

Trade fragmentation, (de-)globalization, or both? *

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Abstract

Amid recent geopolitical tensions, is world trade fragmenting or even receding, and what are the welfare consequences of these shifts? We combine data on bilateral trade flows with a novel quarterly production dataset to estimate a structural gravity equation with domestic trade flows, allowing us to contrast changes in relative trade costs according to geopolitical alignment – geoeconomic fragmentation – with changes in the overall level of trade costs – (de-)globalization. Following the Russian invasion of Ukraine we estimate that trade costs rose between geopolitical rivals. However, this increase was offset by declining common trade costs and, to a lesser extent, by intra-bloc deepening, leading overall to a mild and statistically insignificant decline in average trade costs of -0.21% . In a standard quantitative trade model, these estimates imply an average welfare gain of $+0.08\%$, with large differences across countries. These results indicate that geopolitical realignment and declining trade openness are distinct phenomena, and need not go hand in hand.

Keywords: Geoeconomic fragmentation; deglobalization; trade costs; structural gravity; welfare; geopolitical blocs

JEL classifications: F13; F14; F15; F50; F51

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1 Introduction

In February 2022, following the outset of the Russian invasion of Ukraine, Western countries began to rapidly reduce their economic ties with Russia, leading to renewed debate around the vulnerability of global supply chains and on economic dependence on geopolitical rivals more broadly. The episode has since become the leading exhibit in a much larger argument: whether the world economy is separating into rival blocs – trade fragmentation–, and whether this separation marks the end of a long era of deepening trade integration – (de-)globalization.

In much of the policy discourse, however, the terms *geoeconomic fragmentation* and *deglobalization* are often used loosely, without a clear definition or formal distinction. We use the term *geoeconomic fragmentation* to denote a change in the composition of trade across partners along geopolitical lines, for a given level of trade openness.¹ This reallocation operates through two channels: inter-bloc fragmentation, a rise in trade costs between countries of opposing blocs, and intra-bloc integration, a decline in trade costs within blocs – both measured relative to trade with non-aligned (neutral) countries. By (de-)globalization, in contrast, we mean a change in the overall level of trade costs, i.e. the cost of cross-border trade relative to domestic trade, independent of geopolitical alignment. With these definitions in hand, we then ask how we can characterize the current period of global trade. Is world trade fragmenting along geopolitical lines, and if so, is this driven by rising inter-bloc trade costs or falling intra-bloc trade costs? More fundamentally, has globalization itself slowed or reversed, in the sense of rising overall trade costs or declining openness relative to economic activity? And, using a quantitative trade model, what are the resulting welfare consequences – in aggregate and for the part attributable to *geoeconomic fragmentation*?

In this paper we estimate trade costs from a structural gravity equation with domestic and international trade flows. We find that, following the start of the Russia-Ukraine war, trade costs rose sharply between countries in opposing blocs. This increase is concentrated in trade involving Russia, consistent with the direct effect of sanctions, while non-Russia inter-bloc effects, though present and widening toward the end of the sample, are smaller and more imprecisely estimated on average. Our main finding, however, is that there is no evidence for rising trade costs on average, as the increase in inter-bloc trade costs was offset by declining common trade costs, and, to a lesser extent, declining intra-bloc costs. We find that average

¹The IMF defines *geoeconomic fragmentation* as a “policy-driven reversal of integration guided by strategic considerations” (Aiyar et al., 2023). Our approach is outcome-driven: we let the data speak in terms of whether we observe a fragmentation of trade across blocs without modeling explicitly the policies behind such fragmentation.

trade costs declined by -0.21%, statistically indistinguishable from zero.² In other words, fragmentation has reshaped the geography of trade without reversing globalization, which remained broadly unchanged during this period. Using a standard quantitative trade model, these estimates imply an average welfare gain of +0.08%. Russia incurs the largest losses due to heightened trade costs with the West, while Belarus gains due to more exclusive access to the Russian market. Among neutral and Western economies, the largest gains accrue to countries with relatively high shares of intermediates in expenditure, that benefit from the common decline in trade costs.

