Trade Deflection: The Spillover Effects of U.S. Tariffs on Import Prices in Bystander Countries *

Sofie Grouws[†] Sharon Jeon[‡] Giulia Lo Forte[§] Justin Pierce[¶]

July 15, 2026

Abstract

Even as U.S. imports from China have fallen sharply since tariffs starting in 2018, Chinese exports have continued to expand globally. But despite fears in many countries about a potential surge of low-priced Chinese imports redirected from the U.S. market, there is little systematic evidence on how trade flows and import prices have responded in these bystander countries. This paper estimates the extent to which the U.S. tariffs deflected Chinese exports to bystander countries. We show that products targeted by U.S. tariffs experienced significant reallocation of Chinese exports toward other destinations, especially emerging markets, countries in Asia, established Chinese markets, and low-price markets. In addition, these higher trade flows arrive at lower prices, a finding with implications for both local producers and monetary policymakers.

* Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the Board of Governors or its research staff.

[†] Federal Reserve Board (email: sofie.l.grouws@frb.gov)
[‡] Federal Reserve Board (email: sharon.jeon@frb.gov)
[§] Federal Reserve Board (email: giulia.loforte@frb.gov)
[¶] Federal Reserve Board (email: justin.r.pierce@frb.gov)

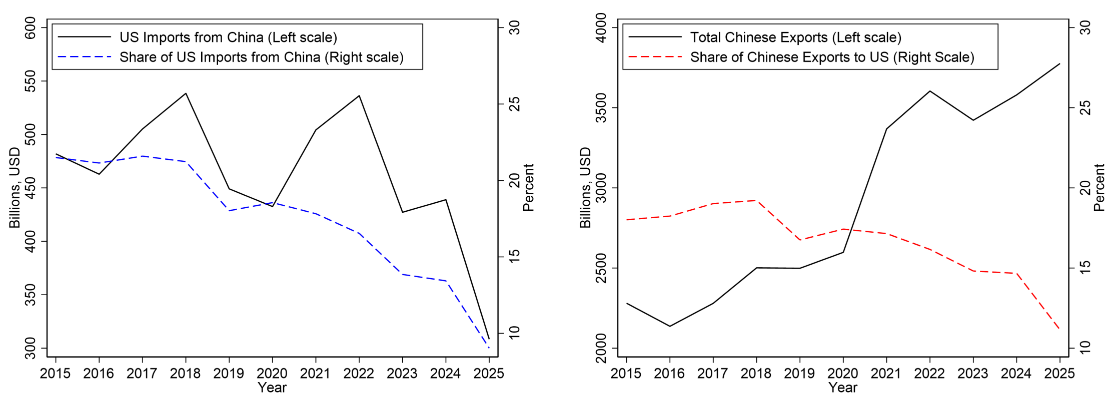
1 Introduction

Since 2018, the United States has pursued a historic increase in trade barriers, with China being a particular target of new tariffs. A literature has quickly sprung up in which a series of influential papers have examined the effects of these tariffs on import prices, economic activity, and welfare in the U.S. and China. However, while the tariffs have been linked to massive shifts in trade flows, there is much less evidence on the spillover effects of this reallocation for countries beyond the U.S. and China, particularly in regards to effects on prices. In this paper, we provide the first comprehensive empirical evidence on the extent and implications of the redirection of Chinese exports due to U.S. tariffs. We find that U.S. tariffs have led to widespread deflection of Chinese exports to other destination countries. Our central finding is that this deflection arrives at lower prices: Bystander countries' import prices for tariffed Chinese products decline systematically and persistently, an outcome that has been the subject of considerable policy concern but, to our knowledge, there is no empirical evidence outside the euro area.

In addition, while much of the concern about the potential effects of deflected Chinese goods has arisen from advanced economies, we find that the largest and most persistent response in terms of higher values and quantities and lower prices is observed in emerging market economies.

The scale of the U.S. trade actions and the resulting reallocation of trade flows is economically important and readily apparent in aggregate data (Figure 1). As shown by the blue dashed line in the left panel, at the end of 2017, on the eve of the initial rounds of tariff increases, the share of U.S. imports sourced from China was over 22 percent. By December 2024, that share had plunged to 13 percent, with further declines to come. The right panel shows that the reallocation of Chinese exports across destination countries was similarly dramatic. The share of China's exports destined for the US (red dashed line) fell from 19 percent in 2017 to 14.6 percent in 2024 as the US imposed tariffs. But despite these new barriers, China's total global exports rose by 57 percent from 2017 to 2024 (black line), indicating that Chinese exports that might have otherwise been sent to the U.S. have been redirected elsewhere, a process known as "trade deflection" (Bown and Crowley, 2007).

Figure 1: U.S. and China Trade Flows

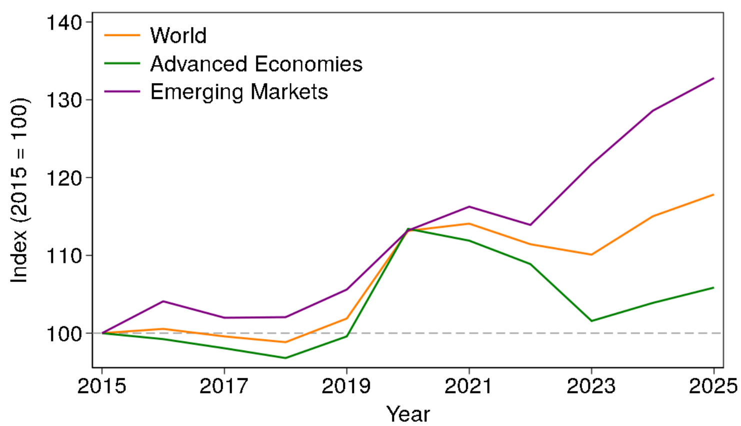


Sources: IMF Direction of Trade via Haver Analytics; authors' calculations.
Notes: Left panel displays total U.S. import values from China on the left scale and the share of U.S. imports from China on the right scale. Right panel displays total value of China export values to the world on the left scale and the share of Chinese exports to the U.S. on the right scale.

Where deflected Chinese exports end up is not obvious ex ante. On one hand, they might flow disproportionately to countries that are similar to the U.S., such as other advanced economies. China was already exporting intensively to some of these markets, suggesting established demand and distribution networks. On the other hand, the demand structure of emerging markets may align more closely with China's export basket, particularly if Chinese producers respond to U.S. tariffs by shifting toward goods with greater appeal in price-sensitive markets.

The aggregate shift in Chinese export destinations, while massive, masks important heterogeneity across country groups. Figure 2 displays indexed import shares from China over the period 2015–2025 for countries at different income levels. Emerging markets stand out: their import share from China has grown by more than 30 percent over the last decade, substantially outpacing the more modest increase observed in advanced economies. This divergence raises the question of whether different country groups experience different degrees of exposure to redirected Chinese exports when trade barriers rise.

Figure 2: Import Share from China Over Time



Sources: IMF Direction of Trade via Haver Analytics; authors' calculations.
Notes: Regions are defined by IMF classifications and the data availability for our main analysis.

The shift in Chinese exports has become a topic of pointed interest in potential destination countries, with widespread media coverage raising the possibility of a surge in imports from China following U.S. tariffs.[1] Much of the coverage focuses on the potential impact of low or declining Chinese import prices on domestic producers.[2] The possible effects are large enough that they have garnered attention from monetary policymakers, particularly the European Central Bank (ECB). But while media coverage has focused on increases in the overall value of imports from China for many countries, and speculated about potential effects on prices, formal empirical analysis of the extent and implications of any deflection of Chinese exports across a wide range of destinations has been lacking.

In this paper, we provide a comprehensive empirical analysis of the extent to which the concerns about redirected Chinese exports are supported in the data. In our baseline analysis, we use six-digit HS import data for all available countries in the United Nations' Comtrade database covering the years 2017-2021.[3] We calculate each product's exposure to the 2018-19 U.S. tariffs on China and employ a differences-in-differences

[1]Examples of media coverage of the deflection of Chinese exports from the U.S. to other markets include "China reroutes clothes exports to Europe after US tariffs upset trade" (Hancock, 2025) and "Pressure grows on Europe to act on Chinese import surge" (Martinez, Reid and Blenkinsop, 2025).

[2]See "With Trump's tariffs, Europe fears a flood of cheap goods from China," (Swanson and Smialek, 2025).

[3]Our paper includes a contribution in economic measurement via an algorithm that yields consistent units of quantity over time in Comtrade international trade data. Previously, the presence of changing units of quantity (e.g. from kilograms to tons) meant that average unit values were subject to spurious large swings from year to year. This algorithm will be useful in a wide range of international trade applications requiring cross-country product-level data.

approach to estimate the spillover effects of the tariffs on bystander countries' import quantities, values, and prices.[4]

We find that the U.S. tariffs are associated with statistically significant increases in the values and quantities of bystander countries' imports from China. These effects are widespread across countries, with precisely estimated increases in the full sample with all available countries, as well as in the country subsets we consider, including those defined by income groups (advanced economies and emerging markets); region (Asia); and individual economies (European Union). While several papers have examined the reallocation of U.S. imports across source countries, and others have examined the ability of bystander countries to increase their own exports (Fajgelbaum et al., 2024), the information we provide on the reallocation of Chinese exports had been previously lacking.

The magnitudes are economically substantial. Quantities of tariffed products imported from China rise by 8 percent in 2019, averaging around 5 percent in subsequent years. The response is larger in emerging markets, where quantities peak at 10 percent above pre-tariff levels, compared to a more moderate and short-lived 5 percent increase in advanced economies.

We also provide the first evidence of how trade deflection of Chinese exports affects import prices in a wide range of bystander countries.[5] We find that, globally, U.S. tariffs are associated with statistically significant declines in bystander countries' prices (unit values) for imports from China, as increases in import quantities outpace growth in import values. This means that import prices do not decline solely from a composition effect due to low-priced Chinese imports capturing a greater share of the market, but rather from a further decline in Chinese import prices relative to pre-tariff levels. The price effects we document are not uniform across country groups. Despite extensive media coverage, the relationship between tariffs and import prices is weaker and relatively short-lived for advanced economies in general, and the EU in particular. The most prominent effects, rather, are for emerging markets, where the negative association with prices is precisely estimated and increasing in magnitude over time.

Next, we examine characteristics of importing countries and Chinese exports that mitigate or exacerbate the average responses just described. This analysis helps identify destinations and products that face the largest shifts in import competition due to trade deflection and speaks to explanations for why import prices decline with the trade deflection we document. We find that products for which the U.S. was an important export destination for China and markets where China was already an established supplier see larger declines in import prices due to U.S. tariffs. These results suggest the presence of economies of scale in China—leading to an incentive to maintain production as U.S. exports shrink—as well as the relevance of destination-specific fixed costs of exporting, as shown by the larger effects in markets where China was already present. The import price response is also stronger in markets where China was already a low-cost supplier. Lastly, consistent with our finding of stronger effects of diverted exports in emerging markets, we find that price declines are less pronounced in countries that import high-priced varieties of goods.

Our baseline results are robust to a range of robustness checks, including weighting by import values in the destination country and using a continuous measure of tariff exposure based on the share of products covered. In addition, while we use a difference-in-differences approach as in Flaaen and Pierce (2024) to present our main results, we show that we obtain similar estimates using two alternative strategies: an event study *a la* Fajgelbaum et al. (2019) and local projections as in Jordà (2005). The presence of major changes in the Harmonized Tariff Schedule limits our baseline sample period to 2017-2021. However, for the subset

[4] We explore alternative empirical strategies including event study and local projections in robustness checks.

[5] As discussed further below, Emlinger et al. (2026) consider effects on EU import prices in the 15 months after tariffs are imposed and find no effect.

of products that we can observe over a longer pre-tariff time period, we examine the extent of pre-existing trends among tariff-targeted goods. We find that coefficient estimates for import prices move sideways close to zero and are not statistically significant prior to 2018 when the tariffs were first imposed.[6]

This paper contributes to the recent growing literature on the economic effects of massive recent tariffs. Substantial attention has been devoted to the effect of tariffs on U.S. import prices (Amiti, Redding and Weinstein, 2019; Fajgelbaum et al., 2019; Flaaen, Hortaçsu and Tintelnot, 2020; Cavallo et al., 2021; Cavallo, Llamas and Vazquez, 2025; Minton and Somale, 2025), U.S. employment and manufacturing activity (Flaaen and Pierce, 2024), U.S. export growth (Handley, Kamal and Monarch, 2025), U.S. sourcing patterns (Bown, 2022; Alfaro and Chor, 2023; Javorcik, Pierce and Wisniewski, 2025), and U.S. welfare when tariffs are interacted with industrial policy (Ju et al., 2024).

However, despite the massive shifts in global trade since 2018, less attention has been devoted to the spillover effects of tariffs to countries beyond the U.S. and China. Papers that do tend to focus on the potential for bystander countries to replace China as a source of U.S. imports (Freund et al., 2024; Alfaro and Chor, 2023), or to increase exports globally (Fajgelbaum et al., 2024), rather than focusing on imports and import prices in those bystander countries. Another example is Utar, Zurita and Torres (2025), who document an increase in net exports by Mexican firms associated with U.S.-China tariffs, particularly for foreign-owned multinationals that produce high-tech goods using imported inputs.[7] Alfaro et al. (2025*a*) and Correa et al. (2025) highlight the relevance of financing in aiding the expansion of third-country exporters as they attempt to expand shipments to the U.S.[8] Our contribution is to provide what is, to our knowledge, the first comprehensive empirical estimates of the effects of the 2018-19 U.S. import tariffs on Chinese exports to alternative destinations, including effects on import prices and an examination of exporting and destination country characteristics that influence the extent of trade deflection.

On the theory side, a highly relevant paper is Reyes-Heroles, Traiberman and Van Leemput (2020), who provide a dynamic general equilibrium trade model that captures features of trade between Emerging Market Economies (EMEs) and Advanced Economies (AEs). They conduct simulations of several scenarios involving higher trade costs including the U.S.-China trade tensions of 2018-19 and find that EMEs experience gains in GDP and welfare, partially due to lower prices on imported capital goods. That paper, therefore, provides a theoretical justification for the types of channels we investigate empirically in this paper.

Our paper also builds on the important work of Bown and Crowley (2007), who provided the first detailed study of the trade deflection effects we examine here, focusing on the effects of antidumping duties. In particular, Bown and Crowley (2007) were the first to explicitly consider the differing reactions of exports to discriminatory tariffs (applied by an importer against one of its import source countries), versus nondiscriminatory tariffs (applied against all source countries).[9] They propose a three-country Cournot model, in which goods are strategic substitutes and marginal costs are increasing in production, and obtain theoretical predictions of adjustments in trade flows under the two types of tariffs. Most relevantly for our setting, they find that the average antidumping duty imposed by the U.S. against Japan led to a 5-7 percent increase in deflected Japanese exports of the affected product to third countries. Building on this work, Grant and Anders (2010) find trade deflection effects arising from U.S. non-tariff barriers on seafood imports, and Crow-

[6]There is some evidence of pre-existing trends for values and quantities, depending on destination country, though those coefficients also display a distinct step up in 2019.

[7]The reliance on Chinese inputs among bystander countries increasing exports to the U.S. has also been noted by others including Alfaro and Chor (2023) and Hoang and Lewis (2024).

[8]Xu (2022) highlights the relevance of trade financing in trade flows in a historical context.

