Supply Chain Diversification and Resilience*

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Abstract

This paper develops a new multi-country and multi-sector general equilibrium trade model to analyze extent to which the diversification of sources of imports mitigates the impact of adverse trade shocks. The model incorporates trade network rigidities arising from frictions in goods, labor, and local factor markets. Because countries cannot immediately reconfigure supply chains in response to shocks, supply chain diversification can potentially improve resilience, at the cost of efficiency. Quantifying the resilience-efficiency trade-off suggests that diversifying the sources of targeted imports—those more exposed to shocks, positioned upstream in the supply chain, and subject to greater rigidities—can enhance expected welfare when the probability of a large trade shock is sufficiently high.

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1 Introduction

Supply chain disruptions in the wake of the pandemic have brought to light the importance of resilience. Notably, shipping costs increased almost sevenfold during the pandemic (Carrière-Swallow et al. 2023). At the same time, rising geopolitical risks—particularly since the 2018–2019 US–China trade hikes—have accelerated trends toward geoeconomic fragmentation (e.g., Aiyar et al. 2023). In response, the Biden-Harris Administration implemented more than 30 strategic actions aimed at strengthening supply chain resilience, including subsidies and tariffs to incentivize diversification and reshoring.[1] The Trump administration has also cited the objective of maintaining a "resilient domestic industrial base" by addressing "critical vulnerabilities and choke points in global supply chains" as a rationale for new tariffs.[2] These, in turn, are prompting the US's trading partners to reconsider their reliance on US supply chains.[3]

This paper analyzes the extent to which diversifying sources of imports—including through on-shoring—can mitigate the adverse effects of trade shocks. By spreading sourcing across multiple origins, diversification enhances resilience by reducing reliance on single or concentrated suppliers. However, these benefits come at a cost, namely, efficiency losses due to sourcing partly from higher cost producers. Accordingly, this paper contributes to the literature by formally analyzing the trade-off between resilience and efficiency in the context of global supply chains.

We begin by presenting three stylized facts on the relationship between supply chain diversification and resilience.[4] Focusing on US imports, we first show that geographically diversified supply chains are less exposed to exporter-specific supply shocks in a manner similar to how a diversified portfolio reduces overall risk from individual assets. Second, we illustrate

[1] See "Fact Sheet: President Biden Announces New Actions to Strengthen America's Supply Chains, Lower Costs for Families, and Secure Key Sectors" (White House 2023).

[2] See "Fact Sheet: President Donald J. Trump Adjusts Imports of Automobiles and Automobile Parts into the United States" (White House 2025).

[3] Rotunno and Ruta (2025) consider the impact of various policy responses by countries to US tariffs.

[4] Throughout the paper, we define supply chain diversification as sourcing imports from multiple countries (including one's home country) such that no single source country accounts for a large share of total imports.

that sectors with more diversification in their source countries are more resilient to trade cost shocks, including tariffs and shipping costs, by estimating product-level aggregate trade elasticities and relating them to a measure of diversification (e.g., Herfindahl-Hirschman Index). Last, using an event study design, we demonstrate that sectors with diversified supply chains exhibited greater resilience to the 2018-2019 tariffs on China: the tariff hikes triggered a decline in imports from China and prompted firms to shift toward suppliers in other countries. This was particularly pronounced in products with diversified supply chains, which helped maintain stable import levels despite the tariffs.

Motivated by these empirical patterns, we develop a multi-country and multi-sector general equilibrium trade model to analyze the impact of diversification on resilience and expected welfare given various risk scenarios. We extend existing models by incorporating trade network rigidities arising from three distinct sources of frictions: goods, labor, and local factor markets. These rigidities imply that countries cannot easily reconfigure supply chains in response to shocks, creating a mechanism by which supply chain diversification can potentially improve welfare, despite efficiency costs.

Our model incorporates constant returns to scale in production and perfectly competitive markets. In each country and for each good, a representative firm produces an intermediate variety demanding labor, a composite local factor (structures), and materials (final goods) from all sectors. A continuum of importers aggregates intermediate varieties from each country (including its own) into a final good. Importers are subject to trade costs and source from the lowest cost supplier, given idiosyncratic productivities à la Eaton and Kortum (2002). However, importer-exporter relationships are sticky, and opportunities to switch suppliers in response to a shock arrive stochastically following a Poisson-distributed process. The supply side of the economy features a labor market following Roy (1951) where workers inelastically supply one unit of labor and choose which sector in which to work. Labor mobility across sectors is inelastic in the short-run, but workers re-skill over time. Similarly, there is a local factors market where owners choose which sector in which to rent. Local factors have heterogeneous sector-specific productivities but can be repurposed over time. These elements deliver a general equilibrium, dynamic discrete choice trade model.

The model delivers a few key insights. Firstly, supply chain diversification can enhance resilience and improve expected welfare by reducing the transition losses associated with trade network rigidities. Gradual reconfiguration of supply chains and factor redeployment following a shock leads to larger losses, which diversification helps mitigate. Standard quantitative trade models without such rigidities, which compare only initial and final steady states, do not capture these transition dynamics and the value of diversification. Second, there is a trade-off between the cost of diversification and resilience. Increasing diversification is costly, as it necessitates that importers source goods from higher cost suppliers. Third, it can be optimal to target diversification towards products that are more exposed to shocks, more upstream in the supply chain, and subject to greater rigidities. Last, diversification only has value against shocks which are differentiated across source countries.

We calibrate the model using sector-level bilateral trade and output data from the OECD's Inter-country Input-Output Tables (ICIO), labor and wage bill data from UN Industrial Development Organization (UNIDO), and tariff data from the World Bank's World Integrated Trade Solution (WITS) database. We develop a new method to estimate stickiness in importer-exporter contracting by product, exploring the variation coming from contemporaneous and lagged tariff rates, and find that our measures of stickiness are negatively correlated with measures of product specificity and complexity used in the literature. We also estimate country-specific labor mobility elasticities using a novel instrument (changes in effective sectoral tax rates) for changes in wages. Our estimates are negatively correlated with the OECD's Employment Protection Legislation (EPL) index, a measure of labor market rigidity. We also show that the labor supply elasticity to wages increases over longer time horizons.

We quantitatively assess the resilience-efficiency tradeoff by simulating the impact of two shock scenarios on welfare, with and without diversification policies in place, from the perspective of the United States. First, we consider a fragmentation scenario where there are rising trade barriers between geopolitical blocs, centered around the two largest economies—China and the United States (based on the scenario considered in Chapter 4 of the April 2023 IMF World Economic Outlook).[5] We show that the cost of diversifying select goods with an import share greater than one-third from the China bloc is a welfare loss of 0.02 percent. However, should the fragmentation scenario materialize, diversification reduces welfare losses by 12 percent (summing to 0.11 percent of welfare) over five years. Depending on the risk aversion of the social planner, such diversification can be optimal if the probability of the fragmentation scenario is at least 7 to 9 percent. A decomposition exercise shows that sticky import-exporter contracting accounts for most of the gains from diversification, followed by frictions in the labor market as labor supply elasticities are in general more inelastic than that of local factors. Further simulations show that targeting diversification towards products with more exposure to shocks, more rigidities, and that are more upstream can improve the trade-off, significantly reducing costs while preserving much of the benefits. For instance, diversifying all products indiscriminately instead of just products with over a third of import share would increase costs by 2.5 times, while increasing benefits by only 40 percent. We also consider the impact of a uniform broad-based tariff on all United States imports and reciprocal retaliation (following the scenario in Costinot and Rodríguez-Clare 2014). We find that re-shoring import products with high rigidities reduces welfare by 0.04 percent, but mitigates welfare losses in the event of such a shock by 5 percent (summing to 0.26 percent of welfare) over five years.

This paper contributes to the theoretical literature on trade disruptions. Bhagwati and Srinivasan (1976) argues that tariffs can improve efficiency by incentivizing agents to internalize the externality their trade activities impose on the probability of a trade restriction. Bergström, Loury, and Persson (1985) explores the potential role of inventories to mitigate the threat of embargo using an infinite horizon model. Cheng (1989) models recurrent em-

[5] See International Monetary Fund (2023).

bargo threats as a stationary Markov process, accounting for constraints on the speed of intersectoral reallocation. Becko and O'Connor (2025) finds that trade dependencies can be a factor limiting the probability of trade conflicts. Our paper is most related to Grossman, Helpman, and Lhuillier (2023) who show in a simple two-country model of production with a critical input and exogenous risks of supply disturbances that diversification can achieve a constrained social optimum. Similar to our paper they conclude that there is a trade-off between lower costs and the greater safety of diversification. Our paper quantifies the impact of trade disruptions in a multi-country and multi-sector model, and considers the impact of diversification policies on resilience.

This paper also contributes to the literature on trade frictions. We incorporate the concept of relationship stickiness in trade into our quantitative model. Monarch (2022) structurally estimates the cost of switching across Chinese suppliers for US importers. Grossman, Helpman, and Redding (2024) develop a simple model where firms conduct costly searches and negotiate with potential suppliers that pass a reservation level of match productivity. Ornelas and Turner (2008) study bilateral relationships in which a foreign supplier must make a relationship-specific investment to sell an input to a downstream home producer. Antràs and Staiger (2012) explores the role of relationship-specific investments in a two country model. Antràs and Chor (2013) and Alfaro, Chor, et al. (2019) consider the integration choices of firms along the global supply chain in the presence of contractual frictions. Christoph E Boehm, Flaaen, and Pandalai-Nayar (2019) exploit the 2011 Tōhoku Earthquake as a natural experiment to provide the evidence of significant rigidity in global supply chains, while Bonadio et al. (2021) perform a quantitative assessment of supply chain resilience in the context of the Covid-19 pandemic. Alfaro, Brussevich, et al. (2024) study the role of bank financing in helping firms reconfigure supply chains in the presence of sticky supply chain relationships. Martin, Mejean, and Parenti (2023) estimate measures of relationship stickiness grounded in a search model using firm-level French exporter data. We estimate a measure of stickiness in importer-exporter contracting based on our model using cross-country trade data, and find that our estimates are well correlated with theirs. Relatedly, Christoph E. Boehm, Levchenko, and Pandalai-Nayar (2023) estimate trade elasticities at various time horizons. Their results are consistent with our model and estimates, which suggest that trade elasticities increase as the time horizon extends, stabilizing in the long run. Das, Roberts, and Tybout (2007), Alessandria and Choi (2007), Alessandria, Choi, and Ruhl (2021), and Steinberg (2023) develop dynamic models where firms pay a large sunk cost to start exporting and a smaller fixed cost to continue exporting in the future.

Our paper also contributes to literature seeking to compute the gains from trade using dynamic multi-country and multi-sector quantitative trade models building on Eaton and Kortum (2002) similar to ours. Capital accumulation typically drives the dynamic transition between steady states, such as in Alvarez (2017), Mutreja, Ravikumar, and Sposi (2018), Anderson, Larch, and Yotov (2020), and Ravikumar et al. (2022). Brooks and Pujolas (2018) allows for variable trade elasticities over time. Our model is novel in introducing trade network rigidities arising from sticky importer-exporter contracts and frictions in labor and local factor mobility, which shape the transition dynamics critical for understanding diversification and resilience. Our paper also relates to the literature that integrates labor markets into such quantitative trade models, including Caliendo, Dvorkin, and Parro (2019) and Lee (2020), which examine the employment effects of trade shocks. Unlike these studies, which assume fixed labor mobility, our model allows labor mobility to become more elastic over time, capturing gradual adjustments key for assessing resilience and diversification. Caliendo, Dvorkin, and Parro (2019) also incorporates local factors, but assumes perfect mobility across sectors.

Our model is limited in a few dimensions. Firstly, we do not incorporate capital accumulation such that investment decisions have persistent effects over time (as in Anderson, Larch, and Yotov (2020) and others). Second, we assume that markets are perfectly competitive and that production is constant returns to scale. We do not allow for monopolistic competition with the free entry of heterogeneous firms, as in Caliendo, Feenstra, et al. (2015)

and Melitz (2003).[6] Third, the model is deterministic rather than stochastic. In addition, the model focuses on changes in actual policies, overlooking the potentially significant effects from policy uncertainty (International Monetary Fund 2025). While the model is well-suited to handling the dynamic adjustment to permanent shocks such as tariffs, which is particularly relevant in today's context, it is less appropriate for analyzing the resilience to temporary supply chain disruptions, such as those experienced during the Covid-19 pandemic." Finally, our model aggregates final production at the country-product level, which may overlook potential distortions occurring at the firm level within sectors in a given country.

The rest of the paper is organized as follows. Section 2 presents stylized facts about diversification and supply chain resilience using data on US imports and trade costs. Section 3 presents the quantitative trade model. Section 4 presents our simulation exercises and results. We conclude in Section 5.

2 Stylized Facts

In this section, we present a set of empirical observations that motivate the case for supply chain diversification. First, we show that geographical concentration of imports increases vulnerability to exporter-specific supply shocks. Second, we provide evidence that a more diversified import structure enhances resilience to trade cost shocks. Finally, we confirm that US imports with more diversified sourcing experienced limited impact from the disruption to Chinese imports during the 2018–2019 tariff hikes with China.

[6] Garcia-Macia and Goyal (2020) finds that capturing monopolistic rents and avoiding technology outflows to a potential rival can be a potential motive for onshoring.