Most of the existing literature on trade fragmentation has focused on reallocation of trade shares without tackling the issue of openness due to data limitations, usually referring to the stability of the trade-to-GDP ratio to discuss (de)globalization trends (Gopinath et al., 2025; Bonadio et al., 2025). While bilateral international trade data are typically readily available for many countries, at monthly frequency and at a high level of product detail, data on domestic trade – typically backed out from production minus exports – are scarce, only available at annual frequency, and at lower levels of detail. We overcome this problem by building a novel quarterly industry-level production dataset using data from UNIDO and from several national statistical institutes. We combine annual nominal production levels from UNIDO INDSTAT with UNIDO’s monthly index of real industrial production, reflatting the latter using producer price indices to obtain a monthly index of nominal production. We then rescale this index to match the annual UNIDO levels and aggregate to quarterly frequency, before computing domestic expenditure as production net of exports. We obtain a dataset with domestic trade data for 43 countries from 2017Q1 to 2024Q4, combined with detailed official customs trade data for imports and exports of these 43 countries with any of 227 trade partners, covering 90.6% of world manufacturing trade on average over 2017-2024.

We then estimate a structural gravity equation including domestic trade flows, which allows us to compare international trade flows to domestic trade flows, within industries, and to contrast changes in relative trade costs according to geopolitical alignment with changes in the overall level of trade costs (Yotov, 2022). We estimate the gravity equation in a panel using bilateral-by-sector fixed effects that absorb the effect of standard gravity determinants such as distance, contiguity, and common language. It follows that identification comes entirely from how trade costs within a bilateral-by-sector relationship change over time. The time-varying component loads on two sets of indicators: a general international-trade indicator, common to all cross-border flows, which captures shifts in the cost of trading across borders relative to trading at home—our empirical counterpart to (de)globalization; and

²The 95% confidence band ranges from -1.47% to +1.06%.

indicators for trade within and between geopolitical blocs, which capture geopolitical reallocation. This framework lets us track the evolution of trade costs over time and separate the geopolitical component from broader trends in trade costs that may happen at the same time. We identify the geopolitical component from variation in bilateral trade between the 43 countries with domestic data and their 227 trading partners distributed along the geopolitical spectrum.

A salient characteristic of the international trade environment over the past years is the use of direct trade policy measures by governments to achieve geopolitical goals, such as export controls, discriminatory tariffs, local content rules, and economic sanctions (Aiyar et al., 2023; Evenett et al., 2024). While some of these policies can be measured, albeit imperfectly, international trade flows may also have been affected by non-policy trade cost changes, e.g. technological, or by uncertainty about future (trade or domestic) policies, which may effectively act as barriers to international trade but are very difficult to measure. Furthermore, it is not clear which trade policies have a geopolitical motivation and which ones are taken with other objectives (e.g. due to domestic industry lobbying). Our goal in this paper is not to estimate the effect of any one trade policy on trade flows, but to back out the extent of all trade frictions linked to geopolitics, as well as the common, non-geopolitical trend in trade costs. Our estimates summarize the effect of all trade policies and unobserved trade frictions linked to geopolitical alignment.

Our empirical estimates imply that, despite large dispersion in trade cost changes, average global trade costs remained broadly unchanged over this period. Even though Russia-West trade declined by 87%, implying a large increase in trade costs, the effect on average global trade costs is moderate because Russia-West trade accounted for only 2.6% of global trade initially. On a trade-weighted basis, rising trade costs between the West and Russia (+0.95%) and between the West and other Eastern bloc countries (+0.30%) are more than offset by declining common costs (−1.07%) and intra-bloc deepening (−0.4%), leaving the net change in average bilateral trade costs at −0.21%.

We then evaluate the implications of the estimated trade cost changes for welfare across countries in a stylized quantitative exercise, using a standard general equilibrium trade model. To account for estimation uncertainty, we draw repeatedly from the estimated asymptotic distribution of the gravity coefficients and solve the general equilibrium model for each draw, which yields a full distribution of welfare effects for every country. We report confidence intervals constructed from these simulated distributions using the basic bootstrap method.

