within each country and index. They identify the particular products that explain why a country appears exposed along a given margin.[21]

Table 10 reports the leading product contribution for the ten economies with the highest export competition exposure. The table illustrates the concentration of export-competition exposure in a small number of HS6 products. For Armenia, colour televisions account for 25.87 percent of the country's $\boldsymbol{ECI}$, while for Kyrgyzstan, radiators and parts account for 26.64 percent of its $\boldsymbol{ECI}$. Even in larger manufacturing exporters, exposure can be concentrated: cellular phones account for 32.19 percent of Vietnam's $\boldsymbol{ECI}$, while lithium-ion batteries are the largest contributor for Hungary, accounting for a remarkable 48.07 percent of this country's export exposure.

Table 11 performs the same exercise for import competition. Product concentration is also substantial, though it varies across countries. Cellular telephones account for 30.80 percent of India's $\boldsymbol{ICI}$ and 20.03 percent of South Korea's, while women's synthetic-fibre trousers account for 20.74 percent of Jordan's $\boldsymbol{ICI}$. At the other end, video game consoles and machines account for only 5.86 percent of Japan's $\boldsymbol{ICI}$. These examples make clear that domestic import-competition exposure is not simply about importing many goods from China; it reflects

[21] The complete country-by-product decompositions are available through the online platform accompanying our paper, which allows users to inspect the products underlying each country's overall index.

Table 10: Top Product Contribution to Export Competition Exposure

Rank	Economy	$\boldsymbol{ECI}_j$	HS6	Top product	Share
1	Armenia	2.46	852872	Colour televisions	25.87
2	Kyrgyzstan	2.31	870891	Radiators and parts	26.64
3	Vietnam	2.26	851712	Cellular telephones	32.19
4	Cambodia	1.56	611030	Synthetic sweaters & cardigans	9.05
5	Bangladesh	1.28	611030	Synthetic sweaters & cardigans	14.45
6	Hungary	1.19	850760	Lithium-ion batteries	48.07
7	Czechia	1.07	850760	Lithium-ion batteries	11.87
8	Sri Lanka	1.00	611610	Knitted gloves, plastic- or rubber-coated	8.03
9	Thailand	0.93	851762	Data transmission and routing apparatus	5.87
10	Mexico	0.92	851762	Data transmission and routing apparatus	12.31

Notes: The table reports the single HS6 product which contributes the most to the $\boldsymbol{ECI}_j$. The final column reports that product's contribution as a percentage of the country-level index.

whether the product-level shock hits sectors that matter for domestic production.

Table 11: Top Product Contribution to Import Competition Exposure

Rank	Economy	$\boldsymbol{ICI}_j$	HS6	Top product	Share
1	Vietnam	3.44	851712	Cellular telephones	13.99
2	Cambodia	3.03	611020	Cotton sweaters and cardigans	16.37
3	Pakistan	2.33	620342	Men's cotton trousers	12.02
4	Madagascar	2.16	620342	Men's cotton trousers	19.82
5	Japan	1.62	950450	Video game consoles and machines	5.86
6	India	1.61	851712	Cellular telephones	30.80
7	South Korea	1.57	851712	Cellular telephones	20.03
8	Jordan	1.57	610463	Women's synthetic-fibre trousers	20.74
9	Bangladesh	1.52	620342	Men's cotton trousers	17.12
10	Kyrgyzstan	1.51	870891	Radiators and parts	19.15

Notes: The table reports the single HS6 product which contributes the most to the $\boldsymbol{ICI}_j$. The final column reports that product's contribution as a percentage of the country-level index.

Table 12 turns to consumer gains. The top products differ noticeably from those in the import-competition table. For Kyrgyzstan, synthetic sweaters and cardigans are the largest contributor, but account for only 5.29 percent of the index. In several other cases, the leading product accounts for less than 10 percent of total exposure. At the same time, concentration can be considerably higher: cellular telephones account for 33.62 percent of Paraguay's $\boldsymbol{CGI}_j$ and 34.47 percent of that of the United Arab Emirates. This is an important distinction, as consumer gains tend to be more diffuse across the import basket than import competition: on average, the top-5 products make up 26.1 percent of the $\boldsymbol{CGI}$ and 37.6 percent of the $\boldsymbol{ICI}$.

Table 12: Top Product Contribution to Consumer Gains Exposure

Rank	Economy	$\boldsymbol{CGI}_j$	HS6	Top product	Share
1	Kyrgyzstan	1.57	611030	Synthetic sweaters & cardigans	5.29
2	Russia	1.20	847130	Portable computers	5.33
3	Paraguay	1.09	851712	Cellular telephones	33.62
4	Venezuela	1.04	852872	Colour televisions	5.49
5	United Arab Emirates	0.92	851712	Cellular telephones	34.47
6	South Africa	0.91	850760	Lithium-ion batteries	28.08
7	Iran	0.91	870899	Motor-vehicle parts and accessories	7.52
8	New Zealand	0.87	847130	Portable computers	12.97
9	Belarus	0.85	852872	Colour televisions	12.23
10	Kazakhstan	0.84	847130	Portable computers	5.27

Notes: The table reports the single HS6 product which contributes the most to the $\boldsymbol{CGI}_j$. The final column reports that product's contribution as a percentage of the country-level index.

Finally, Table 13 reports the analogous decomposition for sourcing gains. It should be emphasized that the listed products are those that benefit disproportionately from cheaper prices of their inputs, and *not* the inputs themselves generating lower costs downstream. The concentration in the $\boldsymbol{SGI}_j$ is often extreme. Crude petroleum oil accounts for 92.57 percent of Kazakhstan's sourcing-gains index and 96.48 percent of Azerbaijan's, as well as 68.71 percent of Venezuela's and 47.03 percent of Russia's. Semi-manufactured gold accounts for 73.99 percent of Uganda's index, while coffee accounts for 59.59 percent of Ethiopia's. These patterns reflect the distinctive nature of the sourcing channel: what matters is not simply whether a country imports a product, but whether the affected Chinese input is important for downstream activity.

Table 13: Top Product Contribution to Sourcing Gains Exposure

Rank	Economy	$\boldsymbol{SGI}_j$	HS6	Top product	Share
1	Uganda	1.22	710813	Semi-manufactured gold	73.99
2	Azerbaijan	1.21	270900	Crude petroleum oil	96.48
3	Kazakhstan	1.06	270900	Crude petroleum oil	92.57
4	Venezuela	0.92	270900	Crude petroleum oil	68.71
5	Ethiopia	0.79	090111	Coffee, not roasted or decaffeinated	59.59
6	Malaysia	0.75	270900	Crude petroleum oil	14.78
7	Vietnam	0.75	270900	Crude petroleum oil	7.36
8	Russia	0.72	270900	Crude petroleum oil	47.03
9	Cambodia	0.70	611020	Cotton sweaters and cardigans	6.12
10	Papua New Guinea	0.67	271111	Liquefied, natural gas	32.43

Notes: The table reports the single HS6 product which contributes the most to the $\boldsymbol{SGI}_j$. The final column reports that product's contribution as a percentage of the country-level index.

Several lessons follow from these decompositions. First, exposure is often highly concentrated. This is particularly true for sourcing gains, where the top product accounts for more than half of the index in five of the ten economies reported in Table 13. Second, the same product can appear in multiple channels but for different reasons. For example, lithium-ion batteries matter for export competition in Hungary, for consumer gains in South Africa, and for import competition in some other economies outside the top ten. Third, the decomposition clarifies why the country rankings differ so much across the four indices. All four indices are built from the same product-level shock Φ_p, but each attaches that shock to a different country-specific weight: export exposure, domestic production exposure, import-consumption exposure, or input-output exposure.[22]

5 Conclusions

The post-2018 period is best understood not as a generalized reversal of globalization, but as a reorganization of trade and production linkages in response to policy shocks and strategic rivalry. Using up-to-date information on the evolving tariff regime and recent trade flows, we have documented that the U.S.–China trade war has generated a sharp reallocation of U.S. import sourcing away from China and a corresponding reorientation of Chinese exports toward other destinations, with an acceleration in adjustment during the most recent escalation following Liberation Day. These shifts have reshaped competitive conditions globally, even when aggregate world trade remains broadly stable.

A central message of the paper is that third-country outcomes cannot be read solely through the lens of simple trade diversion. To discipline an interpretation of these third-market effects, we have proposed a taxonomy that distinguishes four (non-mutually exclusive) margins – export competition, import competition, consumer gains, and sourcing gains – and operationalized them with diagnostic indices. This approach clarifies why some economies appear to benefit on one margin while facing intensified pressure on another.

A broader contribution of the paper is methodological. Commonly used export- and import-similarity indices answer the useful descriptive question of how closely one country's trade basket resembles another's. But these similarity measures do not measure the incidence of a particular supply shock. Incidence is inherently asymmetric and depends on the magnitude of

[22] The online platform accompanying our paper extends this decomposition to all countries, products, and indices. In addition to reporting country-level values and rankings, it allows users to select a country and index and view the products contributing most to that country's exposure. It also allows users to start from an HS6 product and identify the countries for which that product is most salient. This product-level drill-down is useful both for transparency and for interpretation: it shows whether a country's exposure reflects a broad-based pattern across many products or instead a concentrated vulnerability or opportunity tied to a small number of sectors. In this sense, the online platform is not merely a data appendix, but a way of opening the black box of the exposure indices.

the shock across products, China's penetration of the relevant markets, substitution elasticities, and the country-specific revenue, production, expenditure, and input-output weights through which the shock is transmitted. By incorporating these objects, our indices produce assessments of exposure that differ materially from those based on similarity alone.

