

Playing with blocs: Quantifying decoupling*

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Abstract

We adopt a data-driven approach to measure trade fragmentation over the period 2015-2023. Countries are classified into three groups according to changes in their trade costs with the US and China: those shifting toward the US bloc, those shifting toward the China bloc, and those with no change in alignment. Roughly one-quarter of countries moved toward each bloc, while about half showed no realignment. We document while cross-bloc trade costs rose, they were accompanied by falling within-bloc trade costs. We use a quantitative model to compute the real income effects of this reconfiguration of the global trade costs. The median country in the world, and the median country within each bloc, has 0.4-0.6% *higher* real income as a result of the observed decoupling, contrary to the widespread belief that fragmentation has been welfare-reducing. Finally, we find a modest amount of bloc misalignment: the median country moving to the US bloc would actually be better off moving to the China bloc, and vice versa. These results suggest that trade decoupling does not always follow trade-driven economic interests.

Keywords: decoupling, fragmentation, global value chains

JEL Codes: F41, F44, F62, L16

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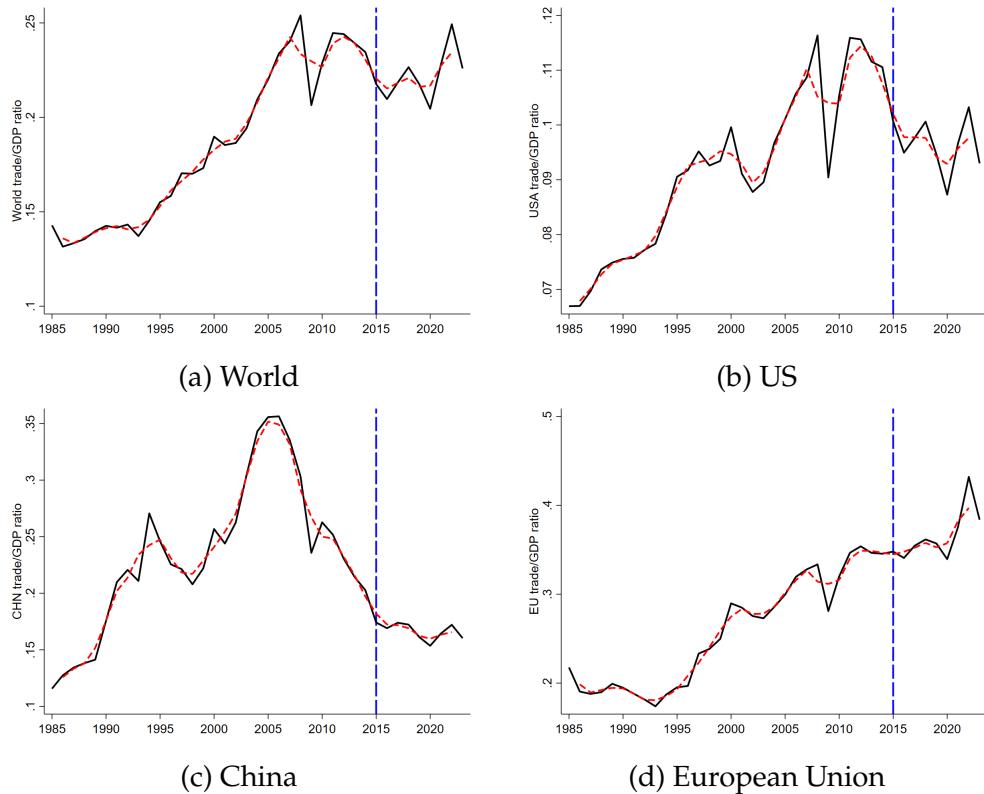
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1. INTRODUCTION

After a long era of ever-increasing globalization, in the past decade the world entered a period of substantial headwinds to economic integration, punctuated by Brexit, the US-China trade war, and the rupture of economic relations between the West and Russia. It is now common to wonder whether these events mark the onset of “deglobalization.”

However, world trade relative to economic activity has not fallen since the onset of these shocks. Figure 1(a) plots the evolution of world goods trade to GDP from 1985 to 2023, with the vertical line at 2015, the year prior to the Brexit vote in the UK and the Trump victory in the US. Since that year, world trade has remained resilient; in fact it partly reversed the downward trend that started in 2009. Even more strikingly, the trade-GDP ratio did not fall even for the large economies at the center of the policy-induced trade disruptions: the US, China, and the EU, as displayed in panels (b)-(d) of Figure 1. Even the main parties to the trade conflicts did not experience a discernible fall in total trade.

Figure 1: Trade/GDP Ratios



Notes: Solid line denotes the trade-GDP ratio, defined as $\frac{0.5 \times (\text{exports} + \text{imports})}{\text{GDP}}$. Dashed line denotes the 3-year moving average of the trade-GDP ratio. Vertical line denotes the beginning of the US-China trade war.

Sources: DOTS, WEO.

The proximate explanation is that even as countries in trade conflicts disengaged from each other, they increased trade with other countries. Table 1 confirms this. It reports the changes in bilateral trade in these major economies. Even as trade between the US and China fell, trade between those

Table 1: Change in trade (2015-2023)

\downarrow Exporter Importer \rightarrow	USA	China	EU	ROW
USA		-0.275	0.262	0.015
China	-0.401		0.237	0.137
EU	0.050	-0.066	0.148	-0.014
ROW	0.012	0.047	0.035	0.105
Change in total imports-to-GDP	-0.070	0.005	0.128	0.076

Notes: Table presents the percentage change in the imports-to-GDP ratio from the source economy to the destination economy between 2015 and 2023. Rows represent exporters and columns represent importers. “ROW” denotes rest-of-the-world.

economies and the rest of the world increased. The world economy is experiencing decoupling or fragmentation, rather than deglobalization.

This paper measures decoupling and quantifies its impact on real GDP and income in a large sample of countries.¹ First, we use an entirely data-driven approach to detect fragmentation fault lines in international trade flows and classify countries into trade blocs. Relying on the gravity tradition of measuring trade costs, we project the log changes in bilateral goods trade over the period 2015-2023 on multilateral resistance (as captured by importer and exporter fixed effects, which absorb all country-specific demand and supply shocks). The residual from this estimation can be interpreted as the relative change in the bilateral component of trade barriers between pairs of countries. Based on these, we classify countries into 3 groups: moving to the US bloc (henceforth, “US bloc”), moving to the China bloc (henceforth, “China bloc”), and moving to neither (henceforth, “unaligned”). Countries moving to the US bloc are those that experienced a relative fall in trade costs with the US, and a relative rise in trade costs with China. The opposite is true for the countries moving to the China bloc. We classify countries whose trade costs with the US and China changed in the same direction as unaligned.² In the full sample of 187 countries for which bilateral trade data are available, 43 are moving to the US bloc, 46 moving to the China bloc, and the remaining 98 are unaligned.

Next, we assess the aggregate consequences of decoupling in a quantitative multi-country, multi-sector international trade model following [Huo, Levchenko, and Pandalai-Nayar \(2025\)](#), [Bonadio et al. \(2021\)](#), and [Bonadio et al. \(2025\)](#). Starting from the 2015 world economy, we apply the matrix of bilateral trade cost changes that occurred between 2015 and 2023, and compute the resulting changes in real GDP and real incomes. This exercise isolates the changes in trade costs occurring over

¹In the paper, we use decoupling and fragmentation interchangeably to denote policy-induced changes in the sources and destinations of cross-border trade flows, which could be guided by strategic considerations, such as national and economic security, sovereignty, and autonomy.

²We stress that we classify countries into blocs based on the *changes* in their relative trade costs, and not based on their initial bilateral trade *levels*. Therefore, countries with high initial bilateral trade flows with the US might still be classified as moving to the China bloc if their relative trade costs with China fell and those with the US increased over this period. For ease of readability, we still sometimes refer to the “moving to the China bloc” more compactly as the “China bloc”. Also note that we only consider trade linkages, and not other international relationships such as FDI, remittances, technology transfers, or migration policies, among others.

this period from other shocks experienced by the world economy, and individual countries, such as productivity or structural change.³

An important challenge we face is that we cannot use the usual model inversion techniques to recover the changes in trade costs that explain the trade data, because we do not have domestic absorption data for 2023. We also cannot compute the absolute changes in trade costs from the gravity regressions, because they only yield changes in trade costs relative to an omitted im/exporter in the regression. To overcome this challenge, we scale the gravity regression-implied bilateral trade cost changes by a common factor so that the model matches the 2015-23 change in the world trade/GDP ratio depicted in Figure 1(a). This approach allows us to preserve the full heterogeneity in trade cost changes at the country pair level, while matching the world trade trend. We find that the across the board shift in worldwide trade costs required to match the change in world trade/GDP ratio is small: 0.3%.

Our baseline quantitative exercises consider the welfare impacts of the full set of inferred and scaled bilateral trade cost changes. A second set of counterfactuals then decomposes the welfare changes arising purely from the *relative* realignment of countries towards or away from the two blocs, holding the worldwide shift in trade costs at zero.

In the first exercise, we find that the median country experienced a 0.6% real GDP and real income *increase* from the trade cost changes occurring from 2015 to 2023. This holds true even when considering only the relative trade cost changes identified from the gravity regression, leaving out the 0.3% worldwide shift decrease in trade costs. Thus, contrary to conventional wisdom, the decoupling process has not reduced world GDP as a whole thus far. Predictably, the income changes are larger for nonaligned countries (0.8%) than the countries in the US or the China blocs, since those countries do not systematically increase their trade costs with either bloc. But even the countries in the US and China blocs on average experience real income gains from these trade cost changes. The positive impacts of these trade cost changes are in fact quite broad-based: 51 out of 66 countries in the sample experienced real income increases from the observed trade cost changes. The ultimate source of this finding is that global trade has remained quite stable relative to global activity between 2015-23, with the decline in trade flows between some countries (e.g. the US and China) more than offset by increasing trade flows between others. Prima facie, this points to no major increases in average trade barriers, with consequent lack of adverse impact on real GDP on average.

We then explore the consequences of bloc alignment. In particular, for each country we compute the counterfactual changes in real GDP and income that would have occurred had it belonged to a different bloc. We find that the bloc alignment uncovered in the data corresponds poorly to trade-related economic interests. On average, countries in the US bloc would gain from moving to the China bloc, while the China bloc countries would gain from moving to the US bloc. Unaligned countries

³In 2020-2021, the world economy faced several disruptions related to the Covid-19 pandemic, including lockdowns, fiscal stimulus, and high inflation, which are not modeled in the counterfactuals. Appendix C.3 presents the results for the 2015-2019 period only.

would on average lose from joining either bloc. These results suggest that other motives (presumably geopolitically driven) are likely at play in the rewiring of trade flows in recent years. Behind these averages is complete heterogeneity across countries within each bloc: one can find both potential winners and losers from inter-bloc moves.

Related Literature. This paper contributes to several fast-growing strands of literature. A number of studies have examined the causes and consequences of recent policies that have heralded greater inward orientation by major advanced economies, such as the US increase in tariffs of Chinese imports (e.g. [Fajgelbaum et al., 2024](#); [Amiti, Redding, and Weinstein, 2019](#)) or Brexit (e.g. [Dhingra and Sampson, 2022](#); [Sampson, 2017](#)). These papers document the negative consequences of these policies on individual countries, but do not provide a quantitative analysis of the GDP impacts worldwide, which is one of our contributions. While the focus of this literature is primarily on large adverse shocks to trade costs, fostering the narrative of rising barriers to globalization, [Bown, Jung, and Zhang \(2019\)](#) document that trade costs did not uniformly increase in all episodes. In fact, during the US-China trade war, China lowered its most favored nation (MFN) tariffs, effectively decreasing the trade barriers it imposes on the rest of the world, while raising them against the US. Our analysis corroborates the highly heterogeneous patterns of changes in bilateral trade costs across country pairs thus far.

The slowdown in the pace of globalization following the Global Financial Crisis in 2008 has generated debate about whether we are in an era of deglobalization. Recent studies have argued that there is no evidence supporting a deglobalization narrative based on trends in aggregate trade to GDP ratios ([Antràs, 2021](#); [Goldberg and Reed, 2023](#)). [Gopinath et al. \(2025\)](#) also find no evidence of a large decrease in trade flows overall, and patterns more suggestive of fragmentation, with trade between geopolitically distant blocs significantly lower than trade within blocs since Russia's invasion of Ukraine. However, that paper documents that the barriers to trade and FDI have continued to increase in recent years. The reallocation of trade and FDI flows and the lengthening of supply chains is documented by an ever growing number of studies (e.g. [Aiyar et al., 2023](#); [Alfaro and Chor, 2023](#); [Blanga-Gubbay and Rubínová, 2023](#); [Freund et al., 2024, 2023](#)). The existing work on fragmentation and reallocation has focused either on the decoupling between the US and China, or fragmentation of trade between pre-defined blocs of countries. We complement these studies by examining the reallocation of trade flows across all country pairs within the gravity framework to deduce the relative changes in bilateral trade costs from the data and quantify their impact. Our methodology also allows us to identify the set of "unaligned" countries based on observed trade patterns, and examine the correlates of being a "connector" in a systematic manner.

Our paper is also related to the fast-growing literature studying geoeconomics including [Aiyar, Presbitero, and Ruta \(2023\)](#), [Attinasi, Boeckelmann, and Meunier \(2025\)](#), [Bolhuis, Chen, and Kett \(2023\)](#), [Cerdeiro et al. \(2021\)](#), [Clayton, Maggiori, and Schreger \(2023\)](#), [Hakobyan, Meleshchuk, and Zymek \(2023\)](#), and [Javorcik et al. \(2024\)](#). A subset of these papers use quantitative models to study

the economic implications of fragmentation. We contribute to this literature by assigning countries to blocs using revealed trade cost changes, and studying whether countries have optimally selected their blocs, given the choices of the rest of the world.

Finally, our approach to bloc assignment uses revealed trade barriers in a simple gravity equation setting. Several recent papers have alternatively used UN votes to assign countries to blocs ([Bolhuis, Chen, and Kett, 2023](#); [Góes and Bekkers, 2022](#)). We find that UN votes are correlated with our revealed blocs, albeit not perfectly. Other approaches to bloc assignment include treating the US-EU as a bloc, and China-Russia as a bloc (e.g. [Fernández-Villaverde, Mineyama, and Song, 2024](#)).⁴

The rest of the paper is organized as follows. Section 2 describes the data and the classification of countries into blocs. Section 3 lays out the quantitative model and results. Section 4 concludes. Further details on bloc classification, model solution, and alternative exercises are collected in the appendix.