[9]As they note, their work also draws on insights regarding trade diversion effects going back to Viner (1950), with subsequent theoretical work on the topic by Bond and Syropoulos (1996), Bagwell and Staiger (1997), and McLaren (2002).

ley, Meng and Song (2018) show that trade policy uncertainty arising from antidumping investigations can lead to similar trade deflection effects. Here, we consider the potential effects of trade deflection—including effects on import prices, which this literature does not examine—following the start of a historically large increase in tariffs on a broad range of products, imposed by the world's largest importer against the world's largest exporter.

Highlighting the relevance of this topic to policymakers, a series of policy pieces—typically focused on the EU as a potential destination for Chinese exports, and often conducted at the ECB—have examined some aspects of the trade deflection of Chinese exports we consider. Al-Haschimi et al. (2025) examines causes for strong global Chinese export growth and finds a role for state investments in the manufacturing sector that have lowered export prices, along with weak domestic demand. Boeckelmann et al. (2025) derive estimates of potential increases in euro area imports of Chinese goods, estimate effects on import prices with a VAR, and translate that impact to a potential decrease in headline inflation of 15 basis points in 2026. Gunnella, Stamato and Kobayashi (2025) consider the effects of U.S. tariffs imposed in the first Trump administration on the redirection of trade flows, including to the EU. Ropele (2026) reports on results of a survey of Italian firms' expectations of the effects of Chinese rerouting and indicates that the most exposed firms (primarily manufacturers) expect downward pressure on both input and output prices. Emlinger et al. (2026) perform a detailed empirical analysis of the implications of U.S. tariffs for the EU, using a staggered differences-in-differences analysis to estimate the reallocation of trade flows in the 15 months after tariffs are imposed.[10] Here, we provide analysis that looks beyond the euro area, use a different empirical approach covering a longer period after tariffs, and provide evidence for a key outcome—import prices—that is not considered at all in most of these pieces and is never considered for destinations other than the EU, which we find to be most affected.

Lastly, a related literature examines the role of geopolitical factors in realigning trade flows between, and across, blocs of countries. Gopinath et al. (2025) find that more geopolitically distant countries—as measured by UN General Assembly voting—have seen decreases in trade, FDI, and portfolio flows following the Russian invasion of Ukraine in 2022. While papers including Fernández-Villaverde, Mineyama and Song (2024) and Javorcik et al. (2024) show that this "fragmentation" can harm the global economy, Bonadio et al. (2025) argue that this need not be the case. In the latter's quantitative model, as countries move toward a U.S.- or China-centric bloc, the median country experiences real income gains. Here, we provide novel evidence on the impact of one of the driving forces behind shifting U.S. and Chinese trade —tariffs— and document effects on bystander countries that may be considering closer trade integration with the U.S. or China.

The remainder of the paper is structured as follows. Section 2 describes the data used and our definition of exposure to tariffs. Section 3 outlines the empirical strategy, while Section 4 presents the results. Section 5 discusses robustness checks, and Section 6 concludes.

[10]Emlinger et al. (2026) examine some responses of trade values to tariffs in other countries, but they do not consider effects on quantities or prices for those countries. In addition, our analysis uses import data from 95 countries, which allows us to control for source-country-specific factors, which is not possible using only Chinese export data as in Emlinger et al. (2026).

2 Data

2.1 Data Source Description

Our study relies on two main data sources. First, we gather information on U.S. tariffs on Chinese imports from the U.S. International Trade Commission (USITC). The dataset provides information on tariffs and U.S. import values at the eight-digit and ten-digit level of the Harmonized Tariff Schedule (HS), at a monthly frequency for the years 2017–2021. We complement tariff information from the USITC with exemptions granted on a small set of ten-digit HS codes.

The second source provides import data for the bystander countries (i.e., not the U.S. or China) that are the focus of our analysis. Our baseline analysis employs data from UN Comtrade (2025) on import values[11] and quantities at the HS six-digit product level between 2017 and 2021.[12] We construct a dataset of import values, quantities, and unit prices for 95 countries. Inclusion in our sample of importing countries is based on availability of import data covering the entire sample period from 2017-2021 and reporting of data in time-consistent six-digit HS codes. We also use 2017 Chinese export values from UN Comtrade for our analysis measuring the pre-trade-war market structure.

2.2 Quantities Harmonization

In order to study the effects of tariffs on bystander countries, we construct a novel dataset encompassing import values, quantities, and unit prices for over 5,000 six-digit Harmonized System products for 95 countries between 2017-2021. A key challenge in constructing consistent trade quantity measures from the data is the heterogeneity and inconsistency of quantity units reported across countries, products, and time. UN Comtrade provides two quantity measures: a primary quantity and an alternative quantity, each with associated unit codes. However, these unit codes may change within the same origin-destination-product group across years or contain missing observations. Such inconsistency inhibits studying changes in quantities and unit prices across many countries over time.

To enable study of these trends, we construct a time-consistent quantity variable by applying an algorithm we develop to the primary and alternative quantity variables provided by UN Comtrade. This algorithm and quantity measure is critical for our study, as it permits examination of unit values across countries, products, and time. The previous unavailability of this information has also limited the ability of researchers to perform a variety of cross-product-country analyses using Comtrade data. In an online appendix to this paper, we provide the code necessary for other researchers to apply the algorithm to Comtrade data, thus yielding what we expect to be a highly useful contribution in terms of economic measurement for future empirical trade research.

For a given origin-destination-product group, our algorithm constructs the time-consistent quantity variable to preserve as many observations with the same unit of quantity as possible. The algorithm sorts the origin-destination-product groups into cases using a hierarchical sorting algorithm that determines how the time-consistent quantity unit is constructed. The algorithm first identifies already-consistent groups (cases 0 - 3); then finds groups where both variables can be combined to construct a fully consistent new quantity (cases 4 - 5); and finally tags groups where it is only possible to construct a consistent unit of quantity code for a subset of years (cases 6 - 9). The sorting algorithm is as follows:

[11] We use CIF (Cost, Insurance, and Freight) values when available and FOB (Free On Board) values otherwise.

[12] We provide the list of available destination countries in Appendix A.

- Case 0: Primary unit code and alternative unit code are fully consistent and match each other.
- Case 1: Primary unit code is fully consistent.
- Case 2: Primary unit code is always missing while alternative unit code is fully consistent.
- Case 3: Primary unit code changes over the years while alternative unit code is fully consistent.
- Case 4: Primary unit code changes, but the alternative unit code is equal to the non-missing modal primary unit code for observations when the primary unit code is not the modal code.
- Case 5: Alternative unit code changes, but the primary unit code is equal to the non-missing modal alternative unit code when alternative unit code is not the modal code.
- Case 6: Primary unit code alternates between a non-missing and missing code, and the alternative unit code matches the non-missing primary unit code in some years when the primary unit code is missing.
- Case 7: Primary and alternative unit codes both alternate between missing and non-missing unit codes.
- Case 8: Primary unit code alternates between a missing and non-missing code, while alternative unit code alternates between two non-missing codes or 3+ codes.
- Case 9: Alternative unit code alternates between a missing and non-missing unit code, while primary unit code alternates between 2 non-missing or 3+ codes.
- Groups that cannot be cleanly categorized by any of the above rules are flagged, and their quantities are treated as missing while preserving the associated trade values.

For origin-destination-product groups that fall into cases 0 - 3, we take the full consistent quantity variable that UN Comtrade provides (either primary or alternative). In cases 4 - 5, we combine the primary and alternative quantities to construct a new quantity that is consistent across our analysis period. In cases 6 - 9, we combine the two variables to produce consistent quantity unit codes for as many years in the analysis period as possible. Table 1 provides the share of the origin-destination-products that fall into each group.

Table 1: Share of Origin-Destination-Product by Case

Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Missing
60.7	28.3	3.3	.7	.08	.005	.03	1.5	1.4	2.2	1.7

Sources: UN Comtrade; author's calculations.
Notes: 92% of the origin-destination-product combinations take the full set of primary or alternative quantity units as provided by UN Comtrade.

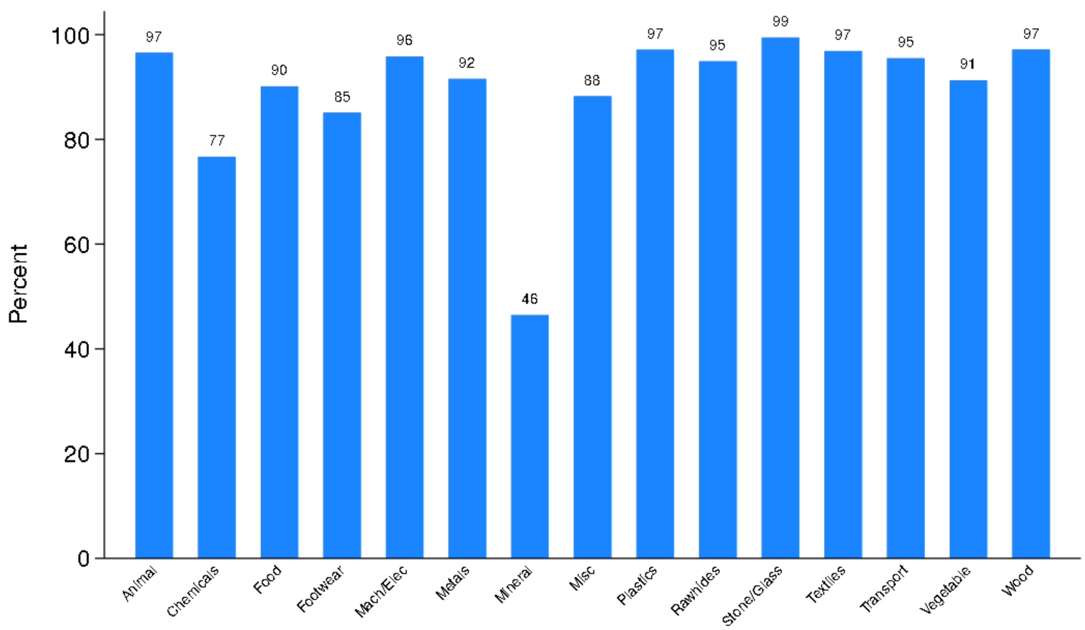
2.3 Product-Level Tariff Exposure

The 2018-19 U.S. tariffs on Chinese imports were applied to eight and ten-digit HS codes. HS codes are harmonized globally only up to six digits. Thus, in order to study the effects of the U.S-China trade war on third-party countries, we construct a measure of tariff exposure defined at the six-digit HS code. We follow Fajgelbaum et al. (2019) and define a dummy variable for tariff status at the six-digit level, which is equal to one if at least one eight- or ten-digit HS code within the broader six-digit product category is tariffed.

We use this binary variable as the baseline exposure indicator in our analysis, but in Section 5.2 we show that our results are robust to using a continuous value of tariff exposure based on the proportion of ten-digit HS codes being tariffed.

We provide a visual representation of the distribution of tariffed products by aggregate sectors known as HS Sections in Figure 3.[13] As shown in the Figure, by 2021, tariffs affect most of the products that the U.S. imports from China, with substantial variation across HS Sections. Only "Minerals" (which includes oil and petroleum products) is affected by tariffs for less than 50 percent of products, while "Stone/Glass" faces tariffs on almost all products within the HS Section.

Figure 3: Product Share of Pre-Trade-War U.S. Imports from China Subject to Tariffs by HS Section



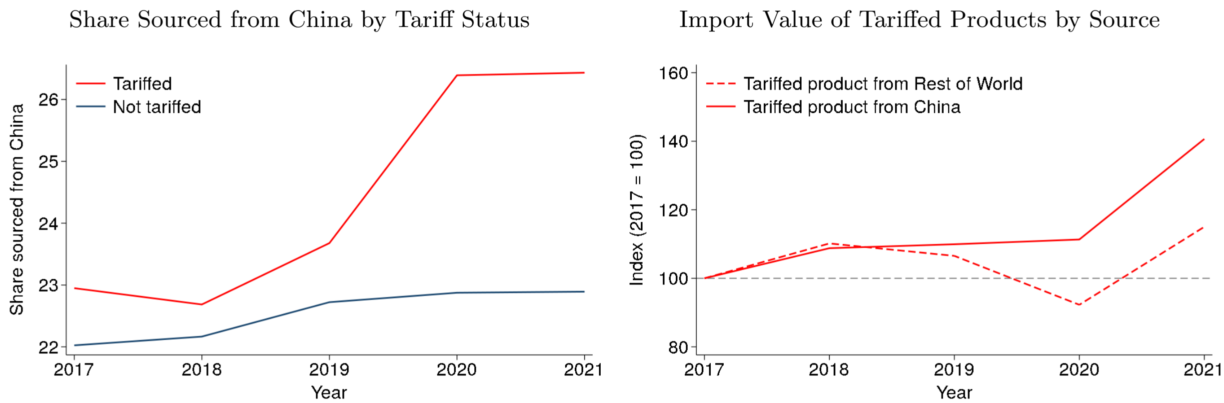
Sources: U.S. International Trade Commission (USITC); U.S. Census; authors' calculations.
Notes: Figure displays the share of products that are tariffed as of 2021 on U.S. imports from China at two-digit product groupings.

The left panel of Figure 4 reports the share of world imports from China of tariffed and non-tariffed six-digit products. There is a notable step up in the China share for tariffed products beginning in 2019—the year following the U.S. tariffs implementation—relative to imports of non-tariffed products. A natural concern is that tariffed products may exhibit distinct trends unrelated to trade diversion, such as common demand shocks affecting these product categories regardless of origin. The right panel of Figure 4 explores this alternative explanation by displaying imports of tariffed products by country of origin. The data reveal a widening gap between tariffed Chinese products (solid red line) and tariffed products from other countries (dashed red line) after 2018, pointing to potential China-specific trade diversion rather than category-specific import trends.[14]

[13] HS Sections are defined in the U.S. Harmonized Tariff Schedule (https://hts.usitc.gov/). As an example, HS Section VI "Products of the Chemical or Allied Industries" includes HTS Chapters 28-38, with products such as organic and inorganic chemicals, pharmaceuticals, fertilizers, and explosives.

[14] As shown in Figure 14, imports sourced from China of non-tariffed products also increase relative to imports from rest of the world. Our origin-year FE capture policies and shocks that affect all products coming from China.

Figure 4: Value Share of Global Imports Sourced from China by Tariff Status and Source



Sources: UN Comtrade; authors' calculations.
Notes: The left panel displays the value share of world imports sourced from China for each year separately for products that are affected by tariffs and products that are not affected by tariffs. The right panel displays the average import value of tariffed products by origin. Values are weighted by the 2017 import value for each origin-destination-product group.

Table 2 provides summary statistics on the key dependent and independent variables in our sample.

Table 2: Basic Summary Statistics for the World Sample: 2017-2021

	count	mean	sd	min	max
Basic tariff status	25,032,101	0.05	0.22	0	1
Basic tariff status (China only)	1,497,439	0.89	0.31	0	1
Value (ln)	25,032,048	9.26	3.34	-7	24
Quantity (ln)	23,878,609	6.15	4.06	-7	31
Unit price (ln)	23,878,567	3.10	2.36	-18	23

Sources: UN Comtrade; author's calculations.
Notes: Table shows summary statistics for the basic tariff variable and the three main outcome variables for the world sample. Basic tariff status is 1 if the observation is from China and in a six-digit HS code that receives a tariff during the trade war, and 0 otherwise. The data is at the origin-destination-year-product level, with destination country being each of the 95 countries in our data and product being defined at a six-digit HS code. There are 53 observations with missing value (ln) and 1,153,492 observations with missing quantity (ln), resulting in 1,154,534 observations for which we cannot recover unit price.