2.1 Data

2.1.1 US Import data

We construct a quarterly dataset of US imports at the country-product level using publicly available monthly data from the US Census Bureau, which report bilateral trade values and quantities at the 10-digit Harmonized System (HS10) level. Our sample spans 2013 to 2024 and includes the full universe of HS-10 codes and trading partners. The data provide information on the value of duties collected, the value of general imports subject to duties, and CIF (cost, insurance, and freight) import values, allowing us to separately construct effectively applied tariff rates and CIF values.

2.1.2 Global Tariff and Trade Data

We construct bilateral tariff data at the 6-digit Harmonized System (HS6) level by combining two databases: one from UNCTAD TRAINS available from WITS and the other through MAcMap-HS6 available at CEPII. The WITS data provides average tariff rates applied to bilateral country pairs at the HS6 level, including: (i) Most Favored Nation (MFN) rates for WTO member pairs without preferential trade agreements; (ii) applied preferential rates for country pairs with such agreements; and (iii) prohibitive non-MFN rates when one of the countries is not a WTO member. All rates incorporate ad valorem equivalents (AVEs) of non–ad valorem tariffs. To account for missing observations and potential measurement errors in the database, we further complement the data with the MAcMap-HS6-CEPII dataset, which covers an exhaustive list of preferential trade agreements for selected years.[7]

We employ the global bilateral HS6-level trade data from BACI (CEPII) database that provides information on bilateral annual trade flows, net of transport costs (i.e., FOB), at the 6-digit Harmonized System (HS6) level.[8] Once merged with the bilateral HS6-level tariff data, this allows us to extract exporter-HS6-year-level supply shock by estimating the

[7]Teti (2024) provides a comprehensive examination of the WITS data. Detailed information on the MAcMap-HS6 dataset can be found in Guimbard et al. (2012).

[8]The data construction process is documented in detail in Gaulier and Zignago 2010.

following specification using the Poisson pseudo-maximum likelihood (PPML) estimator à la Silva and Tenreyro (2006):

$$V_{ijst} = \exp[\beta \ln \tau_{ijst} + FE_{ijs} + FE_{ist} + FE_{jst}]\epsilon_{ijst}, \tag{1}$$

which is consistent with the structural gravity representation, encompassing any class of main theoretical models in the literature (Baier, Kerr, and Yotov 2018).[9] V_{ijst} and τ_{ijst} denote bilateral trade value and applied tariff rates between exporter i and importer j for product s in year t, respectively. Exporter-importer-product fixed effects (FE_{ijs}) absorb any bilateral country pair specific factors at each product level, while importer-product-year fixed effects (FE_{jst}) capture time-varying product-specific demand factors. We recover the supply shock measure by taking exponential of the exporter-product-year fixed effects term (FE_{ist}).

2.2 Geographic Concentration and the Risk of Exporter Supply Shocks

Focusing on US imports, we measure the degree of concentration by applying the respective share of imports from each source country to construct the Herfindahl-Hirschman Index (HHI) at the product level across years:

$$HHI_{st} = \sum_{i=1}^{N_{st}} (S_{ist})^2,$$

where S_{ist} and N_{st} are the share of imports from country i and the total number of exporters for product s in year t, respectively.[10]

[9] While the structural model in Equation 17 will derive a gravity relationship that deviates from Equation 1, we nonetheless use Equation 1 at this stage to present the empirical regularities, as it follows the specification widely used in the literature and helps relate our stylized facts to the conventional empirical framework.

[10] Due to the lack of comparable data on domestic sourcing, the product-level concentration measure relies solely on foreign sourcing.

We relate the concentration measure to a risk measure defined as the weighted covariance of supply shocks at the product level:

$$\sigma_s^2 = \mathbf{WCW}',$$

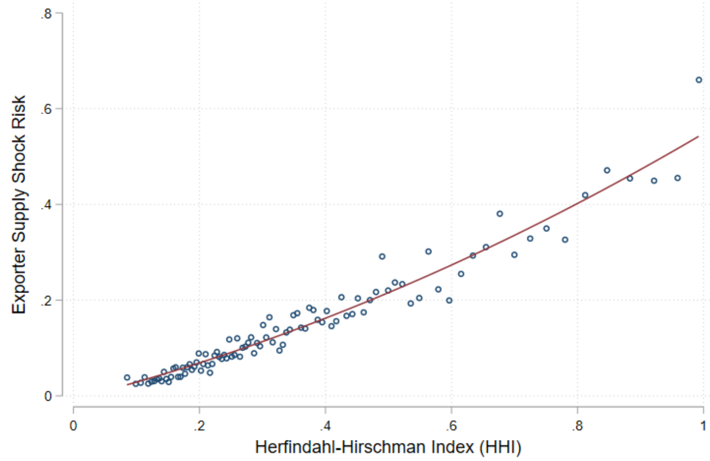
where $\mathbf{W}$ is the row vector of exporter-level (time-averaged) market shares for each product and $\mathbf{C}$ is the covariance matrix of exporter-product-level supply shocks measured from the exporter-product-year fixed effects term, FE_{ist}, by estimating Equation 1.

We can draw an analogy from portfolio theory to interpret our risk measure. In finance, the variance of a portfolio's return—a measure of risk—depends on both the variances and covariances of the returns of individual assets, weighted by their shares in the portfolio. Similarly, in our context, each exporter is like an asset in a portfolio, and the import shares from each exporter represent the portfolio weights. As such, this formulation captures not just the volatility of individual exporters' supply shocks, but also the co-movements between them, highlighting the potential role of diversification.

Figure 1 presents a binned scatter plot illustrating the relationship between the degree of geographic concentration of import sources and the level of exporter supply shock risk. A strong positive correlation suggests that sectors with high concentration among a few exporters are more vulnerable to risks from supply shocks than those where market shares are more evenly distributed across exporters. As in portfolio theory, it thus confirms that diversification—spreading imports more evenly across less correlated suppliers—can reduce overall risk originating from source countries.

Fact 1 *Products with geographically concentrated import sources are more exposed to supply shocks from individual exporters.*

Figure 1: Geographical Concentration and Exporter Supply Shock Risk



Notes: This figure presents a binned scatter plot illustrating the relationship between geographic concentration and exporter supply shock risk at the HS6 product level for US imports. The degree of geographic concentration of import sources is measured using the Herfindahl-Hirschman Index (HHI), based on the share of imports from each source country. Exporter supply shock risk is measured as the import-share-weighted variance-covariance of supply shocks across exporters.

2.3 Geographic Concentration and Resilience to Trade Cost Shocks

While Equation 1 helps estimate the elasticity of trade with respect to trade costs, it only provides information about the relative changes across varieties (i.e., exporter-product pairs), without offering insights into the absolute changes at the product level within a given importer country. Specifically, it is entirely plausible for two products to have similar trade elasticity estimates, yet the actual changes in trade for each product in response to a given trade cost shock may differ substantially. This would be attributable to differences in substitutability across source countries at the product level: It may well be the case that an exporter with relatively lower trade costs could offset a supply reduction from a higher trade cost exporter in one product, but not in another, with the extent of this offset depending on the degree of product-level substitutability.

To assess the degree of product-level substitutability and, consequently, the net effect of product-level trade cost shocks within a given importer country, we consider a product-level version of Equation 1 à la Khwaja and Mian 2008, Gropp et al. 2019, and Jiménez et al. 2020, a commonly used method in the finance literature:

$$V_{st} = \exp[\gamma \ln \overline{\tau_{st}} + FE_s + FE_t]\epsilon_{st}, \tag{2}$$

where the dependent variable is the aggregate US imports of product s and year t and $\overline{\tau_{st}}$ denotes the product-level weighted sum of trade costs, incorporating both tariff rates and CIF cost. The weight is defined as each country's share in US imports of the product in the previous year:

$$weight_{ist} = \frac{V_{ist-1}}{\sum_i V_{ist-1}}$$

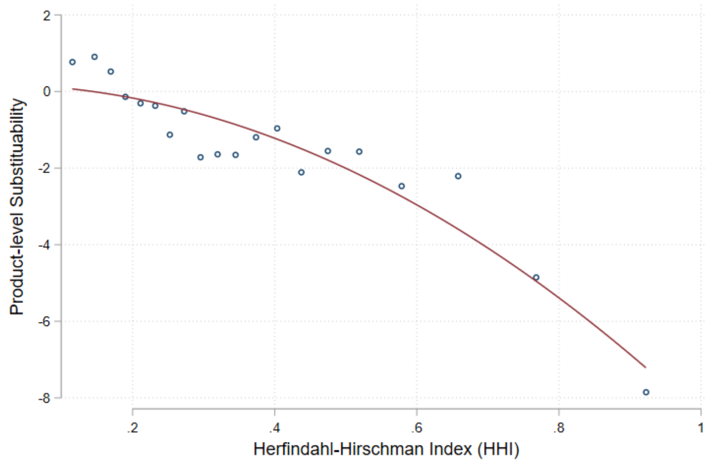
It then follows that a product-level weighted geometric mean of trade costs in log is derived as:

$$\ln \overline{\tau}_{st} = \sum_i (weight_{ist} \times \ln \tau_{ist})$$

In the context of relating product-level diversification to resilience, we estimate product-level substitutability γ_s, by running a separate regression of Equation 2 for each product, dropping any fixed effect terms. Figure 2 presents a binned scatter plot that summarizes these estimates, plotted against the product-level concentration measure. A strong negative correlation suggests that products concentrated among a few exporters tend to experience a substantial reduction in overall imports in response to positive trade cost shocks, and an increase in imports when trade costs decline. By contrast, products with more evenly distributed market shares across exporters are more likely to exhibit a significant level of substitution across suppliers, reflecting greater resilience in product-level imports—or, more broadly, a less elastic response to trade cost shocks.

Fact 2 *Products with more diversified import sources exhibit greater resilience to trade cost shocks.*

Figure 2: Geographical Concentration and Import Resilience



Notes: This figure presents a binned scatter plot illustrating the relationship between geographic concentration and the resilience of US imports at the HS6 product level. The degree of geographic concentration of import sources is measured using the Herfindahl-Hirschman Index (HHI), based on the share of imports from each source country. The resilience of imports is measured by the degree of substitutability at the HS6 product level, as estimated from Equation 2.

2.4 The Case of the 2018-2019 US-China Tariff Hikes

We turn to the case study of the 2018-2019 increase in US-China tariffs, by using the 2018-2019 tariff shocks as a source of variation in the pattern of imports across sectors and source countries. We begin by confirming that the 2018–2019 tariff hikes on China led to a substantial reduction in US imports from China relative to other countries. Specifically, we modify the HS10-level bilateral US import data by aggregating all exporters other than China into a single group and estimate the following specification:

$$\ln V_{ist} = \sum_k \beta_k \cdot \mathbb{I}(k=t) + \sum_k \gamma_k \cdot \mathbb{I}(k=t) \times \text{CHN}_i + FE_{is} + FE_{st} + \varepsilon_{ist}, \quad \text{for } s = \text{Targeted products}, \tag{3}$$

where $\mathbb{I}(k=t)$ is a quarterly indicator variable, CHN_i is a dummy variable equal to 1 if the exporter is China and 0 otherwise, and FE_{is} and FE_{st} are fixed effect terms that capture any country(group)-product-level and product-quarter-level specific characteristics, respectively.

Our coefficient of interest is γ_t, which reflects the time-varying average level of imports from China relative to imports from all other countries. The sample is restricted to products that were subject to newly imposed tariff on Chinese goods during 2018 and 2019.[11]

Figure 3a presents the estimation results for γ_t, normalized to 0 in the third quarter of 2018, with standard errors clustered by country(group)-product and product-quarter-levels. As expected, following the imposition of tariffs, imports of targeted goods from China declined significantly relative to those from the rest of the world after a quarter. This rapid decline in the estimated coefficient likely reflects both substantial substitution from Chinese to other imported products and an absolute decrease in product-level imports due to insufficient substitution.

To the extent that sufficient cross-country substitution—enabling importers to avoid an overall decline in imports—reflects supply chain resilience, we examine whether the degree of geographic concentration in imports is associated with such resilience, by estimating the following product-level specification:

$$\ln V_{st} = \sum_k \beta_t \cdot \mathbb{I}(k=t) + \sum_k \gamma_t \cdot \mathbb{I}(k=t) \times \mathrm{HHI}_s + FE_s + \varepsilon_{st}, \quad \text{for } s = \text{Targeted products}, \tag{4}$$

where HHI_s is a dummy variable equal to 1 if the HHI for product s's imports is above the median value across all products, and 0 otherwise. Now, γ_t is supposed to capture the extent to which greater concentration in import sourcing limited supply chain resilience in response to the tariff shocks on Chinese goods.