2. DATA, BASIC FACTS, AND BLOC CLASSIFICATION

2.1 Data

The analysis uses data from two main sources. Bilateral trade flows up to 2023 come from the IMF's Direction of Trade Statistics (DOTS). This dataset has the advantage of being quite up to date, with 2023 already available. This is important as some of the most significant fragmentation events, such as the 2022 invasion of Ukraine, are quite recent. In addition, it covers 187 countries. We supplement the bilateral data with nominal GDP data from the IMF World Economic Outlook. Model quantification requires more detailed data on production and input use. The quantitative model and the counterfactual exercises use the OECD's Inter-Country Input-Output (ICIO) tables to calibrate input shares. The sample is thus reduced to 66 countries, listed in Appendix Table A1. Our model implementation employs an aggregation to 22 sectors, listed in Appendix Table A2. We use the 2015 as the initial (pre-shock) period when applying the estimated trade cost changes to the world economy.

2.2 Bloc classification

To classify countries into blocs, we start from the standard gravity equation, log-differenced between 2015 and 2023:

$$\Delta \ln X_{mn} = \delta_m + \delta_n + w_{mn}, \quad (2.1)$$

where $\Delta \ln X_{mn}$ is the log change in exports from country m to country n , δ_m and δ_n are importer and exporter fixed effects, and w_{mn} is the residual. The fixed effects δ_m and δ_n capture the changes in

⁴[Yang and Liu \(2024\)](#) study the evolution of international power arising through trade relationships and find countries build up power in anticipation of future disputes. However they do not relate their measures of power to eventual formation of geopolitical blocs.

exporter and importer multilateral resistance terms. These absorb all the country-specific demand and supply shocks, changes in price indices, and any changes in trade barriers that occur at the importer or exporter (rather than bilateral pair) level. The residual then reflects the change in all bilateral trade barriers – observed and unobserved – between country m and country n , up to the trade elasticity. See, among many others, [Anderson and van Wincoop \(2003, 2004\)](#), [Head and Mayer \(2015\)](#), or [Head and Ries \(2001\)](#) for this type of structural interpretation of the gravity estimates, which is standard in the literature. Notice that, as is standard, we do not disentangle the underlying sources of the changes in observed and unobserved bilateral trade barriers. These could reflect changes in trade costs, preference shifts, changes in bilateral markups, or other bilateral shocks that affect bilateral trade barriers. We choose 2015 as the initial year, as the Brexit vote and the election of Donald Trump in 2016 were the first major events of the decoupling era. We end in 2023 as the Russian invasion of Ukraine happened in 2022. The appendix reports results for 2016-2023, since the first US-China trade war tariffs went into force in 2017.

Having recovered the estimated residual \hat{w}_{mn} from estimating (2.1), we transform it into the change in bilateral trade costs by applying the trade elasticity $1 - \gamma$: $\Delta \ln \tau_{mn} = \hat{w}_{mn}/(1 - \gamma)$. This step is also standard, see e.g. [Head and Mayer \(2015\)](#). As these data do not include domestic trade flows, the residual is interpreted as the change in bilateral trade costs relative to a reference (omitted) country pair, rather than in absolute terms.

Our bloc classification scheme is simple. A country is moving to the US bloc if its average import and export costs with respect to the US fell, and the trade costs with respect to China rose. A country is moving to the China bloc if the opposite is true. Formally:

$$n \in l \text{ bloc if } \frac{1}{2}(\tau_{n,l} + \tau_{l,n}) < 0 \text{ and } \frac{1}{2}(\tau_{n,m} + \tau_{m,n}) > 0; \{l, m\} \in \{\text{USA, China}\}, l \neq m.$$

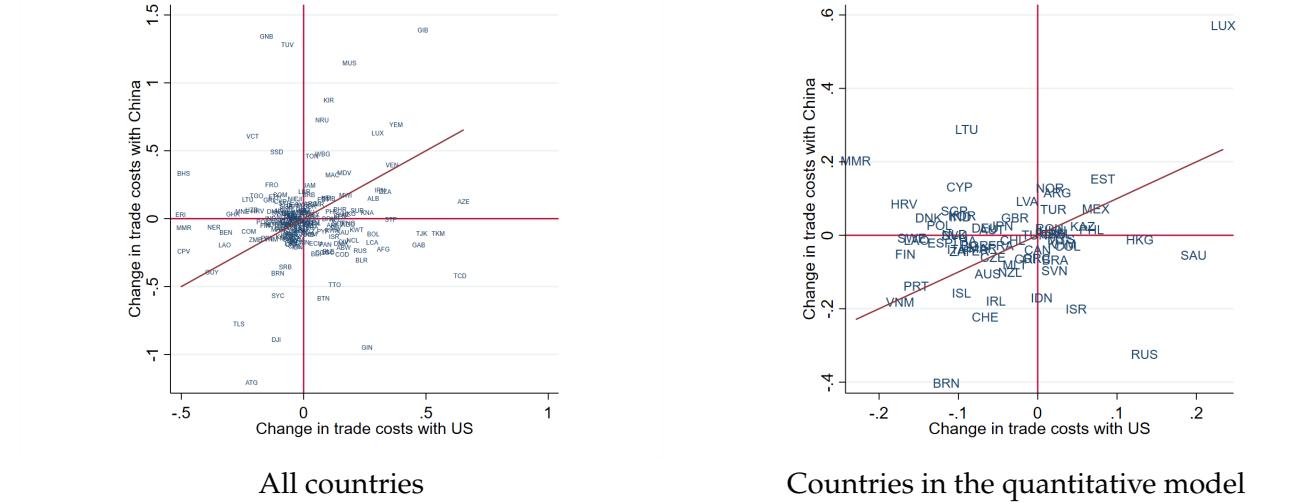
All other countries are unaligned.

Figure 2 illustrates this classification scheme. It displays the changes in trade costs with the US on the horizontal axis and with China on the vertical axis. The left panel displays all countries available in the IMF DOTS dataset, and the right panel retains only countries included in the quantitative model implemented below. The countries in the upper left quadrant are the US bloc, and the countries in the lower right quadrant are the China bloc. The countries in the other quadrants either increased their trade costs with both China and the US, or decreased their trade costs with both. Appendix Table A3 displays the full list of countries in all blocs.

Out of 187 countries, 43 align with the US and 46 with China. The majority of countries (98) remain non-aligned by our metric. Table 2 displays the average trade cost changes across blocs. Focusing on countries included in our quantitative model, Russia, Saudi Arabia, Israel and Hong Kong are clearly aligned with China. Countries in the US bloc are predominantly European, but also include India, Korea, Japan, and Singapore.

We next turn to the quantitative assessment of the global real impact of this cross section of trade

Figure 2: Change in Trade Costs with the US and China (2015-2023)



Notes: The x-axis refers to the change in trade costs with the US, measured as $d \ln \tau_n^{USA} = \frac{1}{2} \left(\frac{1}{1-\gamma} \hat{w}_{n,USA} + \frac{1}{1-\gamma} \hat{w}_{USA,n} \right)$, which is recovered from equation (2.1). Similarly, the y-axis refers to the change in trade costs with China, measured as $d \ln \tau_n^{CHN} = \frac{1}{2} \left(\frac{1}{1-\gamma} \hat{w}_{n,CHN} + \frac{1}{1-\gamma} \hat{w}_{CHN,n} \right)$. The left panel displays all countries for which trade data is available until 2023. The right panel displays the countries included in our quantitative model.

Table 2: Log Change in Average Trade Cost between Blocs (187 countries, 2015-2023)

↓ Exporter Importer →	Bloc USA	Bloc CHN	Unaligned	Overall
Bloc USA	-0.020	0.076	0.006	0.001
Bloc CHN	0.105	-0.043	0.085	0.075
Unaligned	0.013	0.009	0.045	0.025
Overall	0.034	0.031	0.038	0.035

Notes: We classify countries into 3 groups, Bloc USA, Bloc CHN, and Unaligned. Then, all country pairs are classified into 9 group pairs. We report the average $\Delta \ln \tau_{mn}$ for country pairs belonging to each group pair, weighted by bilateral trade flows in 2015. The Overall column is the average $\Delta \ln \tau_{mn}$ of all trade flows from(to) each exporter(importer) group.

cost changes. Since the regression above can only identify relative trade cost changes, an important use of the quantitative model will be to discipline the mean level of trade cost changes.

3. QUANTITATIVE FRAMEWORK

We implement the multi-country multi-sector global production network model of [Huo, Levchenko, and Pandalai-Nayar \(2025\)](#), [Bonadio et al. \(2021\)](#), and [Bonadio et al. \(2025\)](#). This framework enables us to quantify changes in GDP and real income resulting from the observed changes in trade costs for all countries in general equilibrium.

3.1 Setup

Preliminaries. Let there be N countries indexed by n , m , and ℓ , and J sectors indexed by j , i , and k . Each country n is populated by households that consume the final good available in country n and supply labor to firms.

Households. There is a continuum of households indexed by ω , that maximize

$$\max_{\mathcal{F}_n(\omega), H_n(\omega)} \left(\mathcal{F}_n(\omega) - \chi_n \frac{H_n(\omega)^{1+1/\psi}}{1+1/\psi} \right) \quad (3.1)$$

subject to

$$P_n \mathcal{F}_n = W_n(\omega) H_n(\omega)$$

where $\mathcal{F}_n(\omega)$ is consumption of final goods, P_n is its price index, and $H_n(\omega)$ is the supply of hours worked, receiving a wage $W_n(\omega)$. Each household can supply labor to any sector j with household-specific productivity $b_{nj}(\omega)$. If household ω decides to work in sector j , it supplies $b_{nj}(\omega) H_n(\omega)$ effective units of labor and collects the labor income of $W_n(\omega) H_n(\omega) = W_{nj} b_{nj}(\omega) H_n(\omega)$, where W_{nj} is the equilibrium price of one efficiency unit of labor in that country-sector. The household idiosyncratic labor productivity in sector j is distributed $b_{nj}(\omega) \sim \text{Fr\'echet}(\xi_{nj}, \mu)$, with dispersion parameter μ and central tendency parameter ξ_{nj} that can potentially vary by country and sector. With some manipulation (see [Bonadio et al., 2023](#)), labor supply to sector j can be written as:

$$H_{nj} = \xi_{nj} \left(\frac{1}{\chi_n} \frac{W_n}{P_n} \right)^\psi \left(\frac{W_{nj}}{W_n} \right)^{\mu-1}, \quad (3.2)$$

up to a normalization constant and under the regularity condition that $\mu > \psi + 1$, and where $W_n \equiv (\sum_i \xi_{ni} W_{ni}^\mu)^{\frac{1}{\mu}}$ is an economy-wide wage index. Aggregate labor supply is:

$$H_n = \left(\frac{W_n}{P_n \chi_n} \right)^\psi \quad (3.3)$$

up to a normalization constant. Aggregate labor supply thus coincides with the GHH utility formulation ([Greenwood, Hercowitz, and Huffman, 1988](#)), and is governed by the Frisch elasticity ψ . At the same time, conditional on the aggregate labor supply, labor supply to an individual sector is isoelastic with elasticity $\mu - 1$ in that sector's relative wage, as in the "Roy-Fr\'echet" formulation (e.g. [Galle, Rodr\'iguez-Clare, and Yi, 2023](#); [Hsieh et al., 2019](#); [Lagakos and Waugh, 2013](#)).

Final consumption \mathcal{F}_{nt} is a CES aggregate of sectoral consumption bundles:

$$\mathcal{F}_n = \left[\sum_j \zeta_{nj}^{\frac{1}{\rho}} \mathcal{F}_{nj}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \quad P_n = \left[\sum_j \zeta_{nj} (P_{nj}^f)^{1-\rho} \right]^{\frac{1}{1-\rho}},$$

where \mathcal{F}_{nj} is the sector j quantity consumed, and P_{nj}^f is its price. Trade is subject to iceberg costs τ_{mnj}^f to ship final good j from country m to country n (throughout, we adopt the convention that the first subscript denotes source, and the second destination). Sector j bundle is an Armington aggregate of goods coming from different countries:

$$\mathcal{F}_{nj} = \left[\sum_m \mu_{mnj}^{\frac{1}{\gamma}} \mathcal{F}_{mnj}^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}}, \quad P_{nj}^f = \left[\sum_m \mu_{mnj} (\tau_{mnj}^f P_{mj})^{1-\gamma} \right]^{\frac{1}{1-\gamma}},$$

where \mathcal{F}_{mnj} is the final consumption by country n of sector j goods imported from country m , and γ controls the substitution elasticity between different origin-sector goods within a category. The P_{mj} 's are the prices of sector j country m 's product "at the factory gate" in the origin country. No arbitrage in shipping implies that the price faced by the consumer in n is P_{mj} times the iceberg cost τ_{mnj}^f .

The share of sector j composite in total final expenditure π_{nj}^f , and the share of the good from country m in total sector j final expenditure π_{mnj}^f are given by

$$\pi_{nj}^f = \frac{\zeta_{nj} (P_{nj}^f)^{1-\rho}}{\sum_k \zeta_{nk} (P_{nk}^f)^{1-\rho}} \quad \pi_{mnj}^f = \frac{\mu_{mnj} (\tau_{mnj}^f P_{mj})^{1-\gamma}}{\sum_\ell \mu_{\ell nj} (\tau_{\ell nj}^f P_{\ell jt})^{1-\gamma}}.$$

Firms. A representative firm in sector j in country n operates a CRS production function

$$Y_{nj} = Z_{nj} H_{nj}^{\eta_j} X_{nj}^{1-\eta_j}, \quad (3.4)$$

where the total factor productivity is denoted by Z_{nj} , and the intermediate input usage X_{nj} is an aggregate of sectoral inputs:

$$X_{nj} \equiv \left(\sum_i \vartheta_{i,nj}^{\frac{1}{\varepsilon}} X_{i,nj}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}.$$

Because it is the only primary factor of production, H_{nj} should be interpreted as "equipped labor" that encompasses all primary factor services (Alvarez and Lucas, 2007). The total use of sector i inputs in sector j in country n is an Armington aggregate across different source countries:

$$X_{i,nj} \equiv \left(\sum_m \mu_{mi,nj}^{\frac{1}{\nu}} X_{mi,nj}^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}} \quad P_{i,nj}^X = \left(\sum_m \mu_{mi,nj} (\tau_{mi,nj}^x P_{mi})^{1-\nu} \right)^{\frac{1}{1-\nu}},$$

where $X_{mi,nj}$ is the usage of inputs coming from sector i in country m in production of sector j in country n , $\mu_{mi,nj}$ is a taste shifter, and $P_{i,njt}^X$ is the price index of sector i inputs in production of sector j in country n . We allow the iceberg trade cost for intermediate inputs $\tau_{mi,nj}^x$ to generically differ from the iceberg trade cost for final goods τ_{mni}^f .