3 Empirical Strategy

Our empirical strategy exploits a simple yet powerful source of variation: the U.S.–China trade war created differential tariff treatment across narrowly-defined products, while leaving Chinese exports to other destinations unaffected by U.S. policy. This allows us to compare the export performance of tariffed versus non-tariffed Chinese products in third-country markets, holding constant a rich set of confounding factors.

The logic is straightforward. If U.S. tariffs on Chinese goods lead Chinese exporters to divert shipments toward alternative markets, we should observe differential growth in Chinese exports of tariffed products relative to non-tariffed products in destinations outside the United States. Moreover, if this trade diversion puts downward pressure on prices in third markets, we should see larger declines in unit values for products facing higher U.S. tariffs.

We build our baseline approach on the recent literature analyzing pass-through of the 2018-19 tariffs to U.S. import prices (Amiti, Redding and Weinstein, 2019; Fajgelbaum et al., 2019). However, whereas those papers focus on the direct effects of tariffs in the U.S. market, we examine the spillovers to countries not involved in the trade dispute. We adopt a difference-in-differences design as our primary specification and verify robustness using an event study approach that accommodates the staggered timing of tariff implementation and a local projections approach that accounts for longer-run changes and dynamic responses in Section 5.

We begin with a generalized difference-in-differences design that interacts an indicator for exposure to tariffs with the full set of year dummies. Our baseline specification is:

$$\ln y_{odgt} = \alpha_{og} + \alpha_{gt} + \alpha_{ot} + \alpha_{dg} + \alpha_{dt} + \alpha_{od} + \sum_{j=2018}^{2021} \beta_j \text{ treated}_{og} \times \mathbf{I}(t = j) + \varepsilon_{odgt} \tag{1}$$

where y_{odgt} measures the value, quantity, or unit value of six-digit HS product g exported from origin o to destination d in year t, all in logs. The treatment indicator treated_{og} equals one when product g from China ($o =$ China) is subject to U.S. tariffs as of 2021, and zero otherwise.[15] By construction, $\text{treated}_{og,2021}$ takes value of zero for all trading partners other than China. We interact this treatment indicator with year dummies $\mathbf{I}(t = j)$ to trace out the dynamic response, with 2017 serving as the baseline year.

The specification includes a comprehensive battery of fixed effects: origin–product (α_{og}), product–time (α_{gt}), origin–time (α_{ot}), destination–product (α_{dg}), destination–time (α_{dt}), and origin–destination (α_{od}). These six sets of fixed effects absorb stable bilateral trading relationships as well as any shocks specific to products, origins, destinations, or years. Given this rich structure, β_j captures how Chinese exports of tariffed products evolve differently than non-tariffed products within the same origin–destination pair and year. In other words, we compare trade of tariffed versus non-tariffed goods from China to, say, Germany in 2019, while controlling for factors common to all products exported from China to Germany in that year, factors common to all products imported by Germany in that year, and factors common to all products exported by China in that year. This within-pair-year comparison accounts for alternative explanations such as aggregate trade diversion toward particular destinations, shocks to particular product categories, or policies or shocks in particular origin countries, including China. We two-way cluster standard errors at the origin and product level to account for correlation in the error term across destinations and years for a given origin and product, which aligns with the level at which treatment is assigned.

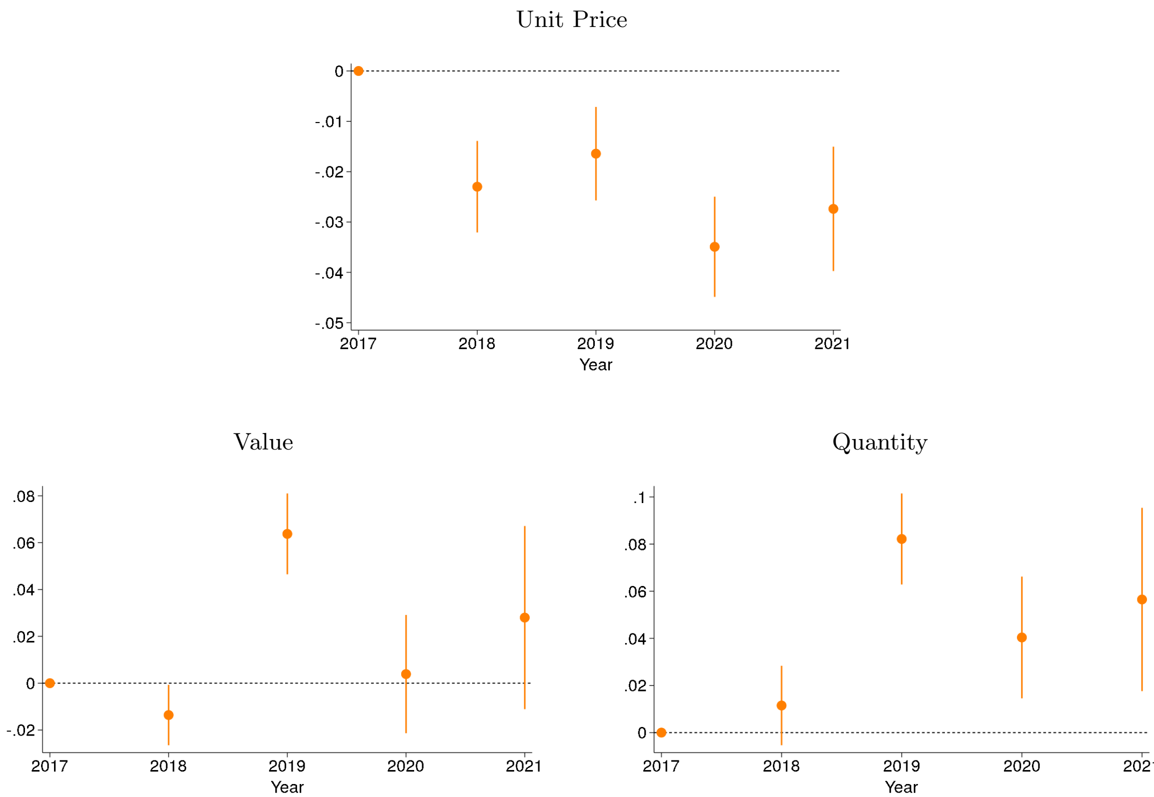
4 Results

This section provides the main results of our analysis. In most cases, we display results visually, with the estimated β_j coefficients of Equation 1, which capture the effects of tariffs on the noted dependent variables, along with the associated 95% confidence intervals. Figure 5 shows the impact of tariffs imposed by the U.S. on Chinese exports to all other countries.[16] We report results separately for trade flow values, quantities, and unit values (prices). Three patterns emerge from these estimates.

[15] Over time, some products received exemptions from tariffs, and those with exemptions in effect as of 2021 have a treated_{og} value of zero.

[16] The regression table for this specification is shown in Table 5 in Appendix C.

Figure 5: World Imports of Tariffed Chinese Goods



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. Error bars show 95% confidence intervals.

First, as shown in the top panel of the figure, we see that products subject to tariffs and imported from China see systematic relative declines in unit prices in third-country markets. The price drop appears immediately in 2018, the year tariffs take effect, and persists through 2021. By the end of the sample period, prices for tariffed products have declined roughly 3 percent relative to non-tariffed products in the same markets.[17] This price reduction is both economically meaningful and statistically significant, suggesting that Chinese exporters systematically cut prices as they redirect shipments away from the United States.

Second, as shown in the lower right panel, these lower prices are accompanied by relative increases in quantities of tariffed products. The quantity response is the mirror image of the price pattern: tariffed products experience higher export volumes to third countries starting in 2018. The magnitude is substantial, with quantities rising by 8 percent in 2019 and then averaging around 5 percent in the later years of our sample. This increase in quantities, combined with falling prices, points to an outward shift in Chinese export supply to non-U.S. destinations. Exporters facing higher costs of accessing the U.S. market redirect their output toward alternative markets, and they lower prices to facilitate absorption of this additional supply.

Third, the value effects are generally not statistically distinguishable from zero. The imprecision in value estimates does not undermine the main findings of increased trade deflection due to tariffs; rather, it shows

[17] $\widehat{\beta}_{2021} = -0.03$, which implies an effect of $(\exp(0.03) - 1) * 100 = 3.05\%$.

that the drop in prices is sufficient to obscure the effects of the increase in quantities. These divergent effects for quantity and unit prices highlight the importance of considering not only value in examinations of trade deflection, but also quantities, which is only possible by standardizing units of quantity in trade data, as we describe in Section 2.2.

Taken together, Figure 5 provides initial evidence of trade deflection: Chinese goods are reallocated toward other destinations as exporters search for new markets able to absorb excess capacity that becomes more costly to export to the U.S. due to higher tariffs, accompanied by systematic price reductions that help sustain demand abroad. The evidence of trade deflection in volumes is in line with the evidence shown in Bown and Crowley (2007) for the Japanese context in the 1990s, and with the theoretical predictions of that paper. Our novel findings on implications for import prices provide a better understanding of how trade deflection works, in practice.

The mechanism appears to operate as follows. U.S. tariffs raise the effective price Chinese exporters can charge in the U.S. market, reducing U.S. sales. Facing this shock, exporters shift production toward other destinations. However, those markets were already in equilibrium before the tariff shock. Absorbing additional Chinese supply requires lower prices to move down the demand curve. The combination of rising quantities and falling prices is exactly what we observe.

4.1 Effects by Country Group

These pooled results aggregate across countries with widely differing economic structures, geographic positions and trade relationships. An important question is whether Chinese exports are deflected more toward countries whose composition of import demand is similar to the U.S.—i.e. other advanced economies—or toward emerging market economies whose demand may align more closely with products that China has comparative advantage in producing. We therefore next document how responses vary across groups of destination countries by income level.

Emerging Markets Emerging Markets (EMs) are natural candidates for absorbing diverted Chinese exports. Many EMs had already become major destinations for Chinese exports in the early 2010s (Brandt and Lim, 2024), establishing trade relationships and distribution networks that could facilitate rapid expansion when U.S. tariffs made that market less profitable. Moreover, EMs may have more elastic demand for Chinese products if consumers are more price-sensitive than in advanced economies.

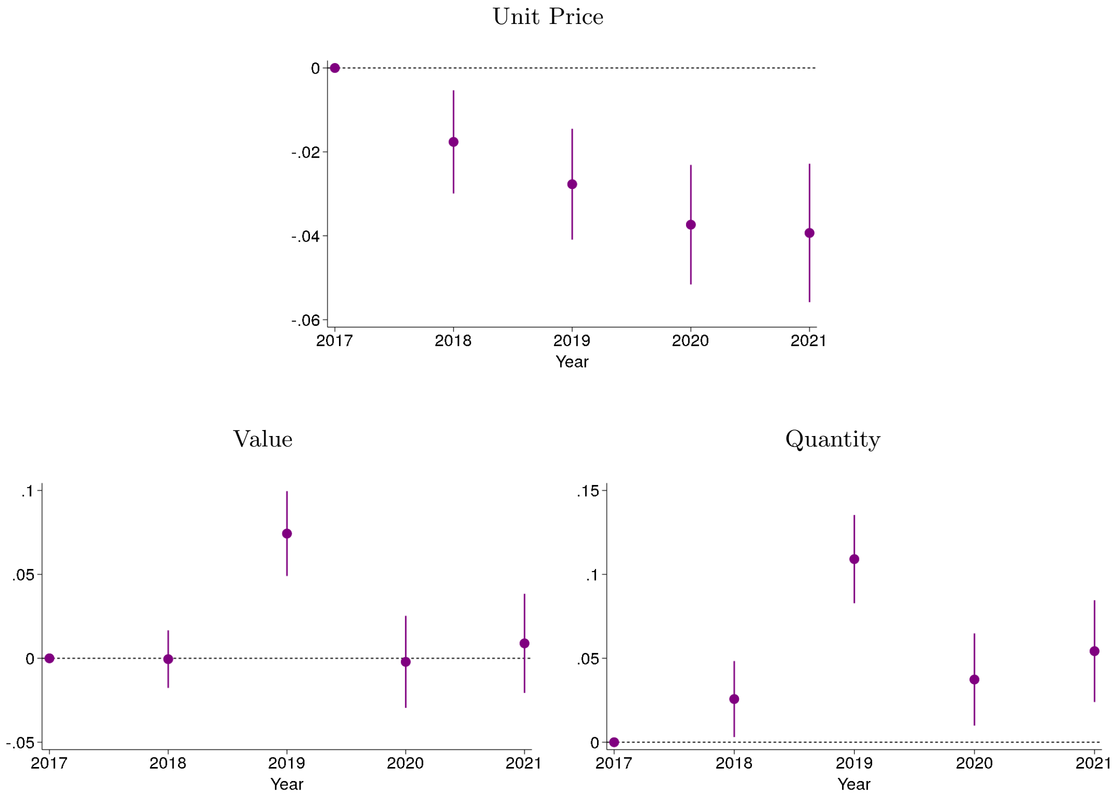
Figure 6 presents results for the 60 EMs in our sample.[18] The pattern closely resembles the results in the global sample, but the magnitudes are somewhat larger, and the decline in unit prices is more precise and increases in magnitude over time. Quantities increase more than values, implying relative unit price declines of roughly 4 percent by 2021.

These magnitudes confirm that EMs play a substantial role in absorbing Chinese goods that face higher costs of accessing the U.S. market. The price declines are consistent with theoretical predictions by Reyes-Heroles, Traiberman and Van Leemput (2020), who show that third countries can experience welfare gains from trade diversion through lower import prices.

Advanced Economies We present results for the 35 economies classified as Advanced Economies (AEs) in Figure 7.[19] The qualitative patterns mirror those for EMs—relative increases in values and quantities,

[18]The regression table for this specification is shown in Table 6 in Appendix C.
[19]The regression table for this specification is shown in Table 7 in Appendix C.

Figure 6: Emerging Markets Imports of Tariffed Chinese Goods



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables for emerging market economies. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals.