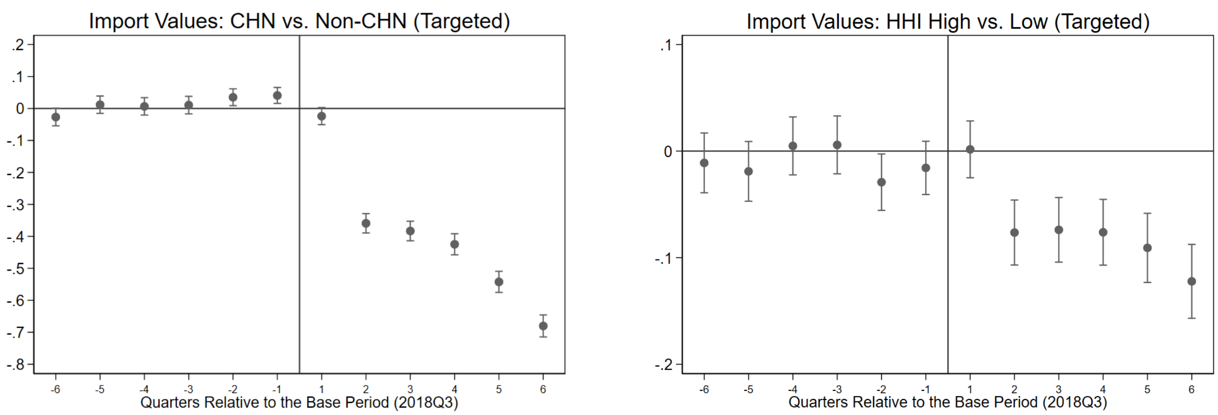
Figure 3b illustrates the estimation results for γ_t, normalized to 0 in the third quarter of 2018, with standard errors clustered at the product level. The figure clearly shows that, following the imposition of tariffs, the decline in imports of targeted goods was particularly pronounced for products with higher import source concentration. Intuitively, when imports of a given product are predominantly sourced from China, it becomes more difficult for

[11] We identify these products using the dataset provided by Fajgelbaum et al. (2024).

importers to quickly find alternative suppliers in response to tariff shocks on Chinese goods. In contrast, when imports are already sourced from a diverse set of countries, adjustment is likely to be much easier. We can confirm that this is not a mechanical result driven simply by higher tariff rates or by a larger share of Chinese imports in more concentrated sectors.

Fact 3 *US imports of geographically more diversified products were more resilient to the 2018-2019 tariffs on China.*

Figure 3: The Impact of the 2018–2019 China Tariffs on US Imports: Targeted Goods



(a) Imports from China vs. Others

(b) Imports by Supply Concentration

Notes: This figure presents estimation results on the impact of the 2018-2019 tariff shocks on US imports. 3a summarizes the estimation result from the country(group)-product-quarter-level regression of Equation 3, while 3b reports the estimation result from the product-quarter-level regression of Equation 4.

3 Model

Motivated by stylized facts, we construct a multi-country and multi-sector general equilibrium trade model with trade network rigidities that can capture the potential benefits of diversification. The model builds on Eaton and Kortum (2002), Caliendo and Parro (2015), and Caliendo, Dvorkin, and Parro (2019).

We consider an economy with N countries and J goods. We denote countries by i and n and goods by j and k. Time is discrete denoted by $t = 0, 1, 2...$. For each country-good, a representative firm produces an intermediate variety under perfect competition with a constant returns to scale technology demanding labor, a composite local factor (structures), and materials (final goods) from all sectors. A continuum of importers aggregates intermediate varieties from from each country—including home country—into a final good. Each country has a fixed supply of total labor and local factors.[12]

The model features three sources of trade network rigidities:

1. **Staggered (sticky) importer-exporter contracts:** Importers receive Poisson-distributed opportunities to switch suppliers, such that a proportion of firms can switch suppliers in each period and the rest remain fixed.[13]

2. **Labor market frictions**: Workers have heterogeneous sector-specific productivities (as in Roy (1951)). Labor mobility across sectors is inelastic in the short-run, but workers re-skill over time.

3. **Immobile local factors:** Local factors, such as structures, have heterogeneous sector-specific productivities and are repurposed over time.

3.1 Workers

There are measure L^n workers in each country n. Each worker has an idiosyncratic productivity (efficiency units of labor) ϵ_L^{nj} for each sector j, randomly drawn from a Fréchet distribution.

$$F_L^{nj}(\epsilon_L) = exp(-T_t^{L,nj}\epsilon_L^{-\theta^{L,n}}) \tag{5}$$

The scale parameters $T_t^{L,nj}$ control the overall level of worker productivity in each sector. The shape parameter $\theta^{L,n}$ determines the dispersion of worker productivities, governing labor

[12]This implies a constraint to aggregate production.

[13]Developing the micro foundations for and building on the concept of relationship stickiness in international trade was proposed by Martin, Mejean, and Parenti (2023).

mobility across sectors. When $\theta^{L,n}$ is low, workers exhibit significant productivity differences across sectors, reducing workers' responsiveness to wage changes and increasing labor market frictions. $\theta^{L,n}$ can vary across countries n, meaning that some countries can reallocate labor to adjust to demand more easily than others.

Workers inelastically supply one unit of time and earn labor income $w_t^{nj}\epsilon_L^{nj}$ where w_t^{nj} is the wage per efficiency unit of labor in country n and sector j. The labor market is perfectly competitive so that workers earn their marginal revenue product.

Each worker solves an occupational choice problem by choosing the sector generating the highest labor income, as in the Roy (1951) model. Using the Fréchet distribution of workers' productivity, sector j's share of labor income is given by

$$\pi_t^{L,nj} = \frac{T_t^{L,nj}(w_t^{nj})^{\theta^{L,n}}}{\sum_k T_t^{L,nk}(w_t^{nk})^{\theta^{L,n}}} \tag{6}$$

The wage index in country n is given by

$$W_t^n = \Gamma\left(\frac{\theta^{L,n}-1}{\theta^{L,n}}\right)\left(\sum_j T_t^{L,nj}(w_t^{nj})^{\theta^{L,n}}\right)^{\frac{1}{\theta^{L,n}}} \tag{7}$$

where $\Gamma(.)$ is the Gamma function.

Workers retrain and adjust their skills based on wages/demand according to

$$\left(\frac{T_t^{L,nj}}{T_{t-h}^{L,nj}}\right) = \left(\frac{w_t^{nj}}{w_{t-h}^{nj}}\right)^{\delta^L(h-1)} \tag{8}$$

for $h > 0$ where δ^L governs the speed of re-skilling. Following a shock in period $t-h$, as $t \to \infty$, wages w_t^{nj} are equalized across sectors. So while in the short run there are labor market frictions, in the long run labor is perfectly mobile.

Workers have Cobb-Douglas preferences over final goods. Utility in period t for a worker living in country n and working in sector j is given by

$$U(C_t^{nj}) = \prod_{k=1}^{J} (c_t^{nj,k})^{\beta^{nk}} \tag{9}$$

where $c_t^{nj,k}$ is the consumption of good k in period t, and β^{nk} is the final consumption share of good k in country n with $\sum_{k=1}^{K} \beta^{nk} = 1$. The price index in country n is $P_t^n = \prod_{k=1}^{J} (P_t^{nk}/\beta^{nk})^{\beta^{nk}}$. Income is derived from wages w_t^{nj}, rents from the ownership of local factors r_t^{nj}, and transfers on a lump-sum basis (tariff revenues).

3.2 Production

3.2.1 Intermediate Varieties

For each country n and good j, a representative firm produces an intermediate variety.

For each country i and good j, there is a continuum of importers $\omega^{ij} \in [0, 1]$. The firm produces for importer ω^{ij} with efficiency ϵ_I^{nj}, randomly drawn from a Fréchet distribution.

$$F_I^{nj}(\epsilon_I) = exp(-T_t^{I,nj} \epsilon_I^{-\theta^{I,j}}) \tag{10}$$

where $\theta^{I,j}$ is the shape parameter which governs the dispersion of efficiency, and varies by good j. $\theta^{I,j}$ is also the elasticity of trade. The larger the dispersion, the larger are the gains from trade integration. The scale parameters $T_t^{I,nj}$ control the overall level of efficiency, which we assume is fixed over time ($T_t^{I,ij} = T^{I,ij}$).

The production technology of good j for importer ω^{ij} is

$$q_t^{nj} = \epsilon_I^{nj} \left(A_t^{nj} (H_t^{nj})^{\xi^{nj}} (L_t^{nj})^{1-\xi^{nj}} \right)^{\gamma^{nj}} \prod_k (M_t^{njk})^{\gamma^{njk}} \tag{11}$$

where the inputs are labor L_t^{nj}, local factors H_t^{nj}, and materials M_t^{njk}. γ^{nj} is the value added share, ξ^{nj} is the share of local factors in value added, and γ^{njk} is the share of materials from sector k in the production of sector j in country n. The production function is constant returns to scale such that $\sum_k \gamma^{njk} + \gamma^{nj} = 1$.

Markets are perfectly competitive so firms price at unit cost. The unit cost of the intermediate variety from country n for importer ω^{ij} is $\frac{x_t^{nj}}{\epsilon_I^{nj} A_t^{nj \gamma^{nj}}}$. The unit price of an input bundle is

$$x_t^{nj} = B^{nj} \left((r_t^{nj})^{\xi^{nj}} (w_t^{nj})^{1-\xi^{nj}} \right)^{\gamma^{nj}} \prod_k (P_t^{nk})^{\gamma^{njk}} \tag{12}$$

where r_t^{nj} is the rental price of local factors in sector j, P_t^{nk} is the price of final good k, and B^{nj} is a constant.[14]

3.2.2 Final Goods

For each good, immediate varieties imported from each country by the continuum of importers are aggregated into a final local good (a bundle of goods purchased from different countries). The production of the final good j in country n is a Dixit-Stiglitz aggregator with elasticity of substitution η^{nj} given by

$$Q_t^{nj} = \left(\int (q_t^{nj} (\omega^{nj})^{1-1/\eta^{nj}} d\omega^{nj} \right)^{\eta^{nj}/(\eta^{nj}-1)} \tag{13}$$

where the demand from importer ω^{nj} is $q_t^{nj}(\omega^{nj})$.

3.3 Trade

Trade costs are represented by $1 + \tau_t^{nij} = (1 + d_t^{nij})(1 + \kappa_t^{nij})$ where κ_t^{nij} is the ad-valorem flat-rate tariff for good j imported by country n from country i and d_t^{nij} is all non-tariff trade costs. Total expenditure on good j in country n is given by $X_t^{nj} = P_t^{nj} Q_t^{nj}$ where P_t^{nj} is the unit price of the final good. Let λ_t^{nij} denote the share of expenditures in country n on good j from country i.

When importers decide which country to import from (including their own), they choose the country with the lowest unit cost, taking into account trade costs, and the price paid

[14] $B^{nj} = (\gamma^{nj}\xi^{nj})^{-\gamma^{nj}\xi^{nj}} (\gamma^{nj}(1-\xi^{nj}))^{-\gamma^{nj}(1-\xi^{nj})} \prod_k (\gamma^{njk})^{-\gamma^{njk}}$.

is:[15]

$$p_t^{nj*}(\omega^{nj}) = \min_i \left\{ \frac{x_t^{ij}(1+\tau_t^{nij})}{\epsilon_I^{ij}(\omega^{nj}) A_t^{nj^{\gamma^{nj}}}} \right\} \tag{14}$$

Importers stochastically receive opportunities to switch suppliers according to a Poisson arrival process such that

$$\frac{d\lambda_t^{nij}}{dt} = \mu^j \left(\lambda_t^{nij*} - \lambda_t^{nij}\right) \tag{15}$$

where λ_t^{nij*} is the optimal long run steady state expenditure share that can be derived from the properties of the Fréchet distribution.

$$\lambda_t^{nij*} = \frac{T_t^{I,ij}\left(x_t^{ij}(1+\tau_t^{nij})\right)^{-\theta^{I,j}} (A_t^{nj})^{\theta^{I,j}\gamma^{nj}}}{\sum_m T_t^{I,mj}\left(x_t^{mj}(1+\tau_t^{nmj})\right)^{-\theta^{I,j}} (A_t^{mj})^{\theta^{I,j}\gamma^{mj}}} \tag{16}$$

μ^j is the Poisson rate parameter. This parameter captures the search and matching frictions between importers and exports which generate sticky or staggered importer-exporter contracting. A larger μ^j implies that importers of good j can more quickly switch the country from which they import following a shock. μ^j can differ by good j, meaning that importer-exporter relationships may be more sticky for some goods than others.

In discrete time, λ_t^{nij} evolves as follows:

$$\lambda_t^{nij} = (\lambda_t^{nij*})^{1-(1-\alpha^j)^h} (\lambda_{t-h}^{nij})^{(1-\alpha^j)^h} \tag{17}$$

where $\alpha^j = 1 - e^{-\mu^j}$ captures the speed of adjustment. So in response to a shock, a proportion of firms can switch suppliers immediately and the rest remain fixed.[16] Following a shock in period $t-h$, as $t \to \infty$, $\lambda_t^{nij} \to \lambda_t^{nij*}$.

Given that the distribution of efficiencies is Fréchet, we can also solve for the distribution

[15] Note that the relative cost of sourcing domestically versus abroad determines the domestic production share.

[16] When $h = 1$, $\lambda_t^{nij} = (\lambda_t^{nij*})^{\alpha^j} (\lambda_{t-1}^{nij})^{1-\alpha^j}$

of prices. The price of final good j in country n for importers who can switch suppliers is:

$$P_t^{nj*} = \Gamma\left(\frac{\theta^{I,j}-1}{\theta^{I,j}}\right)\left(\sum_i T_t^{I,ij}\left(x_t^{ij}(1+\tau_t^{nij})\right)^{-\theta^{I,j}}(A_t^{nj})^{\theta^{I,j}\gamma^{nj}}\right)^{-1/\theta^{I,j}} \tag{18}$$

where $\Gamma(.)$ is the Gamma function. All other importers who do not switch suppliers source from the same country i as before and pay price $\frac{x_t^{ij}(1+\tau_t^{nij})}{\epsilon_I^{ij}(\omega^{nj})A_t^{nj\,\gamma^{nj}}}$.