Although we implement the framework using the product-level shock generated by the U.S.–China tariff conflict, its logic extends beyond this particular episode. Any force that generates heterogeneous changes in Chinese supply or prices across products – including industrial policy, productivity growth, exchange-rate movements, or changes in Chinese domestic demand – can in principle be combined with the same incidence weights. The framework thus provides a portable set of diagnostics for identifying where a supply expansion by a large exporter creates competitive pressure and where it generates gains.

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A Theoretical Appendix: Microfounding our Indices

In this Appendix, we lay out the theoretical model underpinning our exposure measures, and we show how to derive our main four indices of exposure.

A.1 A Baseline Armington-CES Model

We begin by developing a completely standard Armington-CES model of international trade. We will later introduce upward sloping supply schedules to justify the decline in Chinese prices to third markets when facing higher tariffs in a given country (the United States).

Environment The world consists of a finite set of countries indexed by $o, d \in \mathcal{W}$ and a finite set of products indexed by $p \in \mathcal{P}$. We sometimes use the notation $\mathcal{W}_{-}$ to denote the set of countries in the world excluding the U.S. and China. We interpret d as a destination (importing) market, while o denotes an origin (exporting) country. Countries may act as both importers and exporters. At times we will refer explicitly to the U.S. (indexed by u) and China (indexed by c). We will also denote by j a 'third country' whose exposure we are interested in computing.

For each destination d and product p, total nominal expenditure on product p in market d is denoted E_{dp}. Throughout, E_{dp} is treated as a constant in our comparative-static exercises. One way to rationalize this assumption is by invoking Cobb-Douglas preferences over different types of products, while introducing an outside sector that pins down nominal income.

Each origin o supplies a single Armington variety of each product p to each destination d at a delivered price p_{odp}. These delivered prices can be interpreted as incorporating production costs, trade costs, and markups.

Preferences and Demand Fix a destination market d and product p. Consumers in d have CES preferences over country-of-origin varieties of product p:

$$Q_{dp} = \left(\sum_{o \in \mathcal{W}} (Q_{odp})^{\frac{\sigma_{dp}-1}{\sigma_{dp}}} \right)^{\frac{\sigma_{dp}}{\sigma_{dp}-1}}, \qquad \sigma_{dp} > 1, \tag{A.1}$$

where Q_{odp} is quantity of the o-variety of product p consumed in market d, and σ_{dp} is the elasticity of substitution across origins for p in destination d. The CES price index for product p in destination d is

$$P_{dp} = \left(\sum_{o \in \mathcal{W}} p_{odp}^{1-\sigma_{dp}} \right)^{\frac{1}{1-\sigma_{dp}}},$$

where remember that p_{odp} is the delivered price of variety o of good p sold in market d.

Let X_{odp} denote nominal expenditure (revenue) of product p in destination d sourced from origin o:

$$X_{odp} \equiv p_{odp} Q_{odp}.$$

CES demand implies that the expenditure share of origin o in destination d and product p is

$$\chi_{odp} \equiv \frac{X_{odp}}{E_{dp}} = \frac{p_{odp}^{1-\sigma_{dp}}}{\sum_{o' \in \mathcal{W}} p_{o'dp}^{1-\sigma_{dp}}}, \qquad \sum_{o \in \mathcal{W}} \chi_{odp} = 1. \tag{A.2}$$

Thus, bilateral revenues satisfy $X_{odp} = \chi_{odp} E_{dp}$.

A Price Shock and Third-Country Export Losses We are interested in how an exporter-specific price change in a 'destination-product' market reallocates expenditure across origins, and thereby affects third-country export revenues.

Fix a particular origin c (China) and consider a small proportional decline in its delivered price of product p in all destinations $d \in \mathcal{W}_{-}$:

$$d \ln p_{cdp} = -\Phi_p, \qquad \Phi_p > 0, \tag{A.3}$$

holding fixed (i) total expenditure E_{dp} and (ii) the delivered prices of all other origins, p_{odp} for $o \neq c$. For the time being, the shock may be interpreted as a productivity increase, a relative wage decline, or a downward move along an upward-sloping export supply schedule affecting exporters of p from c. We shall return to the latter interpretation below. Because we only consider this China-specific shock, and because it is assumed that all destination prices are affected proportionately, we can safely refer to $-d \ln p_{cdp}$ as a product-level shock, which we denote by Φ_p (see equation (A.3)).

Let j denote a third-country exporter of good p potentially displaced by c in market d. Since $X_{jdp} = \chi_{jdp} E_{dp}$, changes in X_{jdp} arise through changes in χ_{jdp} induced by (A.3). Differentiating the CES share formula (A.2) yields:

$$dX_{jdp} = -(\sigma_{dp} - 1) \times \Phi_p \times \chi_{cdp} \times \chi_{jdp} \times E_{dp}. \tag{A.4}$$

Equation (A.4) captures the crowding out effect of the increased Chinese exports, i.e., the revenue loss of exporter j in a given market. This loss is proportional to (i) the substitution elasticity $\sigma_{dp} - 1$, (ii) the size of the shock Φ_p, (iii) the size of the market E_{dp}, and (iv) the product of the two competitors' initial expenditure shares, χ_{jdp} and χ_{cdp}. Holding fixed the elasticity and market size, third-country losses are largest in destination–product markets where (a) exporter j is important (high χ_{jdp}) and (b) exporter c is also important (high χ_{cdp}). If either exporter has negligible market share, there is little (first-order) displacement in that market.

Aggregation Across Products and Destinations Define total exports of country j excluding sales to the U.S. and China as the sum of revenues across all destinations and products:

$$X_j \equiv \sum_{d \in \mathcal{W}_-} \sum_{p \in \mathcal{P}} X_{jdp}.$$

Summing (A.4) across (p, d) yields the first-order change in total exports:

$$dX_j = - \sum_{d \in \mathcal{W}_-} \sum_{p \in \mathcal{P}} (\sigma_{dp} - 1) \times \Phi_p \times \chi_{cdp} \times \chi_{jdp} \times E_{dp}. \tag{A.5}$$

To express (A.5) in terms of observable trade shares, define:

$$X_{jd} \equiv \sum_{p \in \mathcal{P}} X_{jdp} \qquad \text{(exports of } j \text{ to destination d)}, \tag{A.6}$$

$$s_{jd} \equiv \frac{X_{jd}}{X_j} \qquad \text{(destination share in } j\text{'s total exports)}, \tag{A.7}$$

$$s_{jdp} \equiv \frac{X_{jdp}}{X_{jd}} \qquad \text{(product share within } j\text{'s exports to } d\text{)}. \tag{A.8}$$

Note that $X_{jdp} = X_j \times s_{jd} \times s_{jdp}$, and that $\chi_{cdp} = X_{cdp}/E_{dp}$ is the share of destination d's expenditure on product p sourced from China.

The Export Competition Index (*ECI*) Dividing the change in country j's exports by the initial level of exports, we obtain

$$\frac{dX_j}{X_j} = - \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} (\sigma_{dp} - 1) \times \Phi_p \times \chi_{cdp} \times s_{jdp}.$$

Multiplying this by -100 delivers equation (7) in the main text, defining our export competition index (***ECI***), and shows that indeed it corresponds to the predicted percentage decline of country j's exports resulting from the decline in Chinese prices to all destinations (other than China and the U.S.).

If the elasticity of demand does not vary across products or destinations, $\sigma_{dp} = \sigma$, then notice that

$$\frac{dX_j}{X_j} = -(\sigma - 1) \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} \Phi_p \times \chi_{cdp} \times s_{jdp}. \tag{A.9}$$

We will come back to this expression when introducing the so-called 'basic' versions of our indices.

Exports versus Domestic Sales Notice that because the formula includes exports only, the summation should also omit country j itself. Relatedly, X_j in the formula is the sum of all of country j's *exports* to all destinations other than the U.S. and China. As for χ_{cdp}, in principle this should be computed as the share of total absorption of good p in destination market d accounted for by China, but we shall approximate it by the share of overall imports of good p by country d that originate in China. We do so because we do not have access to information on the domestic sales of producers of good p in d (at least, at a disaggregated enough level). A way to theoretically rationalize this empirical strategy would be to stipulate preferences as being separable in domestic varieties and imported ones, so that all the relevant CES aggregators sum only over foreign varieties. In such a case, the model would dictate that χ_{cdp} should indeed be computed as the ratio of d's imports of good p from China over d's aggregate imports of good p.

The Import Competition Index ($\boldsymbol{ICI}$) We now consider the impact of the same shock on the domestic producers of a destination market j. As stated in the main text, there is a clear connection between this question and our derivations above, in the sense that we are considering a special case of our shock in which the destination market d under study is identical to the origin country j. These considerations have no bearing on the size of the shock Φ_p originating in the U.S., and they are neither relevant, *in theory*, for how the shock impacts market j in general, as proxied by the Chinese absorption share χ_{cjp}. The main difference is that the shock is focused on the domestic market j and that the relevant sales share is the share of domestic sales accounted by sector p, or $s_{jp} = S_{jp}/\sum_{p' \in \mathcal{P}} S_{jp'}$. Overall, the change in domestic sales, referred to as S_j, is given by

$$\frac{dS_j}{S_j} = -\sum_{p \in \mathcal{P}} (\sigma_{jp} - 1) \times \Phi_p \times \chi_{cjp} \times s_{jp},$$

which corresponds to equation (10) in the main text, defining our import competition index (or $\boldsymbol{ICI}$). Ignoring cross-sectoral heterogeneity in demand elasticities ($\sigma_{jp} \simeq \sigma_j$ for all p), will later lead us to the 'basic' version of this import competition index.