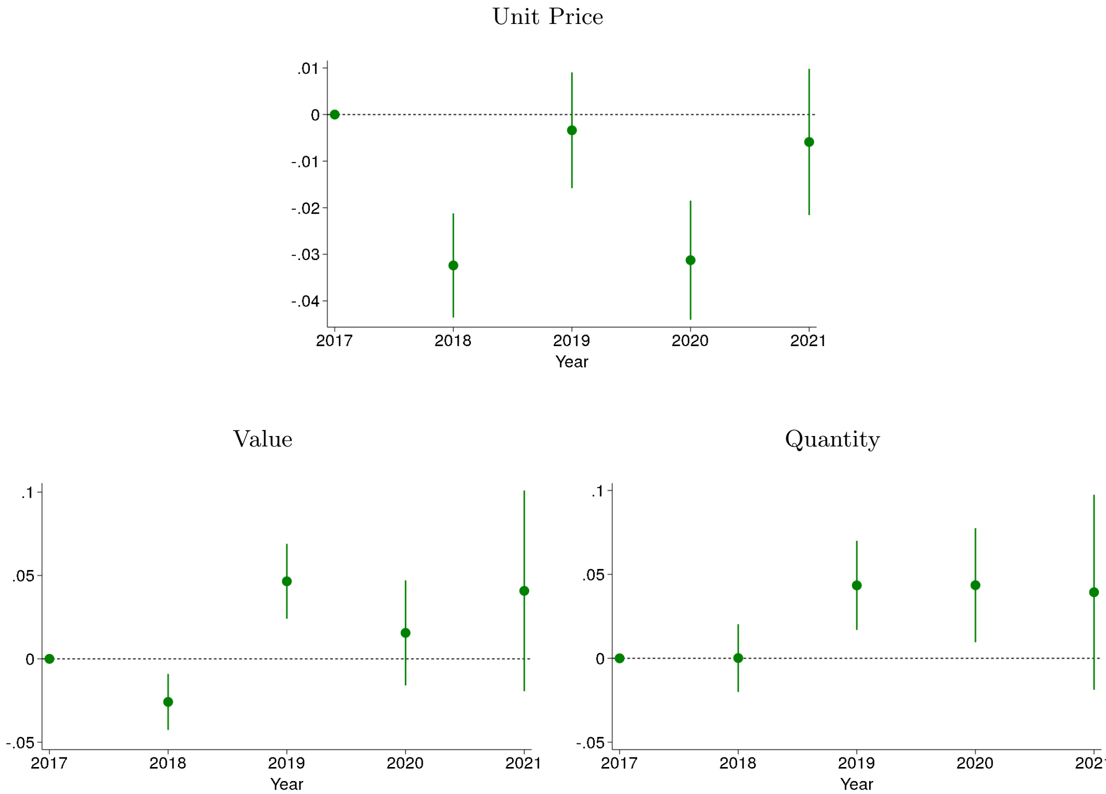
and relative declines in prices—but the magnitudes are slightly smaller. The increase in quantities imported by AEs is also less pronounced (around 5 percent, versus a peak effect of 10 percent for EMs) and more short-lived (in 2019 and 2020 only) than for EMs. Moreover, the estimates for AEs are less precise, with no statistically significant relationship between U.S. tariffs and third-country import prices in 2019 and 2021, likely driven by a high degree of heterogeneity across AEs, which may be driven by different geographic locations.

European Union Countries The potential for trade diversion in Europe has attracted considerable media and policy attention. News coverage has raised concerns about surges in Chinese imports and declining prices that could harm European producers.[20] In addition, the European Central Bank devoted an alternative scenario in its September 2025 Macroeconomic Projections to analyzing the potential effects of lower Chinese export prices (ECB, 2025).

While recent concerns focus on the second Trump administration's tariffs, we can narrow our focus on the 2018–2019 episode, which also featured massive U.S. tariffs that were, in that case, overwhelmingly targeted against China. Figure 8 reveals a nuanced pattern: unit prices did decline in 2018, by 4 percent, consistent

[20] See "With Trump's Tariffs, Europe Fears a Flood of Cheap Goods from China." https://www.nytimes.com/2025/04/14/world/europe/europe-china-dumping-tariffs.html

Figure 7: Advanced Economies Imports of Tariffed Chinese Goods



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables for advanced economies. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals.

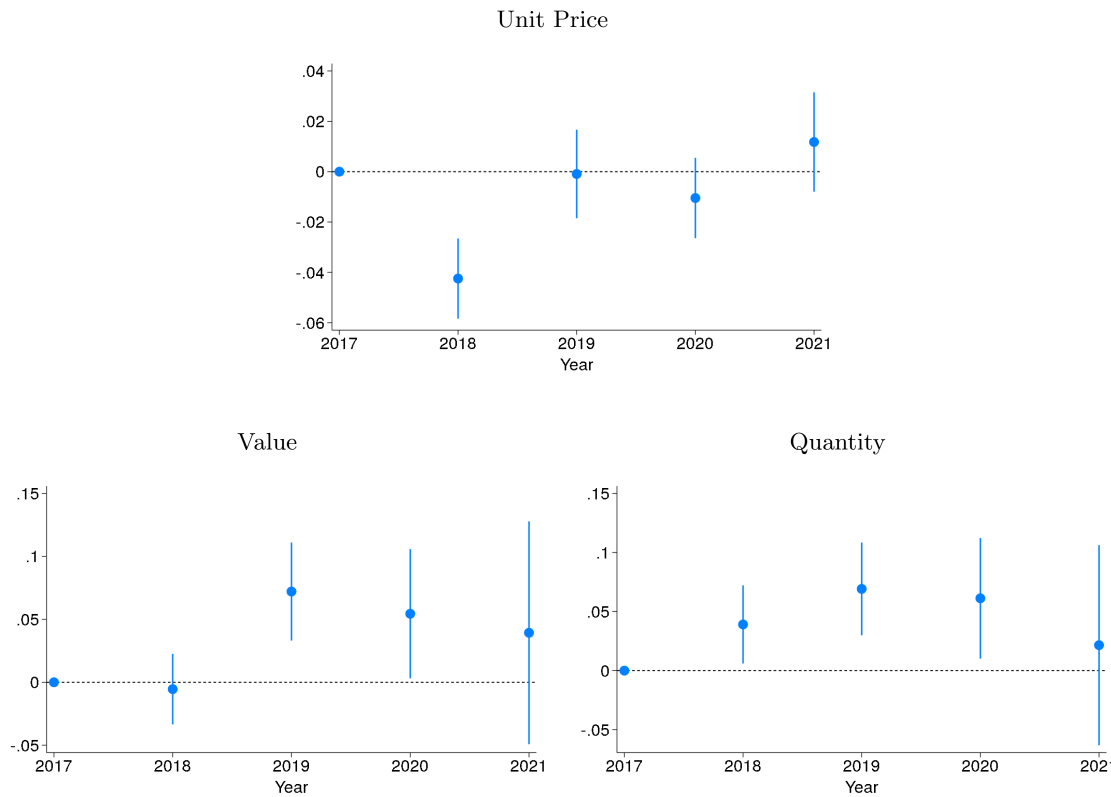
with immediate trade diversion following the initial tariff wave. However, price effects become noisy and statistically indistinguishable from zero after that single year.[21]

In contrast, both value and quantity show statistically significant increases, especially in 2019 and 2020. The rise in quantity and value without sustained price declines differs from the pattern observed for EMs in Figure 6. One interpretation is that the EU has not absorbed additional Chinese exports through the price competition channel: perhaps product differentiation is higher in the EU market, allowing Chinese exporters to redirect different varieties without undercutting prices, or alternatively the EU's anti-dumping enforcement may have constrained aggressive price-cutting. In each of these cases, absorption of increased imports from China may come with less disruption to domestic EU producers if it is not accompanied by lower prices.

Asian Countries Because geographic proximity is a relevant feature to take into account when examining the extent of trade diversion, we examine results for the 24 countries in our sample located in Asia. If transportation costs matter, these nearby markets should be particularly attractive destinations for diverted Chinese exports: shipping to Asia is faster and cheaper than shipping to Europe or the Americas, allowing Chinese exporters to redirect supply with minimal added logistics costs. Such effects would be consistent

[21]The regression table for this specification is shown in Table 8 in Appendix C.

Figure 8: European Union Countries Imports of Tariffed Chinese Goods



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables for EU countries. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. Error bars show 95% confidence intervals.

with the literature highlighting the relevance of regional, as opposed to global, trade linkages (Disdier and Head, 2008; Johnson and Noguera, 2012; Baldwin and Lopez-Gonzalez, 2015; Alfaro et al., 2025*b*).

The results in Figure 9 strongly support this geographic channel.[22] Asian countries experience a substantial price decline, qualitatively similar to the trend shown by EMs in Figure 6 but substantially larger in magnitude: unit prices fall by 6 percent in 2020 and 2021, compared to 4 percent in EMs in the same years. With no statistically significant effect on quantities, these price cuts lead to lower values of Chinese exports to Asian countries (up to -6 percent in 2020).

4.2 Exploring Product- and Market-Specific Drivers of Trade Deflection

Trade deflection from U.S. tariffs need not affect all third-country markets uniformly. In the previous subsection, we have shown that trade deflection changes based on geographic location and level of development. At the same time, Chinese exporters facing tariff barriers may redirect toward destinations where they hold established market positions, or seek new markets with favorable demand characteristics. In this subsection, we examine four dimensions of heterogeneity that capture pre-trade-war market structure and Chinese positioning and help explain why the extent and implications of deflection of Chinese exports have differed across markets. The triple difference-in-differences specification isolates how these features condition trade

[22]The regression table for this specification is shown in Table 9 in Appendix C.

Figure 9: Asian Countries Imports of Tariffed Chinese Goods

Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables for Asian economies. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. Error bars show 95% confidence intervals.

diversion responses, differencing out common shocks and product-specific trends.

We construct four indicators to characterize destination-product pairs. First, $\mathbf{I}(US)$ identifies products where the 2017 U.S. share of Chinese exports exceeded the median export share across all other destinations, capturing products for which the U.S. was an important pre-tariff destination for Chinese exports. These products may require substantial redirection when tariffs hit, necessitating aggressive pricing to penetrate alternative markets. Second, $\mathbf{I}(CN)$ flags destination-product pairs where the importer received an above-median share of Chinese exports for that product, identifying established Chinese markets. These markets offer existing distribution networks and known demand, potentially facilitating volume expansion but also risking intensified competition as redirected exports crowd these destinations. Third, $\mathbf{I}(CNVeryLow)$ identifies destination-product pairs where 2017 Chinese import prices ranked at or below the 25th percentile of all import prices in that destination. These very-low-price positions may face binding constraints on further price reductions, limiting absorption capacity at the bottom of the quality distribution. Fourth, $\mathbf{I}(HighP)$ identifies destinations importing product g at above-median (across countries) unit prices, flagging high-price markets. Such high-price markets may absorb redirected exports with less downward pressure on prices if demand tilts toward differentiation rather than price competition.

The triple interaction $\text{treated}_{og} \times \mathbf{I}(t) \times \mathbf{I}(\text{dimension})$ tests whether tariff effects vary systematically with these pre-existing market characteristics. As before, our specifications include a comprehensive set of fixed effects: destination-product, destination-year, product-year, origin-year, origin-product, and origin-destination. This structure differences out all time-invariant bilateral, product-specific, destination, and origin characteristics, as well as common time trends within each of these dimensions. The triple interaction is identified by residual variation in how tariff exposure affects trade flows differentially across our four heterogeneity dimensions, conditional on this rich set of controls. Standard errors are two-way clustered at the origin and product levels to account for correlation in shocks within these groups.

Table 3 presents price effects for dimensions that relate to market focus. The baseline treatment effects for U.S.-focused (column 1) products show modest but statistically significant price reductions in third markets, ranging from 1.5 to 2.6 percent across 2018–2020. The triple interaction coefficients reveal additional price compression: U.S.-focused products—i.e. those products for which the U.S. was an important destination for Chinese exports prior to tariffs—experience *further* declines of 1.1 percentage points in 2018, rising to 1.6 percentage points in 2020 and 3.0 percentage points by 2021. These findings indicate that products heavily reliant on the U.S. market require increasingly aggressive pricing to redirect exports successfully, consistent with costs of penetrating markets where they previously held limited share.

Destinations where China had an established market presence prior to tariffs (column 2) show near-zero baseline effects of tariffs on unit values, but substantially larger triple interaction coefficients. These markets experience price declines of 4.7 percentage points in 2018, peaking at 8.6 percentage points in 2020, before moderating to 8.3 percentage points in 2021. The magnitudes exceed those for US-focused products, indicating that established Chinese markets face intense price competition when absorbing redirected exports. While existing distribution networks facilitate volume expansion, they do not insulate these destinations from price pressures generated by large inflows of redirected Chinese goods.

The price declines documented in Table 3 facilitate volume expansion: triple interaction coefficients for value and quantity are positive and statistically significant for both US-concentrated products and established Chinese markets, indicating that redirected exports successfully penetrate these destinations despite requiring price concessions (Table 10 in Appendix C).

Table 4 examines heterogeneity in price positioning. Results in the first column indicate that the negative price response associated with tariff-driven trade deflection occurs entirely in markets where China provides low-cost varieties. In particular, the triple interaction coefficients are strongly negative and precisely estimated: markets where China already competed at very low prices see additional price declines of 54 percentage points in 2018, moderating to 37 percentage points by 2021. This effect is large enough to offset a positive relationship between tariffs and unit values for goods where China provides high-cost varieties. The combined effects imply substantial absolute price compression in bottom-quartile markets, suggesting redirected exports intensify competition at the low end of the quality spectrum and crowd existing low-price positions.

Column 2 examines how the effects of U.S. tariffs differ for destinations that are importing high-priced varieties of goods relative to other destination countries. Again, we uncover substantial heterogeneity, and the results show that the price reductions due to trade deflection are concentrated in countries that import low-priced varieties of goods. Given that emerging markets tend to import lower-priced versions of goods than advanced economies (Simonovska, 2015), this result reinforces the difference between advanced economies and emerging markets we have highlighted in the previous subsection. Examining the detailed estimates, baseline treatment effects are negative (8 to 15 percent), but triple interaction coefficients are consistently positive and economically significant. In other words, Chinese exporters redirect toward "premium" (high-priced) market segments without the aggressive price competition observed in low-price destinations, consistent with

Table 3: World - Market focus

	(1) Price (ln)	(2) Price (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	-0.0149***	0.0000256
	(0.00478)	(0.00493)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	-0.0193***	0.00594
	(0.00522)	(0.00480)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	-0.0257***	0.00293
	(0.00542)	(0.00540)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	-0.0109*	0.00851
	(0.00637)	(0.00638)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(US)$	-0.0106***	
	(0.00290)	
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(US)$	0.00562	
	(0.00353)	
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(US)$	-0.0156***	
	(0.00424)	
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(US)$	-0.0295***	
	(0.00385)	
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CN)$		-0.0471***
		(0.00485)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CN)$		-0.0505***
		(0.00458)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CN)$		-0.0857***
		(0.00477)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CN)$		-0.0832***
		(0.00507)
Weighted	No	No
N	23,407,954	23,407,954
Adj. R^2	0.739	0.739

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country being each of the 95 economies in our data and product being defined as a six-digit HS code. The dependent variable is (ln) price of imports. Column (1) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(US)}$, where I(US) identifies products where the 2017 US share of Chinese exports exceeded the median export share across all other destinations. Column (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(CN)}$, where I(CN) identifies destination-product pairs where the importer received an above-median share of Chinese exports for that product in 2017. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: World - Price positioning

	(1) Price (ln)	(2) Price (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	0.343***	-0.148***
	(0.0147)	(0.00658)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	0.272***	-0.115***
	(0.0126)	(0.00657)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	0.241***	-0.115***
	(0.0128)	(0.00613)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	0.214***	-0.0829***
	(0.0139)	(0.00731)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CNVeryLow)$	-0.541***	
	(0.0267)	
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CNVeryLow)$	-0.438***	
	(0.0233)	
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CNVeryLow)$	-0.420***	
	(0.0233)	
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CNVeryLow)$	-0.373***	
	(0.0244)	
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(HighP)$		0.256***
		(0.0116)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(HighP)$		0.196***
		(0.0104)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(HighP)$		0.160***
		(0.00853)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(HighP)$		0.110***
		(0.00825)
Weighted	No	No
N	23,407,954	23,407,954
Adj. R^2	0.739	0.739

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country each of the 95 economies in our data and product being defined as a six-digit HS code. The dependent variable is (ln) price of imports. Column (1) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times$ I(bottom quartile), where the indicator identifies destination-product pairs where 2017 Chinese import prices ranked at or below the 25th percentile of all import prices in that destination. Column (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times$ I(HighP), where I(HighP) identifies destination-product pairs where the destination's 2017 log unit price for that product exceeded the product-specific median across all destinations. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

demand for differentiated varieties or lower price sensitivity at the high end of the quality distribution.