3.4 Local Factors

Workers in country n collectively own local factors H^n and rent them to the local producers. Each unit has an idiosyncratic productivity (efficiency units) ϵ_H^{nj} for each sector j, randomly drawn from a Fréchet distribution.

$$F_H^{nj}(\epsilon_H) = exp(-T_t^{H,nj}\epsilon_H^{-\theta^{H,n}}) \tag{19}$$

The scale parameters $T_t^{H,nj}$ control the overall level of efficiency in each sector. The shape parameter $\theta^{H,n}$ determines the dispersion of efficiencies, governing the mobility of local factors across sectors.

Local factors are rented to the representative firms for each good j at cost $r_t^{nj}\epsilon_H^{nj}$ where r_t^{nj} is the rental rate per efficiency unit. Using the properties of the Fréchet distribution, representative firm j's share of total rent is given by

$$\pi_t^{H,nj} = \frac{T_t^{H,nj}(r_t^{nj})^{\theta^{H,n}}}{\sum_k T_t^{H,nk}(r_t^{nk})^{\theta^{H,n}}} \tag{20}$$

The rental index in country n is given by

$$R_t^n = \Gamma\left(\frac{\theta^{H,n}-1}{\theta^{H,n}}\right)\left(\sum_j T_t^{H,nj}(r_t^{nj})^{\theta^{H,n}}\right)^{\frac{1}{\theta^{H,n}}} \tag{21}$$

where $\Gamma(.)$ is the Gamma function.

Local factors depreciate over time and new factors are purposed based on rents/demand according to

$$\left(\frac{T_t^{H,nj}}{T_{t-h}^{H,nj}}\right) = \left(\frac{r_t^{nj}}{r_{t-h}^{nj}}\right)^{\delta^H(h-1)} \tag{22}$$

where δ^H is the depreciation rate. Following a shock in period $t-h$, as $t \to \infty$, rents w_t^{nj} are equalized across sectors. So local factors are immobile only in the short run.

3.5 Market Clearing

Total expenditure on good j is the sum of the demand for materials from firms and final demand by households. Goods market clearing implies that

$$X_t^{nj} = \sum_k \gamma^{njk} \sum_i \frac{\lambda_t^{ink} X_t^{ik}}{1+\kappa_t^{ink}} + \beta^{nj} I_t^n \tag{23}$$

where

$$I_t^n = W_t^n L^n + R_t^n H^n + \sum_k \sum_i \left(\frac{\kappa_t^{nik} \lambda_t^{nik} X_t^{nk}}{1+\kappa_t^{nik}}\right) + D_t^n \tag{24}$$

represents final absorption in country n as the sum of labor income, rental income, tariff revenues, and the trade deficit D_t^n. The summation of trade deficits across countries is zero, $\sum_n D_t^n = 0$; and national deficits are the summation of the deficits for each good, $D_t^n = \sum_k D_t^{nk}$. The deficit for each good is total imports minus total exports defined by $D_t^{nj} = \sum_i \frac{\lambda_t^{nij} X_t^{nj}}{1+\kappa_t^{nij}} - \sum_i \frac{\lambda_t^{inj} X_t^{ij}}{1+\kappa_t^{inj}}$. Aggregate trade deficits in each country are exogenous in the model ($D_t^n = D^n$), however good-level trade deficits are endogenously determined.

Total expenditure, excluding tariff payments, in country n minus trade deficits equals the sum of each country's total expenditure, excluding tariff payments, on goods from country n.

$$\sum_j \sum_i \frac{\lambda_t^{nij} X_t^{nj}}{1+\kappa_t^{nij}} - D_t^n = \sum_j \sum_i \frac{\lambda_t^{inj} X_t^{ij}}{1+\kappa_t^{inj}} \tag{25}$$

Labor market clearing for country n and good j requires that

$$\pi_t^{L,nj} W_t^n L^n = \gamma^{nj}(1-\xi^{nj}) \sum_i \frac{\lambda_t^{inj} X_t^{ij}}{1+\kappa_t^{inj}} \tag{26}$$

Local factors market clearing for country n and good j requires that

$$\pi_t^{H,nj} R_t^n H^n = \gamma^{nj}\xi^{nj} \sum_i \frac{\lambda_t^{inj} X_t^{ij}}{1+\kappa_t^{inj}} \tag{27}$$

Definition 1. Given $L^n, H^n, A_t^{nj}, T_t^{L,nj}, T_t^{H,nj}$ and D^n, an equilibrium under tariff and non-tariff trade costs $\{\kappa_t^{inj}, d_t^{inj}\}$ is a vector of prices $\{w_t^{nj}, r_t^{nj}\}$ that satisfy the equilibrium conditions of the model.

4 Simulations

In this section, we simulate our model to assess the impact of two shock scenarios on welfare, with and without diversification policies in place, from the perspective of the United States. The first will be a specific fragmentation scenario where there are rising trade barriers between geopolitical blocs, centered around the two largest economies—China and the United States (based on that from Chapter 4 of the April 2024 IMF World Economic Outlook). The second will be a uniform broad-based tariff on all US imports following that from Costinot and Rodríguez-Clare (2014).

4.1 Exact-hat

We use an exact-hat approach as popularized by Dekle, Eaton, and Kortum (2008). Rather than estimating our model in terms of levels, we specify the model in terms of proportional changes between t and $t-h$. We thereby finesse having to assemble proxies for various unobservables in our model such as good sector-level wages and rents, productivities, mean idiosyncratic draws, and so on. We let $\hat{x}_t = x_t/x_{t-h}$ denote the relative change in the endogenous equilibrium variable x.

Given model parameters $\{\theta^{L,n}, \theta^{H,n}, \theta^{I,j}, \delta^L, \delta^H, \alpha^j, \xi^{nj}, \beta^{nj}, \gamma^{nj}, \gamma^{njk}\}$, endogenous variables in $t-h$ $\{\lambda^{nij}_{t-h}, \pi^{L,nj}_{t-h}, \pi^{H,nj}_{t-h}, W^n_{t-h}L^n, R^n_{t-h}H^n, X^{nj}_{t-h}, \kappa^{inj}_{t-h}\}$, and assumed changes in trade costs between t and $t-h$, $\{\widehat{(1+\kappa^{inj}_t)}, \widehat{(1+d^{inj}_t)}\}$, we can solve for relative changes in the equilibrium between t and $t-h$ with the following equations.

Labor. We rewrite Equations 6, 7 and 8 to derive expressions for changes in labor supply, wages, and mean productivities:

$$\hat{\pi}^{L,nj}_t = \frac{\hat{T}^{L,nj}_t (\hat{w}^{nj}_t)^{\theta^{L,n}}}{\sum_k \hat{T}^{L,nk}_t (\hat{w}^{nk}_t)^{\theta^{L,n}} \pi^{L,nj}_{t-h}} \tag{28}$$

$$\hat{W}^n_t = \left(\sum_j \hat{T}^{L,nj}_t (\hat{w}^{nj}_t)^{\theta^{L,n}} \pi^{L,nj}_{t-h} \right)^{\frac{1}{\theta^{L,n}}} \tag{29}$$

$$\hat{T}^{L,nj}_t = (\hat{w}^{nj}_t)^{\delta^L (h-1)} \tag{30}$$

Local Factors. We rewrite Equations 20, 21 and 22 to derive expressions for changes in the supply of local factors, rents, and mean efficiencies:

$$\hat{\pi}^{H,nj}_t = \frac{\hat{T}^{H,nj}_t (\hat{r}^{nj}_t)^{\theta^{H,n}}}{\sum_k \hat{T}^{H,nk}_t (\hat{r}^{nk}_t)^{\theta^{H,n}} \pi^{H,nj}_{t-h}} \tag{31}$$

$$\hat{R}^n_t = \left(\sum_j \hat{T}^{H,nj}_t (\hat{r}^{nj}_t)^{\theta^{H,n}} \pi^{H,nj}_{t-h} \right)^{\frac{1}{\theta^{H,n}}} \tag{32}$$

$$\hat{T}^{H,nj}_t = (\hat{r}^{nj}_t)^{\delta^H (h-1)} \tag{33}$$

Goods. We rewrite Equations 12, 23, and 18 to derive expressions for changes in unit costs, expenditure shares, and prices:

$$\hat{x}_t^{nj} = \left((\hat{r}_t^{nj})^{\xi^{nj}} (\hat{w}_t^{nj})^{1-\xi^{nj}} \right)^{\gamma^{nj}} \prod_k (\hat{P}_t^{nk})^{\gamma^{njk}} \tag{34}$$

$$\tag{35}$$

$$\hat{P}_t^{nj} = \left(\left(\sum_i \left(\hat{x}_t^{ij} (\widehat{1+\tau_t^{nij}}) \right)^{-\theta^{I,j}} \lambda_{t-h}^{nij} \right)^{-1/\theta^{I,j}} \right)^{1-(1-\alpha^j)^h} \left(\sum_i \hat{x}_t^{ij} (\widehat{1+\tau_t^{nij}}) \lambda_{t-h}^{nij} \right)^{(1-\alpha^j)^h} \tag{36}$$

where

$$(\widehat{1+\tau_t^{nij}}) = (\widehat{1+\kappa_t^{inj}})(\widehat{1+d_t^{inj}}) \tag{37}$$

Market Clearing. We rewrite the market clearing conditions, Equations 23, 26, and 27

$$\hat{X}_t^{nj} = \frac{\sum_k \gamma^{njk} \sum_i \frac{\hat{\lambda}_t^{ink} \lambda_{t-h}^{ink} \hat{X}_t^{ik} X_{t-h}^{ik}}{(\widehat{1+\kappa_t^{ink}})(1+\kappa_{t-h}^{ink})} + \beta^{nj} \hat{I}_t^n I_{t-h}^n}{\sum_k \gamma^{njk} \sum_i \frac{\lambda_{t-h}^{ink} X_{t-h}^{ik}}{1+\kappa_{t-h}^{ink}} + \beta^{nj} I_{t-h}^n} \tag{38}$$

where

$$\hat{I}_t^n = \frac{\hat{W}_t^n W_{t-h}^n L^n + \hat{R}_t^n R_{t-h}^n H^n + \sum_k \sum_i \left(\frac{((\widehat{1+\kappa_t^{nik}})(1+\kappa_{t-h}^{nik})-1) \hat{\lambda}_t^{nik} \lambda_{t-h}^{nik} \hat{X}_t^{nk} X_{t-h}^{nk}}{(\widehat{1+\kappa_t^{nik}})(1+\kappa_{t-h}^{nik})} \right) + D^n}{W_{t-h}^n L^n + R_{t-h}^n H^n + \sum_k \sum_i \left(\frac{\kappa_t^{nik} \lambda_t^{nik} X_t^{nk}}{1+\kappa_t^{nik}} \right) + D^n} \tag{39}$$

$$\hat{\pi}_t^{L,nj} \pi_{t-h}^{L,nj} \hat{W}_t^n W_{t-h}^n L^n = \gamma^{nj} (1-\xi^{nj}) \sum_i \frac{\hat{\lambda}_t^{inj} \lambda_{t-h}^{inj} \hat{X}_t^{ij} X_{t-h}^{ij}}{(\widehat{1+\kappa_t^{inj}})(1+\kappa_{t-h}^{inj})} \tag{40}$$

$$\hat{\pi}_t^{H,nj} \pi_{t-h}^{H,nj} \hat{R}_t^n R_{t-h}^n H^n = \gamma^{nj} \xi^{nj} \sum_i \frac{\hat{\lambda}_t^{inj} \lambda_{t-h}^{inj} \hat{X}_t^{ij} X_{t-h}^{ij}}{(\widehat{1+\kappa_t^{inj}})(1+\kappa_{t-h}^{inj})} \tag{41}$$

We solve Equations 28 to 41 starting with an initial guess in each endogenous variable such that $\hat{x} = 1$ (pinned down by $\{\hat{w}_t^{nj}, \hat{r}_t^{nj}\} = 1$), updating our guess until the algorithm has converged to an equilibrium. With the relative changes in endogenous variables $\{\hat{I}_t^n, \hat{P}_t^{nj}\}$, the change in welfare for country n is:

$$\hat{U}_t^n = \frac{\hat{I}_t^n}{\prod_j (\hat{P}_t^{nj})^{\beta^{nj}}} \tag{42}$$

4.2 Data

Our data includes 69 countries and a rest of the world bloc, and 45 sectors (of which 22 are non-tradable) from 2000 to 2020.[17] We obtain bilateral trade shares λ_t^{nij} and gross output X_t^{nj} from the OECD's Inter-country Input-Output Tables (ICIO). Data on total labor income by country $W_t^n L^n$ and labor income share by goods sector in each country $\pi_t^{L,nj}$ come directly from the UN Industrial Development Organization (UNIDO). We define local factors income as value added minus labor income to obtain $R_t^n H^n$ and $\pi_t^{H,nj}$. Bilateral tariff data κ_t^{inj} come from the World Bank's World Integrated Trade Solution (WITS) database, complemented with the MAcMap-HS6-CEPII dataset, and adjusted to account for additional retaliatory tariffs following Fajgelbaum et al. (2024).

4.3 Calibration

4.3.1 Trade Elasticities $\theta^{I,j}$ and Stickiness in Import-Exporter Contracting α^j

We jointly estimate the dispersion parameter $\theta^{I,j}$ for production efficiency and the importer-exporter stickiness parameter α^j for each good j, building on Caliendo and Parro (2015).[18]

Consider three countries indexed by n, i, and h. Take the crossproduct of good j shipped in one direction between the three countries, from n to i, from i to h, and from h to n, and

[17] All years are used for the estimation of parameters. 2019 data is used to calibrate the initial steady state to avoid distortions from the pandemic in 2020.