As argued in the main text, when implementing this measure, researchers cannot typically rely on exact measures of s_{jp}, so in our empirical analysis, we proxy s_{jp} with the share of overall exports of country j that are accounted for by exports of good p, as indicated in equation (11). For similar reasons, and as in the export competition index, we continue to approximate χ_{cjp} with the share of China in country j's imports of good p, as in equation (5) in the main text.

The Consumer Gains Index ($\boldsymbol{CGI}$) In the main text, we stated that the percentage fall in import prices in a given destination market j can be approximated, up to a first order, with the following expression

$$\boldsymbol{CGI}_j = 100 \times \sum_{p \in \mathcal{P}} \Phi_p \times \chi^M_{cjp} \times s^M_{jp},$$

where Φ_p is identical to that in the expressions for $\boldsymbol{ECI}_j$ and $\boldsymbol{ICI}_j$, and where χ^M_{cjp} is the Chinese share in total *imports* of good p in country j (which was already our proxy for χ_{cjp} when empirically implementing our export competition index). The term s^M_{jp} in the above equation for $\boldsymbol{CGI}_{jc}$ is the share of country j's imports accounted for by sector p.

We next offer a simple proof of this claim. Define the CES import price index for product p in destination j as

$$P^M_{jp} \equiv \left(\sum_{o \in \mathcal{W}-\{j\}} p^{1-\sigma_{jp}}_{ojp} \right)^{\frac{1}{1-\sigma_{jp}}},$$

so that $P_{jp} = \left(p^{1-\sigma_{jp}}_{jjp} + \left(P^M_{jp}\right)^{1-\sigma_{jp}} \right)^{1/(1-\sigma_{jp})}$ is the overall price index for good p in country j. The associated import expenditure shares are

$$\chi^M_{ojp} \equiv \frac{p^{1-\sigma_{jp}}_{ojp}}{\sum_{o' \in \mathcal{W}-\{j\}} p^{1-\sigma_{jp}}_{o'jp}}, \qquad \sum_{o \in \mathcal{W}-\{j\}} \chi^M_{ojp} = 1.$$

A first-order log-differentiation of P^M_{jp} yields the standard Divisia result:

$$d \ln P^M_{jp} = \sum_{o \in \mathcal{W}-\{j\}} \chi^M_{ojp} \times d \ln p_{ojp}.$$

Consider now the bilateral shock in (A.3): only China's delivered price changes for product p in market j, so $d \ln p_{cjp} = -\Phi_p$ and $d \ln p_{ojp} = 0$ for all $o \neq c$. It follows immediately that

$$d \ln P^M_{jp} = -\chi^M_{cjp} \times \Phi_p.$$

Next, let the aggregate import price index in destination j be a Cobb–Douglas aggregator over product-level import price indices,

$$P^M_j \equiv \prod_{p \in \mathcal{P}} \left(P^M_{jp}\right)^{s^M_{jp}}, \qquad \text{with} \qquad s^M_{jp} \equiv \frac{M_{jp}}{\sum_{p' \in \mathcal{P}} M_{jp'}},$$

where M_{jp} denotes total imports of product p by destination j.[23] Log-differentiating gives

$$d \ln P^M_j = \sum_{p \in \mathcal{P}} s^M_{jp} d \ln P^M_{jp}.$$

[23] More generally, any smooth aggregator with expenditure weights s^M_{jp} delivers the same first-order log change around the initial allocation.

Substituting the product-level result then implies

$$d\ln P_j^M = -\sum_{p\in\mathcal{P}} s_{jp}^M \chi_{cjp}^M \Phi_p.$$

Therefore, the (positive) percentage fall in the aggregate import price index is, up to a first-order approximation,

$$-\frac{dP_j^M}{P_j^M} \approx -d\ln P_j^M = \sum_{p\in\mathcal{P}} \Phi_p \times \chi_{cjp}^M \times s_{jp}^M,$$

which is equation (12) in the main text, defining our consumer gains index ($\boldsymbol{CGI}$).

A.2 The Armington-CES Model with Intermediate Inputs

We now extend the baseline Armington–CES environment to allow a subset of products, $p \in \mathcal{P}^I \subseteq \mathcal{P}$, to be used as intermediate inputs by downstream producers of final goods ($p \in \mathcal{P}^F \subseteq \mathcal{P}$) in each country j. For each input product $p \in \mathcal{P}^I$, downstream producers in j assemble a CES composite from origin-specific varieties,

$$Q_{jp}^I \equiv \left(\sum_{o\in\mathcal{W}} (Q_{ojp})^{\frac{\sigma_{jp}-1}{\sigma_{jp}}}\right)^{\frac{\sigma_{jp}}{\sigma_{jp}-1}}, \qquad \sigma_{jp} > 1,$$

with associated CES price index

$$P_{jp}^I \equiv \left(\sum_{o\in\mathcal{W}} p_{ojp}^{1-\sigma_{jp}}\right)^{\frac{1}{1-\sigma_{jp}}}.$$

Let E_{jp}^I denote total expenditure by downstream producers in j on input p. Conditional on E_{jp}^I, the optimal sourcing shares are identical to those derived above:

$$\chi_{ojp}^I \equiv \frac{p_{ojp}^{1-\sigma_{jp}}}{\sum_{o'\in\mathcal{W}} p_{o'jp}^{1-\sigma_{jp}}}, \qquad X_{ojp}^I = \chi_{ojp}^I E_{jp}^I, \qquad \text{for } p \in \mathcal{P}^I.$$

Domestic intermediate input sales in sector p are therefore $S_{jp} \equiv X_{jjp}^I = \chi_{jjp}^I E_{jp}^I$.

A Sourcing Import Competition Index $\boldsymbol{ICI}^{upstream}$ Consider again the bilateral shock in (A.3), so that $d\ln p_{cjp} = -\Phi_p$ and $d\ln p_{ojp} = 0$ for all $o \neq c$, and take a first-order approximation around an initial allocation holding E^I_{jp} fixed.[24] Since $\chi^I_{jjp} = (p_{jjp}/P^I_{jp})^{1-\sigma_{jp}}$, we have

$$d \ln S_{jp} = d \ln \chi^I_{jjp} = (\sigma_{jp} - 1) d \ln P^I_{jp} = -(\sigma_{jp} - 1)\chi^I_{cjp}\Phi_p.$$

Aggregating over inputs, let $S^I_j \equiv \sum_{p\in\mathcal{P}^I} S_{jp}$ and define the domestic intermediate-sales weights $s^I_{jp} \equiv S_{jp}/S^I_j$. A first-order log change in aggregate domestic intermediate input sales is then

$$\frac{dS^I_j}{S^I_j} = -\sum_{p\in\mathcal{P}^I} (\sigma_{jp} - 1) \times \Phi_p \times \chi^I_{cjp} \times s^I_{jp}.$$

This measure is analogous to our import competition index ($\boldsymbol{ICI}$), but it restricts attention to intermediate-input products, or products with an upstreamness level higher than 2 (according to the measure in Antràs et al., 2012). In our online platform, we refer to this index as $\boldsymbol{ICI^{upstream}}$. Because we do not have data on domestic sales at a disaggregated product level, when empirically implementing this index, we proxy the domestic share s^I_{jp} with the share of overall intermediate input exports of country j that are accounted by exports of input p, as in equation (11) in the main text.

Other Indices Specific to Final Goods and Intermediate Inputs Other than the above measure of import competition for intermediate inputs, in our online platform, we also report a measure of imported price declines, analogous to our consumer gains index ($\boldsymbol{CGI}$), but constructed only for the subset of products categorized as intermediate inputs. We denote this index by $\boldsymbol{CGI^{upstream}}$, and we plot it against our $\boldsymbol{CGI}$ index in panel (b) of Figure B.4.

Similarly, our online platform also allows users to download versions of the import competition index and of the consumer gains index that restrict attention to goods categorized as consumer goods, i.e., goods with upstreamness levels lower than 2 according to the measure in Antràs et al. (2012). We denote these two measures by $\boldsymbol{ICI^{downstream}}$ and $\boldsymbol{CGI^{downstream}}$, respectively, with the latter being plotted against $\boldsymbol{CGI}$ index in panel (a) of Figure B.4 of the main text.

The Sourcing Gains Index ($\boldsymbol{SGI}$) We finally derive our sourcing gains index which traces the implications of lower intermediate input prices on downstream firms' sales. Unlike the export competition index, which operates through a demand-side shock in third markets, here the mechanism is a supply-side cost shock: a fall in the price of Chinese intermediate inputs lowers marginal costs in j and thus reduces the price of the varieties produced by j, which allows producers in that country to expand their sales.

To allow for product-level heterogeneity in the marginal-cost reduction, let firms producing

[24] This "local" closure obtains exactly, for example, if downstream production uses a Cobb–Douglas aggregator over intermediate inputs so that expenditures on each input are locally proportional to downstream scale.

output good p in country j use a Cobb–Douglas bundle of intermediate inputs $z \in \mathcal{P}^I$ with cost shares a_{pz}, so that the relevant intermediate input price index is

$$P_{jp}^I \equiv \prod_{z \in \mathcal{P}^I} \left(P_{jz}^{M,I}\right)^{a_{pz}}, \qquad \sum_{z \in \mathcal{P}^I} a_{pz} = 1,$$

where $P_{jz}^{M,I}$ is the CES import price index for intermediate input z in country j as defined above. Under the same China-only shock, we have $d \ln P_{jz}^{M,I} = -\chi_{cjz}^M \Phi_z$, where χ_{cjz}^M is China's import expenditure share in country j for input z. It follows that the first-order change in the intermediate input price index relevant for producing output p is

$$-d \ln P_{jp}^I = \sum_{z \in \mathcal{P}^I} a_{pz} \times \Phi_z \times \chi_{cjz}^M.$$

Assuming that this reduction in overall input costs translates one-for-one into a reduction in the producer price of the j-variety of product p, Armington CES demand in a destination country d, holding all other origin-countries fixed, delivers

$$\frac{dX_{jdp}}{X_{jdp}} = -(\varepsilon_{jdp} - 1) d \ln P_{jp}^I = (\varepsilon_{jdp} - 1) \sum_{z \in \mathcal{P}^I} a_{pz} \times \Phi_z \times \chi_{cjz}^M,$$

where $\varepsilon_{jdp} - 1 = (\sigma_{dp} - 1)(1 - \chi_{jdp})$.