As we show in the appendix, volume responses mirror the price patterns: bottom-quartile markets experience positive and significant increases in both value and quantity throughout the triple interaction, while high-price markets show negative coefficients for value and quantity, suggesting that Chinese exporters redirect toward markets where they already competed at low prices rather than attempting to penetrate premium segments (Table 11 in Appendix C).

The heterogeneous trade deflection patterns documented above are not driven by composition effects across destination types. We obtain qualitatively similar results when restricting the sample separately to advanced economy destinations and emerging market destinations. Triple interaction coefficients maintain comparable signs, statistical significance, and economic magnitudes across both subsamples. This consistency indicates that redirection costs, established market absorption dynamics, and price positioning constraints operate through similar mechanisms regardless of destination development level (Table 12, Table 13, Table 14, and Table 15 in Appendix C).

In sum, the heterogeneous responses reveal three mechanisms shaping trade deflection. First, redirection costs vary with pre-trade-war export concentration. US-dependent products face steeper price cuts to access alternative markets, quantifying the costs of geographic concentration. Second, established markets do not provide refuge from price competition. Large redirected volumes overwhelm absorption capacity even where distribution networks exist, generating price pressures that increase with market share. Third, price positioning powerfully conditions deflection patterns. Very-low-price markets experience severe price pressure as redirected exports crowd the bottom of the quality distribution, while high-price markets accommodate inflows with minimal price adjustment. This asymmetry suggests trade diversion flows toward quality segments with remaining absorption capacity, consistent with models featuring quality differentiation and heterogeneous demand elasticities across market tiers.

4.3 Extended Sample

An identifying assumption of the difference-in-differences specification in Equation 1 is that the "treated" and "control" products would have followed similar trends in the absence of tariffs. To examine whether this assumption is supported by the data, we would like to check that the products exhibit parallel trends in the years preceding the imposition of tariffs, but regular revisions to HS codes complicate consistent tracking of products over time. The 2018-19 tariffs apply to products according to the 2017 World Customs Organization revision of the HS codes, so our ability to compare trends of the tariffed and untariffed products before this 2017 update is limited.

To mitigate this limitation and assess whether the parallel-trends assumption holds, we restrict attention to HS codes that remain unchanged between the 2012 and 2017 revision. Using data from 2015–2021, we construct consistent quantities and unit prices using the same hierarchical algorithm in the main analysis. This approach allows us to extend the pre-tariff period by two additional years and examine whether tariffed and non-tariffed products exhibit statistically similar trends prior to the introduction of U.S. tariffs. A drawback of this approach is that omitting codes subject to reclassifications may exclude products experiencing the most substantial changes, which are potentially related to the effects of tariffs.[23] In addition, this approach will necessarily ignore changes in the composition of six-digit HS codes that are determined at the destination country level, such as moving some eight-digit HS codes from one HS to another. Therefore, results based on this selected sample should be interpreted with caution.

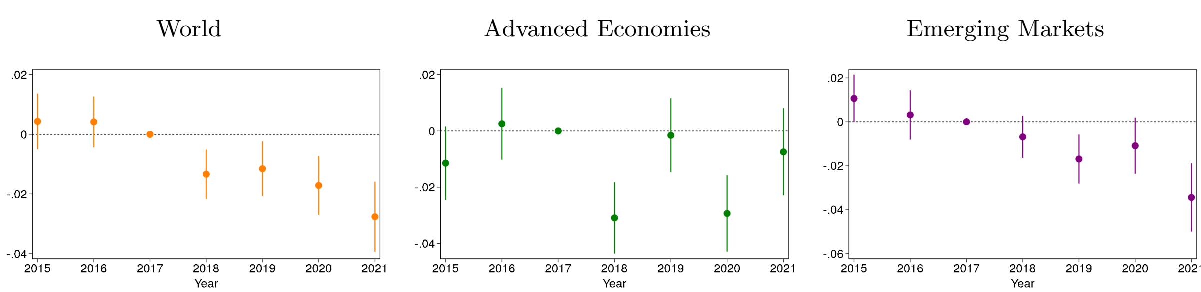
[23] We preserve 88% of the products from the main analysis.

On the other hand, one benefit of this approach, beyond expanding the number of years considered, is that we are also able to significantly expand our set of countries, as many countries were excluded from the main analysis due to reporting in the HS 2012 revision for at least one year in the 2017–2021 period. By allowing for data between 2015 and 2017 to be reported in either HS 2012 or HS 2017, we can include an additional 42 countries in our data, bringing our total number of countries to 137. Extended sample results for values and quantities and results that include only the 95 countries included in our main analysis can be found in Appendix C.3.2 and C.3.3.

Figure 10 shows the estimated unit price coefficients for extending the time horizon for the full sample, advanced economies (AE), and emerging markets (EM). For the full sample, the pre-treatment coefficients cluster tightly around zero. This pattern provides reassuring evidence that the parallel trends assumption underlying our difference-in-differences design is satisfied with respect to average unit values. The post-treatment effects we document appear to be genuine responses to tariffs rather than pre-existing differential trends between tariffed and non-tariffed products.

The emerging markets subsample reveals a similar picture with no significant pre-trends in unit price. Pre-treatment coefficients exhibit a slight downward drift, suggesting some potential divergence in export patterns prior to tariff implementation. Still, this pre-treatment trend is statistically insignificant and substantially smaller in magnitude than the post-treatment estimates. Advanced economies also do not show clear pre-existing trends in unit prices ahead of tariff implementation. We show in Appendix C.3.2 that the extended sample results for value and quantity do exhibit clear evidence of upward pre-trends in both value and quantity, meaning that goods tariffed by the U.S. were already seeing increases in third-country imports from China prior to taking effect. While these trends in trade volumes may be driven by non-tariff factors, such as global demand or Chinese supply shocks, the clear break in trend for unit prices in Figure 10 shows that the tariffs are associated with an economically meaningful and statistically significant change in market conditions.

Figure 10: Unit Price of Tariffed Chinese Goods Imports with Extended Sample



Sources: UN Comtrade; authors' calculations.

Notes: Each panel displays the estimates of difference-in-differences regressions for the log of unit price for different regions. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals. We provide a list of the additional countries in the extended sample in Appendix A.

5 Robustness

This section describes a series of robustness checks that validate our baseline results along three dimensions: how we weight observations across heterogeneous trade flows, how we measure tariff exposure, and how we model the timing and dynamics of tariff effects.

5.1 Weighted versus Unweighted Results

Before turning to alternative specifications, we first examine whether our results are sensitive to how we aggregate across the heterogeneous trade flows in our data. The baseline estimates in section 4 are unweighted, meaning that they give effects for the average origin-destination-product triplet. In this robustness check, we weight each observation by the destination's 2017 import value for that origin-destination-product combination.[24] This weighting scheme estimates the effect on the average dollar of imports from China and ensures our estimates reflect economically important flows rather than treating all products equally regardless of their market size. The weighted specification thus provides policy-relevant estimates of aggregate impacts. However, this approach has a potential drawback. Comparing weighted and unweighted results reveals whether tariff effects are broad-based or concentrated in high-volume flows. If the estimates are similar, the effects operate consistently across large and small trade flows. If they diverge, it signals important heterogeneity.

Figure 11 presents the weighted results. Estimates for value and quantity are estimated much less precisely than in the baseline. This loss of precision stems from a mechanical issue: weighting observations while clustering standard errors at the origin and product level creates an effective mismatch. Some clusters receive very little weight while others are heavily weighted, which in practice reduces the effective number of independent clusters and inflates standard errors. Estimates for unit price, however, continue to indicate a negative and statistically significant relationship with tariffs, with some loss of precision, especially in 2018, but with weighted estimates being larger in magnitude. The similar effects on unit values, whether unweighted or weighted, indicate that the price response to U.S. tariffs in other destination countries is robust to weighting approach. This consistency is reassuring: the price effects appear robust to how we aggregate across heterogeneous products and destinations.

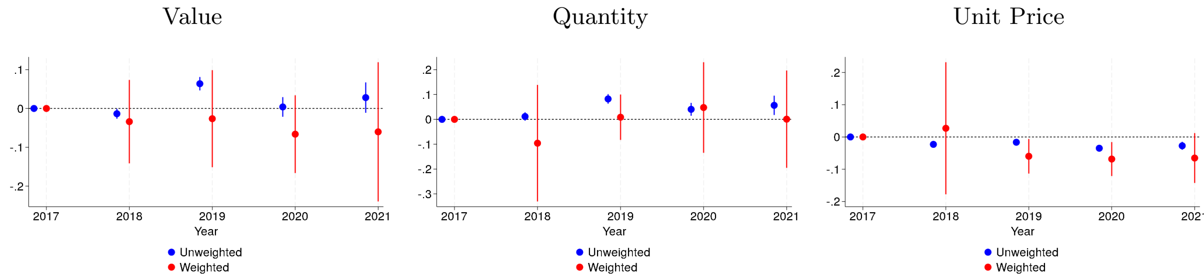
The contrast between value or quantity and price results has a natural interpretation. Price changes reflect market-wide competitive pressures that may operate similarly across large and small markets. Trade diversion in values and quantities, however, may be easier to detect in smaller, more flexible trade flows where the signal is not dominated by other shocks affecting high-volume products. The unweighted results, by giving equal voice to all products, pick up these pervasive but individually small responses that the weighted specification averages out.

5.2 Tariff Share

Our baseline specification uses a binary tariff exposure indicator: a product is either tariffed or not. This simplifies the analysis but discards potentially useful information. In reality, tariffs varied substantially across products, both in their timing and intensity. Moreover, the harmonized system creates a practical challenge: the U.S. applied tariffs at the eight- and ten-digit HS level, but trade data for third countries are only consistently available at the six-digit level where HS codes are globally harmonized. This aggregation problem means that within a single six-digit category, some finely-defined products faced tariffs while others did not. Collapsing this variation into a binary indicator requires choosing an arbitrary threshold. Different thresholds yield different treatment definitions, introducing researcher discretion into what should be a data-driven classification.

[24] For products that are not imported by a destination in 2017, we take the minimum destination-product import value as the weight.

Figure 11: Weighted versus Unweighted Difference-in-Differences - World Sample



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Results are weighted by the 2017 import value for each origin-destination-product group. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals.

In this robustness check, we avoid this arbitrariness by defining a continuous measure of tariff exposure. Our tariff-share variable captures the fraction of U.S. import value within each six-digit HS code that faced tariffs:

$$\text{tariff-share}_g = \sum_{p \in g} \frac{I(\text{tariff}_p) \times \text{Import}_{p,2017}}{\text{Import}_{g,2017}} \tag{2}$$

where $I(\text{tariff}_p)$ indicates whether the ten-digit product p faced a tariff at the end of our sample period, and $\text{Import}_{p,2017}$ is the value of 2017 U.S. imports from China for ten-digit HS product p. This weighting scheme reflects economic importance: if 80% of the value of U.S. imports in a six-digit category faced tariffs, that category experienced more intense treatment than one where only 20% of imports were tariffed.

Using this continuous measure, we estimate a tariff-share version of our baseline DiD:

$$\ln y_{odgt} = \alpha_{og} + \alpha_{gt} + \alpha_{ot} + \alpha_{dg} + \alpha_{dt} + \alpha_{od} + \sum_{j=2018}^{2021} \beta_j \ \text{tariff-share}_{og} \times \mathbf{I}(t = j) + \varepsilon_{odgt} \tag{3}$$

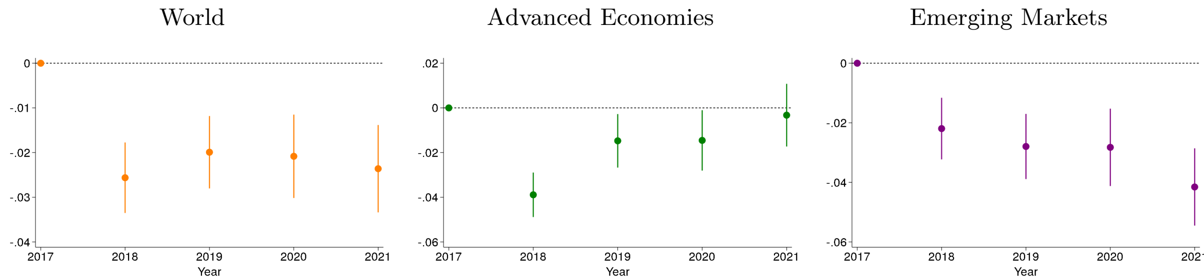
where tariff-share_{og} corresponds to the tariff share applied to a six-digit HS code, defined in Equation 2, which can only be non-zero for imports originating from China.

The interpretation of the coefficients β_j's shifts from tariffed versus non-tariffed to more tariffed versus less tariffed. The coefficient β_j now measures the proportional change in Chinese exports to third countries associated with a one percentage point increase in tariff exposure in year j. This specification exploits more variation in the data and provides a cleaner test of whether trade diversion scales with tariff intensity: we would expect products facing more intense tariff treatment to exhibit larger price declines and quantity increases in third markets.

Figure 12 presents the estimated effects on unit prices for all countries, advanced economies (AE), and emerging markets (EM). All three groups show negative effects on unit prices, confirming that higher tariff exposure leads to systematically lower prices in third-country markets. As in the baseline results, the pattern is clearest for emerging markets, where the effects are persistent and precisely estimated throughout the sample period. By 2021, the coefficient for emerging markets reaches -0.04, implying a ten percentage point increase in tariff exposure reduces prices by 4 percent. For advanced economies, unit prices decrease in the aftermath of the tariffs, but then gradually recover over time.

These tariff-share results verify that the binary treatment findings are not artifacts of how we aggregate finely-defined tariffs to the six-digit level. The consistency between binary and continuous treatment specifications strengthens confidence in the main results.

Figure 12: Unit Prices of Chinese Imports using Tariff Share



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of unit price. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals.

5.3 Alternative Empirical Strategies

We explore two alternative empirical strategies to estimating the effect of tariffs on Chinese exports to bystander countries that offer different ways to capture the timing and dynamic effects of effects: An event study as in Fajgelbaum et al. (2019) and local projections as in Jordà (2005).

5.3.1 Event Study

The U.S.-China trade war unfolded in waves, rather than a single shock. The first tariffs took effect in the summer of 2018, but 22 percent of tariffed products were tariffed only in 2019. Products hit by the first wave had experienced tariffs for more than one year in 2019, while products added in later rounds had shorter exposure. Our baseline difference-in-differences specification in Section 4 tracks differential responses for tariffed versus untariffed products over time, but does not distinguish products with different tariff start dates.