[18] While exploring the more granular nature of trade data could help address the potential aggregation bias (e.g., Imbs and Mejean (2015)) or even allow for the identification of high concentration levels within more detailed segments of production networks, it would require additional assumptions to reconcile sector-level output data with product-level classifications.

then the cross-product of the same goods shipped in the other direction, from n to h, from h to i; and from i to n: Using Equations 16 and 17 and we can calculate each expression and then take the ratio:

$$\frac{\lambda_t^{nij}\lambda_t^{ihj}\lambda_t^{hnj}}{\lambda_t^{nhj}\lambda_t^{hij}\lambda_t^{inj}} = \prod_{k=0}^{K-1}\left(\frac{\tilde{\tau}_{t-k}^{nij}\tilde{\tau}_{t-k}^{ihj}\tilde{\tau}_{t-k}^{hnj}}{\tilde{\tau}_{t-k}^{nhj}\tilde{\tau}_{t-k}^{hij}\tilde{\tau}_{t-k}^{inj}}\right)^{-\theta^{I,j}(1-\alpha^j)^k\alpha^j}\left(\frac{\lambda_{t-K}^{nij}\lambda_{t-K}^{ihj}\lambda_{t-K}^{hnj}}{\lambda_{t-K}^{nhj}\lambda_{t-K}^{hij}\lambda_{t-K}^{inj}}\right)^{(1-\alpha^j)^K} \tag{43}$$

where $\tilde{\tau}_t^{nij} = 1 + \tau_t^{nij} = (1 + d_t^{nij})(1 + \kappa_t^{nij})$

All the terms involving prices and parameters are canceled out and we end up with a relation between bilateral trade shares and trade costs. Trade depends on costs not only in period t but also in previous periods, due to stickiness in exporter-importer contracting.

We model non-tariff trade costs as $\log(1 + d_t^{nij}) = \nu_t^{nij} + \phi_t^{nj} + \psi_t^{ij} + \epsilon_t^{nij}$

where $\nu^{nij} = \nu^{inj}$ captures symmetric bilateral trade costs like distance, language, and common border. ϕ_t^{nj} and ψ^{ij} captures an importer-good and exporter-good fixed effects. ϵ^{nij} is a random disturbance term that represents remoteness deviation from symmetry and is assumed to be orthogonal to tariffs.

We can rewrite Equation 43 as

$$\log\left(\frac{\lambda_t^{nij}\lambda_t^{ihj}\lambda_t^{hnj}}{\lambda_t^{nhj}\lambda_t^{hij}\lambda_t^{inj}}\right) = \sum_{k=0}^{K-1} -\theta^{I,j}(1-\alpha^j)^k\alpha^j \log\left(\frac{\tilde{\kappa}_{t-k}^{nij}\tilde{\kappa}_{t-k}^{ihj}\tilde{\kappa}_{t-k}^{hnj}}{\tilde{\kappa}_{t-k}^{nhj}\tilde{\kappa}_{t-k}^{hij}\tilde{\kappa}_{t-k}^{inj}}\right) + (1-\alpha^j)^K \log\left(\frac{\lambda_{t-K}^{nij}\lambda_{t-K}^{ihj}\lambda_{t-K}^{hnj}}{\lambda_{t-K}^{nhj}\lambda_{t-K}^{hij}\lambda_{t-K}^{inj}}\right) + \tilde{\epsilon}_t^{nih,j} \tag{44}$$

where $\tilde{\epsilon}_t^{nih,j} = \sum_{k=0}^{K-1} \epsilon_{t-k}^{nij} - \epsilon_{t-k}^{nij} + \epsilon_{t-k}^{nij} - \epsilon_{t-k}^{nij} + \epsilon_{t-k}^{nij} - \epsilon_{t-k}^{nij}$ and $\tilde{\kappa}_t^{nij} = (1 + \kappa_t^{nij})$. All the symmetric and asymmetric components of the iceberg trade costs cancel out.

Using data from 2010 to 2019, for each product j we estimate the following equation:

$$\log\left(\frac{\lambda_t^{nij}\lambda_t^{ihj}\lambda_t^{hnj}}{\lambda_t^{nhj}\lambda_t^{hij}\lambda_t^{inj}}\right) = \beta_1^j \log\left(\frac{\tilde{\kappa}_t^{nij}\tilde{\kappa}_t^{ihj}\tilde{\kappa}_t^{hnj}}{\tilde{\kappa}_t^{nhj}\tilde{\kappa}_t^{hij}\tilde{\kappa}_t^{inj}}\right) + \beta_2^j \log\left(\frac{\tilde{\kappa}_{t-1}^{nij}\tilde{\kappa}_{t-1}^{ihj}\tilde{\kappa}_{t-1}^{hnj}}{\tilde{\kappa}_{t-1}^{nhj}\tilde{\kappa}_{t-1}^{hij}\tilde{\kappa}_{t-1}^{inj}}\right) + \beta_3^j \log\left(\frac{\tilde{\kappa}_{t-2}^{nij}\tilde{\kappa}_{t-2}^{ihj}\tilde{\kappa}_{t-2}^{hnj}}{\tilde{\kappa}_{t-2}^{nhj}\tilde{\kappa}_{t-2}^{hij}\tilde{\kappa}_{t-2}^{inj}}\right) + \Psi_t + \varepsilon_t^{nih,j} \tag{45}$$

$\varepsilon_t^{nih,j}$ includes $\tilde{\epsilon}_t^{nj}$ and tariffs in all years before $t-2$. Note that as $K \to \infty$, $(1-\alpha^j)^K \to 0$.

We assume $\tilde{\epsilon}_t^{nj}$ is orthogonal to tariffs as in Caliendo and Parro (2015). Tariffs before $t-2$ are orthogonal to tariffs in year t and $t-1$ conditional on tariffs in year $t-2$. Thus, our estimates of $\hat{\beta}_1^j$ and $\hat{\beta}_2^j$ which pin down estimates of $\hat{\alpha}^j$ and $\hat{\theta}^{I,j}$ are unbiased.

$$\hat{\alpha}^j = 1 - \frac{\hat{\beta}_2^j}{\hat{\beta}_1^j} \tag{46}$$

$$\hat{\theta}^{I,j} = \frac{\hat{\beta}_1^j}{\hat{\alpha}^j} \tag{47}$$

Results. Our estimates of the dispersion parameter $\theta^{I,j}$ by good are reported in Table 1. The elasticities range from 1.7 to 13.2. This heterogeneity was confirmed by being able to reject the null hypothesis of common estimates. Our estimates are also in the range of the trade elasticities estimated in the broader literature.[19] In Figure 4a, we show that our estimates are correlated with that of Caliendo and Parro (2015).

Table 1 also presents our estimates of the importer-exporter stickiness parameter α^j for each good. α^j ranges from 0.69 to 0.99. A larger α^j implies less stickiness, in that importers of good j can more quickly switch the country from which they import following a shock. In Figure 4b and Table 2, we show that our estimates are correlated with Martin, Mejean, and Parenti (2023)'s measure of relationship stickiness.[20] Table 2 shows that our importer-exporter stickiness parameter is negatively correlated with measures of product specificity and complexity used in the literature. Differentiated products tend to be more sticky, as shown by the negative correlation with the classification of differentiated products from Rauch (1999). More complex goods also involve more stickiness, as shown by the negative correlation of α^j with both the measures from Nunn (2007) and Hausmann and Hidalgo (2014). Our importer-exporter stickiness parameters imply that long-run trade elasticities

[19]Eaton and Kortum (2002) estimates trade elasticities for the manufacturing sector as a whole using data from 1990, ranging between 3.60 and 12.86, and with their preferred estimate being 8.28. Simonovska and Waugh (2014) find values between 2.79 and 4.46, while Antras, Fort, and Tintelnot (2017) report the estimate of 1.789.

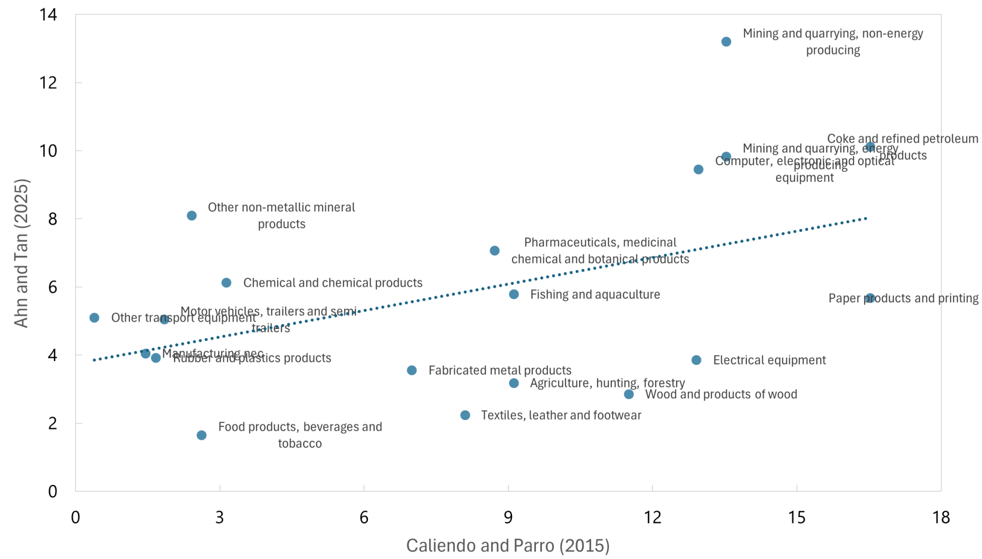
[20]Martin, Mejean, and Parenti (2023)'s measure of relationship stickiness is grounded in a search model and estimated using exporting firm level data from France.

Table 1: Trade Elasticities $\theta^{I,j}$ and Stickiness in Import-Exporter Contracting α^j

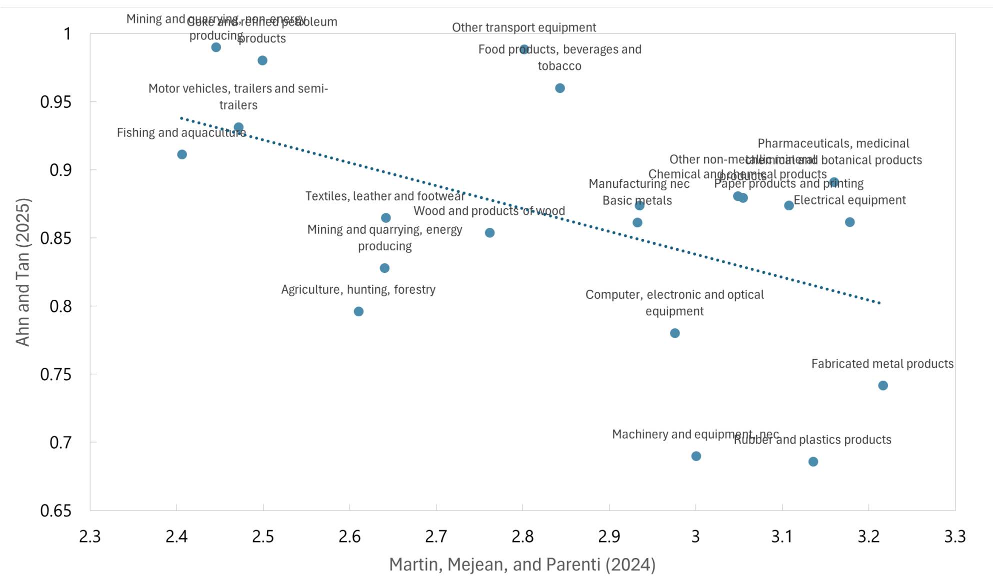
Good	$\theta^{I,j}$	α^j
Agriculture, hunting, forestry	3.19	0.80
Fishing and aquaculture	5.79	0.91
Mining and quarrying, energy producing products	9.83	0.83
Mining and quarrying, non-energy producing products	13.20	0.99
Food products, beverages and tobacco	1.66	0.96
Textiles, textile products, leather and footwear	2.24	0.86
Wood and products of wood and cork	2.86	0.85
Paper products and printing	5.68	0.87
Coke and refined petroleum products	10.11	0.98
Chemical and chemical products	6.13	0.88
Pharmaceuticals, medicinal chemical and botanical products	7.07	0.89
Rubber and plastics products	3.92	0.69
Other non-metallic mineral products	8.10	0.88
Basic metals	9.11	0.86
Fabricated metal products	3.56	0.74
Computer, electronic and optical equipment	9.46	0.78
Electrical equipment	3.86	0.86
Machinery and equipment, nec	9.74	0.69
Motor vehicles, trailers and semi-trailers	5.04	0.93
Other transport equipment	5.10	0.73
Manufacturing nec; repair and installation of machinery and equipment	4.05	0.87

Notes: This table presents estimates of trade elasticities $\theta^{I,j}$ and importer-exporter stickiness α^j using Equations 46 and 47, following the methodology outlined in Section 4.3.1.

Figure 4: Comparison of $\theta^{I,j}$ and α^j to the Literature



(a) Trade Elasticities $\theta^{I,j}$: Comparison with Caliendo and Parro (2025)



(b) Importer-Exporter Stickiness α^j: Comparison with Martin, Mejean, and Parenti (2024)

Notes: This figure presents scatter plots of trade elasticities from this paper and Caliendo and Parro (2015), and this paper's measure of importer-exporter stickiness α^j *and Martin, Mejean, and Parenti (2023)'s measure of relationship stickiness.*

stabilize after up to around 5 years, consistent with Christoph E. Boehm, Levchenko, and Pandalai-Nayar (2023).