We then use the model to compare the contribution of geoeconomic fragmentation to overall trade cost dynamics using different counterfactual scenarios. Inter-bloc fragmentation alone creates an average welfare loss (−0.09%) that is more than

offset by the welfare gains caused by common trade cost changes—a continued decline in the relative cost of cross-border versus domestic trade – (+0.13% of the baseline) and, to a lesser extent, by intra-bloc integration, leading to an average welfare change in the full scenario of +0.08%. However, due to estimation uncertainty we cannot exclude small average welfare losses. This muted average effect on welfare conceals sizable redistributive effects. Russia emerges as the main loser, due to heightened trade costs with the West, and Belarus as the main beneficiary as it benefits from trade diversion away from the Russian market. Neutral countries tend to gain in the full scenario but their welfare changes are often not statistically significant because they rely heavily on a decline in common trade costs which is measured noisily. The few countries with positive and statistically significant welfare gains tend to be smaller Western countries such as Ireland, Austria, Iceland, and Portugal, that are characterized by relatively high intra-bloc integration and small direct trade links with Russia.

Our paper makes three main contributions. First, we document both the relative and the absolute trade cost dynamics of the current episode of geopolitical tensions, showing that rising inter-bloc barriers did not translate into higher average trade costs. Second, we contribute a novel high-frequency dataset. We construct quarterly sector-level domestic production series for 43 countries extending to 2024, matched with trade with 227 trading partners, providing more recent and higher-frequency coverage than existing datasets such as the International Trade and Production Database for Estimation (Borchert et al., 2021) and the CEPII Trade and Production Database (Mayer et al., 2023). Incorporating domestic flows alongside international trade allows us to assess changes in *absolute* trade costs and to test directly for deglobalization. Third, we contribute a welfare evaluation of geo-economic fragmentation using a quantitative multi-country, multi-sector general equilibrium model with global value chains.

Beyond the Ukraine episode, our results point to a broader lesson for future episodes of rising geopolitical tension: fragmentation and (de-)globalization are conceptually and empirically separable processes. A bloc realignment need not, by itself, mean the end of global trade integration – the two can move in opposite directions, as they did here, if reallocation toward geopolitical allies coincides with a broader decline in the cost of cross-border trade. Telling the two apart in any given episode, however, requires a framework that speaks to both relative and absolute trade costs, which is what we build in this paper.

Relation to the literature. We contribute to different strands of the literature. The role of geopolitical alignment for the facilitation or deterioration of trading relationships has been the subject of a growing literature that leverages international trade data (Hakobyan et al., 2023; Alfaro and Chor, 2025; Fernández-Villaverde

et al., 2024; Kleinman et al., 2024; Attinasi et al., 2025; Gopinath et al., 2025; Bonadio et al., 2025; Fan et al., 2026), and sparked a nascent theoretical literature (Kleinman et al., 2024; Mayer et al., 2025; Meyer and Wesseler, 2025; Clayton et al., 2026). Gopinath et al. (2025) is an important reference. They estimate a gravity equation in which geopolitical alignment is based on UN-voting patterns and, like we do, find that a trend towards fragmentation unfolded since the invasion of Ukraine, comparing it to the geoeconomic fragmentation of the Cold War. Bonadio et al. (2025) find increasing trade fragmentation using a revealed-cost-based classification, assigning a bloc precisely because its trade costs with that bloc fell. In their work, therefore, any bilateral divergence, geopolitical or not, is therefore read by construction as bloc realignment, whereas our design leaves open the possibility that political alignment bears no relationship to trade-cost changes at all.

We complement previous works in two important ways. First, while the literature estimates trade costs changes with respect to an omitted importer or exporter, we provide the first estimates of *absolute* trade costs changes, which are crucial when thinking about the welfare effect of fragmentation. Second, we estimate the common change in the cost of cross-border relative to domestic trade at the country-by-sector level, controlling for exporter- and importer-side multilateral resistance, so that the globalization trend is identified from within-sector-pair variation over time, net of shifts in country size, sectoral composition, or other confounds that could otherwise drive a single aggregate trade-to-GDP ratio. Our paper delivers an integrated analysis of fragmentation, deglobalization and their welfare consequences using novel data and state-of-the-art quantitative methods. Doing so, we add to the debate on the evolution of globalization that has sparked a lot of attention in recent years (Antràs, 2021; Goldberg and Reed, 2023). We also add to the literature studying the effect of specific policies (e.g. Felbermayr et al. (2021) on sanctions), by providing outcome-based measures of fragmentation backed out from a structural gravity framework.