Let $\pi_{i,nj}^x$ be the share of sector i in total intermediate expenditure by (n, j) , and $\pi_{mi,nj}^x$ be the share of intermediates from country m in total intermediate spending on sector i by (n, j) :

$$\pi_{i,nj}^x = \frac{\vartheta_{i,nj} \left(P_{i,nj}^X \right)^{1-\varepsilon}}{\sum_k \vartheta_{k,nj} \left(P_{k,nj}^X \right)^{1-\varepsilon}} \quad \pi_{mi,nj}^x = \frac{\mu_{mi,nj} \left(\tau_{mi,nj}^x P_{mi} \right)^{1-\nu}}{\sum_\ell \mu_{\ell i,nj} \left(\tau_{\ell i,nj}^x P_{\ell it} \right)^{1-\nu}}.$$

To summarize, both final use and intermediate input bundles have two nests, governed by different elasticities. The upper nest combines broad sectors, such as textiles and apparel, machinery, or retail trade. The lower nest is an Armington aggregate of items coming from different source countries.

Firms are competitive and price at marginal cost. Cost minimization implies that the payments to primary factors and intermediate inputs are:

$$W_{nj} H_{nj} = \eta_j P_{nj} Y_{nj} \tag{3.5}$$

$$P_{mi,nj} X_{mi,nj} = \pi_{i,nj}^x \pi_{mi,nj}^x (1 - \eta_j) P_{nj} Y_{nj}. \tag{3.6}$$

Equilibrium. An equilibrium in this economy is a set of goods and factor prices $\{P_{nj}, W_{nj}\}$, factor allocations $\{H_{nj}\}$, and goods allocations $\{Y_{nj}\}$, $\{\mathcal{F}_{mnj}, X_{mi,nj}\}$ for all countries and sectors such that (i) households maximize utility; (ii) firms maximize profits; and (iii) all markets clear.

At the sectoral level, the following market clearing condition has to hold for each country n sector j :

$$P_{nj} Y_{nj} = \sum_m P_m \mathcal{F}_m \pi_{mj}^f \pi_{nmj}^f + \sum_m \sum_i (1 - \eta_i) P_{mi} Y_{mi} \pi_{j,mi}^x \pi_{nj,mi}^x. \tag{3.7}$$

Meanwhile, trade balance implies that each country's final expenditure equals the sum of value added across domestic sectors:

$$P_m \mathcal{F}_m = \sum_i \eta_i P_{mi} Y_{mi}. \tag{3.8}$$

Our simulations shock the world economy with changes in iceberg trade costs and compute changes relative to the pre-shock equilibrium. We report results for two aggregate outcomes: real GDP and real income. The real GDP change in any country n following a vector of trade cost shocks is to first order given by

$$d \ln G_n = \sum_{j=1}^J \eta_j \frac{P_{nj,0} Y_{nj,0}}{G_{n,0}} d \ln H_{nj}, \tag{3.9}$$

Table 3: Parameter values

Param.	Value	Source	Related to
ρ	1		final cross-sector substitution elasticity
ε	1		intermediate cross-sector subst. elasticity
γ	4	Broda and Weinstein (2006)	trade elasticity in final consumption
ν	4	Broda and Weinstein (2006)	trade elasticity in intermediate inputs
ψ	1	Chetty et al. (2011)	Frisch elasticity of labor supply
μ	1.5	Galle, Rodríguez-Clare, and Yi (2023)	Sectoral labor supply elasticity
η_j		ICIO	value added share in gross output
$\pi_{njt}^f, \pi_{i,njt}^x$		ICIO	sectoral consumption and intermediate shares
$\pi_{mnjt}^f, \pi_{mi,njt}^x$		ICIO	final and intermediate trade shares

Notes: This table summarizes the parameters and data targets used in the quantitative model and their sources.

where the items subscripted by a “0” denote the steady state/pre-shock values. This expression for the real GDP follows from the systems of national accounts definition of real GDP as output evaluated at base prices minus inputs evaluated at base prices. (For the complete detail see, e.g. [Huo, Levchenko, and Pandalai-Nayar, 2025](#); [Bonadio et al., 2023](#)). The advantage of real GDP is that it is a familiar object that is tracked by national accounts. The disadvantage is that because it keeps prices at their pre-shock values, it does not take into account the fact that changes in trade costs affect import prices, which are in the consumption price index. Thus, we will also report results for the real income, defined as W_n/P_n (and also referred to as real wage).

Equilibrium in changes. We use exact-hat algebra to solve the model in changes. We denote gross proportional changes from an initial equilibrium using “hat” variables: $\hat{X} = \frac{X'}{X}$, where X is the initial equilibrium value and X' is the new equilibrium value. For a given change in trade costs $\hat{\tau}_{mi,nj}^x$ and $\hat{\tau}_{mnjt}^f$, we can solve for the change in all endogenous variables according to the formulas derived in Appendix B.

3.2 Calibration

Table 3 summarizes the parameters we use. We set the substitution elasticities between sectors in final consumption (ρ) and intermediate use (ε) to 1. For the Armington elasticities of substitution between goods coming from different source countries in the final (γ) and intermediate (ν) bundles, we adopt a conventional value of 4 (e.g. [Broda and Weinstein, 2006](#)). The Frisch labor supply elasticity is set to 1 following the business cycle literature ([Chetty et al., 2011](#)), and the parameter μ which governs the sectoral labor supply elasticity μ is set to 1.5 following [Galle, Rodríguez-Clare, and Yi \(2023\)](#). Production function parameters and final/input shares are taken directly from the data.

3.3 Baseline trade cost change scenario

As mentioned above, the gravity estimation only identifies the relative trade cost changes. To pin down the absolute changes, we use the model to target the data on the world trade to GDP ratio. Specifically, we start from the 2015 equilibrium and shock it with the following trade cost changes for all exporting manufacturing sectors i :

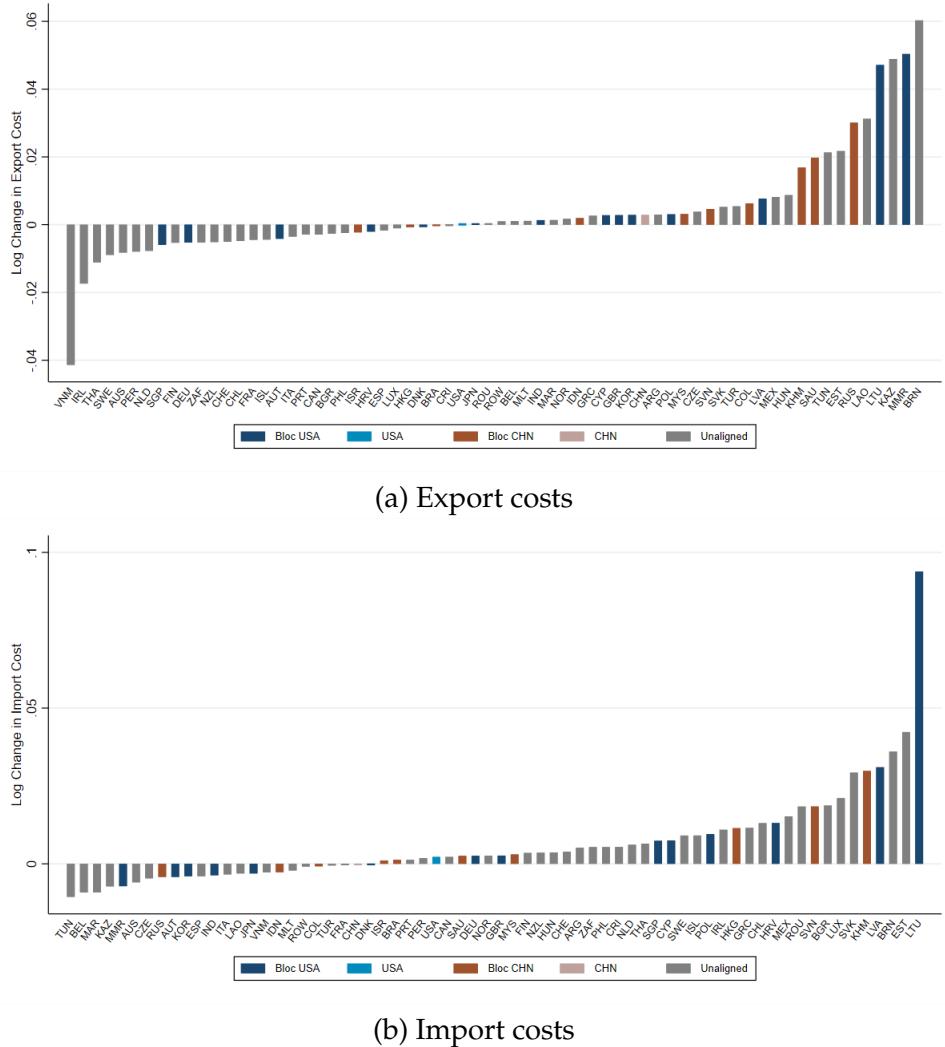
$$\hat{\tau}_{mi,nj}^x = \hat{\tau}_{mni}^f = \exp\left(\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}\right) \quad \forall m \neq n, \quad (3.10)$$

where $\Delta \ln \tau_{mn}$ are the bilateral (relative) trade costs backed out in Section 2.2, and $\Delta \ln \tau^{base}$ is a trade cost shifter common to all country pairs. We search for a $\Delta \ln \tau^{base}$ such that the change in the world trade to GDP ratio in the model matches the change in the data from 21.8% in 2015 to 22.6% in 2023, a 0.8 percentage point increase.

We find a $\Delta \ln \tau^{base} = -0.003$, implying that if anything, on average trade costs decreased by 0.3%. Note that we assume all changes in bilateral trade flows after country fixed effects come from changes in trade costs, and abstract from other shocks that might affect bilateral trade flows in this exercise. While the model can accommodate standard shocks such as productivity or demand, these shocks are absorbed by the country fixed effects. Such additional shocks would help match the evolution of GDP in each country. We discipline the average (“base”) trade cost change using the differential change in trade relative to GDP worldwide. World GDP growth and its level are not pinned down by this exercise. While we refer to the base change as a change in average trade costs, these incorporate average changes in preferences for foreign goods as well. We also do not separately consider other bilateral shocks that might directly affect trade flows or cause changes in bilateral trade costs, such as exporters’ changes in markups charged to a specific importer, or changes in the patterns of global energy production.

Figure 3 displays the trade-weighted import and export trade cost changes for each country. Table 4 shows the average trade cost changes across blocs, inclusive of the calibrated $\Delta \ln \tau^{base}$, as well as the overall trade cost changes for each bloc pair. As expected, trade costs between the US and China bloc have increased. Trade costs from the China bloc to the US bloc increased by 11.7%, and in the opposite direction they rose by 4.3%. However, these increases are counteracted by reductions in within-bloc trade costs, as well as in import trade costs from the unaligned countries. Only the China bloc experiences an overall increase in export costs, and none of the blocs see significant increases in overall import costs. Hence, the more structural approach confirms the picture emerging from the raw data in Table 1 in the Introduction: while fragmentation has happened, overall trade costs have not increased. Appendix Table B1 presents the classification of the countries in the model into blocs. This classification is done based on the calibrated absolute changes in trade costs $\hat{\tau}_{mni}^f / \hat{\tau}_{mi,nj}^x$ in (3.10), rather than the relative ones in Section 2. According to the classification, 14 countries are in the US bloc and 10 in the China bloc (beyond the US and China themselves).

Figure 3: Baseline Change in Trade Costs (2015-2023)



Notes: The top and bottom panels show the log change in export and import costs implied by the model factual, respectively. The changes in trade costs are measured as the trade-weighted mean change in trade cost across all sectors.

Table 4: Log Change in Average Trade Costs between Blocs (2015-2023)

\downarrow Exporter Importer \rightarrow	Bloc USA	Bloc CHN	Unaligned	Overall
Bloc USA	-0.043	0.043	0.007	0.000
Bloc CHN	0.117	-0.069	0.027	0.053
Unaligned	-0.030	-0.032	-0.005	-0.021
Overall	0.005	-0.009	0.007	0.003

Notes: We classify countries into 3 groups, Bloc USA, Bloc CHN, and Unaligned. Then, all country pairs are classified into 9 group pairs. We report the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ for country pairs belonging to each group pair, weighted by bilateral trade flows in 2015. The Overall column/row is the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ of all trade flows from(to) each exporter(importer) group.

Table 5: Baseline Change in Real GDP and Real Income, Percentage Points (2015-2023)

Bloc	Real GDP			Real Income		
	Median	p25	p75	Median	p25	p75
Overall	0.588	0.061	1.297	0.619	0.059	1.322
Bloc USA	0.532	0.125	0.712	0.536	0.147	0.699
Bloc CHN	0.299	-0.263	0.773	0.372	-0.261	0.780
Unaligned	0.787	0.034	1.397	0.755	0.066	1.432

Notes: Baseline change in GDP and real income are reported in percentage points.