Aggregating across products and export destinations (other than the U.S. and China), the first-order percentage response of country j's exports to cheaper Chinese intermediate inputs is thus given by:

$$\frac{dX_j}{X_j} = \sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} (\varepsilon_{jdp} - 1) \times s_{jdp} \times \sum_{z \in \mathcal{P}^I} a_{pz} \times \chi_{cjz}^M \times \Phi_z, \tag{A.10}$$

which corresponds to equation (13) in the main text, defining our sourcing gains index ($\boldsymbol{SGI}$).

It is important to emphasize that the sourcing gains index $\boldsymbol{SGI}$ captures the direct cost-side benefit from lower Chinese input prices, holding input shares, technology, wages, markups, and non-Chinese input prices fixed. We do not solve for the full vector of induced price changes among non-Chinese producers. A richer input-output model would propagate the sourcing shock through a Leontief inverse, but our $\boldsymbol{SGI}$ is intentionally the direct-input component of that broader object.

A.3 Opening the Black Box of Φ_p

We next provide a structural interpretation of the reduced-form China export price shock Φ_p featuring prominently in our analysis above. In particular, we show how a U.S. ad-valorem tariff on Chinese imports of a given product p leads to a common decline in China's export price across non-U.S. destinations when Chinese export supply is upward sloping.

To begin, consider a single product p exported by China to a set of destination countries $d \in \mathcal{W}$, including the United States ($d = u$). China charges a common producer (FOB) price p_{cp} across destinations, while delivered prices are given by

$$p_{cdp} = (1 + \tau_{cdp})p_{cp},$$

where (for simplicity) only the United States imposes a tariff:

$$\tau_{cup} > 0, \qquad \tau_{cdp} = 0 \text{ for } d \neq u.$$

Demand in each destination follows the Armington-CES structure described above. As in the rest of the Appendix, we treat destination expenditure on product p, E_{dp}, as locally fixed. Under Armington-CES demand in destination d for product p, China's expenditure share is

$$\chi_{cdp} \equiv \frac{p_{cdp}Q_{cdp}}{E_{dp}},$$

and the exact own-price elasticity of demand for the Chinese variety (holding competitor's prices fixed) is

$$\varepsilon_{cdp} \equiv -\frac{d\ln Q_{cdp}}{d\ln p_{cdp}} = \sigma_{dp} - (\sigma_{dp} - 1)\chi_{cdp}.$$

We can alternatively write this as

$$d\ln Q_{cdp} = -\varepsilon_{cdp} d\ln p_{cdp}.$$

Aggregating Chinese export demand across destinations, we have that

$$d\ln Q_{cp} = \sum_{d \in \mathcal{W}-\{c\}} \phi_{cdp} d\ln Q_{cdp} = -\sum_{d \in \mathcal{W}-\{c\}} \phi_{cdp}\varepsilon_{cdp} d\ln p_{cdp},$$

where aggregate output is

$$Q_{cp} \equiv \sum_{d \in \mathcal{W}-\{c\}} Q_{cdp},$$

and destination quantity shares are

$$\phi_{cdp} \equiv \frac{Q_{cdp}}{Q_{cp}}, \qquad \sum_{d \in \mathcal{W}-\{c\}} \phi_{cdp} = 1.$$

Since $p_{cdp} = (1 + \tau_{cdp})p_{cp}$, we have

$$d \ln p_{cdp} = d \ln p_{cp} + d \ln (1 + \tau_{cdp}) \,.$$

And because we hold all non-U.S. tariffs constant, we can write

$$d \ln Q_{cp} = -\bar{\varepsilon}_{cp} d \ln p_{cp} - \phi_{cup} \varepsilon_{cup} \, d \ln(1 + \tau_{cup}),$$

where

$$\bar{\varepsilon}_{cp} \equiv \sum_{d \in \mathcal{W} - \{c\}} \phi_{cdp} \varepsilon_{cdp} \quad \text{and} \quad \varepsilon_{cup} = \sigma_{up} - (\sigma_{up} - 1)\chi_{cup}.$$

Assume now that China faces an upward-sloping export supply curve for product p, summarized by

$$d \ln p_{cp} = \frac{1}{\eta_{cp}} d \ln Q_{cp},$$

where $\eta_{cp} > 0$ is the Chinese export supply elasticity, which is allowed to vary across products.

Substituting the export-demand aggregation into the supply relation and solving yields

$$d \ln p_{cp} = -\phi_{cup} \frac{\varepsilon_{cup}}{\eta_{cp} + \bar{\varepsilon}_{cp}} d \ln(1 + \tau_{cup}), \tag{A.11}$$

which is exactly equation (4) in the main text.

How f.o.b. Chinese prices react to the U.S. tariff depends on five key objects: (i) the share of Chinese exports (in quantity terms) that is shipped to the United States, ϕ_{cup}; (ii) the elasticity of demand faced by Chinese exporters in the U.S., ε_{cup}; (iii) the elasticity of supply of Chinese exports, η_{cp}; (iv) a weighted-average elasticity of demand faced by Chinese exporters worldwide, $\bar{\varepsilon}_{cp}$; and (v) the size of the U.S. tariff.

A.4 Basic Versions of Our Indices

In our online platform, we also make available basic versions of our indices, which do not rely on potentially problematic demand and supply elasticity estimates, or on unobserved changes in effective trade barriers faced by Chinese firms in the U.S. market.

In terms of our indices above, these indices consider a special case in which the U.S. policy shock is common across sectors ($\tau_{cup} = \tau$), demand parameters σ_p and supply elasticities η_p are also common across sectors, and China constitutes a small enough share of absorption in all countries ($\chi_{cdp} \simeq 0$). Under these assumptions, equation (A.11) reduces to

$$d \ln p_{cp} = -\phi_{cup} \frac{\varepsilon}{\eta + \varepsilon} d \ln(1 + \tau),$$

and thus the relative size of the shock in different sectors depends only on $\phi_{cup} = Q_{cup}/Q_{cp}$. Furthermore, if unit values are approximately common across destinations (FOB), ϕ_{cup} is well approximated by the corresponding export share:

$$\frac{Q_{cup}}{Q_{cp}} \simeq \frac{X_{cup}}{\sum_{\mathcal{W}-\{c\}} X_{cdp}} \equiv \phi_p,$$

which corresponds to equation (3) in the main text.

Under these assumptions, the ranking of countries in the various indices depends solely on the observable objects emphasized in the main text. For instance, for the specific case of the export competition index ($\boldsymbol{ECI}$), we have:

$$\frac{\boldsymbol{ECI}_j}{\boldsymbol{ECI}_{j'}} = \frac{\sum_{d \in \mathcal{W}_-} \frac{X_{jd}}{X_j} \sum_{p \in \mathcal{P}} s_{jdp} \times \chi_{cdp} \times \phi_p}{\sum_{d \in \mathcal{W}_-} \frac{X_{j'd}}{X_{j'}} \sum_{p \in \mathcal{P}} s_{j'dp} \times \chi_{cdp} \times \phi_p}.$$

A.5 Implications for Chinese Exports

In this section, we use our model to derive the empirical specifications explored in our reduced-form regressions in section 4.2.

Chinese exports to the rest of the world. Consider a destination d other than the U.S. ($d \neq u$). Because U.S. tariffs do not directly affect the price paid by buyers in destination d, the change in the delivered price of the Chinese variety is simply the change in its f.o.b. price. Recalling that $\Phi_p \equiv -\Delta \log p_{cp}$ denotes the decline in the Chinese f.o.b. price, the Armington-CES model implies:

$$\Delta \log X_{cdp} = -(\varepsilon_{cdp} - 1) \times \Delta \log p_{cp} = (\varepsilon_{cdp} - 1) \times \Phi_p, \tag{A.12}$$

where ε_{cdp} is demand elasticity faced by China in destination d. This corresponds exactly to equation (14) in the main text, which we test empirically in Table 8.

Chinese export contraction in the United States. We next turn to the implications of the model for Chinese exports to the United States. The tariff-inclusive price paid by U.S. buyers is $p_{cup} = p_{cp}(1 + \tau_{cup})$, and U.S. demand satisfies

$$d \log Q_{cup} = -\varepsilon_{cup} \left[d \log p_{cp} + d \log(1 + \tau_{cup}) \right].$$

Because f.o.b. export revenue is $\tilde{X}_{cup} = p_{cp} Q_{cup}$,

$$\begin{aligned} d\log \tilde{X}_{cup} &= d\log p_{cp} + d\log Q_{cup} && \text{(A.13)} \\ &= -\varepsilon_{cup} \times d\log(1+\tau_{cup}) + (1-\varepsilon_{cup}) \times d\log p_{cp} && \text{(A.14)} \\ &= -\varepsilon_{cup} \times d\log(1+\tau_{cup}) + (\varepsilon_{cup}-1) \times \Phi_p, && \text{(A.15)} \end{aligned}$$

where $\Phi_p = -d\log p_{cp}$. The direct tariff effect is negative, while the endogenous decline in the Chinese f.o.b. price partly offsets the increase in the tariff-inclusive price paid by U.S. buyers.