Here, we adopt an event study design that addresses this timing heterogeneity by aligning each product to its own treatment year. Instead of using calendar years, we measure time in years relative to when tariffs actually took effect for each product. Following Amiti, Redding and Weinstein (2019) and Fajgelbaum et al. (2019), we estimate:

$$\ln y_{odgt} = \alpha_{og} + \alpha_{gt} + \alpha_{ot} + \alpha_{dg} + \alpha_{dt} + \alpha_{od} + \sum_{j=0}^{3} \beta_j \text{ treated}_{og} \times \mathbf{I}(\text{event}_{odgt} = j) + \varepsilon_{odgt} \tag{4}$$

where treated_{og} is defined as before. The event time indicator $\mathbf{I}(\text{event}_{odgt} = j)$ tracks years since tariffs were first applied to product g from China, with the year before tariffs serving as the excluded comparison period. By construction, $\mathbf{I}(\text{event}_{odgt} = j)$ equals zero for all goods from origins other than China. This design offers an alternative visualization of how export performance evolves around the tariff shock. The coefficients β_j trace out the trajectory relative to the pre-tariff year, revealing whether effects emerge immediately upon tariff implementation or accumulate over time. This matters for understanding the adjustment process: immediate effects suggest rapid trade diversion, while gradual effects point to search frictions or contracts that take time to unwind. The fixed effects structure remains identical to Equation 1, ensuring that identification continues to rely on variation across products within the same origin–destination–year cell. Standard errors are again two-way clustered at the origin and product level.

The left panel of Figure 13 shows the event study estimates β_j and corresponding 95% confidence intervals for unit prices. The patterns align closely with our baseline difference-in-differences results from Section 4, providing reassurance that the main findings are not artifacts of how we handle treatment timing. Unit prices decline steadily starting in the year following tariff implementation, both for weighted (red) and unweighted (blue) specifications.

The weighted estimates continue to indicate larger magnitudes of effects on unit prices, as in the baseline DID approach, indicating that tariff effects are larger in high-volume trade flows rather than spreading uniformly across all products. The typical dollar of trade experiences a 10 percent decline in prices, compared to around 2 percent for the typical trade flow.

Comparing the event study to our baseline difference-in-differences, the event study framework provides an alternative lens for understanding dynamics because it synchronizes products to their actual treatment dates. However, the substantive conclusions remain the same: tariffs trigger trade diversion accompanied by systematic price reductions that persist and deepen over time.

5.3.2 Local Projections

Next, we consider estimates based on the local projections technique of Jordà (2005), which we estimate in levels, with lagged values of the dependent variable and product, importer, exporter, and year fixed effects:

$$(\ln y_{odgt+h} - \ln y_{odgt}) = \alpha_o + \alpha_d + \alpha_g + \alpha_t + \text{treated}_{odgt} + \ln y_{odgt-1} + \varepsilon_{odgt} \tag{5}$$

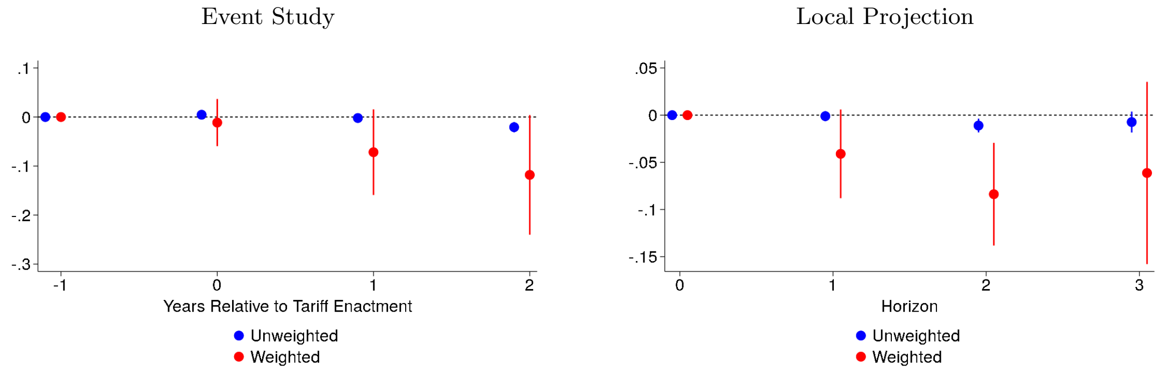
Impulse responses for log average unit value for the world sample are displayed in the right panel of Figure 13. The figure indicates a step down in the destination country's import unit values following tariffs that is precisely estimated and at its largest magnitude two years after the imposition of tariffs. This finding is present in both the unweighted (blue) and weighted (red) estimates and is broadly consistent with the baseline difference in difference results presented in Section 4.

The lack of precision in other horizons following tariffs could be due, in part, to the dynamic structure of the local projections approach combined with highly restrictive fixed effects. In Appendix Section C.4, we report results for a version of the specification that excludes origin country fixed effects. Given that well over 80 percent of products exported by China were subject to tariffs, these origin fixed effects may absorb some of the effects of tariffs. Indeed, as shown in Figure 21 of the appendix, estimated coefficients are indeed highly significant from one year after imposition of tariffs, with cumulative effects growing through a three year horizon.

6 Conclusion

While a growing number of papers have studied the effects of the U.S.–China trade war on those two countries, much less is known about the implications of the ongoing reallocation that tariffs set in motion. One topic that has received considerable attention, recently, is the possibility that U.S. tariffs might lead to a redirection of Chinese exports to other countries. Comprehensive empirical evidence of any such effects, however, has been lacking.

Figure 13: Unit Price Regressions with Alternative Empirical Strategies - World Sample



Sources: UN Comtrade; authors' calculations.
Notes: Each panel displays the estimates of separate regressions for logged unit price. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Results are weighted by the 2017 import value for each origin-destination-product group. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals.

This paper analyzes the impact of the U.S.–China trade war on bystander economies, contributing to a broader discussion of the spillover effects of this bilateral shock on other economies. Using a difference-in-differences specification inspired by Fajgelbaum et al. (2019), we estimate changes in the value, quantity, and price of Chinese goods imported by third countries as U.S. tariffs increase.

We find that as U.S. imports from China fall sharply following the imposition of tariffs, Chinese exports to other destinations rise. Higher U.S. tariffs are associated with increases in the value and quantity of imports from China globally, and these effects are widespread across country groups. We also provide the first evidence that higher U.S. tariffs are associated with lower prices on Chinese imports, and show that these price effects are strongest in Asian and Emerging Market countries. Our findings are robust to weighting observations across heterogeneous trade flows, using alternative measures of tariff intensity, and accounting for dynamic effects.

We also explore the role of product and market characteristics that determine heterogeneous responses to the U.S. tariffs. We find that effects of tariffs are larger for products in which the U.S. was an important pre-tariff destination for Chinese exports—meaning that there was more trade to deflect—and in markets where China was already an established supplier. In addition, we show that pre-tariff pricing behavior is also an important determinant of these heterogeneous responses. We find larger reductions in import prices in markets where China was a low cost supplier and in those that tend to import low-priced varieties. These results provide information on the products and markets that might expect to see larger effects of new round of U.S. tariffs imposed since 2025 and also provide economic intuition for the responses to tariffs we document.

Our results provide new information that is relevant to local producers in destination countries, as well as to monetary policymakers. On the one hand, our findings indicate that goods producers and their workers in countries seeing increases in low-priced imports from China may experience disruption due to deflected trade. On the other hand, the greater availability of low-priced goods suggests a channel through which consumers in bystander countries may benefit from this bilateral trade dispute. These potential effects on economic activity and prices provide novel information to policymakers as they consider appropriate responses.

References

Alfaro, Laura, and Davin Chor. 2023. "Global Supply Chains: The Looming "Great Reallocation"." National Bureau of Economic Research Working Paper 31661.

Alfaro, Laura, Mariya Brussevich, Camelia Minoiu, and Andrea Presbitero. 2025*a*. "Bank Financing of Global Supply Chains." Social Science Research Network (SSRN) Working Paper abstract_id 4840501.

Alfaro, Laura, Paola Conconi, Fariha Kamal, and Zachary Kroff. 2025*b*. "Trade within Multinational Boundaries." National Bureau of Economic Research Working Paper 33887.

Al-Haschimi, Alexander, Natálie Dvořáková, Julien Le Roux, and Tajda Spital. 2025. "China's growing trade surplus: why exports are surging as imports stall." *ECB Economic Bulletin – Focus*, , (2025/01). Accessed: 2025-11-20.

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

Bagwell, Kyle, and Robert W. Staiger. 1997. "Multilateral tariff cooperation during the formation of free trade areas." *International Economic Review*, 38: 291–319.

Baldwin, Richard, and Javier Lopez-Gonzalez. 2015. "Supply-chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses." *The World Economy*, 38(11): 1682–1721.

Boeckelmann, Lukas, Lorenz Emter, Vanessa Gunnella, Karin Klieber, and Tajda Spital. 2025. "China-US trade tensions could bring more Chinese exports and lower prices to Europe." *The ECB Blog*, Accessed: 2025-11-20.

Bonadio, Barthélémy, Zhen Huo, Elliot Kang, Andrei A Levchenko, Nitya Pandalai-Nayar, Hiroshi Toma, and Petia Topalova. 2025. "Playing with Blocs: Quantifying Decoupling." National Bureau of Economic Research Working Paper 34302.

Bond, Eric W., and Constantine Syropoulos. 1996. "The size of trading blocs: market power and world welfare effects." *Journal of International Economics*, 40: 411–437.

Bown, Chad. 2022. "Four Years Into the Trade War, Are the US and China Decoupling." Peterson Institute for International Economics Working Paper.

Bown, Chad P., and Meredith A. Crowley. 2007. "Trade deflection and trade depression." *Journal of International Economics*, 72(1): 176–201.

Brandt, Loren, and Kevin Lim. 2024. "Opening up in the 21st century: A quantitative accounting of Chinese export growth." *Journal of International Economics*, 150: 103895.

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

Cavallo, Alberto, Paola Llamas, and Franco M. Vazquez. 2025. "Tracking the Short-Run Price Impact of U.S. Tariffs." National Bureau of Economic Research NBER Working Paper 34496.

Correa, Ricardo, Andrea Fabiani, Matias Ossandon Busch, and Miguel Sarmiento. 2025. “The Ripple Effect: Supply Chain Reconfigurations and Cross-border Credit Dynamics.” Working paper, Paris School of Economics, May 2025.

Crowley, Meredith, Ning Meng, and Huasheng Song. 2018. “Tariff scares: Trade policy uncertainty and foreign market entry by Chinese firms.” *Journal of International Economics*, 114: 96–115.

Disdier, Anne-Célia, and Keith Head. 2008. “The Puzzling Persistence of the Distance Effect on Bilateral Trade.” *The Review of Economics and Statistics*, 90(1): 37–48.

ECB. 2025. “ECB Staff Macroeconomic Projections for the Euro Area, September 2025.” European Central Bank. Accessed: 2025-11-20.

Emlinger, Charlotte, Isabelle Méjean, Kevin Lefebvre, and Vincent Vicard. 2026. “EU under Pressure? Exploring Chinese Trade Deflection.” In *Paris Report 4: The New Global Imbalances.* , ed. Hélène Rey, Beatrice Weder di Mauro and Jeromin Zettelmeyer, Chapter 14. Paris and London:CEPR Press.

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal. 2019. “The Return to Protectionism*.” *The Quarterly Journal of Economics*, 135(1): 1–55.

Fajgelbaum, Pablo, Pinelopi Goldberg, Patrick Kennedy, Amit Khandelwal, and Daria Taglioni. 2024. “The US-China Trade War and Global Reallocations.” *American Economic Review: Insights*, 6(2): 295–312.

Fernández-Villaverde, Jesús, Tomohide Mineyama, and Dongho Song. 2024. “Are We Fragmented Yet? Measuring Geopolitical Fragmentation and Its Causal Effect.” National Bureau of Economic Research Working Paper 32638.

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

Flaaen, Aaron, and Justin Pierce. 2024. “Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector.” *The Review of Economics and Statistics*, 1–45.

Freund, Caroline, Aaditya Mattoo, Alen Mulabdic, and Michele Ruta. 2024. “Is US trade policy reshaping global supply chains?” *Journal of International Economics*, 152: 104011.

Gopinath, Gita, Pierre-Olivier Gourinchas, Andrea F. Presbitero, and Petia Topalova. 2025. “Changing global linkages: A new Cold War?” *Journal of International Economics*, 153: 104042.

Grant, Jason, and Sven Anders. 2010. “Trade Deflection Arising from U.S. Import Refusals and Detentions in Fishery and Seafood Trade.” *American Journal of Agricultural Economics*, 93(2): 573–580.

Gunnella, Vanessa, Giovanni Stamato, and Alicja Kobayashi. 2025. “The implications of US–China trade tensions for the euro area: lessons from the tariffs imposed by the first Trump Administration.” *ECB Economic Bulletin – Focus*, , (2025/02). Accessed: 2025-11-20.

Hancock, Alice. 2025. “China reroutes clothes exports to Europe after US tariffs upset trade.” *Financial Times.*

Handley, Kyle, Fariha Kamal, and Ryan Monarch. 2025. "Rising Import Tariffs, Falling Exports: When Modern Supply Chains Meet Old-Style Protectionism." *American Economic Journal: Applied Economics*, 17(1): 208–38.

Hoang, Trang, and Gordon Lewis. 2024. "As the U.S. is Derisking from China, Other Foreign U.S. Suppliers are Relying More on Chinese Imports." Federal Reserve Board. Accessed: 2024-11-14.

Javorcik, Beata, Justin Pierce, and Emily Wisniewski. 2025. "Importers Big and Small: The Heterogeneous Effects of U.S.-China Tariffs on Sourcing and Prices." Mimeo.

Javorcik, Beata, Lucas Kitzmüller, Helena Schweiger, and Muhammed A. Yıldırım. 2024. "Economic Costs of Friendshoring." *The World Economy*, 47(7): 2871–2908.

Johnson, Robert C., and Guillermo Noguera. 2012. "Accounting for intermediates: Production sharing and trade in value added." *Journal of International Economics*, 86(2): 224–236.

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

Ju, Jiandong, Hong Ma, Zi Wang, and Xiaodong Zhu. 2024. "Trade wars and industrial policy competitions: Understanding the US-China economic conflicts." *Journal of Monetary Economics*, 141: 42–58. CARENGIE-ROCHESTER-NYU APRIL 2023 CONFERENCE.

Martinez, Maria, Helen Reid, and Philip Blenkinsop. 2025. "Pressure grows on Europe to act on Chinese import surge." *Reuters*. Accessed: 2025-11-19.

McLaren, John E. 2002. "A theory of insidious regionalism." *Quarterly Journal of Economics*, 117: 571–608.

Minton, Robert, and Mariano Somale. 2025. "Detecting Tariff Effects on Consumer Prices in Real Time." *FEDS Notes, Board of Governors of the Federal Reserve System.*

Reyes-Heroles, Ricardo, Sharon Traiberman, and Eva Van Leemput. 2020. "Emerging Markets and the New Geography of Trade: The Effects of Rising Trade Barriers." *IMF Economic Review*, 69: 456–508.

Ropele, Tiziano. 2026. "Rerouting of Chinese products in response to US trade tariffs: evidence from Italian firms' expectations." Bank of Italy, Directorate General for Economics, Statistics and Research Questioni di Economia e Finanza (Occasional Papers) 1000.

Simonovska, Ina. 2015. "Income Differences and Prices of Tradables: Insights from an Online Retailer." *The Review of Economic Studies*, 82(4): 1612–1656.