Figure 4 illustrates the changes in real GDP and real incomes for each country in the model factual. Table 5 displays summary statistics of the changes in real GDP and incomes. While there is quite a bit of heterogeneity, the median country actually sees a 0.6% gain, and three-quarters of the countries experience an increase in both real GDP and real incomes, with the median changes positive in all blocs. The US and China themselves see changes close to zero. Neither countries in the US bloc nor countries in the China bloc see uniform gains or losses. Even at the 25th percentiles, only in the China bloc the changes are negative. Recall that this scenario mutes any productivity or demand shocks. The equilibrium changes in GDP predicted here are entirely due to the observed trade cost changes in the data during the decoupling period. The factual suggests that, given the observed pattern of trade cost changes and taking into account the general equilibrium effects such as substitution towards partners facing lower trade costs, most countries' output and real incomes increased during this period.⁵

The modest positive average effects are accompanied by large heterogeneity in GDP and income impacts across countries. At the top, Vietnam and Laos strongly benefit, gaining 6.9% and 3.5%, respectively. Vietnam and Laos experienced trade cost declines with both the US and China. While our classification considers Vietnam and Laos unaligned, the quantification shows large increases in bilateral trade with these countries, and increases in their GDP and real incomes. This is consistent with the anecdotal accounts of supply chains shifting away from China and towards countries like Vietnam.⁶ At the opposite extreme are the Baltic countries, whose close trade links with Russia unraveled, without a compensating decrease in trade costs elsewhere. As a result, these countries experienced losses of 3-5%.

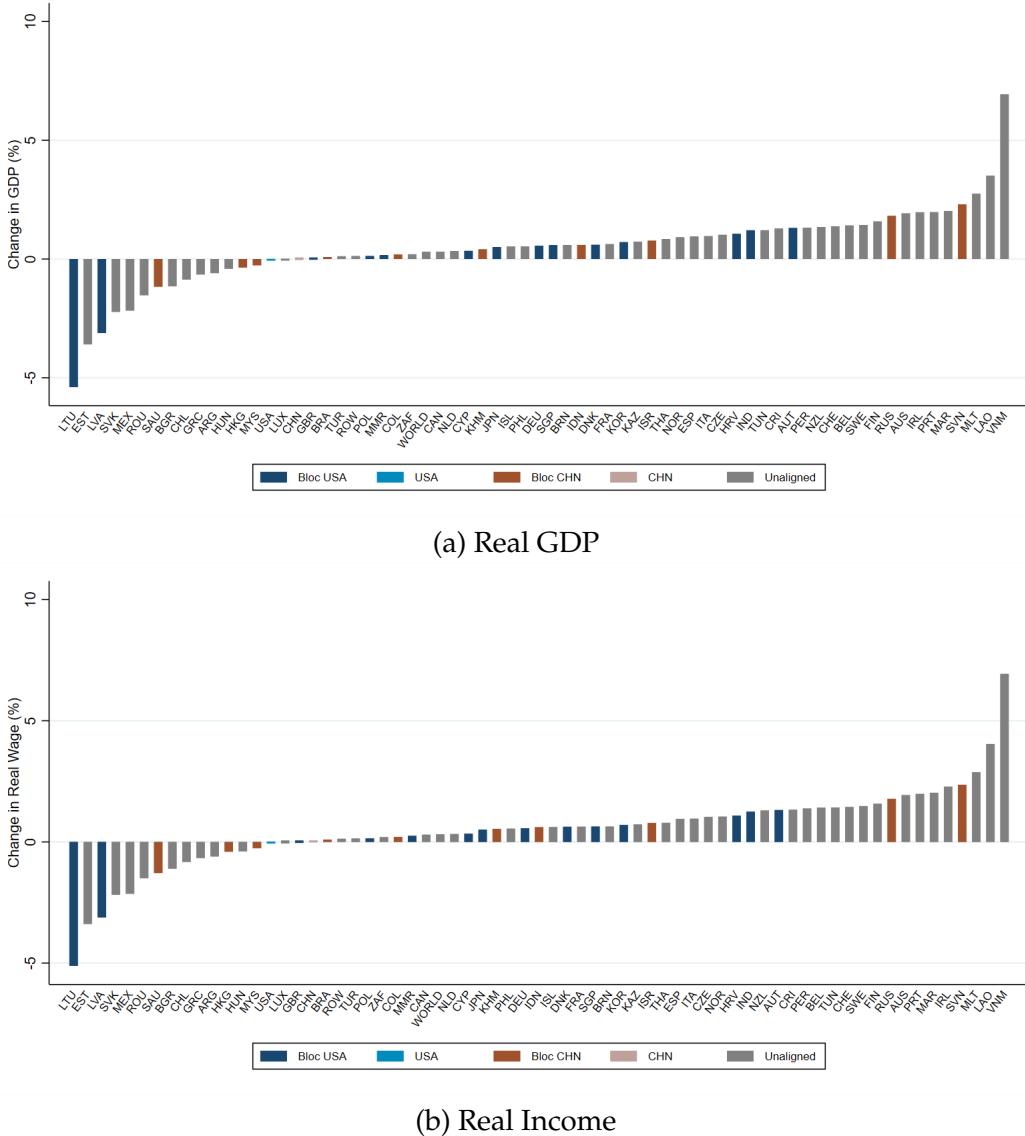
3.4 Counterfactuals

According to the factual simulation above, most countries are actually better off in the fragmented world, as trade costs decreases within blocs more than offset trade cost increases across blocs. A natural question is whether countries sort into blocs according to benefits arising from international

⁵ Appendix Table B2 decomposes the changes into the effects of the bilateral relative trade cost changes (τ_{mn}) and of the worldwide trade cost shift (τ^{base}), see eq. (3.10). About 90% (e.g. $\approx 0.574/0.637$) of the total real income change is due to the bilateral relative trade cost changes.

⁶See for example "Vietnam is emerging as a winner from the era of deglobalisation", The Economist, Sept. 22, 2022.

Figure 4: Baseline Change in Real GDP and Real Income (2015-2023)



Notes: The top panel shows the change in GDP, in percentage points, implied by the model baseline change in trade costs. The bottom panel shows the change in real income implied by the model baseline change in trade costs.

trade. To answer this question, we perform counterfactual exercises in which we move countries to different blocs and compare their real outcomes to the baseline.

Specifically, we first construct the average import and export trade cost change between each country and a given bloc. For each country m and bloc l , we compute the average export cost change from the bloc to country m :

$$d \ln \tau_{l,m} = \frac{1}{N_l} \sum_{n \in l} d \ln \tau_{n,m}$$

and the average import cost change from m to the bloc:

$$d \ln \tau_{m,l} = \frac{1}{N_l} \sum_{n \in l} d \ln \tau_{m,n}.$$

Thus, $d \ln \tau_{l,m}$ and $d \ln \tau_{m,l}$ are the average export and import trade cost changes for countries in bloc $= l$ with respect to country m .

Then, we move each country n to a particular bloc by replacing its factual trade cost changes with the averages for that bloc for every potential partner m . However, country n 's factual average change in trade costs might differ from the bloc-level average. To avoid this type of mechanical level effect, we renormalize the country's counterfactual trade cost changes such that their trade-weighted average change is equal to the factual. Specifically, for each country n moving to bloc l , we compute an adjustment factors $d \ln \tau_{n,imports}^{adj,l}$ and $d \ln \tau_{n,exports}^{adj,l}$ such that:

$$\underbrace{\sum_{m,i,j,u=\{f,x\}} \frac{IM_{mi,nj}^u}{IM_n} d \ln \tau_{mi,nj}}_{\text{actual}} = \underbrace{d \ln \tau_{n,imports}^{adj,l}}_{\text{adjustment factor}} + \underbrace{\sum_{m,i,j,u=\{f,x\}} \frac{IM_{mi,nj}^u}{IM_n} d \ln \tau_{m,l}}_{\text{counterfactual: moving to bloc}},$$

and

$$\underbrace{\sum_{m,i,j,u=\{f,x\}} \frac{EX_{nj,mi}^u}{EX_n} d \ln \tau_{nj,mi}}_{\text{actual}} = \underbrace{d \ln \tau_{n,exports}^{adj,l}}_{\text{adjustment factor}} + \underbrace{\sum_{m,i,j,u=\{f,x\}} \frac{EX_{nj,mi}^u}{EX_n} d \ln \tau_{l,m}}_{\text{counterfactual: moving to bloc}},$$

where $IM_{mi,nj}^u$ is imports of category $u \in \{f, x\}$ from country sector mi to sector j in n , IM_n are n 's total imports, and similarly for exports $EX_{mi,nj}^u$ and EX_n . We then construct the counterfactual trade cost changes when putting country n into bloc l as:

$$d \ln \tau_{m,n}^{CF:l} = d \ln \tau_{m,l} + d \ln \tau_{n,imports}^{adj,l}$$

$$d \ln \tau_{n,m}^{CF:l} = d \ln \tau_{l,m} + d \ln \tau_{n,exports}^{adj,l}.$$

This counterfactual answers the question, what is the effect of rearranging the country's trade costs such that it looks like bloc l , while keeping its average trade cost change the same? While there are many permutations of groups of countries that could be subjected to this counterfactual, we perform it one country at a time, keeping the trade cost changes for all other countries at their factual values.

Since each country is in exactly one bloc in the factual, for each country there are 2 possible moves, into one of the other 2 blocs. Thus, for each unaligned country the counterfactuals put it into the US and China blocs. For countries already in the US or China bloc, the counterfactuals put it into the other bloc or into the unaligned group.

Figure 5 displays the results for real GDP, while Appendix Figure B1 displays the results for real

Table 6: Counterfactual GDP and Real Income, Percentage Points (2015-2023)

Counterfactual	Bloc	Real GDP			Real Income		
		Median	p25	p75	Median	p25	p75
Moving to Bloc USA	Overall	-0.445	-1.534	0.969	-0.448	-1.512	0.945
	Bloc USA	-	-	-	-	-	-
	Bloc CHN	0.658	-0.411	1.796	0.661	-0.410	1.906
	Unaligned	-0.710	-1.638	0.618	-0.762	-1.636	0.589
Moving to Bloc CHN	Overall	-0.269	-1.465	0.740	-0.289	-1.430	0.717
	Bloc USA	0.211	-0.405	1.527	0.238	-0.369	1.612
	Bloc CHN	-	-	-	-	-	-
	Unaligned	-0.501	-1.856	0.676	-0.476	-1.951	0.606
Moving to Unaligned	Overall	-0.593	-0.944	1.203	-0.589	-0.967	1.253
	Bloc USA	-0.622	-0.943	0.065	-0.629	-0.940	0.020
	Bloc CHN	-0.324	-1.131	1.589	-0.328	-1.138	1.581
	Unaligned	-	-	-	-	-	-

Notes: Counterfactual change in GDP and real income, relative to baseline, are reported in percentage points.

income. Table 6 reports the summary statistics of the counterfactuals by bloc. The top panel of the figure and the table shows the change compared to the factual when moving countries to the US bloc. Countries in the China bloc are marked in brown. Six out of ten China bloc countries would actually benefit from switching to the US bloc, with the median real income benefit of 0.66%. The unaligned countries would on average lose from moving to the US bloc, through there is wide heterogeneity of effects ranging from positive to negative.

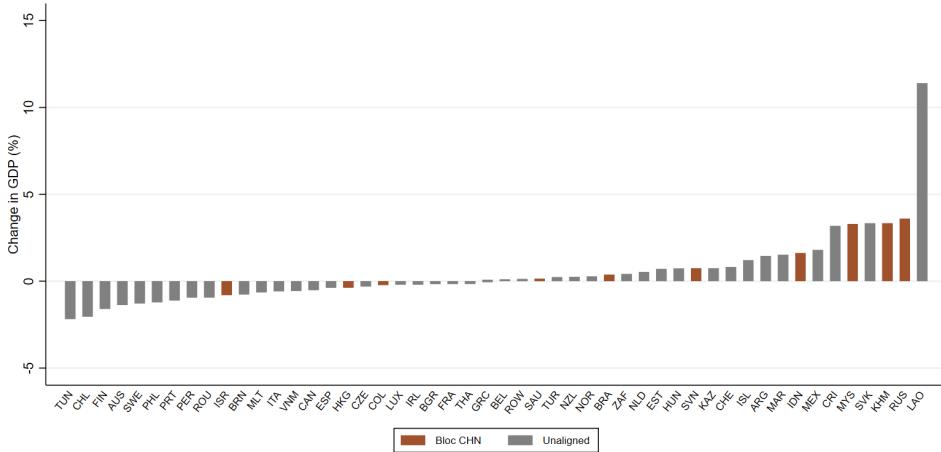
The middle panel shows the results of moving countries not aligned with China to the China bloc. Countries in the US bloc would on average benefit from moving to the China bloc, with eight out of fourteen of the US bloc countries gaining from moving to the China bloc, with the median US bloc country gaining 0.2% from the move. Once again in both the US bloc and unaligned groups, the benefits range from positive to negative. The bottom panel shows the results of moving the aligned countries to the non-aligned bloc. While on average moving countries from the US and China blocs to unaligned reduces real GDP and income, a few countries such as Saudi Arabia, Latvia, and Lithuania would see GDP increases of over 2% by becoming unaligned. Figure B1 in the Appendix displays the counterfactual changes in real incomes with similar results.

Overall, it appears that on average countries in the US and China blocs are in the “wrong” bloc. At the same time, countries in these blocs would also on average lose from becoming unaligned. The averages hide complete variation from negative to positive within each possible category of move.

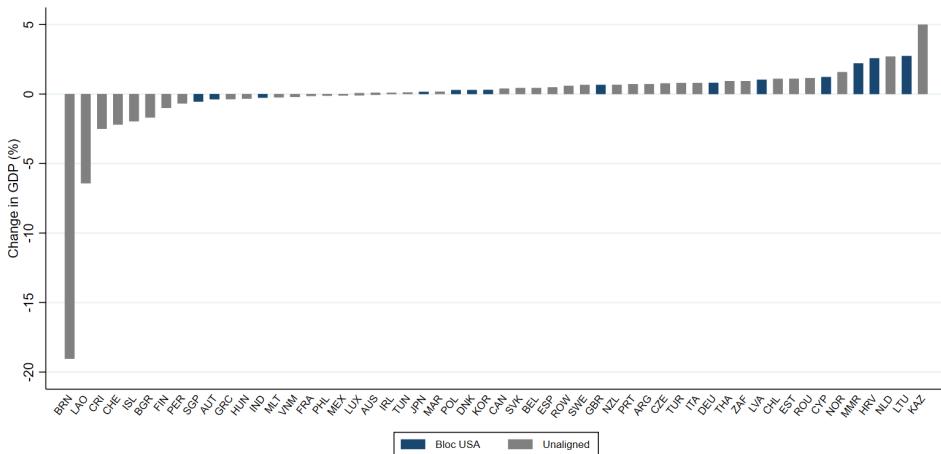
3.5 Robustness and sensitivity

We now perform several sensitivity checks on the bloc assignment and the inferred trade cost changes.