Let $\tilde{X}_{cp,0} = \sum_{d \neq c} \tilde{X}_{cdp,0}$ denote China's total baseline exports of product p. Since $\tilde{X}_{cup,0} = \phi_p \tilde{X}_{cp,0}$, a first-order approximation gives

$$\begin{aligned} \frac{\Delta \tilde{X}_{cup}}{\tilde{X}_{cp,0}} &\simeq \frac{\tilde{X}_{cup,0}}{\tilde{X}_{cp,0}} \times d\log \tilde{X}_{cup} && \text{(A.16)} \\ &= -\varepsilon_{cup} \times \phi_p \times d\log(1+\tau_{cup}) + (\varepsilon_{cup}-1) \times \phi_p \times \Phi_p. && \text{(A.17)} \end{aligned}$$

Equation (A.17) is the heterogeneous-tariff and heterogeneous-elasticity expression taken to the data in Table 9. It separates the direct contraction in initially exposed U.S. sales from the offset generated by the equilibrium f.o.b. price decline.

B Data Appendix

B.1 Data Sources

Trade Data. Trade data for the construction of indices comes from the CEPII-BACI (Gaulier and Zignago, 2010), which contains annual, bilateral trade flows at the six-digit commodity level. We classify trade flows to "Asia, not elsewhere specified" as Taiwan, as the authors report "it almost exclusively reflects trade with Taiwan."

Trade data for certain figures in section 2 and for the empirical tests in section 4.2 (i.e., Tables 8 and 9), come from the Trade Data Monitor (TDM). We default to using reported imports as the measure of bilateral trade flows. When import data are missing but a record of trade exists from the corresponding export partner, then we impute the missing import value with the export value of the partner.

Elasticities. Elasticity estimates come from Soderbery (2018). Demand elasticities σ_{dp} are reported at the destination-HS four-digit level. Inverse-supply elasticities $\omega_{odp} = 1/\eta_{odp}$ are reported at the origin-destination-HS four-digit level. Elasticities are cross-walked from their 1992 vintage to the 2017 vintage used in the trade data using the Concordance R package (Liao et al., 2020). Inverse-supply elasticities are averaged across destinations using export values in 2017, to get an elasticity that is at the origin-HS4 level, $\omega_{op} = 1/\eta_{op}$. We truncate demand and supply elasticities at the 99.5th percentile. Using an earlier period avoids endogeneity between the trade weights and tariff shocks being studied.

In addition, Soderbery (2018) reports standard errors for estimated elasticities. Let θ denote an estimated elasticity, and σ_θ the associated standard error. We drop any elasticities where $\theta/\sigma_\theta < 1.96$. These are estimates that cannot be distinguished from zero under standard significance conventions.

Note that the Soderbery (2018) elasticities are estimated from trade data over the period 1993-2007, and there is certainly scope for preferences and technology to change before our baseline period of 2023. Hence, we continue to report 'basic' measures as they are free of any structural elasticities and use observed trade shares alone.

Tariffs. Tariff data come from Rodríguez-Clare et al. (2026). This data primarily contains tariff data for the US. We consider two tariff windows. First, a short difference surrounding the second Trump administration: January 2025 to September 2025 (the final period of available data). Second, a long tariff difference beginning from before the first Trump administration's tariff policies to present, January 2018 to September 2025.

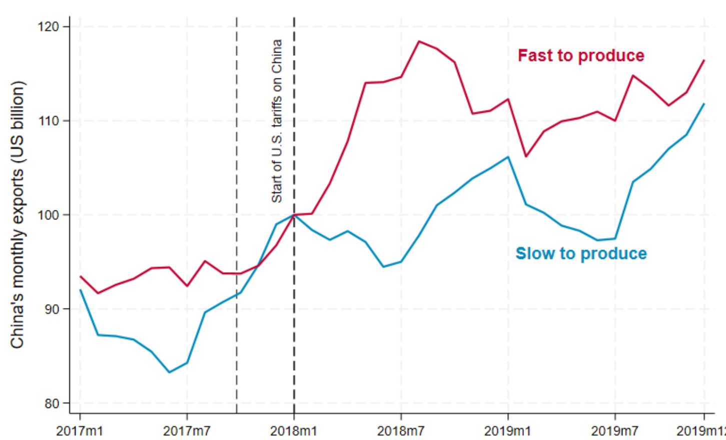
Additional Data. The ***SGI*** requires input-output data at the HS six-digit level. We use binary input-output connections provided by Fetzer et al. (2024). One limitation of this data is that no data on the extent of input usage is provided, outside of the binary classification of whether an upstream HS code is used in the production of another downstream HS code. Therefore, we give a uniform weight to each input.

The Upstream and Downstream variants of the ***CGI*** require classifying goods as inputs or final goods. To do so we use the upstreamness measure from Antràs et al. (2012), and classify any goods with an upstreamness greater than 2 as intermediate goods and less than 2 as final goods. The upstreamness measure is reported for Input-Output Commodity Codes which we crosswalk to HS codes with data provided by the BEA.

B.2 The Average Period of Production and Trump 1.0 Tariffs

Figure B.1 provides evidence for a novel channel contributing to the gradual nature of the U.S.–China decoupling. More specifically, building on a measure of the duration of production developed by Antràs and Tubdenov (2025) – the so-called average period of production or $\mathcal{APP}$ – Figure B.1 shows that reallocation of Chinese exports away from the U.S. was faster in products with a shorter $\mathcal{APP}$, while products with longer production cycles adjusted more slowly. Indeed, the figure shows that the initial jump in Chinese exports to countries other than the U.S. after the introduction of the first U.S. tariffs in January 2018 was entirely driven by "fast to produce" goods.

Figure B.1: The Great Reallocation and the Temporal Dimension of Production



Notes: Monthly exports are computed as backward-looking 6-month moving averages. We define goods as 'fast to produce' if their $\mathcal{APP}$ is in the bottom quartile of the distribution and we label the others as "slow to produce".

Sources: Trade Data Monitor and Antràs and Tubdenov (2025).

B.3 Data Coverage for Our Indices

In Table B.1 we report the fraction of products for which we observe the relevant elasticities needed to compute the shock to Chinese export prices in equation (4). At the very least, these products are included in our analysis. When elasticities are missing but China reports no exports to the USA, we include the price shock with a value of 0. For computing subsequent measures, we may need to drop additional trade flows because of additional missing parameters. For example, the $\boldsymbol{ECI}$ requires import demand elasticities at all export markets, should these be absent a trade flow needs to be excluded from the $\boldsymbol{ECI}$ construction. In Table B.2 we report the fraction of trade flows where we observe the relevant price shock and import-demand elasticity.

Another consequence of partial coverage is that, when computing indices that take an average over products, e.g. the $\boldsymbol{ECI}$, we must re-normalize export/import shares so that they sum to one over the set of included products. Otherwise, indices will be correlated with coverage statistics. Since some products need to be dropped, this leads to the possibility that the indices do not accurately reflect the aggregate trade flows of a country. In the tables and figures within the paper we therefore limit ourselves to countries where at least 25 percent of trade flows are covered by each index. In Table B.3 we report statistics for the share of trade flows covered within each country for the main indices.

Table B.1: Product Coverage

Component	HS6 products	% products	% trade value
US-China demand elasticity (ε_{cup})	4,206	78.2%	88.1%
Chinese supply elasticity (η_{cp})	4,569	84.9%	83.7%
Avg destination elasticity ($\bar{\varepsilon}_{cp}$)	5,200	96.7%	98.6%
Tariff change ($\Delta \log(1+\tau)$)	5,229	97.2%	95.2%
All components	3,773	70.1%	72.7%
Zero US exposure ($\phi_{cup} = 0$)	761	14.1%	11.6%
Price shock (Φ_p)	4,254	79.1%	76.2%
Upstreamness measure	4,477	83.2%	79.8%

Note. For each 'component' row, 'HS6 products' reports the number of HS codes where we observe the component, '% products' the share of products we observe the component, and '% trade value' the share of trade flows accounted for by the observed products. 'All components' refers to HS codes that contain demand elasticity, supply elasticities, and tariff changes needed to compute Chinese price shocks. 'Price shock' is available for more HS codes, as Zero US exposure ($\phi_{cup} = 0$) implies a price shock of zero regardless of what missing elasticities would suggest.

Table B.2: Trade Flow Coverage

Component	% trade flows	% trade value
Price shock (Φ_p)	84.4%	76.2%
Demand elasticity (σ_{dp})	81.0%	86.7%
Price shock and elasticity	71.5%	70.1%

Note. For each 'component' row, '% trade flows' reports the fraction of observations where we observe the component and '% trade value' the share of trade values accounted for by the observed components.

Table B.3: Index Flow Coverage

Measure	Median	Mean	Min	Max	Economies	Zero
$\boldsymbol{ICI}_j$	43.3	41.1	0.0	92.3	177	21
$\boldsymbol{ECI}_j$	65.1	59.1	3.4	95.8	177	0
$\boldsymbol{CGI}_j$	73.7	72.2	23.7	89.1	177	0
$\boldsymbol{SGI}_j$	59.7	55.3	2.2	94.7	177	0

Note. Coverage is the share of a country's own trade basket – its import basket for $\boldsymbol{CGI}$, its export basket for $\boldsymbol{ICI}$, $\boldsymbol{ECI}$ and $\boldsymbol{SGI}$ – accounted for by products whose required inputs are all observed. Statistics are in percent across the 177 economies for which the measures are reported (population of at least 200,000, excluding Hong Kong, Macao, China and the United States). 'Zero' counts economies with no covered product.