Our paper also speaks to the broader literature on the estimation of structural gravity equations and the importance of using data on domestic trade flows for the proper identification of trade costs Head and Mayer (2014a); Yotov (2022). We show how to construct recent data on domestic trade flows at higher frequencies from publicly available sources, opening a wide range of potential applications. Our empirical approach owes to Head and Mayer (2021), who apply a structural gravity framework with domestic flows to study changes in trade costs brought up by the European Union.³

³Playing a word game with the notion of “Fortress Europe” that they test in their paper, our result that trade fragmentation increased because of raising inter-bloc costs rather than lowering intra-bloc ones would lead to the idea of a “Fortress West”.

Finally, our paper relates to a literature quantifying the welfare effects of geoeconomic fragmentation, typically by simulating hypothetical decoupling scenarios in quantitative trade models (Javorcik et al. (2024), Hakobyan et al. (2023), and Attinasi et al. (2025)). We differ in that our trade cost shocks are estimated from realized trade flows rather than assumed, and include the common, non-geopolitical component alongside the bloc-specific one. This proves decisive for the aggregate result: the rise in inter-bloc barriers alone implies a welfare loss, in line with this literature, but it is more than offset once the general decline in trade costs is taken into account.

The remainder of the paper is organized as follows. Section 2 describes our data, including the construction of the quarterly domestic production dataset and the classification of countries into geopolitical blocs. Section 3 presents the structural gravity framework and estimates the evolution of trade costs, separating the geopolitical reallocation of trade from the broader globalization trend. Section 4 develops the quantitative trade model, constructs the underlying trade cost shocks, and evaluates their welfare consequences under a set of counterfactual scenarios. Section 5 concludes.

2 Data

International trade data. Our main dataset consists of quarterly bilateral trade flows disaggregated at the 2-digit level of the ISIC Rev. 4 classification for the period 2017Q1-2024Q4. The data are sourced from Trade Data Monitor (TDM), a commercial provider that collects and harmonizes official customs statistics from a large set of countries.⁴ We download data from 65 countries reporting their detailed bilateral exports and imports. The underlying data are reported monthly at the HS6 product level and are aggregated to the 2-digit industry level using a product-to-industry concordance in order to match the sectoral aggregation of the production data.

To assess the representativeness of the underlying trade database, we compare TDM with the BACI database of Gaulier and Zignago (2010) and evaluate coverage by restricting BACI to flows whose destination country reports to TDM. We find that these reporting countries account for 89.4% of world manufacturing trade on average over 2017–2024, with these shares remaining stable over time, as shown in Table A1 of Appendix A.1.

In our estimations we will use both reported imports and reported exports. That is, trade of countries that do not report to TDM is captured through reported values of their trade partners (mirror flows). Some flows are reported twice, once by the

⁴Relative to public sources such as COMTRADE, TDM provides trade data with substantially shorter publication lags.

exporter and once by the importer. In such cases we prefer the importer reported flows, and we only use flows reported by the exporter if the importer reported flows are unavailable.⁵

Domestic trade data. Our goal is to build a series of quarterly levels of domestic trade values – in current EUR for comparability with our trade data – at the country-by-industry level. Following standard practice in the literature, we create measures of domestic trade flows by subtracting exports from total output in a given sector (Bradley et al. (2024)). Given the lack of a unified ready-to-use dataset with granular information at higher than annual frequency levels and for recent periods, we combine several datasets.⁶ We give a brief overview of the data construction here, but refer to Appendix A.2 for more details.

Our first main data source is UNIDO INDSTAT, which provides us with annual levels of nominal industrial production. We aggregate these production figures to the 2-digit ISIC level, for each country and year. The downsides of the data are that they are only available at an annual frequency, and that the publication lag is long. As of end-2024, the series for most countries end in 2021. To overcome these limitations we use a second data source from UNIDO, the monthly index of industrial production (IIP). This index measures real output growth at the two-digit ISIC level and is supplied by country statistical institutes to UNIDO. Since this index measures real instead of nominal output growth, it cannot be directly used together with the annual production figures to compute a monthly series of nominal production levels. Unfortunately, UNIDO only supplies real production growth but not the corresponding price indices. In a first step, we therefore collect industry producer price indices for as many countries as possible from several national statistical institutes. For some remaining countries for which we cannot find detailed producer price series, we use a more aggregate producer price series (manufacturing sector if available, or if not, for the entire economy), and assume that relative industry inflation is proportional to the US.