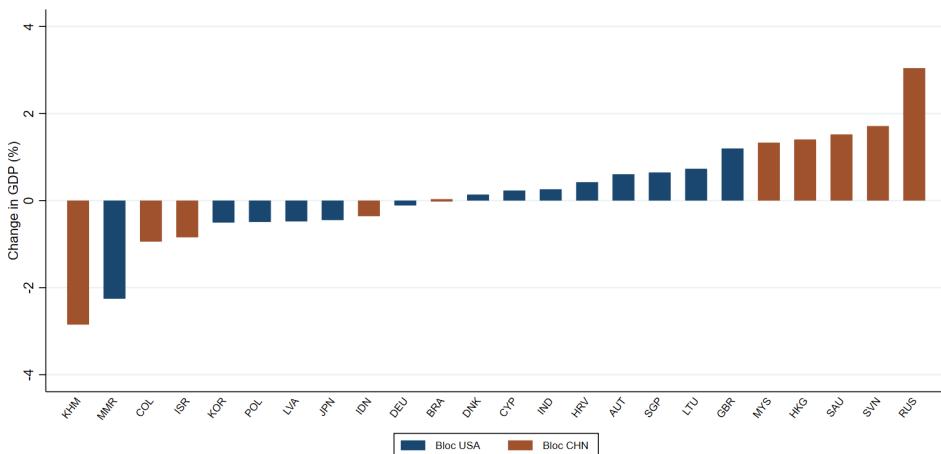
Figure 5: Counterfactual Real GDP Changes (2015-2023)



(a) Moving to USA bloc



(b) Moving to China bloc



(c) Moving to unaligned bloc

Notes: Each bar in each plot shows the percentage change in GDP for each country, relative to factual, when the country is moved to different bloc.

Observable trade costs: tariffs. Since the absolute level of trade cost changes is pinned down by our model matching the overall trade to GDP ratio change, one might worry that the outcome is model-dependent. Appendix Figure C1 provides support for our finding that some trade costs rose and some fell by using the component of trade costs directly observable in the data: tariffs. The most recent tariff data are for 2021, so we document the tariff changes between 2015 and 2021. The source of the tariff data is UN-TRAINs. The left panel plots the histogram of the applied tariff changes. Because MFN tariff changes are measured with less error (Teti, 2024), the right panel also reports the histogram of MFN tariff changes only. While there is large dispersion in the effectively applied tariff changes, the average change is close to 0, and 39.5% of bilateral pairs experience tariff decreases.

Bloc assignments. We next use an alternative methodology to assign countries to blocs, based on the Leiden algorithm (Traag, Waltman, and van Eck, 2019). The Leiden algorithm is a machine learning method designed to detect non-overlapping communities in large networks. We feed in the same residualized trade growth between 2015 and 2023 as in our baseline classification, but use the Leiden algorithm to classify the countries in blocs. The algorithm contains a random component, so we perform many draws and assign countries to blocs based on the percentage of times they are classified in the same community as the US or China. Appendix C.1 presents the details of the procedure. Table C1 summarizes the overlap between our baseline and the Leiden algorithm approach. Overall, our baseline procedure is more conservative in that it classifies more countries as unaligned. However, the two methods agree more than 70% of the time when both assign the country to either the US or China bloc.

Alternative start and end years. Our baseline uses 2015 as the pre-period, since it is the year before the Brexit referendum and the Donald Trump election. In the Appendix, we instead use 2016 as a start date, since the tariffs in US-China trade war first increased in 2017. Tables C2 and C3 show that the bloc assignment in that case is similar to our baseline. While some countries move to being unaligned, no country in our quantitative model sample is classified in the opposite bloc to the baseline results. Tables C4 and C5 display summary statistics of the changes in trade costs and GDP respectively. The results are qualitatively the same as our baseline scenario: while trade costs across blocs are increasing, they are compensated by decreases within bloc and to/from the unaligned bloc.

We also repeat the analysis for the pre-Covid years 2015-2019 and present the results in the Appendix C.3. Table C6 shows the change in trade costs between blocs. The trade costs between the moving-to-US and moving-to-China blocs already increase in this sample. However, the decrease in within-bloc trade costs is less pronounced and almost null for the USA bloc so that the overall trade costs increase slightly. As a result, the welfare changes depicted in Table C7 show a negligible negative change of -0.06% for the median country (compared to $+0.6\%$ in the 2015-2023 exercise), though more negative for the US and China bloc countries. This reveals a potentially interesting timing of the cross-bloc increases vs. within-bloc decreases in trade costs: the latter lagged the former. Evidently it took countries some time to reduce the within-bloc trade barriers following the

initial US-China fragmentation shock.

Placebo period. We conduct a placebo exercise, where we repeat our procedure with data from before the US-China trade tensions, between 2002 and 2007. In that case, we find no evidence of fragmentation. Table C8 displays the bloc assignment compared to our baseline 2015-23 classification. Only 3 countries are assigned to the China bloc, including China. More countries are unaligned than in our baseline (70% instead of 60% in our baseline). Table C9 displays the change in trade costs across bloc pairs between 2002 and 2007. Most bloc pairs, including China bloc to US bloc, experience trade cost declines.

We also compute the changes in trade costs between 2002 and 2007, for the blocs identified in our baseline using 2015-23 trade data. Table C10 reports the average 2002-2007 trade cost changes across the 2015-23 bloc pairs. Contrary to the 2015-23 trade cost changes, we find no evidence of fragmentation: all cross-bloc pairs experience trade cost decreases, in the same order of magnitude as the within bloc pairs.

Fit of trade costs. Our procedure matches the global trade to GDP ratio to pin down the level of trade cost changes. The reason is that domestic absorption data are not available for 2023, which prevents us from identifying trade costs levels following the Head and Ries (2001, henceforth HR) method. To provide evidence that our trade/GDP-targeting procedure is reliable, we implement our procedure on years where domestic absorption data are available, which allows us to compare our method to HR. We use 8-year windows starting from 2000 until 2010. On average, our procedure and the HR method produce similar trade cost changes: the difference between our approach and the HR method is -0.9% at the mean (-0.03% at the median), and the correlation is 0.79. Appendix C.5 details the exercise.

3.6 Determinants of trade changes

The counterfactual results from Section 3.4 imply that some countries do not necessarily sort into their economically optimal bloc. In this section, we investigate potential drivers of changes in trade patterns after 2015.

We start by regressing the change in bilateral trade flows between 2015 and 2023 on the United Nations general assembly vote agreement in 2015 (Bailey, Strezhnev, and Voeten, 2017). We control for trade flows in 2015, historical trade flows from 2000, and distance. The first column of Table 7 displays the results. Country pairs who voted together at the UN assembly in 2015 witnessed a relative increase in bilateral trade flows after 2015. Large flows in 2015 tend to decrease subsequent trade growth, while trade flows from 2000 are positively correlated with the growth of trade post-2015. This indicates that trade grew more for geopolitically close pairs, and patterns moved away from 2015 partners back towards historical 2000 partners. The second column of Table 7 reports results of a placebo regression that uses instead the change in trade flows between 2010 and 2015. There, there is

Table 7: Explanatory Variables for Trade Flow Changes

	Placebo	
	2015 to 2023	2010 to 2015
UN vote agreement	0.672*** (0.197)	0.184 (0.186)
Log initial flows	-0.423*** (0.0294)	-0.354*** (0.0435)
Log 2000 flows	0.148*** (0.0212)	0.0957*** (0.0313)
Log distance	-0.288*** (0.0563)	-0.291*** (0.0428)
Observations	3674	3674
Importer FE	✓	✓
Exporter FE	✓	✓

Notes: Vote agreement measures the likelihood of agreement between country pairs in the UN voting at the initial year (2015 in the first column, 2010 in the second column). Log initial trade flows is the log of bilateral trade flow between country pairs at the initial year. Distance comes from CEPPII gravity database. The sample includes all country pairs in our quantitative model sample. Standard errors are clustered two-way at the exporter and importer level.

no correlation with UN agreement.

To probe this further, we perform an event-study type regression:

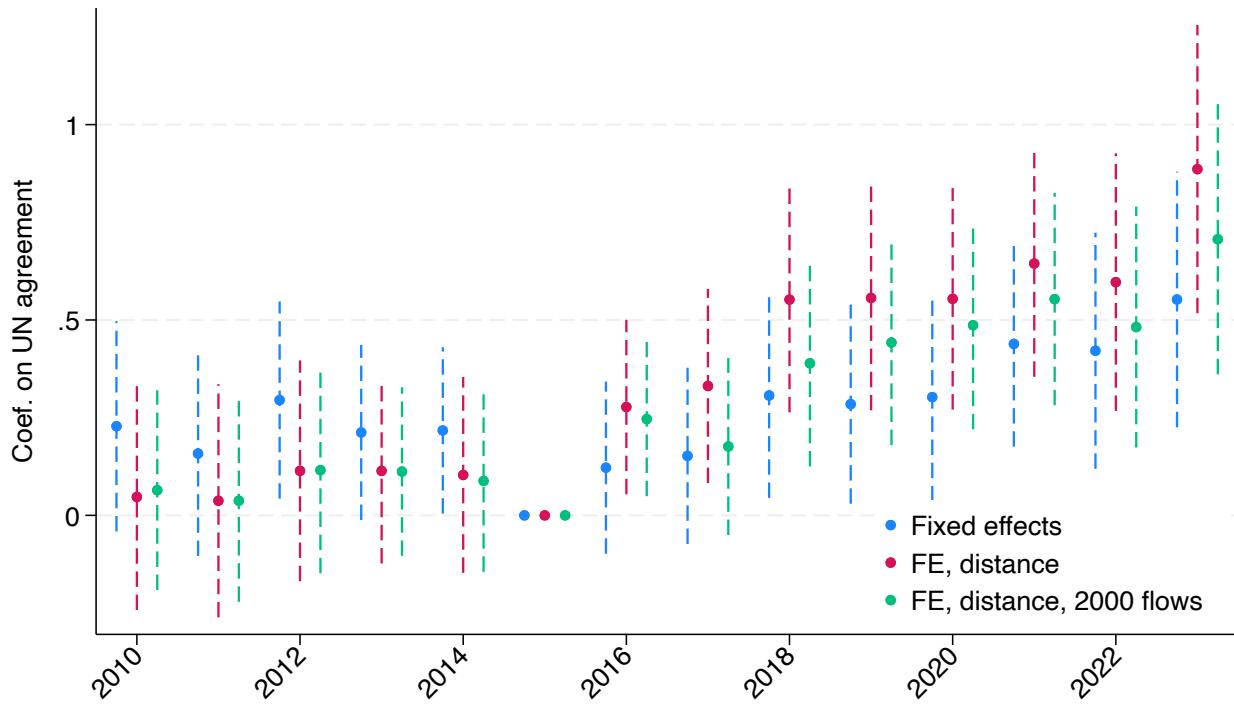
$$\ln X_{mn,t} = \eta_{mt} + \gamma_{nt} + \delta_{mn} + \sum_t \beta_t^{UN} UN agree_{mn} + \sum_t X'_{mn} \beta_t^x + \varepsilon_{mnt}. \quad (3.11)$$

We include importer-year and exporter-year fixed effects, as well as bilateral pair fixed effects that capture any time-invariant trade costs. We then add a year-specific coefficient β_t^{UN} on UN vote agreement, as well as year-specific coefficients on a vector of other controls potentially correlated with vote agreement X_{mn} , such as 2000 trade flows and bilateral distance. The UN vote agreement is measured as the average voting similarity over the UN voting sessions between 2000 and 2022, as computed by [Bailey, Strezhnev, and Voeten \(2017\)](#).

Figure 6 displays the results of estimating specification (3.11), with the coefficient for 2015 normalized to 0. All specifications indicate that prior to 2015, there is no impact of the UN agreement on trade, relative to the reference year. After 2015, the correlation between UN vote and trade flow starts to increase, getting progressively stronger over time.

Overall, the results suggest that 2015-2017 marked the start of an increase in the role of geopolitical forces in international trade. After 2015, countries increased trade with their pre-2015 allies, at the

Figure 6: Bilateral trade flows and political alignment: coefficient on UN agreement (β_t^{UN})



Notes: The figure displays the estimates of β_t^{UN} from regression 3.11. Each dot color corresponds to different controls. The blue coefficients only include the fixed effects. The red coefficients include time-varying coefficients on distance, and the green coefficients include time-varying coefficients on 2000 bilateral trade flows. The sample covers countries in our quantitative model. Appendix Figure C4 replicates the findings with all available country pairs.

expense of trade with non-allies.

4. CONCLUSION

The year 2016 ushered an era of significant changes in policies that are weighing on international trade: the Brexit vote, the US-China trade war, the Russian invasion of Ukraine and the resulting severing of trade links between Russia and the West, and the Biden administration's semiconductor export bans, to name a few of the most important ones. A reasonable expectation is that world trade would have decreased over this period. However, at least as of 2023, this has not been the case. Instead, these policies have triggered a reallocation of trade flows across sources and destinations as also argued by a number of recent studies.

To understand how this rewiring of international trade is occurring, this paper adopts a data-driven approach to measure trade cost changes in a large sample of countries and detect which countries are in which blocs. We do find evidence of decoupling: about half the countries in the world appear to have aligned themselves with either the US or China, at the expense of higher trade costs with the other bloc. However, we find that as cross-bloc trade costs went up, within-bloc trade costs fell. On net, the median country in the world, and the median country within each bloc, has slightly *higher* real income as a result of this reconfiguration of the global trade costs. At the same time, we find a modest level of bloc misalignment: the median country in the US bloc would actually be better off in the China bloc, and vice versa. This suggests that considerations other than international trade are dominating bloc alignment, at least so far.

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ONLINE APPENDIX
(NOT FOR PUBLICATION)

A. DATA AND BLOC ASSIGNMENT

Country coverage. Table A1 lists the countries.

Sectoral classification and aggregation. Table A2.