Swanson, Ana, and Jeanna Smialek. 2025. "Why Europe Fears a Flood of Cheap Goods From China." *The New York Times*. Accessed 2026-06-19.

UN Commodity Trade Statistics Database (Comtrade). 2025. Accessed: 2025-11-20.

Utar, Hale, Alfronso Cebreros Zurita, and Luis Torres. 2025. "The US-China Trade War and Relocation of Global Value Chains to Mexico." *Review of Economics and Statistics*.

Viner, Jacob. 1950. *The Customs Union Issue.* New York:Carnegie Endowment for International Peace.

Xu, Chenzi. 2022. "Reshaping Global Trade: The Immediate and Long-Run Effects of Bank Failures*." *The Quarterly Journal of Economics*, 137(4): 2107–2161.

A Country Details

We consider 95 economies for our analysis. Each region consists of the following importing countries:

Advanced Economies (AE): Andorra, Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Rep. of Korea, Slovakia, Slovenia, Spain, Sweden, Switzerland, Taiwan, United Kingdom.

Emerging Market (EM): Albania, Armenia, Bahrain, Belarus, Bermuda, Bolivia (Plurinational State of), Bosnia Herzegovina, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Cambodia, Chile, Colombia, Costa Rica, Dominican Rep., Ecuador, El Salvador, Eswatini, Fiji, Georgia, Guatemala, Honduras, Hungary, India, Indonesia, Iran, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Lao People's Dem. Rep., Liberia, Madagascar, Malaysia, Maldives, Mauritius, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nicaragua, North Macedonia, Oman, Pakistan, Panama, Paraguay, Peru, Poland, Romania, Russian Federation, Serbia, South Africa, Thailand, Türkiye, United Rep. of Tanzania, Uruguay, Zambia.

European Union Member Countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden.

We exclude the United Kingdom from the EU importer group, as it formally left the European Union in January 2020 (Brexit) and therefore does not maintain EU membership throughout the full analysis period.

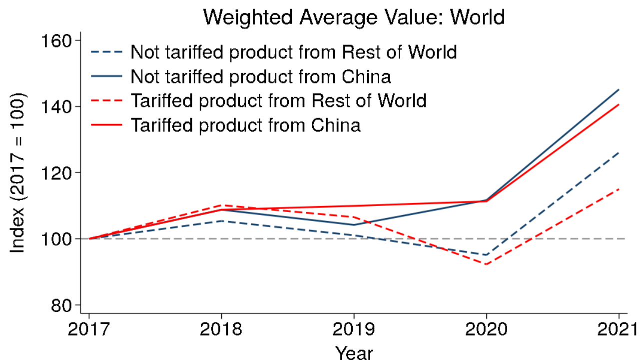
Asia Countries: Armenia, Bahrain, Brunei Darussalam, Cambodia, Georgia, India, Indonesia, Iran, Israel, Japan, Jordan, Kazakhstan, Kuwait, Kyrgyzstan, Lao People's Dem. Rep., Malaysia, Mongolia, Myanmar, Oman, Pakistan, Rep. of Korea, Taiwan, Thailand, Türkiye.

Extended analysis: For the extended analysis, our data goes back to 2015 and include the the previous revision (HS2012) of the Harmonized System. We add 42 more importing countries: Angola, Argentina, Aruba, Azerbaijan, Bahamas, Belize, Benin, Botswana, Burundi, Cabo Verde, Cameroon, Comoros, Congo, Côte d'Ivoire, Dem. Rep. of the Congo, Egypt, Ethiopia, French Polynesia, Grenada, Jamaica, Kenya, Lebanon, Lesotho, Malawai, Mexico, Nepal, Niger, Nigeria, Qatar, Rep. of Moldova, Rwanada, Saudi Arabia, Senegal, Singapore, State of Palestine, Togo, Tunisia, Uganda, Ukraine, United Arab Emirates, Viet Nam, Zimbabwe.

B Additional Motivational Figures

This section presents additional motivational figures.

Figure 14: Weighted Import Index by Tariff Status and Origin



Sources: UN Comtrade; authors' calculations.

Notes: Figure displays the weighted average import value of tariffed and untariffed products by source for the 95 destination countries in our main world sample. Values are weighted by the 2017 import value for each origin-destination-product group.

C Additional Results and Robustness Checks

C.1 Tables for Main Difference-in-Differences Results

This section reports tables for the main difference-in-differences results presented in Section 4.

Table 5: Main DiD Results - World Imports

	(1) Value (ln)	(2) Quantity (ln)	(3) Unit Price (ln)
$\text{treated}_{og} \times \mathbf{I}(2018)$	-0.014**	0.012	-0.023***
	(0.007)	(0.009)	(0.005)
$\text{treated}_{og} \times \mathbf{I}(2019)$	0.064***	0.082***	-0.016***
	(0.009)	(0.010)	(0.005)
$\text{treated}_{og} \times \mathbf{I}(2020)$	0.004	0.040***	-0.035***
	(0.013)	(0.013)	(0.005)
$\text{treated}_{og} \times \mathbf{I}(2021)$	0.028	0.057***	-0.027***
	(0.020)	(0.020)	(0.006)
Adj. R^2	0.624	0.669	0.738
Observations	24,902,265	23,747,846	23,747,803

Standard errors in parentheses

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

Table 6: Main DiD Results - Emerging Markets Imports

	(1) Value (ln)	(2) Quantity (ln)	(3) Unit Price (ln)
$\text{treated}_{og} \times \mathbf{I}(2018)$	-0.000	0.026**	-0.018***
	(0.009)	(0.011)	(0.006)
$\text{treated}_{og} \times \mathbf{I}(2019)$	0.074***	0.109***	-0.028***
	(0.013)	(0.013)	(0.007)
$\text{treated}_{og} \times \mathbf{I}(2020)$	-0.002	0.037***	-0.037***
	(0.014)	(0.014)	(0.007)
$\text{treated}_{og} \times \mathbf{I}(2021)$	0.009	0.054***	-0.039***
	(0.015)	(0.015)	(0.008)
Adj. R^2	0.608	0.663	0.729
Observations	13,976,141	13,433,195	13,433,154

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: UN Comtrade; author's calculations.
Notes: Table 5 and Table 6 show the estimated coefficients for the difference-in-differences design in Equation 1. The data is at the origin-destination-year-product level, with destination country being each of the 95 countries for Table 5 and 60 countries for Table 6 and product being defined as a six-digit HS code. The dependent variable is (ln) value in column (1), (ln) quantity in column (2), and (ln) unit prices in column (3). All specifications include product-time, origin-time, origin-product, destination-product, destination-time, and origin-destination fixed effects. Standard errors are in parentheses and clustered at the six-digit HS code and origin level.

Table 7: Main DiD Results - Advanced Economies Imports

	(1) Value (ln)	(2) Quantity (ln)	(3) Unit Price (ln)
$\text{treated}_{og} \times \mathbf{I}(2018)$	-0.026***	0.000	-0.032***
	(0.009)	(0.010)	(0.006)
$\text{treated}_{og} \times \mathbf{I}(2019)$	0.047***	0.043***	-0.003
	(0.011)	(0.013)	(0.006)
$\text{treated}_{og} \times \mathbf{I}(2020)$	0.016	0.044**	-0.031***
	(0.016)	(0.017)	(0.006)
$\text{treated}_{og} \times \mathbf{I}(2021)$	0.041	0.039	-0.006
	(0.031)	(0.029)	(0.008)
Adj. R^2	0.675	0.710	0.764
Observations	10,832,084	10,220,991	10,220,991

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Main DiD Results - European Union Imports

	(1) Value (ln)	(2) Quantity (ln)	(3) Unit Price (ln)
$\text{treated}_{og} \times \mathbf{I}(2018)$	-0.005	0.039**	-0.042***
	(0.014)	(0.017)	(0.008)
$\text{treated}_{og} \times \mathbf{I}(2019)$	0.072***	0.069***	-0.001
	(0.020)	(0.020)	(0.009)
$\text{treated}_{og} \times \mathbf{I}(2020)$	0.054**	0.061**	-0.010
	(0.026)	(0.026)	(0.008)
$\text{treated}_{og} \times \mathbf{I}(2021)$	0.039	0.022	0.012
	(0.045)	(0.043)	(0.010)
Adj. R^2	0.660	0.703	0.738
Observations	6,213,387	5,940,368	5,940,368

Standard errors in parentheses

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

Sources: UN Comtrade; author's calculations.

Notes: Table 7 and Table 8 show the estimated coefficients for the difference-in-differences design in Equation 1. The data is at the origin-destination-year-product level, with destination country being each of the 35 countries for Table 7 and 27 countries for Table 8 and product being defined as a six-digit HS code. The dependent variable is (ln) value in column (1), (ln) quantity in column (2), and (ln) unit prices in column (3). All specifications include product-time, origin-time, origin-product, destination-product, destination-time, and origin-destination fixed effects. Standard errors are in parentheses and clustered at the six-digit HS code and origin level.

Table 9: Main DiD Results - Asian Imports

	(1) Value (ln)	(2) Quantity (ln)	(3) Unit Price (ln)
$\text{treated}_{og} \times \mathbf{I}(2018)$	-0.034***	-0.024	-0.011
	(0.012)	(0.015)	(0.007)
$\text{treated}_{og} \times \mathbf{I}(2019)$	-0.004	0.020	-0.021***
	(0.014)	(0.017)	(0.008)
$\text{treated}_{og} \times \mathbf{I}(2020)$	-0.065***	-0.022	-0.052***
	(0.016)	(0.018)	(0.007)
$\text{treated}_{og} \times \mathbf{I}(2021)$	-0.018	0.037*	-0.056***
	(0.019)	(0.022)	(0.007)
Adj. R^2	0.640	0.697	0.765
Observations	6,529,492	6,310,006	6,310,006

Sources: UN Comtrade; author's calculations.

Notes: Table 9 shows the estimated coefficients for the difference-in-differences design in Equation 1. The data is at the origin-destination-year-product level, with destination country being each of the 24 countries and product being defined as a six-digit HS code. The dependent variable is (ln) value in column (1), (ln) quantity in column (2), and (ln) unit prices in column (3). All specifications include product-time, origin-time, origin-product, destination-product, destination-time, and origin-destination fixed effects. Standard errors are in parentheses and clustered at the six-digit HS code and year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2 Additional Heterogeneous Responses Results

This section reports tables corresponding to the triple difference-in-differences specification shown in Section 4.2. We report value and quantity results for the full sample, as well as price results for advanced economies and emerging markets separately.

Table 10: World - Market concentration

	(1) Value (ln)	(2) Quantity (ln)	(3) Value (ln)	(4) Quantity (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	-0.0247***	-0.00690	-0.426***	-0.433***
	(0.00720)	(0.00948)	(0.0157)	(0.0178)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	0.0720***	0.0916***	-0.336***	-0.345***
	(0.00926)	(0.0108)	(0.0168)	(0.0179)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	-0.00980	0.0170	-0.389***	-0.394***
	(0.0132)	(0.0140)	(0.0167)	(0.0182)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	0.0109	0.0237	-0.371***	-0.380***
	(0.0194)	(0.0200)	(0.0238)	(0.0245)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(US)$	0.0195***	0.0292***		
	(0.00398)	(0.00535)		
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(US)$	-0.0167***	-0.0193***		
	(0.00497)	(0.00680)		
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(US)$	0.0192***	0.0366***		
	(0.00719)	(0.00813)		
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(US)$	0.0288***	0.0573***		
	(0.00870)	(0.0102)		
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CN)$			0.939***	1.003***
			(0.0466)	(0.0497)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CN)$			0.913***	0.975***
			(0.0484)	(0.0499)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CN)$			0.894***	0.992***
			(0.0489)	(0.0506)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CN)$			0.921***	1.012***
			(0.0555)	(0.0575)
Weighted	No	No	No	No
N	24,546,766	23,407,997	24,546,766	23,407,997
Adj. R^2	0.624	0.669	0.624	0.669

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country being each of the 95 economies in our data and product being defined as a six-digit HS code. The dependent variable is (ln) value of imports in columns (1) and (3), and (ln) quantity in columns (2) and (4). Columns (1) and (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(US)}$, where I(US) identifies products where the 2017 US share of Chinese exports exceeded the median export share across all other destinations. Columns (3) and (4) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(CN)}$, where I(CN) identifies destination-product pairs where the importer received an above-median share of Chinese exports for that product in 2017. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: World - Price positioning

	(1) Value (ln)	(2) Quantity (ln)	(3) Value (ln)	(4) Quantity (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	-0.333***	-0.721***	0.130***	0.280***
	(0.00940)	(0.0207)	(0.0128)	(0.0179)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	-0.242***	-0.545***	0.195***	0.311***
	(0.0115)	(0.0179)	(0.0146)	(0.0181)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	-0.285***	-0.552***	0.116***	0.233***
	(0.0141)	(0.0182)	(0.0188)	(0.0215)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	-0.273***	-0.506***	0.144***	0.226***
	(0.0215)	(0.0257)	(0.0223)	(0.0234)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CNVeryLow)$	0.500***	1.084***		
	(0.0172)	(0.0422)		
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CNVeryLow)$	0.482***	0.950***		
	(0.0178)	(0.0388)		
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CNVeryLow)$	0.451***	0.899***		
	(0.0175)	(0.0386)		
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CNVeryLow)$	0.478***	0.868***		
	(0.0233)	(0.0448)		
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(HighP)$			-0.276***	-0.546***
			(0.0226)	(0.0327)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(HighP)$			-0.254***	-0.457***
			(0.0219)	(0.0293)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(HighP)$			-0.221***	-0.388***
			(0.0221)	(0.0283)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(HighP)$			-0.224***	-0.337***
			(0.0227)	(0.0271)
Weighted	No	No	No	No
N	24,546,766	23,407,997	24,546,766	23,407,997
Adj. R^2	0.624	0.669	0.624	0.669

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country each of the 95 economies in our data and product being defined as a six-digit HS code. The dependent variable is (ln) value of imports in columns (1) and (3), and (ln) quantity in columns (2) and (4). Columns (1) and (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(CNVeryLow)}$, where the indicator identifies destination-product pairs where 2017 Chinese import prices ranked at or below the 25th percentile of all import prices in that destination. Columns (3) and (4) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(HighP)}$, where I(HighP) identifies destination-product pairs where the destination's 2017 log unit price for that product exceeded the product-specific median across all destinations. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Emerging Markets - Market Concentration

	(1) Price (ln)	(2) Price (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	-0.0146**	0.00462
	(0.00663)	(0.00623)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	-0.0291***	-0.0131**
	(0.00747)	(0.00658)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	-0.0303***	-0.0136*
	(0.00778)	(0.00726)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	-0.0245***	-0.0171**
	(0.00867)	(0.00828)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(US)$	-0.00430	
	(0.00388)	
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(US)$	0.00455	
	(0.00478)	
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(US)$	-0.00868*	
	(0.00506)	
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(US)$	-0.0254***	
	(0.00584)	
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CN)$		-0.0523***
		(0.00536)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CN)$		-0.0328***
		(0.00549)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CN)$		-0.0530***
		(0.00497)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CN)$		-0.0533***
		(0.00489)
Weighted	No	No
N	13,423,331	13,423,331
Adj. R^2	0.729	0.729