B.4 Variants of Our Indices

B.4.1 Export Similarity

As robustness tests, we also compute coarser indices of export similarity that only consider similarity in the types of products exported (regardless of where they are sold) and in the destination of sales (regardless of which goods are sold in those destinations). The product-level similarity index, when computed in some baseline year is given by

$$ESI_j^{prod} = 100 \times \sum_{p \in \mathcal{P}} \min \left(\frac{\sum_{d \in \mathcal{W}_-} X_{jdp}}{X_j}, \frac{\sum_{d \in \mathcal{W}_-} X_{cdp}}{X_c} \right), \tag{B.1}$$

and it may capture better than the ESI in equation (2) situations in which the shock (e.g., Liberation Day) leads to a disproportionate increase in Chinese exports to destinations in which it sold relatively less in the baseline year. On the other hand, the coarser similarity index based on the destination of sales is given by

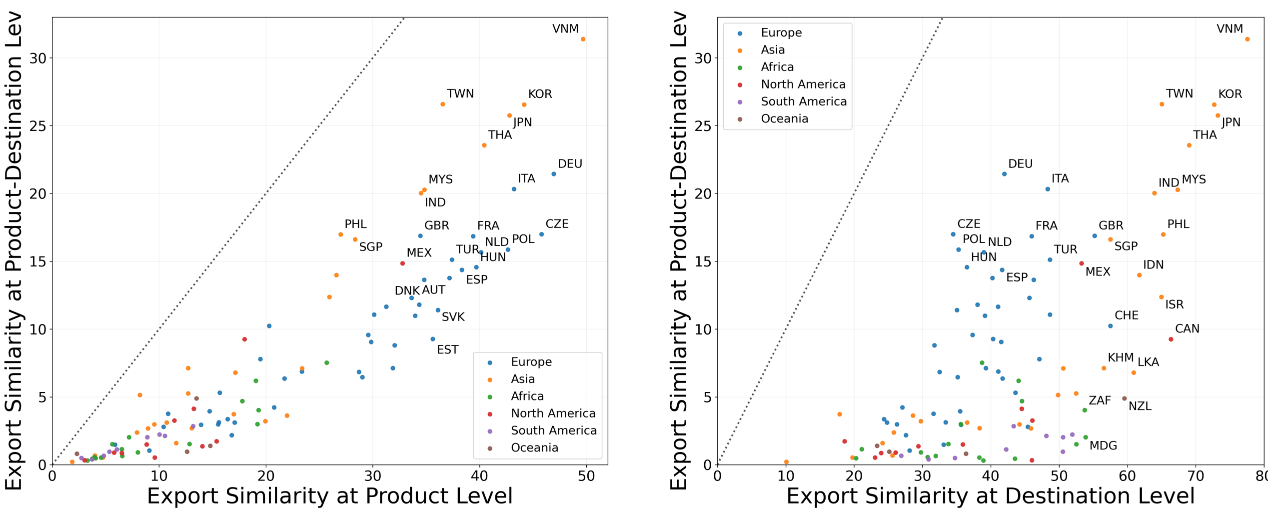
$$ESI_j^{dest} = 100 \times \sum_{d \in \mathcal{W}_-} \min\left(\frac{\sum_{p\in\mathcal{P}} X_{jdp}}{X_j}, \frac{\sum_{p\in\mathcal{P}} X_{cdp}}{X_c} \right), \tag{B.2}$$

and it may better capture concerns about China disproportionately increasing the sales of *new* types of goods in markets in which both j and China had sizeable market shares in the baseline year.

Figure B.2 plots our benchmark export similarity index (equation (2)) against the two coarser measures that allow for more flexible channels of export competition. Panel (a) plots export similarity when computed at the product level. The correlation between the two indices is very high (0.905) but, at the product level, export similarity with China is always larger. The figure further indicates that European countries tend to be much more impacted by this measure, reflecting the fact that these countries export the same products as China does, but not necessarily to the same destinations. This further implies that if Chinese exporters were to reorient their sales to these destinations currently favored by European firms, the shock could be much more intensively felt in European countries.

Panel (b) is analogous but plots export similarity when computed at the destination level. This captures threats stemming from China ramping up their exports of new or low-selling products in the destinations in which the potentially impacted countries concentrate their sales in the baseline year. European countries seem to be more immune from this shock, but many Asian economies – as well as Canada and New Zealand – would face much fiercer enhanced export competition on this account.

Figure B.2: Alternative Measures of Export Similarity



(a) Export Similarity at the Product Level **(b)** Export Similarity at the Destination Level

B.4.2 Import Similarity

A limitation of the import similarity index (equation (9)) is that it may not properly predict a surge of imports into country j whenever the type of products in which China suffers an excess supply happen to be goods that China was *not* exporting to country j in the baseline year. The following alternative import similarity index may better capture these situations:

$$ISI_j^{prod} = 100 \times \sum_{p \in \mathcal{P}} \min \left\{ \frac{\sum_{o \in \mathcal{W}} X_{ojp}}{\sum_{p' \in \mathcal{P}} \sum_{o \in \mathcal{W}} X_{ojp'}}, \frac{X_{cup}}{X_{cu}} \right\}. \tag{B.3}$$

The key difference is that product p's market share for country j is now computed aggregating across origin countries, and not just based on imports from China.

A remaining drawback is that both the baseline ISI and its alternative may not capture exposure stemming from Chinese exporters redirecting (or "dumping") into third-country markets certain products with limited exports to the United States in the benchmark year. This can occur in sectors where Chinese capacity has expanded rapidly but direct exports to the United States have been constrained by U.S. tariffs and other regulatory barriers since the onset of the trade war (if not earlier). Electric vehicles (EVs) illustrate the point: even though Chinese EV sales in the U.S. remain limited, they have sparked significant concern in Europe, despite the consumer gains that would be associated with cheaper EVs. To some extent, these concerns are linked to the U.S.–China trade war: had trade between the two economies remained more liberalized, U.S. demand could have absorbed part of China's surging EV supply, reducing the incentive to push those exports into other markets. To capture these situations, we suggest the following index:

$$ISI_j^{broad} = 100 \times \sum_{p \in \mathcal{P}} \min \left\{ \frac{X_{cjp}}{\sum_{p' \in \mathcal{P}} \sum_{o \in \mathcal{W}} X_{ojp'}}, \frac{X_{cp}}{X_c} \right\}, \tag{B.4}$$

which captures similarity between the set of products country j imports from China and the set of goods China exports to *all* destinations (not just the U.S.) in the baseline year.[25]

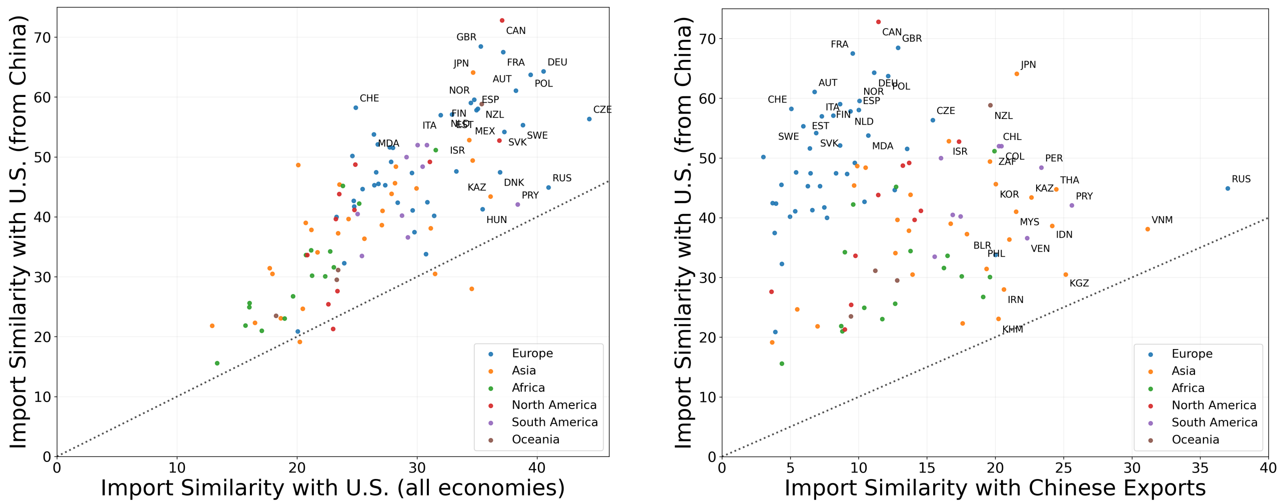
Figure B.3 plots our benchmark import similarity measure against the two alternative measures developed in equations (B.3) and (B.4). In panel (a), we consider an import similarity index that compares the products China exported to the U.S. in the baseline year with the products imported by country j from all countries (and not just China). The correlation between the two series is high (0.773), but most countries have a higher import similarity vis à vis the U.S. when focusing on imports originating from China, indicating that the possibility that China starts exporting to those countries (or ramps its exports of) products it previously

[25] Similarly, one could also envision an even more agnostic measure in which the first element of the min operator is replaced with $\sum_{o \in \mathcal{W}} X_{ojp} / \sum_{p' \in \mathcal{P}} \sum_{o \in \mathcal{W}} X_{ojp'}$ as in equation (B.3).

sold to the U.S. does *not* constitute a notable *additional* source of exposure for most countries.