Table A1: Country list, model

Country code	Country name	Country code	Country name
AUS	Australia	KAZ	Kazakhstan
ARG	Argentina	KHM	Cambodia
AUT	Austria	KOR	Korea
BEL	Belgium	LAO	Lao People's Democratic Republic
BGR	Bulgaria	LTU	Lithuania
BRA	Brazil	LUX	Luxembourg
BRN	Brunei Darussalam	LVA	Latvia
CAN	Canada	MAR	Morocco
CHE	Switzerland	MEX	Mexico
CHL	Chile	MLT	Malta
CHN	China	MMR	Myanmar
COL	Colombia	MYS	Malaysia
CRI	Costa Rica	NLD	Netherlands
CYP	Cyprus	NOR	Norway
CZE	Czech Republic	NZL	New Zealand
DEU	Germany	PER	Peru
DNK	Denmark	PHL	Philippines
ESP	Spain	POL	Poland
EST	Estonia	PRT	Portugal
FIN	Finland	ROU	Romania
FRA	France	ROW	Rest of the World
GBR	United Kingdom	RUS	Russian Federation
GRC	Greece	SAU	Saudi Arabia
HKG	Hong Kong	SGP	Singapore
HRV	Croatia	SVK	Slovak Republic
HUN	Hungary	SVN	Slovenia
IDN	Indonesia	SWE	Sweden
IND	India	THA	Thailand
IRL	Ireland	TUN	Tunisia
ISL	Iceland	TUR	Turkey
ISR	Israel	USA	United States
ITA	Italy	VNM	Viet Nam
JPN	Japan	ZAF	South Africa

Notes: This table displays the list of countries included in our quantitative model.

Table A2: Sector key

ICIO code	ICIO description	Sector code	Sector description
01T02	Agriculture, hunting, forestry	1	Agriculture, hunting, forestry and fishing
03	Fishing and aquaculture	1	Agriculture, hunting, forestry and fishing
05T06	Mining and quarrying, energy producing products	2	Mining and quarrying, energy producing products
07T08	Mining and quarrying, non-energy producing products	3	Other mining and quarrying
09	Mining support service activities	3	Other mining and quarrying
10T12	Food products, beverages and tobacco	4	Food products, beverages and tobacco
13T15	Textiles, textile products, leather and footwear	5	Textiles, textile products, leather and footwear
16	Wood and products of wood and cork	6	Wood products, paper products and printing
17T18	Paper products and printing	6	Wood products, paper products and printing
19	Coke and refined petroleum products	7	Coke and refined petroleum products
20	Chemical and chemical products	8	Chemical products
21	Pharmaceuticals	8	Chemical products
22	Rubber and plastics products	8	Chemical products
23	Other non-metallic mineral products	9	Other non-metallic mineral products
24	Basic metals	10	Metal products
25	Fabricates metal products	10	Metal products
26	Computer, electronic and optical equipment	11	Computer, electronic and optical equipment
27	Electrical equipment	12	Electrical equipment
28	Machinery and equipment nec	13	Machinery and equipment nec
29	Motor vehicles, trailers and semi-trailers	13	Machinery and equipment nec
30	Other transport equipment	13	Machinery and equipment nec
31T33	Manufacturing nec	14	Manufacturing nec
35	Electricity, gas, steam and air conditioning supply	15	Electricity, gas, steam and water supply
36T39	Water supply; sewage, waste management	15	Electricity, gas, steam and water supply
41T43	Construction	16	Construction
45T47	Wholesale and retail trade; repair of motor vehicles	17	Wholesale and retail trade; repair of motor vehicles
49	Land transport and transport via pipelines	18	Transportation and postal services
50	Water transport	18	Transportation and postal services
51	Air transport	18	Transportation and postal services
52	Warehousing and support activities for transportation	18	Transportation and postal services
53	Postal and courier activities	18	Transportation and postal services
55T56	Accommodation and food service activities	19	Accommodation and food service activities
58T60	Publishing, audiovisual and broadcasting activities	20	Broadcasting, telecommunications and IT services
61	Telecommunications	20	Broadcasting, telecommunications and IT services
62T63	IT and other information services	20	Broadcasting, telecommunications and IT services
64T66	Financial and insurance activities	21	Financial, real estate, professional and administrative services
68	Real estate activities	21	Financial, real estate, professional and administrative services
69T75	Professional, scientific and technical activities	21	Financial, real estate, professional and administrative services
77T82	Administrative and support services	21	Financial, real estate, professional and administrative services
84	Public administration and defense	22	Public administration, education and other services
85	Education	22	Public administration, education and other services
86T88	Human health and social work activities	22	Public administration, education and other services
90T93	Arts, entertainment and recreation	22	Public administration, education and other services
94T96	Other service activities	22	Public administration, education and other services
97T98	Activities of households as employers	22	Public administration, education and other services

Table A3: Bloc Assignment, 187 Countries (2015-2023)

Country	Bloc	Country	Bloc	Country	Bloc
AUT	USA	GTM	CHN	HTI	Unaligned
BGD	USA	HND	CHN	HUN	Unaligned
BHS	USA	ISR	CHN	IDN	Unaligned
CYP	USA	KGZ	CHN	IRL	Unaligned
DEU	USA	KWT	CHN	IRN	Unaligned
DNK	USA	LCA	CHN	IRQ	Unaligned
EGY	USA	LSO	CHN	ISL	Unaligned
ERI	USA	MLT	CHN	ITA	Unaligned
ETH	USA	MYS	CHN	JAM	Unaligned
FJI	USA	NCL	CHN	JOR	Unaligned
FRO	USA	NPL	CHN	KAZ	Unaligned
GHA	USA	NZL	CHN	KEN	Unaligned
GNB	USA	PAN	CHN	KHM	Unaligned
GNQ	USA	PNG	CHN	KIR	Unaligned
GRL	USA	PYF	CHN	KNA	Unaligned
HRV	USA	RUS	CHN	LAO	Unaligned
IND	USA	RWA	CHN	LBN	Unaligned
JPN	USA	SAU	CHN	LBR	Unaligned
KOR	USA	SLB	CHN	LUX	Unaligned
LTU	USA	SLE	CHN	MAC	Unaligned
LVA	USA	SLV	CHN	MAR	Unaligned
MLI	USA	STP	CHN	MDA	Unaligned
MNE	USA	TCD	CHN	MDG	Unaligned
MRT	USA	TJK	CHN	MDV	Unaligned
NIC	USA	TKM	CHN	MEX	Unaligned
NLD	USA	TTO	CHN	MKD	Unaligned
NOR	USA	ALB	Unaligned	MMR	Unaligned
SGP	USA	ARG	Unaligned	MNG	Unaligned
SOM	USA	ARM	Unaligned	MOZ	Unaligned
SSD	USA	ATG	Unaligned	MUS	Unaligned
SWE	USA	AUS	Unaligned	MWI	Unaligned
SYR	USA	AZE	Unaligned	NAM	Unaligned
TGO	USA	BEL	Unaligned	NER	Unaligned
THA	USA	BEN	Unaligned	NGA	Unaligned
TUR	USA	BGR	Unaligned	NRU	Unaligned
TUV	USA	BHR	Unaligned	OMN	Unaligned
UGA	USA	BIH	Unaligned	PAK	Unaligned
UKR	USA	BLZ	Unaligned	PER	Unaligned
URY	USA	BMU	Unaligned	PHL	Unaligned
UZB	USA	BRB	Unaligned	POL	Unaligned
VCT	USA	BRN	Unaligned	PRT	Unaligned
VUT	USA	BWA	Unaligned	PRY	Unaligned
WSM	USA	CAF	Unaligned	QAT	Unaligned
ABW	CHN	CHE	Unaligned	ROU	Unaligned
AFG	CHN	CHL	Unaligned	SEN	Unaligned
AGO	CHN	CMR	Unaligned	SRB	Unaligned
ARE	CHN	COM	Unaligned	SUR	Unaligned
BDI	CHN	CPV	Unaligned	SVK	Unaligned
BFA	CHN	CRI	Unaligned	SVN	Unaligned
BLR	CHN	CZE	Unaligned	SWZ	Unaligned
BOL	CHN	DJI	Unaligned	SYC	Unaligned
BRA	CHN	DZA	Unaligned	TLS	Unaligned
BTN	CHN	ESP	Unaligned	TON	Unaligned
CAN	CHN	EST	Unaligned	TUN	Unaligned
CIV	CHN	FIN	Unaligned	TZA	Unaligned
COD	CHN	FRA	Unaligned	VEN	Unaligned
COG	CHN	GBR	Unaligned	VNM	Unaligned
COL	CHN	GEO	Unaligned	WBG	Unaligned
DMA	CHN	GIB	Unaligned	YEM	Unaligned
DOM	CHN	GMB	Unaligned	ZAF	Unaligned
ECU	CHN	GRC	Unaligned	ZMB	Unaligned
GAB	CHN	GUY	Unaligned	ZWE	Unaligned
GIN	CHN	HKG	Unaligned		

Notes: “USA” bloc refers to the group of countries moving towards the US bloc, “CHN” refers to the group of countries moving towards the China bloc, and unaligned refers to the rest of the countries. A country is assigned to the USA bloc if $d \ln \tau_i^{USA} < 0$ and $d \ln \tau_i^{CHN} > 0$. Similarly, a country is assigned to the CHN bloc if $d \ln \tau_i^{CHN} < 0$ and $d \ln \tau_i^{USA} > 0$. All other countries are assigned to the Unaligned bloc.

B. QUANTIFICATION

This section presents how to solve for the equilibrium change following a change in exogenous trade costs $\hat{\tau}_{mnj}^f$ and $\hat{\tau}_{mi,nj}^x$ and potential exogenous change in trade deficit \hat{D}_n . The following system of equations determines output \hat{Y}_{nj} , prices \hat{P}_{nj} , consumption sectoral shares $\hat{\pi}_{mj}^f$, final trade shares $\hat{\pi}_{nmj}^f$, intermediate sectoral shares $\hat{\pi}_{j,mi}^x$, intermediate trade shares $\hat{\pi}_{nj,mi}^x$, and sectoral wages \hat{W}_{nj} :

$$\begin{aligned} \left(\hat{P}_{nj} \hat{Y}_{nj} \right) (P_{nj} Y_{nj}) &= \sum_m \left(\sum_i \eta_i \left(\hat{P}_{mi} \hat{Y}_{mi} \right) (P_{mi} Y_{mi}) + \hat{D}_m D_m \right) \pi_{mj}^f \hat{\pi}_{mj}^f \pi_{nmj}^f \hat{\pi}_{nmj}^f \\ &+ \sum_m \sum_i (1 - \eta_i) \left(\hat{P}_{mi} \hat{Y}_{mi} \right) (P_{mi} Y_{mi}) \pi_{j,mi}^x \hat{\pi}_{j,mi}^x \hat{\pi}_{nj,mi}^x \pi_{nj,mi}^x \\ \hat{\pi}_{nj}^f &= \frac{\left(\hat{P}_{nj}^F \right)^{1-\rho}}{\sum_k \pi_{nk,t}^f \left(\hat{P}_{nk}^F \right)^{1-\rho}} \end{aligned}$$

$$\text{where } \hat{P}_{nj}^F = \left[\sum_m \pi_{mnj,t}^f (\widehat{\tau}_{mnj}^f \hat{P}_{mj})^{1-\gamma} \right]$$

$$\begin{aligned} \hat{\pi}_{mnj,t+1}^f &= \frac{\left(\widehat{\tau}_{mnj}^f \hat{P}_{mj} \right)^{1-\gamma}}{\sum_k \pi_{knj,t}^f \left(\widehat{\tau}_{knj}^f \hat{P}_{kj} \right)^{1-\gamma}} \\ \hat{\pi}_{i,nj,t+1}^x &= \frac{\left(\hat{P}_{i,nj}^X \right)^{1-\varepsilon}}{\sum_k \pi_{k,nj,t}^x \left(\hat{P}_{k,nj}^X \right)^{1-\varepsilon}} \end{aligned}$$

$$\text{where } \hat{P}_{i,nj}^X = \left[\sum_i \pi_{mi,nj,t}^x \left(\widehat{\tau}_{mi,nj}^x \hat{P}_{mi} \right)^{1-\nu} \right]^{\frac{1}{1-\nu}}$$

$$\hat{\pi}_{mi,nj,t+1}^x = \frac{\left(\widehat{\tau}_{mi,nj}^x \hat{P}_{mj} \right)^{1-\nu}}{\sum_k \pi_{ki,nj,t}^x \left(\widehat{\tau}_{ki,nj}^x \hat{P}_{kj} \right)^{1-\nu}}$$

$$\hat{P}_{nj} = \left(\hat{Z}_{nj} \right)^{-1} \hat{W}_{nj}^{(1-\alpha_j)\eta_j} \left(\hat{P}_{nj} \hat{Y}_{nj} \right)^{\alpha_j\eta_j} \left(\hat{K}_{nj} \right)^{-\alpha_j\eta_j} \left(\hat{P}_{nj}^X \right)^{1-\eta_j}$$

$$\text{where } \hat{P}_{nj}^X = \left[\sum_i \pi_{i,nj,t}^x \left(\hat{P}_{i,nj}^X \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}$$

$$\hat{W}_{nj} \left(\frac{\hat{W}_n}{\hat{P}_n} \right)^\psi \left(\frac{\hat{W}_{nj}}{\hat{W}_n} \right)^{\mu-1} = \hat{P}_{nj} \hat{Y}_{nj}$$

$$\text{where } \hat{W}_n = \left(\sum_j \pi_{nj}^H \left(\hat{W}_{nj} \right)^\mu \right)^{\frac{1}{\mu}}, \hat{P}_n = \left[\sum_j \pi_{nj,t}^f (\hat{P}_{nj}^F)^{1-\rho} \right]$$

The following algorithm provides a numerical solution to the above system of equations:

1. Guess \hat{P}_{nj}

2. Solve for $\hat{\pi}_{nj}^f, \hat{\pi}_{mnj}^f, \hat{\pi}_{i,nj}^x, \hat{\pi}_{mi,nj}^x$ using:

$$\hat{\pi}_{nj}^f = \frac{\left(\hat{P}_{nj}^F\right)^{1-\rho}}{\sum_k \pi_{nk,t}^f \left(\hat{P}_{nk}^F\right)^{1-\rho}}$$

where $\hat{P}_{nj}^F = \left[\sum_m \pi_{mnj,t}^f (\widehat{\tau_{mnj}^f} \hat{P}_{mj})^{1-\gamma} \right]$

$$\hat{\pi}_{mnj}^f = \frac{\left(\widehat{\tau_{mnj}^f} \hat{P}_{mj}\right)^{1-\gamma}}{\sum_k \pi_{knj,t}^f \left(\widehat{\tau_{knj}^f} \hat{P}_{kj}\right)^{1-\gamma}}$$

$$\hat{\pi}_{i,nj}^x = \frac{\left(\hat{P}_{i,nj}^X\right)^{1-\varepsilon}}{\sum_k \pi_{k,nj,t}^x \left(\hat{P}_{k,nj}^X\right)^{1-\varepsilon}}$$

where $\hat{P}_{i,nj}^X = \left[\sum_i \pi_{mi,nj,t}^x (\widehat{\tilde{\tau}_{mi,nj}^x} \hat{P}_{mi})^{1-\nu} \right]^{\frac{1}{1-\nu}}$

$$\hat{\pi}_{mi,nj}^x = \frac{\left(\widehat{\tilde{\tau}_{mi,nj}^x} \hat{P}_{mj}\right)^{1-\nu}}{\sum_k \pi_{ki,nj,t}^x \left(\widehat{\tilde{\tau}_{ki,nj}^x} \hat{P}_{kj}\right)^{1-\nu}}$$

3. Solve for $\hat{P}_{nj} \hat{Y}_{nj}$ using the new trade shares

$$\begin{aligned} \left(\hat{P}_{nj} \hat{Y}_{nj}\right) (P_{nj} Y_{nj}) &= \sum_m \left(\sum_i \eta_i \left(\hat{P}_{mi} \hat{Y}_{mi}\right) (P_{mi} Y_{mi}) + \hat{D}_m D_m \right) \pi_{mj}^f \hat{\pi}_{mj}^f \pi_{nmj}^f \hat{\pi}_{nmj}^f \\ &\quad + \sum_m \sum_i (1 - \eta_i) \left(\hat{P}_{mi} \hat{Y}_{mi}\right) (P_{mi} Y_{mi}) \pi_{j,mi}^x \hat{\pi}_{j,mi}^x \hat{\pi}_{nj,mi}^x \pi_{nj,mi}^x \end{aligned}$$

4. Solve for wages \hat{W}_{nj} using

$$\hat{W}_{nj} \left(\frac{\hat{W}_n}{\hat{P}_n}\right)^\psi \left(\frac{\hat{W}_{nj}}{\hat{W}_n}\right)^{\mu-1} = \hat{P}_{nj} \hat{Y}_{nj}$$

5. Solve for prices \hat{P}_{nj}

$$\hat{P}_{nj} = \left(\hat{Z}_{nj}\right)^{-1} \hat{W}_{nj}^{(1-\alpha_j)\eta_j} \left(\hat{P}_{nj} \hat{Y}_{nj}\right)^{\alpha_j \eta_j} \left(\hat{K}_{nj}\right)^{-\alpha_j \eta_j} \left(\hat{P}_{nj}^X\right)^{1-\eta_j}$$

where $\hat{P}_{nj}^X = \left[\sum_i \pi_{i,nj,t}^x \left(\hat{P}_{i,nj}^X\right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}$

6. Go back to 1

Table B1: Bloc Assignment, 66 Model Countries (2015-2023)

Country	Bloc	Country	Bloc	Country	Bloc
AUT	USA	ARG	Unaligned	NZL	Unaligned
CYP	USA	AUS	Unaligned	PER	Unaligned
DEU	USA	BEL	Unaligned	PHL	Unaligned
DNK	USA	BGR	Unaligned	PRT	Unaligned
GBR	USA	BRN	Unaligned	ROU	Unaligned
HRV	USA	CAN	Unaligned	ROW	Unaligned
IND	USA	CHE	Unaligned	SVK	Unaligned
JPN	USA	CHL	Unaligned	SWE	Unaligned
KOR	USA	CRI	Unaligned	THA	Unaligned
LTU	USA	CZE	Unaligned	TUN	Unaligned
LVA	USA	ESP	Unaligned	TUR	Unaligned
MMR	USA	EST	Unaligned	VNM	Unaligned
POL	USA	FIN	Unaligned	ZAF	Unaligned
SGP	USA	FRA	Unaligned		
USA	USA	GRC	Unaligned		
		HUN	Unaligned		
BRA	CHN	IRL	Unaligned		
CHN	CHN	ISL	Unaligned		
COL	CHN	ITA	Unaligned		
HKG	CHN	KAZ	Unaligned		
IDN	CHN	LAO	Unaligned		
ISR	CHN	LUX	Unaligned		
KHM	CHN	MAR	Unaligned		
MYS	CHN	MEX	Unaligned		
RUS	CHN	MLT	Unaligned		
SAU	CHN	NLD	Unaligned		
SVN	CHN	NOR	Unaligned		

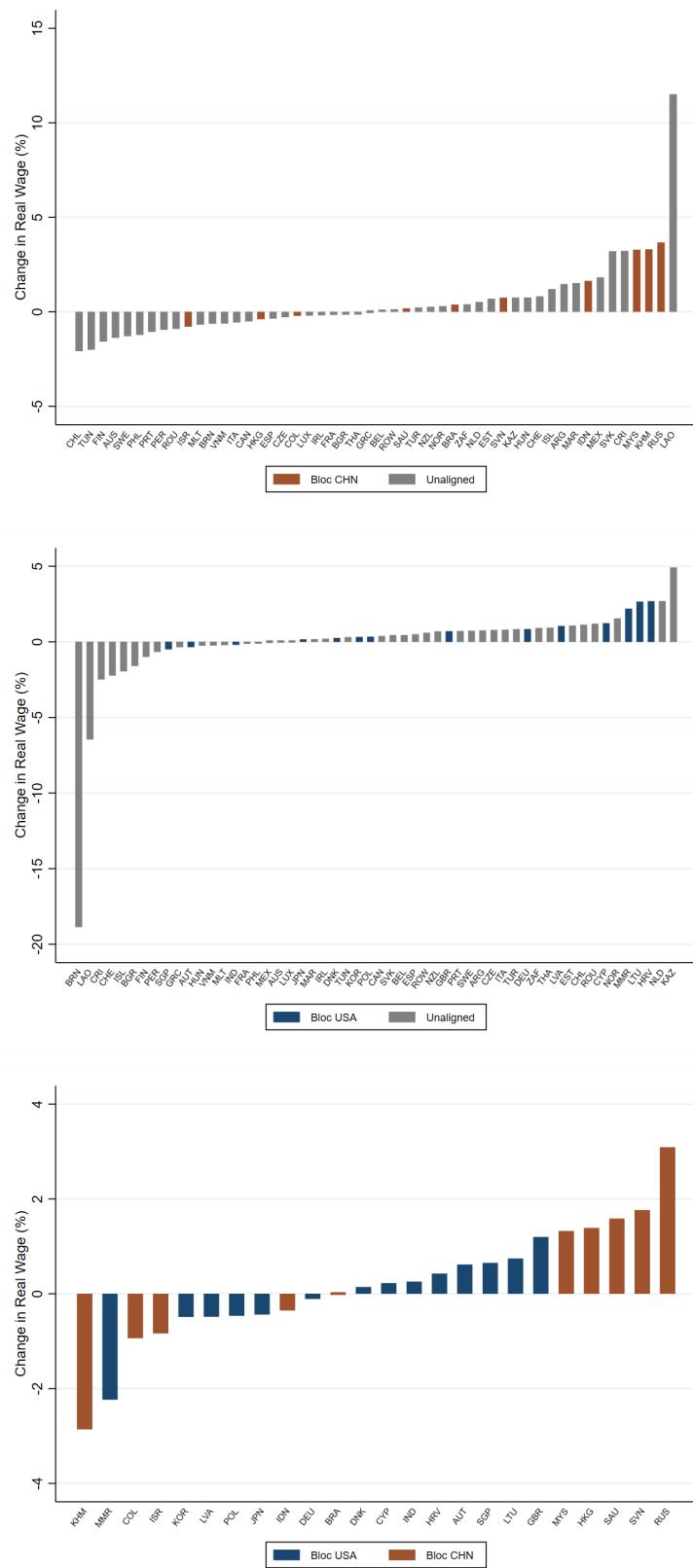
Notes: This table displays the list of countries in the quantitative model, together with their bloc assignment when running our procedure described in section 2.2 on those countries only. “USA” bloc refers to the group of countries moving towards the US bloc, “CHN” refers to the group of countries moving towards the China bloc, and unaligned refers to the rest of the countries. A country is assigned to the USA bloc if $d \ln \tau_i^{USA} < 0$ and $d \ln \tau_i^{CHN} > 0$. Similarly, a country is assigned to the CHN bloc if $d \ln \tau_i^{CHN} < 0$ and $d \ln \tau_i^{USA} > 0$. All other countries are assigned to the Unaligned bloc.

Table B2: Decomposition of baseline change in GDP and Real Income (2015-2023)

Bloc	Real GDP			Real Income		
	Total	$\Delta \ln \tau_{mn}$	$\Delta \ln \tau^{base}$	Total	$\Delta \ln \tau_{mn}$	$\Delta \ln \tau^{base}$
Overall	0.637	0.574	0.074	0.690	0.610	0.074
Bloc USA	0.585	0.533	0.073	0.589	0.537	0.073
Bloc CHN	0.418	0.301	0.072	0.459	0.374	0.071
Unaligned	0.878	0.788	0.074	0.845	0.756	0.074

Notes: We decompose the results from Table 5 into changes in GDP coming from the bilateral relative trade cost changes ($\Delta \ln \tau_{mn}$) and those coming from the overall average change ($\Delta \ln \tau^{base}$). The total column does not match the result from Table 5 exactly because of nonlinearities.

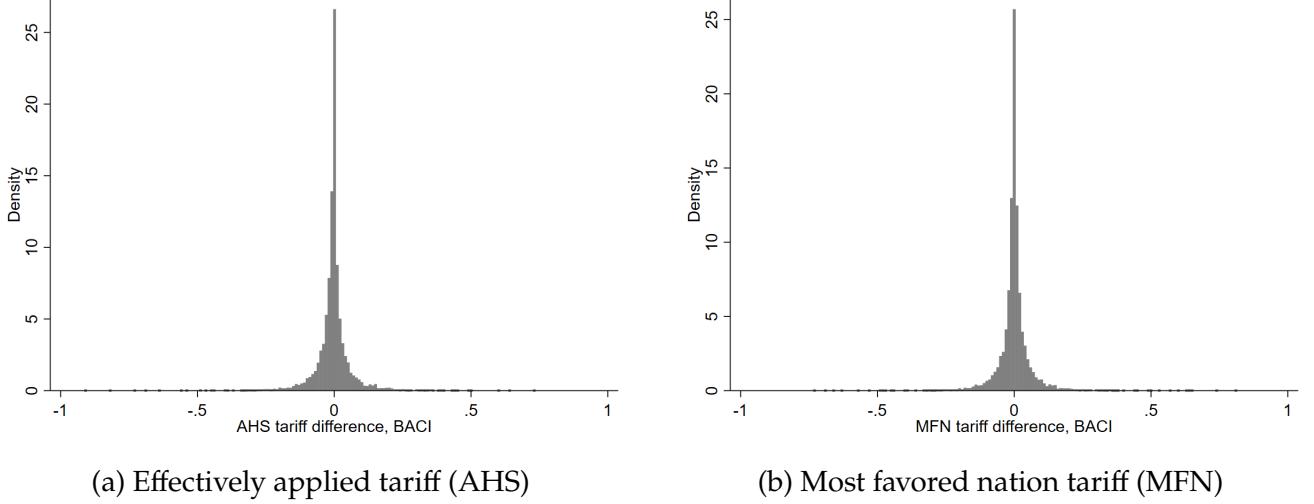
Figure B1: Counterfactual Real Income Changes (2015-2023)



Notes: Each bar in each plot shows the percentage change in real income for each country, relative to factual, when the country is moved to a different bloc.

C. ADDITIONAL EXERCISES AND ROBUSTNESS

Figure C1: Bilateral tariff changes, 2021-2015



Notes: Figure shows histogram of the non-zero changes in bilateral average tariffs between 2021-2015.

Sources: BACI, TRAINS.

C.1 Community detection algorithm

In this section we perform an alternative exercise where we classify countries into blocs using a community detection algorithm. More specifically, we use the Leiden algorithm ([Traag, Waltman, and van Eck 2019](#)), which is designed to find non-overlapping communities in large networks.

In the first step, we run the regression

$$\Delta \ln x_{mn}^{2023-2015} = \alpha_m + \alpha_n + \varepsilon_{mn},$$

where $\Delta \ln x_{mn}^{2023-2015}$ is the log-change in aggregate trade flows from source m to destination n between 2015 and 2023, while α_m and α_n are source and destination fixed effects, respectively. As in the main text, the trade data we use comes from the Direction of Trade Statistics (DOTS) dataset and has an annual frequency.

Then, we recover the predicted residual $\widehat{\varepsilon}_{mn}$ and calculate the undirected trade weight w_{mn} as

$$w_{mn} = \frac{\widehat{\varepsilon}_{mn} + \widehat{\varepsilon}_{nm}}{2}.$$

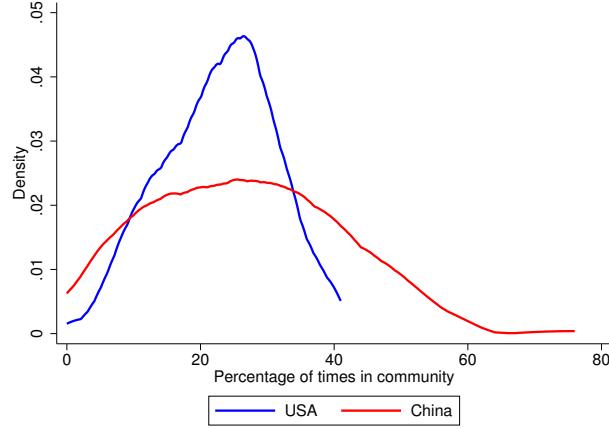
The undirected trade weight w_{mn} captures the average effect of the trade occurring between countries m and n that is not due to source-specific or destination-specific characteristics. With this measure, we rule out the effect of countries that increased or decreased trade with all their partners between 2015 and 2023, focusing only on the bilateral effects. Because $w_{mn} = w_{nm}$, we drop any repeated pair from our dataset.