With the price indices in hand, we next combine them with the monthly IIP data to arrive at an index of nominal production. We then use monthly exchange rate data to transform this index into an index of nominal production measured in USD. Finally, we can then combine this index of nominal production with the annual production levels from UNIDO to back out nominal monthly production

⁵Import and export flows are often recorded in different valuations, with imports often including costs of insurance and freight (cif), and exports excluding them (fob). We make no adjustment to harmonize these valuations. As will become clear later, our estimation uses only time variation within a given exporter-importer-sector triplet. If the share of insurance and freight in the import value is constant within an exporter-importer-sector cell, this will be netted out in the estimation.

⁶The data in Bradley et al. (2024) is at the yearly level and stops in 2019.

levels in USD, before aggregating this series to the quarterly level. In Appendix A.2 we provide evidence that the extrapolated series are very close to the true ones, and that median and average production errors are very small, by extrapolating years for which we observe the true data and comparing the constructed versus the observed values.

As a last step we compute domestic expenditure as production minus total exports, and total expenditure as domestic expenditure plus imports. We arrive at a series of nominal sectoral production for a set of 43 countries.

Geopolitical alignment of countries. We allocate countries in our sample into one of three geopolitical blocs: *West*, *East* and *Neutral*. We use the approach developed in Den Besten et al. (2023) that combines a set of measures of political alignment and economic ties between countries. In particular, it uses the recent history (past 10 years) of sanctions, military imports, UN voting and China’s official lending to measure the closeness of each country to a US-centered West bloc and a China-centered East bloc. The index lies between 0 and 1, with values close to 0 representing alignment with the United States and values close to 1 representing alignment with China. Geopolitical blocs are then constructed as follows: countries with an index below 0.25 are assigned to the western bloc, those with an index above 0.75 are allocated to the eastern bloc and those with values in between are classified as neutral. Appendix A.3 provides more details on the index’s construction. This approach extends the one used in the recent literature that uses UN voting, either the 2022 February vote opposing Ukraine’s invasion by Russia (Javorcik et al. (2024)) or voting during the past decade (Gopinath et al. (2025)). As in those papers, geopolitical bloc composition is held fixed throughout the sample period. Section B.3 presents a comparison of bloc affiliation between the main measure used in this paper (Den Besten et al. (2023)) and the measure by Bailey et al. (2017) that uses UN voting data and is used, e.g. in Gopinath et al. (2025). Out of 184 countries that are classified in a bloc in both measures (the measure by Bailey et al. (2017) cannot classify 43 out of 227 original countries), 108 countries (59%) are classified in the same bloc, and these 108 countries account for roughly three quarters of global trade. Figure B9 in Section B.3 shows that our main results remain unchanged if we use the UN voting measure instead.

Final sample. After merging the TDM trade data (reported exports and imports) with the data on domestic expenditure, our final dataset consists of quarterly sectoral bilateral trade flows between any of the 43 countries with domestic expenditure data and any of the 227 partner countries.⁷ Trade of countries that do not report

⁷The 43 countries are Austria, Belgium, Bulgaria, Brazil, Canada, Switzerland, China, Colom-

to TDM or for which we do not have production data (e.g. Russia) is captured to the extent that they trade with one of the 43 countries through the mirror flows.

In some cases, the calculation of domestic expenditure leads to negative values.⁸ To analyze the dynamics of the domestic share of expenditure over time, we therefore define a consistent set of country-sector series for which domestic expenditure (and therefore also total expenditure) are always positive.

This sample consists of 579 country $\times$ sector combinations where a sector is one out of 24 two-digit ISIC code (codes 10-33) and the country is one out of 43 countries for which we have both trade and production data. The full time period for this panel is 2014Q1–2024Q4, although we focus on data starting in 2017 for the main part of the analysis. The retained origin–destination pairs after the mirroring procedure account for 90.6% of world manufacturing trade on average over 2017–2024, with these shares remaining stable over time, as shown in Table A2 of Appendix A.1.