Table 2: Correlates of Stickiness in Import-Exporter Contracting

	Dependent variable: α^j			
	(1)	(2)	(3)	(4)
Relationship Stickiness (Martin et al.)	-0.018^{***}			
	(0.002)			
Product complexity (Haussman & Hidalgo)		-0.006^{***}		
		(0.001)		
Differentiated (Rauch)			-0.033^{***}	
			(0.002)	
Share of not homogen. products (Nunn)				-0.165^{***}
				(0.007)
Observations	3,464	3,182	3,282	2,994
R^2	0.018	0.011	0.067	0.161

*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents regression estimates of importer-exporter stickiness α^j *on Martin, Mejean, and Parenti (2023)'s measure of relationship stickiness in column (1), Hausmann and Hidalgo (2014)'s measure of product complexity in column (2), Rauch (1999)'s indicator for differentiated products in column (3) and Nunn (2007)'s measure of product specificity in column (4). Each observation is a HS6 product.*

4.3.2 Labor Mobility $\theta^{L,j}$ and Speed of Re-skilling δ^L

We can rewrite Equation 6 and 8 to relate equilibrium changes in sectoral labor supply to changes in sectoral wages over horizon h. Denote by Δ_h a time difference in a variable between periods $t-1$ and $t+h$.

$$\Delta_h \log \pi_t^{L,nj} = (\theta^{L,n} + h\delta^L)\Delta_h \log w_t^{nj} - \Delta_h \log(\sum_k T_t^{L,nk}(w_t^{nk})^{\theta^{L,n}}) \tag{48}$$

We estimate the following equation using two-stage least squares.

$$\Delta_h \log \pi_t^{L,nj} = \beta_h \Delta_h \log w_t^{nj} + X_{njt} + \phi_{nt} + \psi_{jt} + \varphi_{nj} + \varepsilon_{njt} \tag{49}$$

where ϕ_{nt}, ψ_{jt}, φ_{nj} denote country-year, sector-year and country-sector fixed effects, respectively, and ε_{njt} is an error term. Note that the fixed effects absorb $\Delta_h \log(\sum_m T_t^{L,nm}(w_t^{nm})^{\theta^{L,n}})$. X_{njt} is a vector of controls that includes lagged sectoral wage changes ($\Delta \log w_{t-k}^{nj}$) to absorb the persistent effects of past wage dynamics.

To account for the simultaneous determination of sectoral labor supply and wages, we instrument sectoral wage changes $\Delta_h \log w_t^{nj}$, with changes in effective sectoral tax rates calculated as the ratio of Taxes less subsidies on products and Output at basic prices. $\hat{\beta}_0$ is our estimate of θ^L the aggregate labor elasticity, and $\hat{\beta}_1 - \hat{\beta}_0$ is our estimate of δ^L.

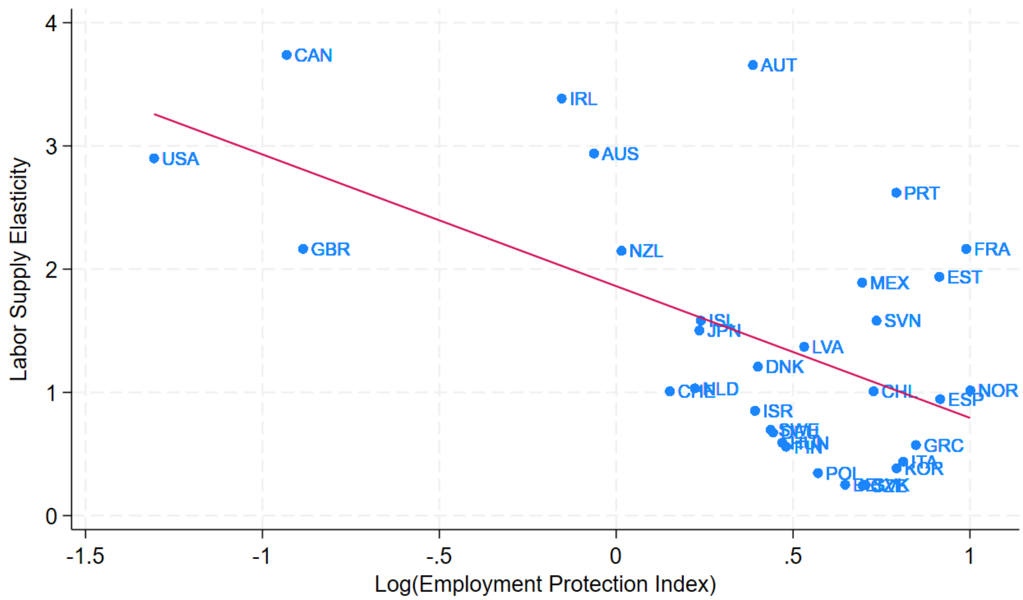
We present our estimates in Column 1 of Table 3. Our estimate of θ^L is 2.5. Existing work estimates θ^L as the Fréchet shape parameter that fits the distribution of the residual log hourly wage computed from household surveys after controlling for occupation dummies, age, and gender (Lee 2020; Hsieh et al. 2019; Burstein, Morales, and Vogel 2019).[21] By using a time-differenced and instrumental variables specification, we address omitted variable bias concerns. Our estimate of δ^L is 0.21 ($= 2.679 - 2.468$). We also verify that our implied estimates of $\theta^L + h\delta^L$ lie within the confidence intervals of the regression estimates $\hat{\beta}_h$ for $h \in [2, 5]$.

For country-specific labor mobility elasticities, we estimate Equation 49 for each country n and $\hat{\beta}_1$ is our estimate of $\theta^{L,n}$. We show in Figure 5 and Table 4, that our country-specific estimates are negatively correlated with the OECD's Employment Protection Legislation (EPL) index which basically measures the degree of labor market rigidity.[22]

[21] Lee (2020) estimates elasticities between 1.05 and 1.47 across countries, Hsieh et al. (2019) estimates are on average 1.42 for the US, and Burstein, Morales, and Vogel (2019)'s average estimate for the US is 1.81 without controlling for time trend and 1.26 with time trend controlled.

[22] For countries with imprecise estimates (s.e. > 10) due to insufficient variation in tax rates, we use an estimate of $\theta^{L,n}$ implied by its level of labor market rigidity for our simulations.

Figure 5: Labor Mobility and Labor Market Rigidity



Notes: This figure presents a scatter plot of estimates of $\theta^{L,n}$ and the log of the OECD's strictness of employment protection index.

Table 3: Calibration of θ^L and δ^L

	Dependent Variable: $\Delta_h \log \pi_t^{L,nj}$				
	(1)	(2)	(3)	(4)	(5)
$\hat{\beta}_0$	2.468***	2.500***	2.580***	2.636***	2.572***
	(0.124)	(0.123)	(0.125)	(0.128)	(0.137)
Observations	6,251	6,251	6,251	6,251	7,048
$\hat{\beta}_1$	2.679***	2.632***	2.722***	2.732***	2.773***
	(0.184)	(0.170)	(0.190)	(0.181)	(0.187)
Observations	5,516	5,537	5,539	5,560	6,243
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Good-Year FE	Yes	Yes	No	No	Yes
Country-Good FE	Yes	No	Yes	No	Yes
$\Delta \log w_{t-2}^{nj}$ Control	Yes	Yes	Yes	Yes	No
$\Delta \log w_{t-1}^{nj}$ Control	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents estimates of Equation 49. All columns include country-year fixed effects. Columns 1 and 2 include good-year fixed effects, Columns 1 and 3 include country-good fixed effects.

4.3.3 Other Parameters

We assume the dispersion parameter for local factors efficiency $\theta^{H,n} = 7$ as in Tintelnot (2017), and a depreciation rate of $\delta^H = 0.1$ (based on the BEA's depreciation estimates).[23] Each country's capital and value-added shares ξ^{nj}, γ^{nj} are taken from the UN Industrial Development Organization data. Input-output coefficients γ^{njk} are taken from the OECD Inter-country Input-Output Tables.[24]

We calculate the consumption shares for each country by taking its total expenditure on

[23] https://www.bea.gov/itable/fixed-assets.

[24] Due to computational limitations arising from the dimensionality of solving for wages and rents across N x J sector-country pairs, in the main simulations we assume that materials are used in production, $\gamma^{nj} < 1$; but we zero out the off-diagonal elements of the I-O matrix. Firms can only use materials sourced from the same sector they operate, $\gamma^{njj} = 1 - \gamma^{nj}$. We use I-O tables for each country to calibrate γ^{njj}. In Appendix Figure A2, we show simulation results assuming instead that labor and capital is perfectly mobile $w_t^{nj} = W_t^n$ and $r_t^{nj} = R_t^n$ and to reduce dimensionality while allowing non-zero off-diagonal elements of the I-O matrix to verify that our results are consistent.

Table 4: Labor Mobility and Labor Market Rigidity

	Dependent Variable: $\Delta \log \pi_t^{L,nj}$			
	(1)	(2)	(3)	(4)
$\Delta \log w_t^{nj}$	2.033***	2.005***	2.272***	2.261***
	(0.132)	(0.126)	(0.157)	(0.153)
$\Delta \log w_t^{nj} * \log$(Employment Protection Index)	-0.518***	-0.474***	-0.514***	-0.461***
	(0.149)	(0.144)	(0.169)	(0.167)
Country-Year FE	Yes	Yes	Yes	Yes
Good-Year FE	Yes	Yes	No	No
Country-Good FE	Yes	No	Yes	No
Observations	4,429	4,429	4,429	4,429

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents estimates of the log changes in labor share regressed on the log changes in wages interacted with the log of the OECD's Employment Protection Strictness Index. All columns include country-year fixed effects. Columns 1 and 2 include good-year fixed effects, Columns 1 and 3 include country-good fixed effects.

good j, subtracting intermediate goods expenditure, and dividing by total final absorption.

$$\beta^{nj} = \frac{X_t^{nj} - \sum_k \gamma^{njk} \sum_i \frac{\lambda_t^{ink} X_t^{ik}}{1+\kappa_t^{ink}}}{W_t^n L^n + R_t^n H^n + \sum_k \sum_i \left(\frac{\kappa_t^{nik} \lambda_t^{nik} X_t^{nk}}{1+\kappa_t^{nik}} \right) + D_t^n} \tag{50}$$

4.4 Fragmentation Scenario

First, we consider the impact of a geopolitical fragmentation scenario on United States welfare with and without diversification policies in place. In this scenario, there is a decoupling between geopolitical blocs centered around the two largest economies—China and the United States – which is likely to be the most economically consequential form of fragmentation. This scenario is based on that from Chapter 4 of the April 2023 IMF World Economic Outlook (International Monetary Fund 2023). The scenario assumes that EU+ and other advanced economies are aligned with the US, India, Indonesia and Latin America and the Caribbean remain nonaligned, while the rest of the world is aligned with China (Table 5). We model rising trade barriers between the two geopolitical blocs as a 50% bilateral non-tariff barrier imposed on the imports from opposing-bloc members.

Table 5: Geopolitical Fragmentation Scenario: Country Alignment

Regions	**Closer to US**	**Closer to China**	**Nonaligned**
1. United States	✓		
2. China		✓	
3. Europe	✓		
4. Other Advanced Economies	✓		
5. India and Indonesia			✓
6. Other Southeast Asia		✓	
7. Latin America & the Caribbean			✓
8. Rest of the World		✓	

Notes: This table presents the country alignments for the fragmentation scenario considered in Section 4.4.

4.4.1 Baseline: No Diversification

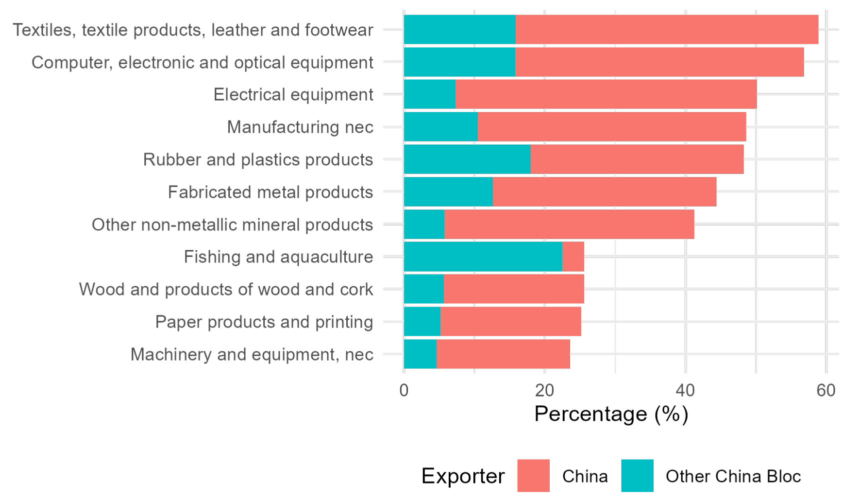
The United States faces significant costs from such a geopolitical fragmentation scenario.

The United States is highly reliant on imports from the China bloc in certain sectors. For instance, for textiles, textile products, leather and footwear, computer, electronic and optical equipment, and electrical equipment over 50 percent of US imports come from the China bloc. Figure 6 lists the good sectors with over 20 percent of US imports from the China bloc.

In response to the fragmentation shock, US supply chains are slow to reconfigure due to frictions in importer-exporter contracting, and in reallocating labor and local factors across sectors. Figure 7a shows how the share of imports from the China bloc evolves over time following the shock. In the first year, the share of imports from the China bloc declines from 25 to 9 percent, but it is not until after 4 years from the shock that the import share reaches a new steady state at 5 percent.