In the next step, we run the Leiden algorithm using the undirected trade weights w_{mn} as inputs. In terms of the country trade-based network, the larger the weight between two countries, the stronger their link and vice versa. We perform 100 draws of the Leiden algorithm, where each draw returns a list of communities to which each country belongs.⁷ Intuitively, a community is a group of countries with particularly strong links between them with respect to the other countries. Moreover, because communities are non-overlapping, a country may not belong to more than one community.

⁷We perform 100 draws because the Leiden algorithm contains a random component. We only count draws where (i) USA and China belong in different communities and (ii) there are 5 communities or less.

As we run the algorithm 100 times, we can calculate the percentage of times each country belongs to the same community as the US or China out of the total draws. Let p_{USA} be the percentage of times a country belongs to the same community as the US and p_{CHN} be the percentage of times a country belongs to the same community as China. We present the density of these percentages in Figure C2.

Figure C2: Density of percentages, Leiden algorithm



Notes: Figure shows the density of the percentage of times a country belongs to the same community as the US and the same community as China. Each observation is a country.

We now introduce a frequency-based classification of countries into blocs. First, we classify a country as belonging to the US bloc if $p_{USA} > 0.2$ and $p_{USA} > p_{CHN}$. Second, we classify a country as belonging to the China bloc if $p_{CHN} > 0.2$ and $p_{CHN} > p_{USA}$. Finally, we classify a country as unaligned if $p_{USA} < 0.2$ and $p_{CHN} < 0.2$.

Table C1: Bloc comparison, community detection algorithm and baseline classification

		Baseline		
		USA bloc	China bloc	Unaligned
Community detection, Leiden alg.	USA bloc	24	10	32
	China bloc	11	28	57
	Unaligned	7	7	10

Notes: Table shows number of countries in each bloc according to each classification.

Table C1 presents the comparison between the blocs resulting from the community detection algorithm and the baseline classification. We see that after using a different method to classify countries into blocs, we get similar results to the baseline ones. The baseline procedure is more conservative in classifying more countries as unaligned. However, for the 73 countries assigned by both procedures to either the USA or China bloc, 52 (or 71%) are assigned to the same bloc.

C.2 Start year: 2016

Table C2: Bloc comparison, Baseline 2015 vs Baseline 2016 (All Countries)

		Baseline 2015		
		USA bloc	China bloc	Unaligned
Baseline 2016	USA bloc	31	2	18
	China bloc	2	38	10
	Unaligned	11	7	71

Notes: Table shows number of countries in each bloc according to each classification. USA(CHN) bloc includes USA(CHN) itself.

Table C3: Bloc comparison, Baseline 2015 vs Baseline 2016 (Model Countries)

		Baseline 2015		
		USA bloc	China bloc	Unaligned
Baseline 2016	USA bloc	12	0	5
	China bloc	0	6	2
	Unaligned	3	5	33

Notes: Table shows the number of countries in each bloc according to each classification. USA(CHN) bloc includes USA(CHN) itself.

Table C4: Log Change in Average Trade Cost between Blocs (Model countries, 2016-2023)

↓ Exporter Importer →	Bloc USA	Bloc CHN	Unaligned	Overall
Bloc USA	-0.051	0.040	-0.034	-0.027
Bloc CHN	0.081	-0.150	-0.020	0.019
Unaligned	-0.053	-0.059	-0.050	-0.053
Overall	-0.020	-0.027	-0.037	-0.010

Notes: We classify countries into 3 groups, Bloc USA, Bloc CHN, and Unaligned. Then, all country pairs are classified into 9 group pairs. We report the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ for country pairs belonging to each group pair, weighted by bilateral trade flows in 2016. The Overall column is the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ of all trade flows from(to) each exporter(importer) group.

Table C5: Baseline Change in GDP and Real Income (2016-2023)

Bloc	GDP			Real Income		
	Median	p25	p75	Median	p25	p75
Overall	1.262	0.720	1.868	1.257	0.748	1.919
Bloc USA	0.774	0.210	1.135	0.815	0.203	1.137
Bloc CHN	1.672	0.903	2.554	1.855	0.895	2.562
Unaligned	1.581	0.839	2.521	1.607	0.846	2.519

Notes: Baseline change in GDP and real income are reported in percentage changes.

C.3 Pre-Covid: 2015-2019

Table C6: Log Change in Average Trade Cost between Blocs (Model countries, 2015-2019)

↓ Exporter Importer →	Bloc USA	Bloc CHN	Unaligned	Overall
Bloc USA	-0.001	0.065	-0.006	0.010
Bloc CHN	0.051	-0.038	0.004	0.016
Unaligned	0.010	0.009	-0.013	0.000
Overall	0.018	0.018	-0.007	0.003

Notes: We classify countries into 3 groups, Bloc USA, Bloc CHN, and Unaligned. Then, all country pairs are classified into 9 group pairs. We report the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ for country pairs belonging to each group pair, weighted by bilateral trade flows in 2015. The Overall column is the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ of all trade flows from(to) each exporter(importer) group.

Table C7: Baseline Change in GDP and Real Income (2015-2019)

Bloc	GDP			Real Income		
	Median	p25	p75	Median	p25	p75
Overall	-0.063	-0.732	0.696	-0.059	-0.737	0.691
Bloc USA	-0.239	-0.790	0.111	-0.211	-0.818	0.109
Bloc CHN	-0.228	-1.029	0.567	-0.221	-1.121	0.582
Unaligned	0.373	-0.648	0.990	0.358	-0.661	1.000

Notes: Baseline change in GDP and real income are reported in percentage changes.

C.4 Placebo: 2002-2007

Table C8: Bloc comparison, Baseline 2015 vs Baseline 2002 (Model Countries)

		Baseline 2015		
		USA bloc	China bloc	Unaligned
Baseline 2002	USA bloc	5	3	9
	China bloc	1	2	0
	Unaligned	9	6	31

Notes: Table shows the number of countries in each bloc according to each classification. USA(CHN) bloc includes USA(CHN) itself.

Table C9: Log Change in Average Trade Cost between Blocs (Model countries, 2002-2007)

↓ Exporter Importer →	Bloc USA	Bloc CHN	Unaligned	Overall
Bloc USA	-0.081	0.081	-0.140	-0.102
Bloc CHN	-0.032	-0.063	-0.135	-0.075
Unaligned	-0.159	-0.085	-0.196	-0.176
Overall	-0.122	-0.009	-0.174	-0.145

Notes: We classify countries into 3 groups, Bloc USA, Bloc CHN, and Unaligned. Then, all country pairs are classified into 9 group pairs. We report the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ for country pairs belonging to each group pair, weighted by bilateral trade flows in 2002. The Overall column is the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ of all trade flows from(to) each exporter(importer) group.

Table C10: Log Change in Average Trade Costs between 2015 Blocs (Model countries, 2002-2007)

↓ Exporter Importer →	Bloc USA	Bloc CHN	Unaligned	Overall
Bloc USA	-0.145	-0.004	-0.139	-0.124
Bloc CHN	-0.118	-0.015	-0.172	-0.127
Unaligned	-0.165	-0.124	-0.180	-0.167
Overall	-0.152	-0.055	-0.160	-0.145

Notes: Using 2015 blocs, we classify countries into 3 groups, Bloc USA, Bloc CHN, and Unaligned. Then, all country pairs are classified into 9 group pairs. We report the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ for country pairs belonging to each group pair, weighted by bilateral trade flows in 2002. The Overall column is the average $\Delta \ln \tau_{mn} + \Delta \ln \tau^{base}$ of all trade flows from(to) each exporter(importer) group.

C.5 Validation of the trade cost estimates

For each 8-year period since 2000 for which the ICIO dataset is available, we compute the Head and Ries ratio to back out estimates of trade cost changes implied by trade data including own-trade data. Starting from the gravity equation in changes:

$$d \ln X_{mn} = \eta_m + \gamma_n + (1 - \gamma) d \ln \tau_{mn}, \quad (\text{C.1})$$

we can recover the change in bilateral trade cost from:

$$\tilde{\tau}_{mn}^{HR} = \Delta_{t,t-8} (\ln \tau_{mn} + \ln \tau_{nm}) = \frac{1}{(1-\gamma)} \Delta_{t,t-8} \ln \left(\frac{X_{mn}}{X_{nn}} * \frac{X_{nm}}{X_{mm}} \right). \quad (C.2)$$

For every 8-year period from 2000-2008 to 2010-2018, we compute $\tilde{\tau}_{mn}^{HR}$ from trade data, and we also compute an estimate of $\Delta_{t,t-8} (\ln \tau_{mn} + \ln \tau_{nm})$ from our procedure using residuals of the gravity regression, and then targeting the change in world trade to GDP ratio to pin down the level.

Table C11 shows summary statistics of the difference between $\tilde{\tau}_{mn}^{HR}$ and our estimates. Figure C3 shows a scatter plot.

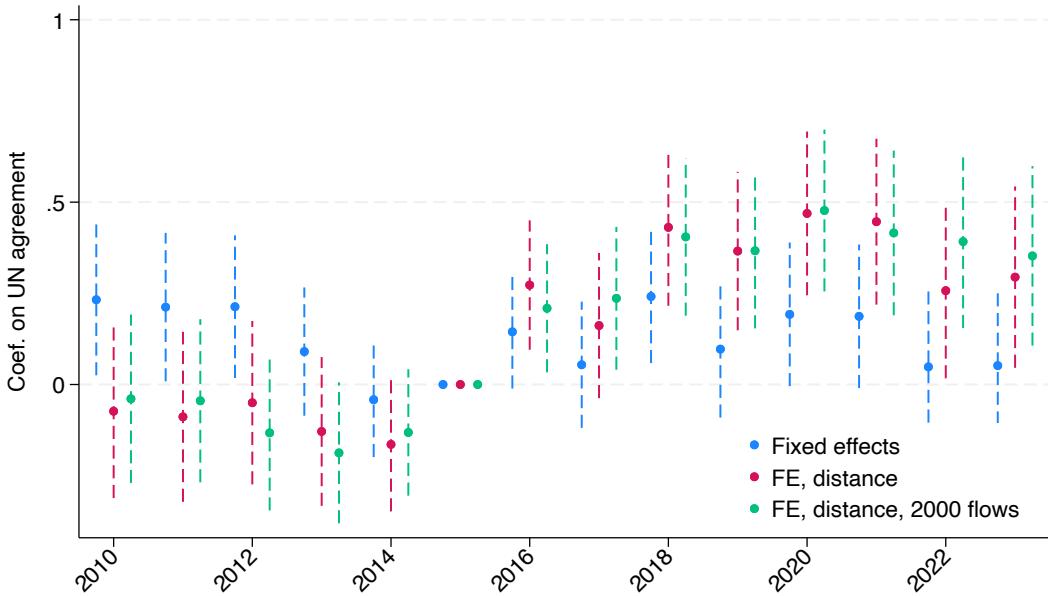
Table C11: Model implied Trade Cost and Head-Ries Trade Cost

	Average	Median	p25	p75
Log Change in Model implied Trade Cost	-0.105	-0.097	-0.308	0.106
Log Change in Head-Ries Trade Cost	-0.096	-0.084	-0.303	0.104
Difference	-0.009	-0.0004	-0.161	0.157

Notes: We report the summary statistics for our model implied $\Delta \ln \tau_{mn} + \Delta \ln \tau_{nm}$ and the counterpart from the observed Head-Ries trade cost using ICIO dataset between 2002 and 2007. The last row displays the summary statistics of the difference.

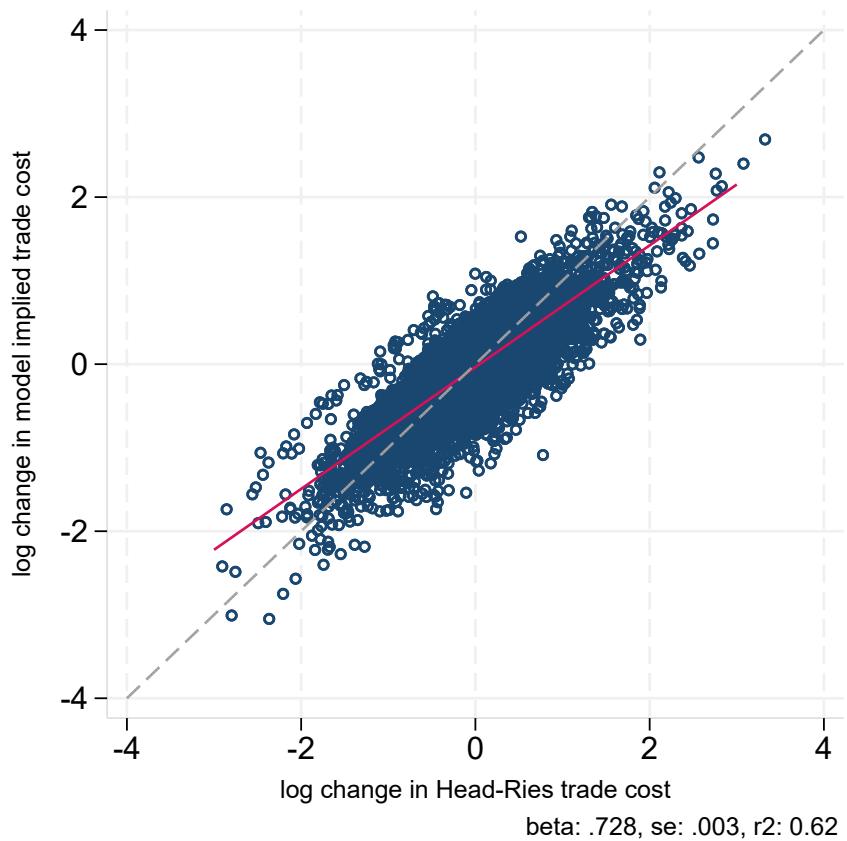
C.6 UN agreement regressions, all countries

Figure C4: Event study of bilateral trade flows, all countries



Notes: The figure displays the estimates of β_t^{UN} from regression 3.11. Each dot color corresponds to different controls. The blue coefficients only include the fixed effects. The red coefficients include time-varying coefficients on distance, and the green coefficients include time-varying coefficients on 2000 bilateral trade flows. The sample covers all countries in the DOTS dataset.

Figure C3: Model implied Trade Cost and Head-Ries Trade Cost



Notes: The scatterplot compares our model implied $\Delta \ln \tau_{mn} + \Delta \ln \tau_{nm}$ to the counterpart from the observed Head-Ries trade cost using ICIO dataset.