Sample composition. Among the 43 countries with domestic expenditure data, 34 belong to the Western bloc, 7 to the Neutral bloc and 2 to the Eastern bloc. These countries account, on average, for 44.5%, 8.9% and 46.6% of domestic expenditure, respectively, with little variation over time. The 227 partner economies comprise 84 Western, 92 Neutral and 61 Eastern countries. Western countries account for 62.7% of trade in the sample, compared with 20.6% for Neutral countries and 16.7% for Eastern countries. Figures in Appendix A.3 illustrate the distribution of countries and flows across geopolitical blocs. Appendix A.4 reports the repartition of observations and trade value across the 24 manufacturing industries.

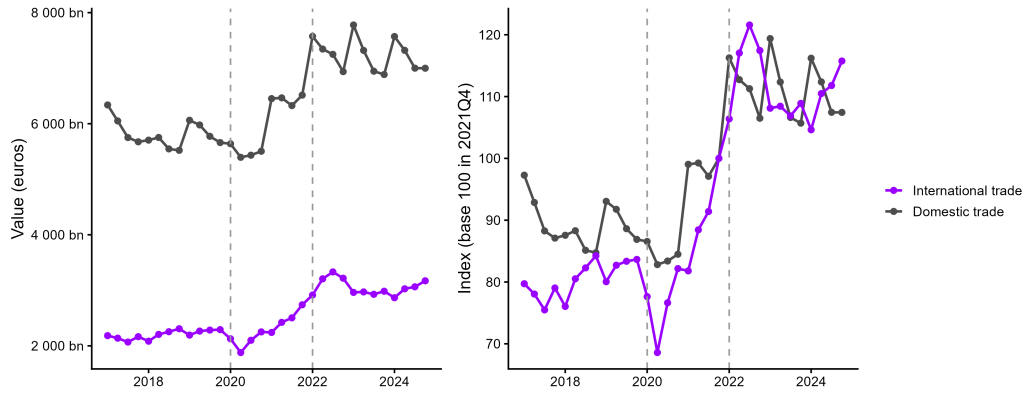
Descriptive Statistics. Figure 1 presents the time series for domestic expenditure and imports for the 43 countries aggregate, both in nominal values (left figure) and indexed to 100 in 2021Q4, the last quarter before the Russian invasion of Ukraine. Expenditure on domestically produced goods are significantly larger than imports, reflecting the large weight of economies with high domestic expenditure shares, such as China and the United States (see Figure B1). After Covid, imports grew slightly faster than expenditure on domestically produced goods, but this faster growth came to a halt shortly after the Russian invasion of Ukraine. Post-war, both

bia, Cyprus, Czech Republic, Germany, Denmark, Egypt, Spain, Estonia, Finland, France, United Kingdom, Greece, Hungary, India, Israel, Italy, Japan, South Korea, Luxembourg, Latvia, Lithuania, Mexico, Netherlands, Norway, Pakistan, Poland, Portugal, Romania, Singapore, Slovakia, Slovenia, Sweden, Thailand, Taiwan, Ukraine, and United States.

⁸Negative values can arise from measurement errors in the production data or through the presence of re-exports, that is, exported goods that are not produced locally but imported. While some datasets provide reexport flows (e.g. COMTRADE) the data is not complete enough to incorporate this variable into the analysis.

series are roughly stagnant, suggesting that recent geopolitical tensions are associated with a slowdown of globalization, but no outright reversal of globalization.⁹

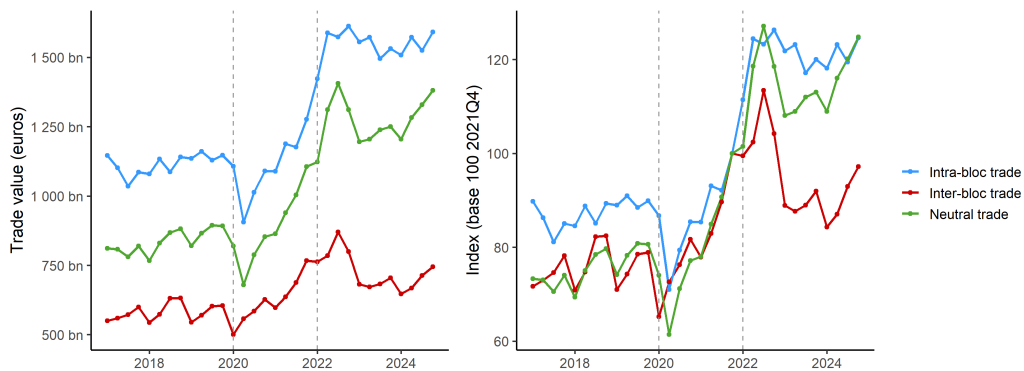
Figure 1: Aggregate Domestic Expenditure and Aggregate Imports



Notes: Domestic Expenditure and Imports for the aggregate of 43 countries in the data. Domestic expenditure computed as production minus exports. Source: Authors' calculations based on data from TDM, UNIDO, and national statistical institutes.