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country being each of the emerging markets in our data and product being defined as a six-digit HS code. The dependent variable is (ln) price of imports. Column (1) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(US)}$, where I(US) identifies products where the 2017 US share of Chinese exports exceeded the median export share across all other destinations. Column (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(CN)}$, where I(CN) identifies destination-product pairs where the importer received an above-median share of Chinese exports for that product in 2017. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Emerging Markets - Price Positioning

	(1) Price (ln)	(2) Price (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	0.291***	-0.121***
	(0.0171)	(0.00762)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	0.223***	-0.103***
	(0.0146)	(0.00788)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	0.199***	-0.0966***
	(0.0148)	(0.00786)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	0.167***	-0.0693***
	(0.0171)	(0.00842)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CNVeryLow)$	-0.455***	
	(0.0283)	
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CNVeryLow)$	-0.378***	
	(0.0246)	
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CNVeryLow)$	-0.354***	
	(0.0238)	
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CNVeryLow)$	-0.314***	
	(0.0249)	
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(HighP)$		0.241***
		(0.0129)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(HighP)$		0.174***
		(0.0107)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(HighP)$		0.141***
		(0.00921)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(HighP)$		0.0717***
		(0.00899)
Weighted	No	No
N	13,423,331	13,423,331
Adj. R^2	0.729	0.729

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country each of the emerging markets in our data and product being defined as a six-digit HS code. The dependent variable is (ln) price of imports. Column (1) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times$ I(CNVeryLow), where the indicator identifies destination-product pairs where 2017 Chinese import prices ranked at or below the 25th percentile of all import prices in that destination. Column (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times$ I(HighP), where I(HighP) identifies destination-product pairs where the destination's 2017 log unit price for that product exceeded the product-specific median across all destinations. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Advanced Economies - Market Concentration

	(1) Price (ln)	(2) Price (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	-0.0196***	-0.00839
	(0.00557)	(0.00583)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	-0.00891	0.0337***
	(0.00647)	(0.00686)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	-0.0172***	0.0273***
	(0.00641)	(0.00729)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	0.0121	0.0605***
	(0.00781)	(0.00763)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(US)$	-0.0125***	
	(0.00426)	
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(US)$	0.0123***	
	(0.00358)	
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(US)$	-0.0208***	
	(0.00481)	
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(US)$	-0.0283***	
	(0.00568)	
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CN)$		-0.0369***
		(0.00604)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CN)$		-0.0737***
		(0.00558)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CN)$		-0.116***
		(0.00620)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CN)$		-0.136***
		(0.00817)
Weighted	No	No
N	9,881,855	9,881,855
Adj. R^2	0.767	0.767

Sources: UN Comtrade; authors' calculations.
Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country being each of the advanced economies in our data and product being defined as a six-digit HS code. The dependent variable is (ln) price of imports. Column (1) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(US)}$, where I(US) identifies products where the 2017 US share of Chinese exports exceeded the median export share across all other destinations. Column (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(CN)}$, where I(CN) identifies destination-product pairs where the importer received an above-median share of Chinese exports for that product in 2017. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Advanced Economies - Price Positioning

	(1) Price (ln)	(2) Price (ln)
$\text{treated}_{og} \times \mathbf{I}(t = 2018)$	0.390***	-0.174***
	(0.0140)	(0.00754)
$\text{treated}_{og} \times \mathbf{I}(t = 2019)$	0.313***	-0.113***
	(0.0141)	(0.00751)
$\text{treated}_{og} \times \mathbf{I}(t = 2020)$	0.270***	-0.117***
	(0.0140)	(0.00799)
$\text{treated}_{og} \times \mathbf{I}(t = 2021)$	0.264***	-0.0706***
	(0.0140)	(0.00902)
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(CNVeryLow)$	-0.620***	
	(0.0260)	
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(CNVeryLow)$	-0.476***	
	(0.0240)	
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(CNVeryLow)$	-0.459***	
	(0.0247)	
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(CNVeryLow)$	-0.416***	
	(0.0265)	
$\text{treated}_{og} \times \mathbf{I}(t = 2018) \times \mathbf{I}(HighP)$		0.247***
		(0.00980)
$\text{treated}_{og} \times \mathbf{I}(t = 2019) \times \mathbf{I}(HighP)$		0.185***
		(0.00946)
$\text{treated}_{og} \times \mathbf{I}(t = 2020) \times \mathbf{I}(HighP)$		0.145***
		(0.00782)
$\text{treated}_{og} \times \mathbf{I}(t = 2021) \times \mathbf{I}(HighP)$		0.111***
		(0.00677)
Weighted	No	No
N	9,881,855	9,881,855
Adj. R^2	0.767	0.767

Sources: UN Comtrade; authors' calculations.

Notes: Table shows estimated coefficients for the triple difference-in-differences specification. The data is at the origin-destination-year-product level, with destination country each of the advanced economies in our data and product being defined as a six-digit HS code. The dependent variable is (ln) price of imports. Column (1) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(CNVeryLow)}$, where the indicator identifies destination-product pairs where 2017 Chinese import prices ranked at or below the 25th percentile of all import prices in that destination. Column (2) presents the triple interaction $\text{treated}_{og} \times \text{I}(t) \times \text{I(HighP)}$, where I(HighP) identifies destination-product pairs where the destination's 2017 log unit price for that product exceeded the product-specific median across all destinations. Results are unweighted. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered by origin country and six-digit HS product level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Additional Extended Sample Results

C.3.1 Basic Summary Statistics for the Extended Sample

Table 16 provides summary statistics on the key dependent and independent variables in our extended sample.

Table 16: Basic Summary Statistics for the Extended World Sample: 2015-2021

	count	mean	sd	min	max
Basic tariff status	39,734,676	0.06	0.23	0	1
Basic tariff status (China only)	2,527,262	0.89	0.31	0	1
Value (ln)	39,734,631	9.16	3.30	-7	24
Quantity (ln)	37,278,301	6.30	4.01	-7	32
Unit price (ln)	37,278,266	2.85	2.32	-18	23

Sources: UN Comtrade; author's calculations.
Notes: Table shows summary statistics for the basic tariff variable and the three main outcome variables for the full extended world sample. Basic tariff status is 1 if the observation is from China and in a six-digit HS code that receives a tariff during the trade war, and 0 otherwise. The data is at the origin-destination-year-product level, with destination country being each of the 138 countries in our data and product being defined at a six-digit HS code. 45 observations have missing value (ln) and 2,456,375 observations have missing quantity (ln), resulting in 2,456,410 observations for which we cannot construct unit price.

C.3.2 Value and Quantity Results for the Extended Sample

This section reports the value and quantity extended analysis results for the expanded set of 137 importing countries. The unit price results are reported in Section 4. In contrast to the unit price results, we do see clear evidence of upward pre-trends in both value and quantity across the world, AE, and EM results. The relationship between the value and quantity does, however, appear to change after the implementation of tariffs, as shown by the lack of pre-trends in our unit price results.

Figure 15: Extended Sample DiD - World, Expanded Sample

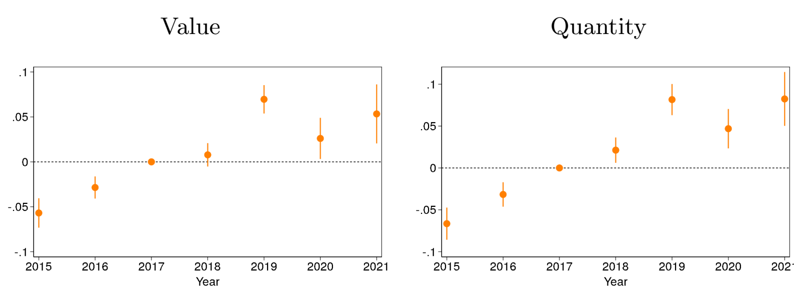


Figure 16: Extended Sample DiD - Emerging Markets, Expanded Sample

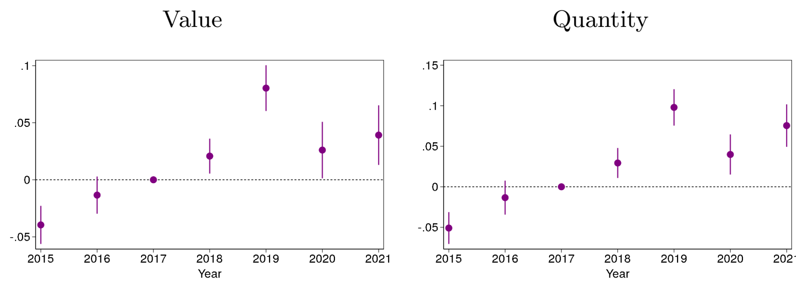
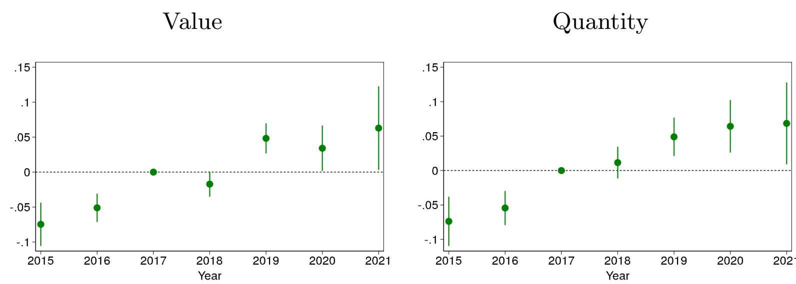


Figure 17: Extended Sample DiD - Advanced Economies, Expanded Sample



Sources: UN Comtrade; authors' calculations.

Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals. We provide a list of the additional countries in the extended sample in Appendix A.

C.3.3 Extended Time-Frame DiD Results with Main Analysis Countries

This section reports the extended analysis difference-in-differences results for the set of 95 importing countries included in our main analysis. The results displayed here do not differ importantly from the results reported in Section 4 which employ the same empirical strategy but with an expanded set of 137 countries.

Figure 18: Extended Sample DiD - World, Main Sample

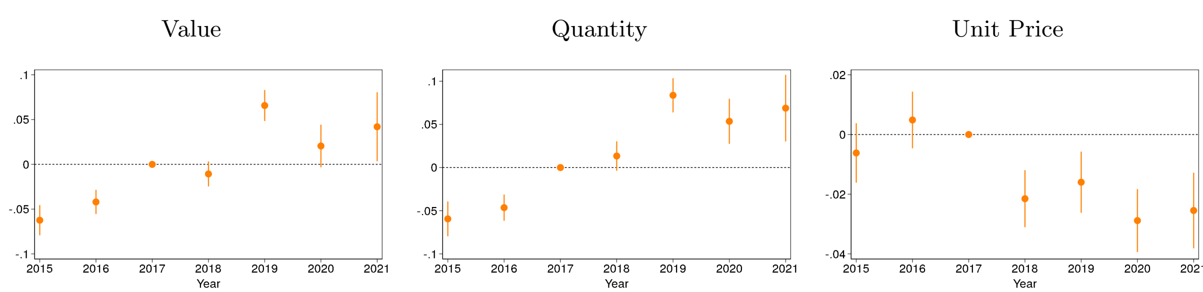


Figure 19: Extended Sample DiD - Emerging Markets, Main Sample

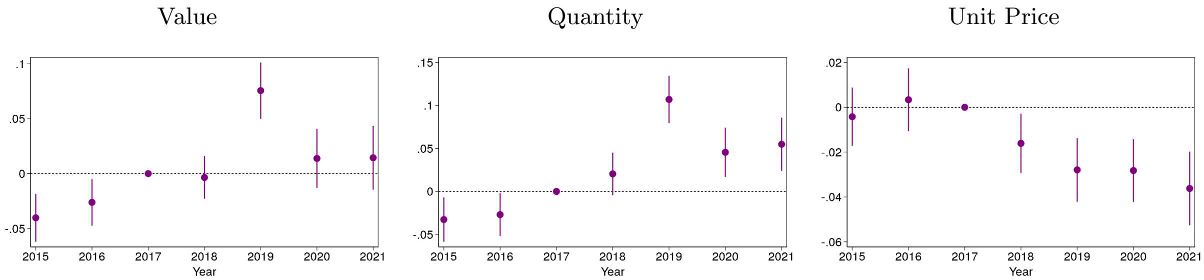
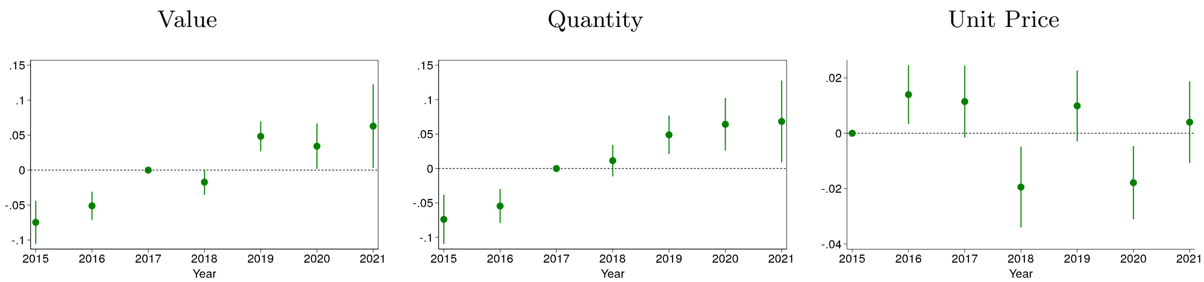


Figure 20: Extended Sample DiD - Advanced Economies, Main Sample



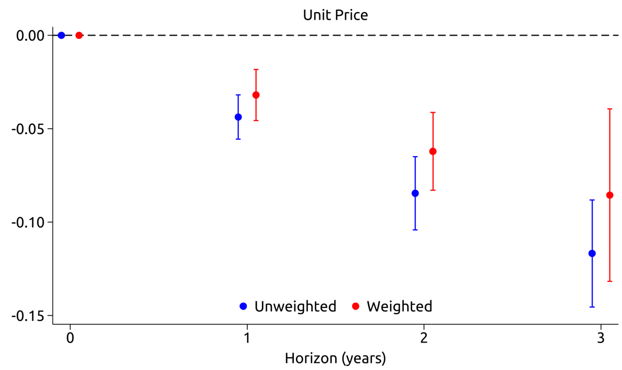
Sources: UN Comtrade; authors' calculations.

Notes: Each panel displays the estimates of separate difference-in-differences regressions for the noted log of the dependent variables. Regressions include origin–product, product–time, origin–time, destination–product, destination–time, origin–destination fixed effects. Standard errors are clustered at the origin country and six-digit HS product level. Error bars show 95% confidence intervals.

C.4 Additional Local Projections Specification

This section reports impulse response functions from a local projections regression as described in Section 5.3.2, but excluding the origin country fixed effect which may absorb effects of tariffs given that over 80 percent of products from China were subject to tariffs. The results show a marked and precisely estimated decline in destination countries' import unit values following the imposition of U.S. tariffs. The higher precision of these estimates relative to those in Section 5.3.2 suggests that origin country fixed effects may indeed be capturing some of the effects of U.S. tariffs imposed on China.

Figure 21: Local Projections - World Sample, Less Restrictive Fixed Effects



Sources: UN Comtrade; authors' calculations.

Notes: Figure displays impulse response functions from the local projections approach described in Section 5, Equation 5, with destination, product, and year fixed effects (origin country fixed effect excluded). Dots display coefficient estimates and bars are 95 percent confidence intervals.