When exploring our second alternative import similarity index in equation (B.4), the picture is quite different. The correlation between this broad index and our baseline ISI is essentially zero (-0.005). This indicates that similarity to China's overall export basket captures a distinct source of exposure from similarity to the basket of goods China shipped to the U.S. in the baseline year.

Figure B.3: Alternative Measures of Import Similarity



(a) ISI_j versus ISI_j^{prod} **(b)** ISI_j versus ISI_j^{broad}

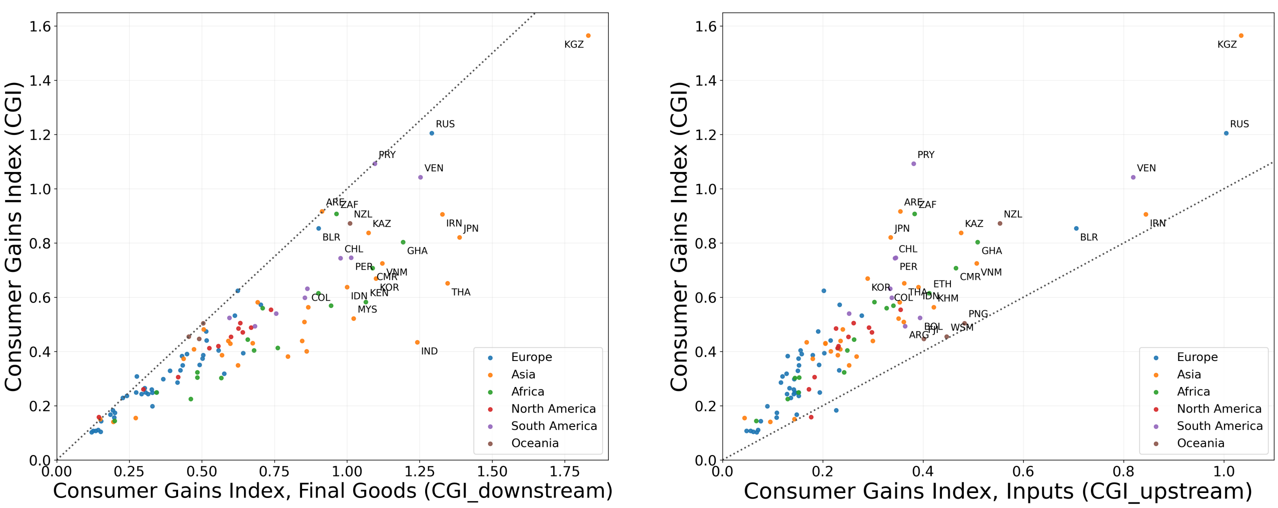
B.4.3 Consumer Gains

The baseline $\boldsymbol{CGI}$ aggregates over *all* imported products, but lower import prices can in principle operate through two conceptually distinct channels. When the affected goods are final or near-final products, cheaper Chinese imports translate more directly into lower prices for consumers, as implicitly assumed in the $\boldsymbol{CGI}$. When the affected goods are intermediate inputs, however, the immediate beneficiaries are instead firms that use those inputs in production; the relevant effect is then closer to a sourcing-cost shock than to a direct consumer-price shock. Section 3.4 in the main text develops this sourcing channel explicitly. In the following we separate the consumer gains index into a final-goods component and an input-goods component.

Operationally, we distinguish inputs from final goods using the value-chain position of products in the spirit of Antràs et al. (2012): products that are more *upstream* (i.e., typically used as inputs into further production stages before reaching final demand) are classified as intermediates, whereas more *downstream* products are closer to final absorption. We label product p as a final good if its upstreamness measure is lower than 2. We define the set of final products by $\mathcal{P}^F \subseteq \mathcal{P}$.[26]

Panel (a) of Figure B.4 plots our baseline $\boldsymbol{CGI}$ against the same index computed restricting attention to final goods. Although there are some notable differences for certain countries, the correlation between these two series is very high (0.903). Interestingly, the gains tend to be relatively higher for this alternative measure, reflecting the fact that China is a relatively downstream economy in global value chains, and thus most countries tend to import relatively downstream goods from China. For completeness, panel (b) of Figure B.4 plots our baseline $\boldsymbol{CGI}$ against the same index computed only for intermediate inputs (products with upstreamness higher than 2). The two series are also very highly correlated (0.887), but to better understand the benefits of lower input prices, we develop our sourcing gains index ($\boldsymbol{SGI}$) in section 3.4 of the main text.

Figure B.4: Consumer Gains Indices: Final Goods vs. Inputs



(a) $\boldsymbol{CGI}_j$ versus $\boldsymbol{CGI}^{downstream}$

(b) $\boldsymbol{CGI}_j$ versus $\boldsymbol{CGI}^{upstream}$

Table B.4: Value and Quantity Based Measures

Measure pair	Pearson	Spearman	Products
Price shock, Φ_p vs. Φ_p^q	0.890	0.960	4,254
excluding $\phi_p = 0$ products	0.881	0.928	3,493
U.S. export share, ϕ_p vs. ϕ_p^q	0.862	0.939	5,380
excluding $\phi_p = 0$ products	0.853	0.905	4,619

Note. Φ_p^q and ϕ_p^q replace China's export share to the United States, originally measured by value, with its share by quantity (metric tons). 'Pearson' is the raw correlation and 'Spearman' the rank correlation.

B.5 Additional Figures and Tables

Table B.5: Price Shocks

Rank	HS6	Description	ϕ_{cup}	σ_{up}	ε_{cup}	η_{cp}	$\bar{\varepsilon}_{cp}$	$\Delta\tilde{\tau}_{cup}$	Φ_p
1	842549	Jacks and hoists, other than hydraulic, for vehicles	0.445	2.9	1.9	0.8904	1.961	0.824	0.245
2	732181	Non-electric domestic appliances for gas fuel, of iron or steel	0.579	3.1	1.6	0.6214	1.591	0.510	0.209
3	732119	Solid-fuel cooking appliances and plate warmers	0.627	3.1	1.2	0.6214	1.330	0.531	0.200
4	901510	Rangefinders	0.279	2.3	1.9	0.3616	1.880	0.824	0.200
5	830230	Base-metal mountings and fittings for motor vehicles	0.316	2.6	2.3	0.6282	2.506	0.813	0.190
6	870870	Road wheels and parts	0.299	3.1	2.3	1.1155	2.138	0.817	0.175
7	293080	Organo-sulphur compounds	0.959	2.7	1.0	0.4034	1.006	0.248	0.170
8	090112	Decaffeinated coffee, not roasted	0.843	3.8	3.8	1.3189	3.773	0.254	0.159
9	732111	Gas cooking appliances and plate warmers, of iron or steel	0.410	3.1	2.1	0.6214	1.873	0.439	0.152
10	732189	Non-electric domestic appliances for solid fuel, of iron or steel	0.437	3.1	1.7	0.6214	1.918	0.501	0.144
11	851130	Distributors and ignition coils for combustion engines	0.291	3.0	2.3	1.8878	2.012	0.813	0.141
12	870830	Brakes, servo-brakes and parts	0.250	3.1	2.6	1.1155	2.697	0.817	0.137
13	030563	Salted anchovies, not dried or smoked	0.949	2.8	2.6	1.3304	2.658	0.213	0.134
14	030615	Frozen Norway lobsters (*Nephrops norvegicus*)	0.843	5.6	4.9	2.1377	4.633	0.215	0.132
15	870880	Vehicle suspension systems and parts	0.228	3.1	2.7	1.1155	2.749	0.819	0.131
16	491191	Printed pictures, designs and photographs	0.619	5.9	3.2	0.9398	2.907	0.253	0.131
17	300449	Medicaments containing alkaloids or derivatives	0.764	4.2	4.1	0.5607	3.834	0.182	0.128
18	030242	Fresh or chilled anchovies (*Engraulis* spp.)	0.974	2.9	2.8	1.8454	2.802	0.215	0.127
19	851140	Starter motors and starter-generators	0.218	3.0	2.7	1.8878	2.134	0.813	0.120
20	292022	Phosphite esters and their salts	0.616	3.3	1.5	0.6342	1.370	0.254	0.118

Note. The term ϕ_{cup} is the share of Chinese exports of goods p going to the US, σ_{up} is the US import demand elasticity for good p, $\varepsilon_{cup} = \sigma_{up} - (\sigma_{up} - 1) \times \chi_{cup}$ where χ_{cup} is the share of US import expenditure in good p on goods coming from China, η_{cp} is the export supply elasticity of China in good p, $\bar{\varepsilon}_{cp}$ is the export-weighted average ε_{cdp} faced by China across export markets, $\Delta\tilde{\tau}_{cup} \equiv \Delta \log(1 + \tau_{cup})$ is the change in tariffs between January 2025 and September 2025, and the price shock is $\Phi_p = -d \log p_{cp} = \Delta\tilde{\tau}_{cup} \times \phi_{cup} \times \varepsilon_{cup}/(\bar{\varepsilon}_{cp} + \eta_{cp})$. We use trade data from 2023 to compute shares.

[26] In the implementation, this requires mapping the upstreamness measure to our HS product classification and defining the final-good set $\mathcal{P}^F \subseteq \mathcal{P}$ at the HS6 level.

Table B.6: Across-Index Pearson Correlation

	ECI	ESI	ICI	ISI	CGI	SGI
ECI	1.000	—	—	—	—	—
ESI	0.493	1.000	—	—	—	—
ICI	0.725	0.457	1.000	—	—	—
ISI	0.085	0.463	-0.039	1.000	—	—
CGI	0.152	-0.030	0.250	0.074	1.000	—
SGI	0.091	-0.018	0.294	-0.222	0.581	1.000

Note. Each cell reports a Pearson correlation coefficient between the country-specific indices referenced in the row and column. Correlations are computed using the sample of 110 economies.