In Figure 2 we next decompose aggregate imports into imports from within the same geopolitical bloc (intra-bloc imports), imports coming from countries of the opposing bloc (inter-bloc imports), and imports from neutral countries. The acceleration of trade post-Covid is visible for all three types of trade. Following the Russian invasion of Ukraine, intra-bloc trade and neutral trade are roughly constant, while inter-bloc trade is noticeably declining. Figures in Appendix B.2 show that this pattern is partly, but not exclusively, explained by the evolution of Western trade with Russia, and also goes beyond trade within the US-China relationship.

Figure 2: Aggregate Trade Flows: Intra-Bloc, inter-bloc, and neutral trade



Notes: Intra-Bloc, inter-bloc, and neutral trade for the aggregate of international trade flows. Source: Authors' calculations based on data from TDM.

⁹Figures B2 and B3 repeat this exercise separately for the aggregate of Western countries and China. The acceleration of trade post-Covid is mostly driven by the Western bloc, but the overall dynamics of imports and domestic expenditure are roughly similar.

While the descriptive evidence suggests stable globalization alongside increasing inter-bloc fragmentation, these aggregate trends may also reflect changes in sectoral composition or country-specific growth patterns. Likewise, the pre-war dynamics of trade suggest that the relative importance of cross-border trade was far from stable, reflecting possibly significant changes in trade costs over time. In the next section we therefore employ a structural gravity framework, controlling for confounding factors through multilateral resistance terms, to evaluate absolute trade cost dynamics.

3 The effect of geoeconomic fragmentation on trade costs

We estimate a standard structural gravity equation and pay particular attention to the modeling of trade costs, in order to distinguish changes in average international trade costs, which we interpret as the evolution of globalization, from changes in trade costs associated with fragmentation.¹⁰ We include both domestic flows and cross-border flows in the estimation, allowing us to assess the level of trade cost changes, not just relative trade cost changes. For exporter i , importer j , sector s and time t we specify the following gravity equation.

$$X_{ijst} = S_{ist}M_{jst}\phi_{ijst} \quad (1)$$

where S_{ist} is exporter multilateral resistance, and M_{jst} is importer multilateral resistance. In the estimation, S_{ist} and M_{jst} are absorbed by exporter $\times$ sector $\times$ time and importer $\times$ sector $\times$ time fixed effects. The term ϕ_{ijst} captures trade costs τ_{ijst} and random measurement error:

$$\log(\phi_{ijst}) = \epsilon_s \log(\tau_{ijst}) + v_{ijst}$$

We parameterize bilateral trade costs τ_{ijst} as the sum of a time-invariant exporter–importer–sector component, a set of time-varying trade-cost shifters, and seasonal trade-cost controls.

$$\epsilon_s \log(\tau_{ijst}) = \alpha_{ijs} + Z'_{ij}\beta_t + Z'_{ij}\delta_{q(t)} \quad (2)$$

Relative to structural gravity estimated period-by-period in the cross-section, our panel with pair-sector fixed effects α_{ijs} identifies trade-cost changes purely from within-pair-sector time variation. Any time-invariant unobserved bilateral cost component such as geography or historical ties, but also the permanent level of

¹⁰ Anderson and van Wincoop (2003) provide the foundational treatment of multilateral resistance in structural gravity; Head and Mayer (2014b) provide a general derivation.