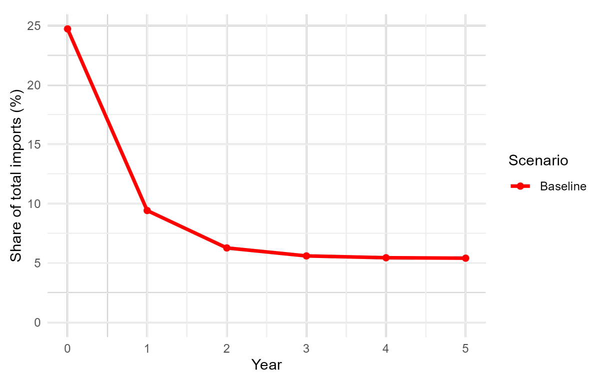
Figure 7b presents the welfare impact on the United States by year following the shock (relative to a no shock scenario). The impact is largest in the first year at a 0.34% decline in welfare. The impact is much smaller in the second year at -0.17%, steadily decreasing until

Figure 6: Share of Imports From China Bloc: Top Industries

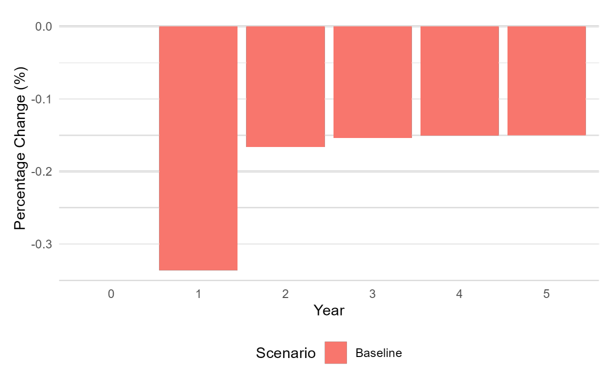


Notes: This figures presents share of imports from the China Bloc for sectors with a share of above 20 percent.

Figure 7: Fragmentation Scenario – Baseline



(a) Impact on China Bloc Imports



(b) Impact on US Welfare

Notes: This figure presents the impact of fragmentation on the share of total imports from the China bloc in (a), and on welfare in panel (b) for the United States.

the long run steady state is reached (once supply chains are fully reoptimized). The long run decline in welfare is 0.15%. For completion, the welfare impact on each country bloc is presented in Figure A1. In line with the findings from Chapter 4 of the April 2024 IMF World Economic Outlook (International Monetary Fund 2023), the welfare impact is larger for the China bloc, than for the US, and those who are nonaligned benefit.

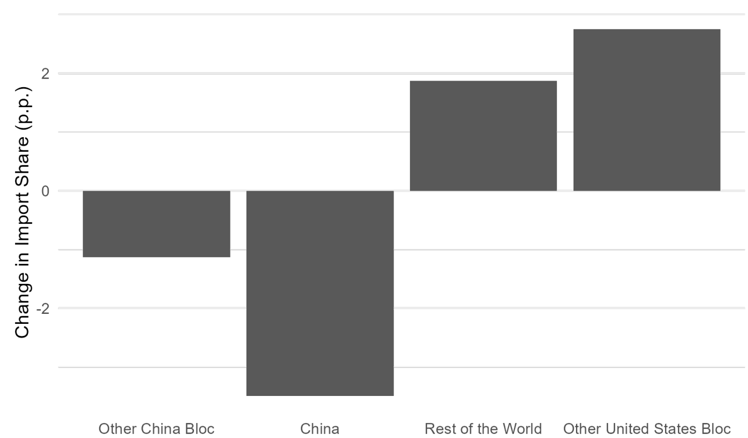
4.4.2 Diversification

Next, we consider the impact of diversification. We assume that the United States diversifies its imports of select goods—those with more than one-third sourced from the China bloc—away from that bloc, in anticipation of a potential geopolitical fragmentation shock. We assume that the share of imports from China and the rest of the China bloc decline by 3.5 p.p. and 1.1 p.p. respectively, while the share of imports from others in the US bloc and the rest of the world increase by 2.8 p.p. and 1.9 p.p. respectively (see Figure 8). The assumed diversified trade shares result from a simulated 10% increase in trade costs between the United States and the China Bloc for goods with an import share from the other bloc greater than one-third.

Since US imports are less reliant on the China bloc, its supply chains are less exposed to the shock and closer in configuration to what is optimal post-fragmentation. Figure 9a presents how the share of imports from the China bloc evolves over time following the shock with greater diversification compared to the baseline. The share of imports from the China bloc is lower and closer to the optimal long-run steady-state share in all years following the shock. This is because it starts from a lower (less concentrated) level before fragmentation.

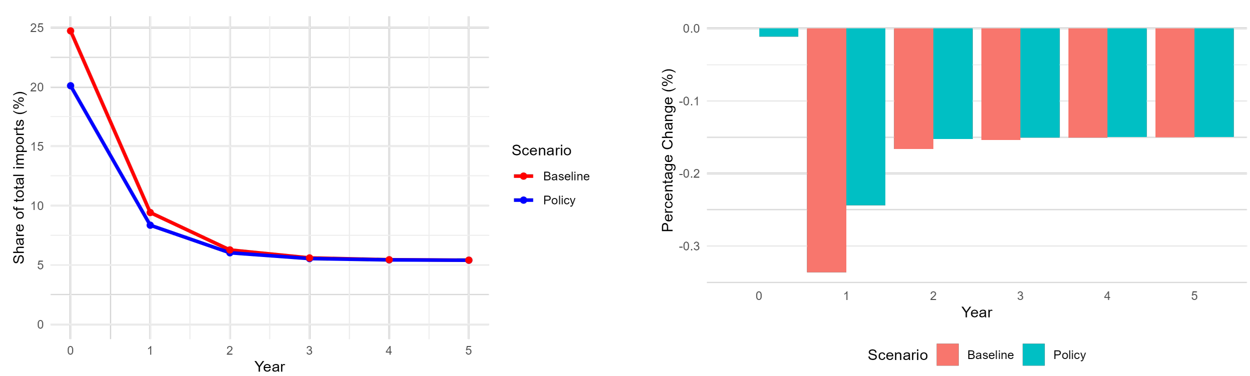
As a result, the transition losses from supply chain rigidity are reduced and the negative welfare impact from fragmentation is smaller under diversification, as presented in Figure 9b. The welfare decline with diversification is 0.24 percent in the first year compared to 0.34 percent in the baseline. Cumulatively, the welfare losses over five years are 12 percent smaller with diversification compared to the baseline without diversification. However, there

Figure 8: Diversified Supply Chains Compared to Baseline



Notes: This figure presents the impact of diversification as described in Section 4.4.2 on the share of imports from each country bloc. The diversified trade shares result from a simulated 10% increase in trade costs between the United States and the China Bloc for goods with an import share from the other bloc greater than one-third.

Figure 9: Fragmentation Scenario – Diversification



(a) Impact on China Bloc Imports

(b) Impact on US Welfare

Notes: This figure presents the impact of fragmentation on the share of total imports from the China bloc in (a), and on welfare in panel (b) for the United States under baseline and diversification policies.

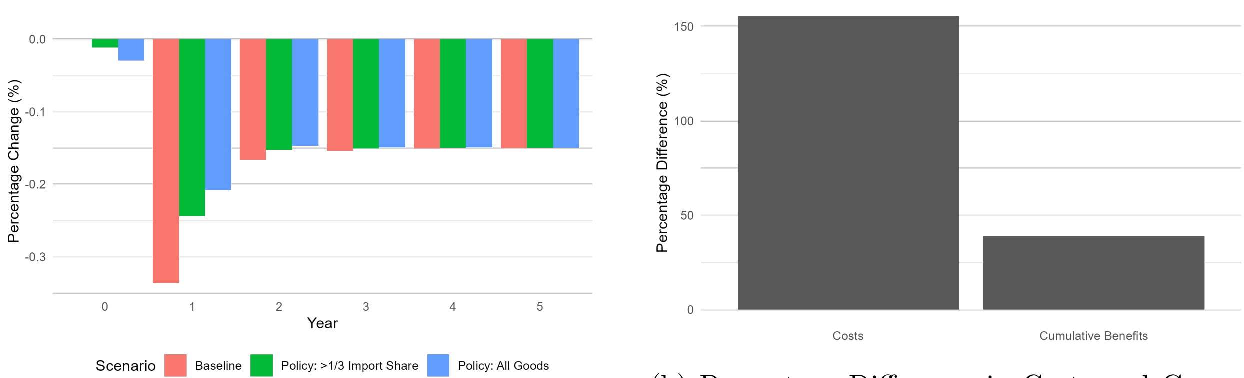
is a cost to diversification since imports are diverted away from the China bloc towards more costly sources. The impact on welfare in the pre-fragmentation shock steady state is a 0.02 percent decline.[25]

4.4.3 Targeting

Targeting diversification towards products with more exposure to shocks, more rigidities, and that are more upstream can improve efficiency.

First, we consider the diversification of all products instead of just products with over a third of import share. Here, we assume diversified trade shares that result from a simulated 10% increase in trade costs between the United States and the China Bloc for all goods. We find that under such diversification the costs are much larger with relatively small gains. Figure 10 presents the results. The costs are 2.5 times larger, while the cumulative benefits are only 40 percent larger.

Figure 10: Diversification of All Products vs Products with Import Share >1/3



(a) Impact on US Welfare

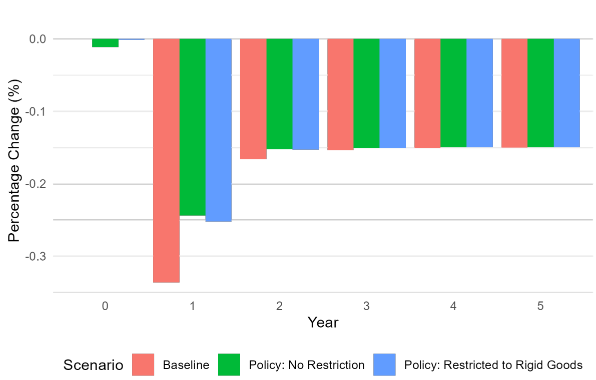
(b) Percentage Difference in Costs and Cumulative Benefits

Notes: This figure presents the impact of fragmentation on welfare for the United States under baseline policies, diversification of all products, and diversification of products with an import share greater than one-third in panel (a). The percentage difference in cost of diversification in year 0 and the cumulative benefits of diversification from year 1 to 5 between diversification of all products versus diversification that targets products with an import share greater than one-third is presented in panel (b).

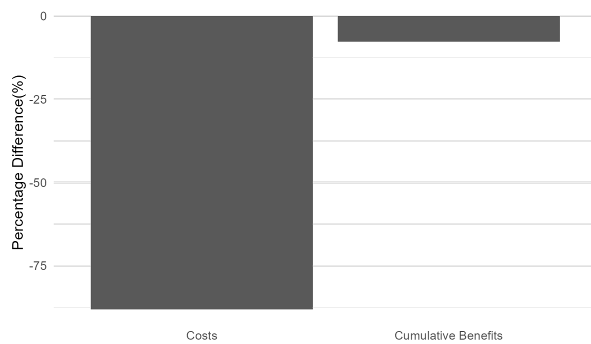
[25]The costs of diversification could be higher if the measures enacted or path taken to achieve diversification introduce fiscal costs or other economic distortions not captured in the model.

Next, we consider diversification restricted to products with greater rigidities in terms of import-exporter contracting stickiness (α^j below the median), among products with over a third of import share. Here, we assume diversified trade shares that result from a simulated 10% increase in trade costs between the United States and the China bloc limited to these products. We find that such diversification is less costly and preserves much of the benefits. Figure 11 presents the results. The costs are 88 percent smaller, while the cumulative benefits are only 8 percent smaller.

Figure 11: Restricting Diversification to Products with High Rigidity



(a) Impact on US Welfare



(b) Percentage Difference in Costs and Cumulative Benefits

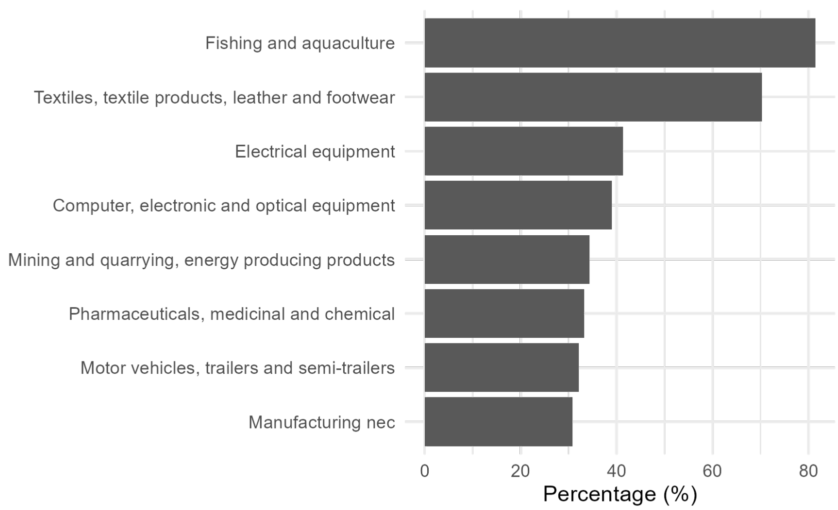
Notes: This figure presents the impact of fragmentation on welfare for the United States under baseline policies, diversification restricted to products with greater rigidities defined as α^j below the median, and diversification without the further restriction in panel (a). The percentage difference in cost of diversification in year 0 and the cumulative benefits of diversification from year 1 to 5 between diversification which targets products with greater rigidities versus diversification that does not is presented in panel (b).