Table B.7: Across-Index Spearman Rank Correlation

	ECI	ESI	ICI	ISI	CGI	SGI
ECI	1.000	—	—	—	—	—
ESI	0.742	1.000	—	—	—	—
ICI	0.784	0.550	1.000	—	—	—
ISI	0.220	0.555	0.155	1.000	—	—
CGI	-0.020	-0.084	0.321	0.090	1.000	—
SGI	0.058	-0.131	0.339	-0.250	0.700	1.000

Note. Each cell reports a Spearman rank correlation coefficient between the country-specific indices referenced in the row and column. Correlations are computed using the sample of 110 economies.

Table B.8: Within-Index Pearson Correlation

Index	Full vs. Basic	Full vs. Long	Full vs. Basic Full
ICI	0.977	0.826	0.928
ECI	0.974	0.963	0.855
CGI	0.985	0.979	0.977
SGI	0.783	0.878	0.733

Note. For each index (labeled in the row), each cell reports a (Pearson) correlation coefficient between the variants labeled in the column. "Full" is the baseline index; "Basic" is the index without trade elasticities or tariffs but using the same set of products as Full; "Long" is the baseline index constructed using tariff differences over the 2018–2025 period; and "Basic Full" is the same as Basic but extended to the full set of products. Product coverage differs between Full and Basic Full because of missing elasticity estimates, as discussed in Table B.1. All correlations use our baseline 110 economies.

Table B.9: Within-Index Rank Correlation

Index	Full vs. Basic	Full vs. Long	Full vs. Basic Full
ICI	0.980	0.923	0.951
ECI	0.983	0.971	0.966
CGI	0.990	0.977	0.975
SGI	0.915	0.972	0.823

Note. For each index (labeled in the row), each cell reports a Spearman rank-correlation coefficient between the variants labeled in the column. "Full" is the baseline index; "Basic" is the index without trade elasticities or tariffs but using the same set of products as Full; "Long" is the baseline index constructed using tariff differences over the 2018–2025 period; and "Basic Full" is the same as Basic but extended to the full set of products. Product coverage differs between Full and Basic Full because of missing elasticity estimates, as discussed in Table B.1. All correlations use our baseline 110 economies.

Table B.10: Predicted price responses and Chinese export reallocation across destinations

	$\Delta \log X_{cdp}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome winsorized at 2.5/97.5 percentiles	0.961***	0.790***	2.879***	1.846**	1.562***	1.280**
	(0.178)	(0.217)	(0.699)	(0.914)	(0.465)	(0.524)
Aggregate 2023 exports > \$1 million	1.280***	0.998***	3.370***	2.115**	1.714***	1.413**
	(0.223)	(0.230)	(0.810)	(0.968)	(0.501)	(0.557)
Unweighted	0.137**	0.113**	0.799***	0.482**	0.795***	0.588***
	(0.056)	(0.047)	(0.245)	(0.228)	(0.123)	(0.114)
Unmirrored (reported imports only)	1.306***	1.063***	3.308***	1.779**	1.508***	0.998**
	(0.233)	(0.246)	(0.906)	(0.878)	(0.505)	(0.463)
Alternate pre (Jan2023-Dec2023, fix post at original window)	1.573***	1.161***	3.987***	2.568**	2.079***	1.725***
	(0.287)	(0.262)	(0.947)	(1.122)	(0.566)	(0.616)
Alternate post (Dec2024-Nov2025, fix pre at original window)	1.117***	0.917***	2.778***	1.783**	1.535***	1.313**
	(0.197)	(0.207)	(0.754)	(0.900)	(0.452)	(0.517)

Notes: The dependent variable is $\Delta \log X_{cdp}$ between the pre-period (April 2023 to March 2024) and the post-period (April 2025 to March 2026), unless noted otherwise below. The United States, Hong Kong, and Macao are excluded as destinations of Chinese exports. Relative to the baseline Table 8, each row changes one feature of the specifications. Columns report the same coefficients as the specifications in Table 8, but are collapsed for readability to fit on one row. The winsorized specification caps the dependent variable at -3.532 and 4.208 and uses the baseline weights. The size restriction is based on each product's aggregate 2023 Chinese exports to the included non-U.S. destinations and uses the baseline weights. For the baseline sample, observations in columns (1)–(2), (3)–(4), and (5)–(6) are 479,835, 391,915, and 300,862. The unmirrored specification measures Chinese exports using each destination's reported imports alone without mirrored flow. The alternate-pre specification uses January 2023 to December 2023 as the pre-period (and for weights), holding the post-period fixed. The alternate-post specification uses December 2024 to November 2025 as the post-period, holding the pre-period fixed with baseline weights. Standard errors are two-way clustered by HS6 product and destination and reported in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table B.11: Product-Level Exposure and Log Changes in Chinese Exports to the United States

	ϕ_p specifications			Φ_p specifications		
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: $\Delta \log \tilde{X}_{cup}$					
U.S. export share, ϕ_p	-1.481*	-1.474*				
	(0.849)	(0.828)				
U.S. export share × elasticity, $\phi_p(\varepsilon_{cup} - 1)$			0.435			
			(0.508)			
Price shock, Φ_p				-5.979	-11.121*	
				(4.876)	(5.894)	
Price shock × elasticity, $\Phi_p(\varepsilon_{cup} - 1)$						0.203
						(1.345)
Tariff change, $\Delta \log(1 + \tau_{cup})$		-0.210			1.312**	
		(0.586)			(0.525)	
Tariff change × elasticity, $\Delta \log(1 + \tau_{cup})\varepsilon_{cup}$			0.224***			0.245**
			(0.080)			(0.103)
Observations	4,464	4,434	3,603	3,418	3,415	3,405
R^2	0.049	0.051	0.027	0.058	0.094	0.018

Notes: The dependent variable is $\Delta \log \tilde{X}_{cup}$ between the pre-period (April 2023 to March 2024) and the post-period (April 2025 to March 2026). The sample contains HS6 products with strictly positive China-to-U.S. exports in both periods. Regressions are weighted by each product's 2023 China-to-U.S. export value. Heteroskedasticity-robust standard errors are reported in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table B.12: Product-level exposure and changes in Chinese exports to the United States

	Dependent variable: $Y_p \equiv (\tilde{X}^{post}_{cup} - \tilde{X}^{pre}_{cup})/\tilde{X}^{pre}_{cp}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome winsorized at the 2.5th and 97.5th percentiles						
	−0.383***	−0.447***	−0.754***	−0.782***	−0.285	−0.307
	(0.053)	(0.056)	(0.245)	(0.268)	(0.190)	(0.193)
Price-offset component					0.618	0.386
					(0.961)	(0.817)
Unweighted						
	−0.403***	−0.425***	−1.398***	−1.448***	−0.380***	−0.384***
	(0.032)	(0.037)	(0.116)	(0.134)	(0.055)	(0.060)
Price-offset component					−0.835**	−0.870**
					(0.419)	(0.399)
2023 China-to-U.S. exports greater than $1 million						
	−0.446***	−0.503***	−0.873***	−0.868***	−0.310	−0.338
	(0.070)	(0.071)	(0.281)	(0.304)	(0.222)	(0.217)
Price-offset component					0.498	0.274
					(1.220)	(0.981)
Unmirrored (reported imports only)						
	−0.471***	−0.534***	−0.915***	−0.900***	−0.320	−0.344
	(0.071)	(0.073)	(0.289)	(0.315)	(0.228)	(0.226)
Price-offset component					0.489	0.250
					(1.258)	(1.026)
Alternate pre (Jan2023-Dec2023, fix post at original window)						
	−0.444***	−0.507***	−0.858***	−0.864***	−0.299	−0.338
	(0.075)	(0.074)	(0.298)	(0.316)	(0.241)	(0.230)
Price-offset component					0.439	0.304
					(1.391)	(1.026)
Alternate post (Dec2024-Nov2025, fix pre at original window)						
	−0.318***	−0.359***	−0.616**	−0.575**	−0.250	−0.208
	(0.058)	(0.058)	(0.247)	(0.268)	(0.191)	(0.197)
Price-offset component					0.850	0.146
					(0.934)	(0.819)

Notes: The dependent variable is $\Delta\tilde{X}_{cup}$ between the pre-period (April 2023 to March 2024) and the post-period (April 2025 to March 2026), normalized by total product-level Chinese exports $\tilde{X}_{cp}$ in the pre-period, unless noted otherwise. The sample contains HS6 products with positive China-to-U.S. exports in 2023, unless noted otherwise below. Within each robustness variant, the first row reports the same regressor as the corresponding column in Table 9, but collapsed for readability – ϕ_p in columns (1)–(2), $\phi_p \Delta \log(1 + \tau_{cup})$ in columns (3)–(4), and the direct tariff component in columns (5)–(6) – and the second row reports the price-offset component, estimated jointly with the direct tariff component in the same columns (5)–(6) regression. Winsorization caps Y_p at -0.219 and 0.087 and uses the baseline weights. The size restriction filters to products with more than $1 million of 2023 China-to-U.S. exports. The baseline sample contains 4,617 observations in columns (1)–(2), 4,580 in columns (3)–(4), and 3,485 in columns (5)–(6). The unmirrored specification measures Chinese exports using US reported imports alone without mirrored flow. The alternate-pre specification uses January 2023 to December 2023 as the pre-period (and for weights), holding the post-period fixed. The alternate-post specification uses December 2024 to November 2025 as the post-period, holding the pre-period fixed with baseline weights. Heteroskedasticity-robust standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.