Last, Figure A2b also shows that targeting more upstream products (above the median following the measure proposed by Antràs, Chor, et al. (2012)) also significantly reduces the costs of diversification while preserving a large share of the benefits. The costs are 57 percent smaller, while the cumulative benefits are only 34 percent smaller.

4.5 Global Tariff Scenario

Next, we consider the impact of a uniform broad-based tariff on all United States imports following the scenario in Costinot and Rodríguez-Clare (2014). We model the shock as a 40% tariff imposed on all trade with retaliation. We find that the implications of such a shock are large. Imports make up about 10 percent of US expenditures. This is particularly high for certain goods such as fishing and aquaculture, and textiles, textile products, leather and footwear. Figure 12 presents the goods sectors with the highest import shares.

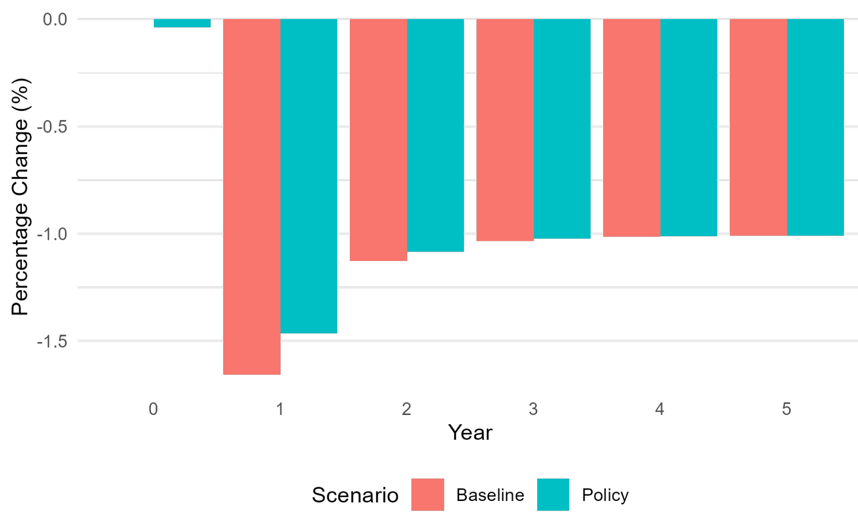
Figure 12: Import Share of Total Expenditure: Top Industries



Notes: This figure presents share of total expenditure that is imported for the US by industry, including only industries with a share greater than 30 percent.

Figure 13 presents the impact on US welfare by year following the shock (relative to a no shock scenario) with and without diversification in place. We assume diversified (or re-shored) trade shares that result from a simulated 10% increase in trade costs between the United States and all other countries restricted to goods with high rigidities (α^j below the median). Diversification re-shores 15 percent of imports with high rigidities, but this has a small negative impact on welfare (-0.04 percent) as producing domestically is more costly than importing from abroad. However, following the global tariff shock, the welfare losses are 12 percent smaller in the first year (-1.66 percent without diversification and -1.46 percent with diversification) and 4 percent smaller in second year. The cumulative welfare losses over five years are 5 percent smaller with diversification.

Figure 13: Global Tariff Scenario



Notes: This figure presents the impact of the global tariff shock scenario on US welfare.

5 Conclusion

This paper explores the resilience-efficiency tradeoff by assessing the extent to which diversified supply chains mitigate the impact of trade shocks at the cost of efficiency.

We establish three stylized facts on the impact of diversification on supply chain resilience, focusing on US imports. First, we show that concentrated supply chains are more exposed to exporter-specific supply shocks. Second, we present that imports are less sensitive to trade costs when the supply chain is diversified. Last, using an event study design, we demonstrate that sectors with diversified supply chains exhibited greater resilience to the 2018-2019 tariffs on Chinese imports.

We develop a new multi-country and multi-sector general equilibrium trade model to analyze the impact of diversification on resilience and expected welfare given various risk scenarios. The model incorporates trade network rigidities arising from frictions in goods, labor, and local factor markets. Supply chain diversification can enhance resilience and improve expected welfare by reducing the transition losses associated with trade network rigidities. However, there is a trade-off between the cost of diversification and resilience. Simulations indicate that diversifying the sources of targeted imports—those more exposed to shocks, positioned upstream in the supply chain, and subject to greater rigidities—can enhance expected welfare when the probability of a large trade shock is sufficiently high. In future work, we aim to leverage our model to study the design and implications of optimal diversification policy.

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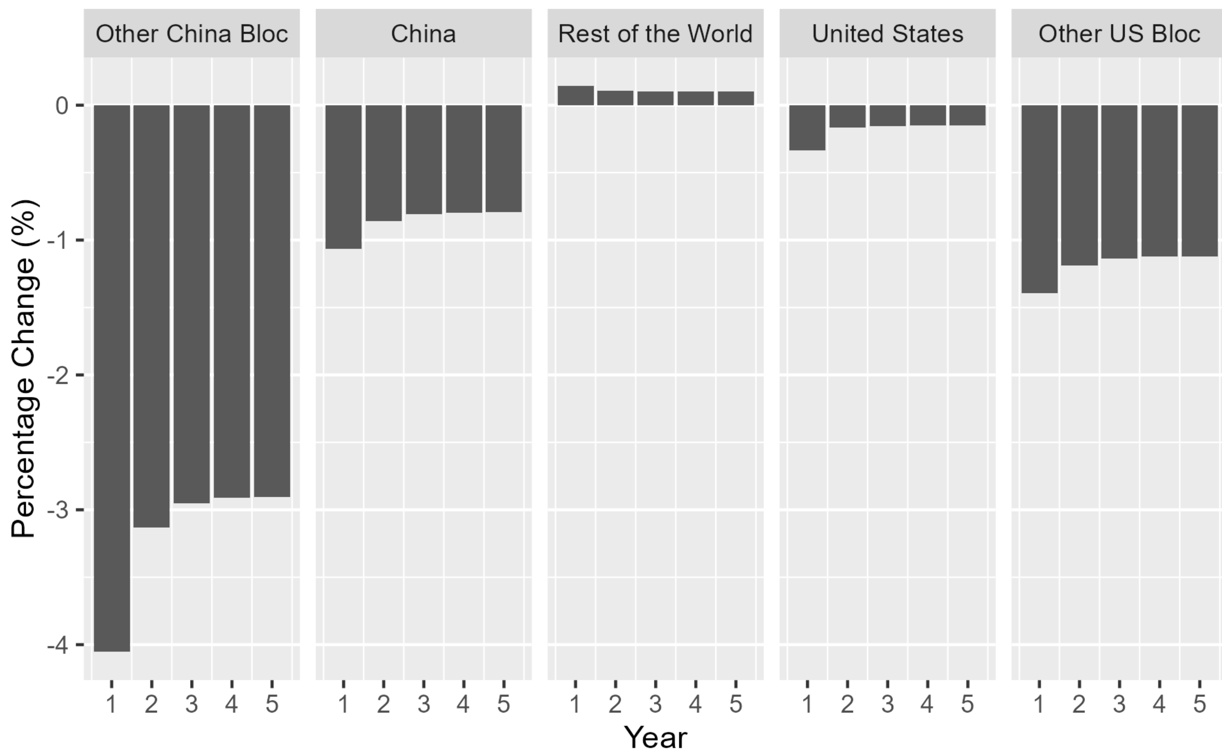
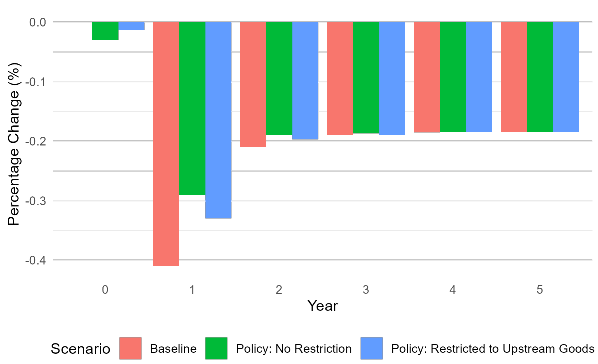
Appendix A. Tables and Figures

Figure A1: Fragmentation Shock – Baseline: Impact on Welfare (All Blocs)

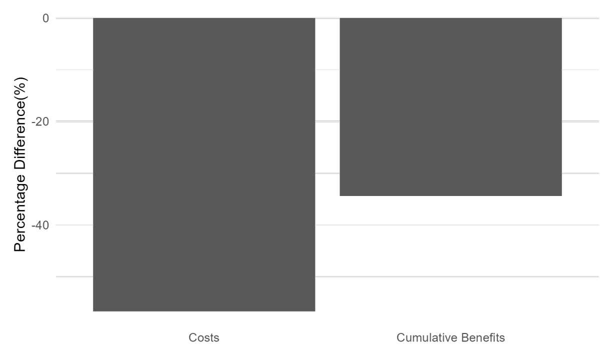


Notes: This figure presents the impact of the fragmentation scenario on welfare by country bloc.

Figure A2: Targeting Upstream Products - Model with Perfectly Mobile Labor and Capital and Input-output Linkages (Fragmentation Scenario)



(a) Impact on US Welfare



(b) Percentage Difference in Costs and Cumulative Benefits

Notes: This figure presents the impact of fragmentation on welfare for the United States under under baseline policies, diversification on all goods with over 1/3 import share, and diversification restricted to upstream good with over 1/3 import share in panel (a). The percentage difference in cost of diversification in year 0 and the cumulative benefits of diversification from year 1 to 5 between diversification which targets upstream products versus diversification that does not is presented in panel (b).

Appendix B. Data Description

This appendix provides details on the datasets used for the main quantitative exercises presented in Section 4 as well as the procedures used to construct them.

B.1. Sector-level Gross Output and Bilateral Trade

We employ the global input-output data from the OECD's Inter-country Input-Output Tables (ICIO) database to obtain information on sector-level bilateral trade, gross output, and input-output linkages. The original data maps flows of production, consumption, investment within countries, as well as cross-country flows of goods, broken down by 45 sectors for 76 countries and the rest of the world (ROW) over the period 1995-2020. To ensure compatibility with other datasets described below, we restrict the sample to 69 countries plus ROW and shorten the time span to 2000–2020.

B.2. Sector-level Labor and Capital Income Shares

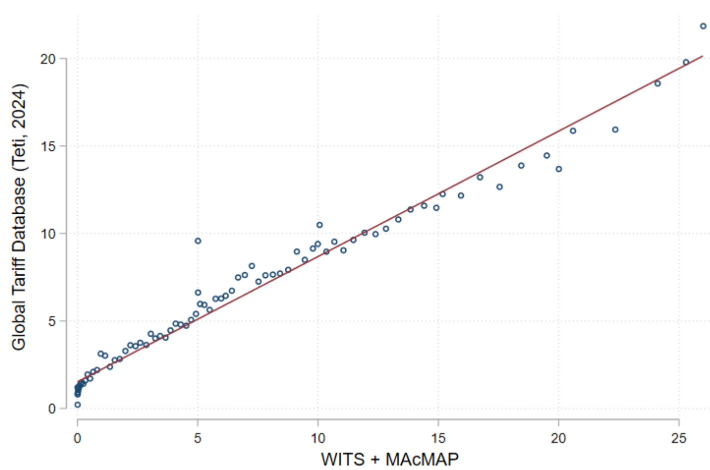
We use the UNIDO INDSTAT4 data from the UNIDO Industrial Statistics (INDSTAT) Revision 4 Database to construct sector-level labor and capital income shares. The data follow the ISIC Rev.4 sector classification, which we map to the 45 sectors in the OECD ICIO through the two-digit ISIC Rev.4 codes. Information on labor compensation is available for 69 of the original 76 countries in the OECD ICIO database, starting from the year 2000. Sector-level capital income share is calculated as the residual of sectoral value added after subtracting labor compensation.

B.3. Sector-level Bilateral Tariff

The primary source of bilateral tariff data is the UNCTAD TRAINS available from WITS, complemented with the MAcMap-HS6 dataset available at CEPII, and further adjusted to account for additional retaliatory tariffs following Fajgelbaum et al. (2024).

Specifically, we employ bilateral tariff data at the 6-digit Harmonized System (HS6) level from the WITS data with average tariff rates applied to bilateral country pairs at the HS6 level. To account for missing observations and potential measurement errors in the database, we undertake several procedures. First, we apply zero tariff rates to intra-EU trade and fill in missing rates among EU importers using common EU-wide rates. Second, for observations with missing tariff data, we apply the latest available bilateral tariff rates, and for any remaining missing values, we replace them with the closest available future tariff rates. Third, we merge the data with the MAcMap-HS6-CEPII database—which is interpolated for missing years—and retain the lower of the two values, likely better reflecting effectively applied rates. Finally, we use the concordance between HS6 and ISIC Rev.4 classifications to construct bilateral tariff rate data at the 45-sector level of the OECD ICIO. The resulting tariff data are consistent at the aggregate level with the Global Tariff Database from Teti (2024), which revamps the WITS data through a close examination (Figure A3).

Figure A3: Aggregate Weighted Average Bilateral Effective Tariff Rates



Notes: This figure presents a binned scatter plot illustrating the relationship between weighted average bilateral effective tariff rates from two distinct sources at the aggregate level for the year 2017. The values on the x-axis are calculated by combining the WITS and MAcMap databases, as described in the text, while those on the y-axis are taken from the Global Tariff Database in Teti (2024).