home bias and fixed measurement differences between our constructed domestic series and international trade data, is absorbed by α_{ijs} .¹¹ In our basic specification the vector Z_{ij} captures three dummy variables,

$$Z_{ij} := \begin{pmatrix} INTERNATIONAL_{ij} \\ INTRA_{ij} \\ INTER_{ij} \end{pmatrix}, \quad (3)$$

where $INTERNATIONAL_{ij}$ equals one for cross-border flows and zero for domestic flows, i.e. it captures general trade cost changes common to all international transactions, independent of geopolitical alignment of trading partners. $INTRA_{ij}$ equals one for cross-border flows within the same geopolitical bloc (within West or within East),

$$INTRA_{ij} = \begin{cases} 1 & \text{if } (i, j \in \mathcal{W} \text{ and } i \neq j) \text{ or } (i, j \in \mathcal{E} \text{ and } i \neq j), \\ 0 & \text{otherwise.} \end{cases}$$

and $INTER_{ij}$ equals one for any flows between the Western and Eastern blocs.

$$INTER_{ij} = \begin{cases} 1 & \text{if } (i \in \mathcal{W}, j \in \mathcal{E}) \text{ or } (i \in \mathcal{E}, j \in \mathcal{W}) \\ 0 & \text{otherwise} \end{cases}$$

Given the nested structure of the dummy variables, the coefficients on $INTRA$ and $INTER$ estimate relative trade cost changes of intra-bloc and inter-bloc flows compared to all other cross-border flows (flows involving at least one neutral country). We trace the evolution of trade costs quarter-by-quarter by estimating time-varying coefficients β_t . Finally, $Z'_{ij}\delta_{q(t)}$ controls for seasonal variation in trade costs that may differ across different types of flows by interacting the Z_{ij} vector with a set of quarter-of-year dummies.¹²

The vector of coefficients β_t associated with the variable capturing international flows and with the intra-and inter-bloc flows are the main variables of interest. The intra- and inter-bloc dummies jointly capture the geopolitical reallocation of trade, i.e. the change in trade growth relative to the reference group of international trade, which is made up of any trade flows with or among neutral countries. The international variable captures any difference in cross-border flows relative to domestic

¹¹Absorbing all fixed pair-sector variation with fixed effects implies that we cannot separately identify the baseline level of international trade costs compared to domestic trade costs ($\tau - 1$).

¹²We estimate the equation using data from 2017Q1 to 2024Q4. Estimating β_t for all quarters would completely absorb the seasonality controls $\delta_{q(t)}$. We therefore interact β_t with a dummy indicating years 2018 or later, essentially reserving the year 2017 to estimate the seasonality controls, such that β_t captures any trade growth that goes above and beyond any normal seasonal variation.

flows, and therefore allows us to assess changes in average trade costs and provide an indicator of globalization. The equation is estimated by PPML (Santos Silva and Tenreyro, 2006), relative to the reference period 2021Q4. Standard errors are clustered by exporter $\times$ importer $\times$ sector, i.e. at the level of the bilateral-sector panel unit defined by α_{ijs} , allowing for arbitrary serial correlation within each pair-sector cell over time (Bertrand et al., 2004).

We show the dynamics of the estimated coefficients in Figure 3, with the left panel showing the dynamics of the geopolitical reallocation coefficients and the right panel that of average international trade growth. While all coefficients fluctuate somewhat pre-war, there is a noticeable divergence of the intra-bloc and inter-bloc coefficients post-war, with inter-bloc trade growing substantially slower than trade with neutral countries and intra-bloc trade slightly faster. At the same time, the right panel shows that international trade coefficients fluctuate throughout the full period and that international trade tends to grow slightly faster than domestic trade, especially post-war. Under a structural interpretation, this suggests that geoeconomic fragmentation has not increased average trade costs, or that any potential increase in average trade costs brought about by geopolitical events was not strong enough to overshadow the average decline in trade costs from other factors¹³.

We next decompose the dummy for international inter-bloc flows into a component that captures trade with Russia, and a component that captures trade without Russia:

$$INTER_{ij} = INTER_{ij}^{RU} + INTER_{ij}^{-RU} \quad (4)$$

where $INTER_{ij}^{RU} \equiv INTER_{ij} \times RU_{ij}$ and RU_{ij} is a dummy that equals one if Russia is either the exporting or the importing country. That is, $INTER_{ij}^{RU}$ identifies all inter-bloc flows that include Russia as trade partner. Likewise, $INTER_{ij}^{-RU} \equiv INTER_{ij} \times (1 - RU_{ij})$ identifies any inter-bloc flows that do not involve Russia. We then define the vector of regressors as

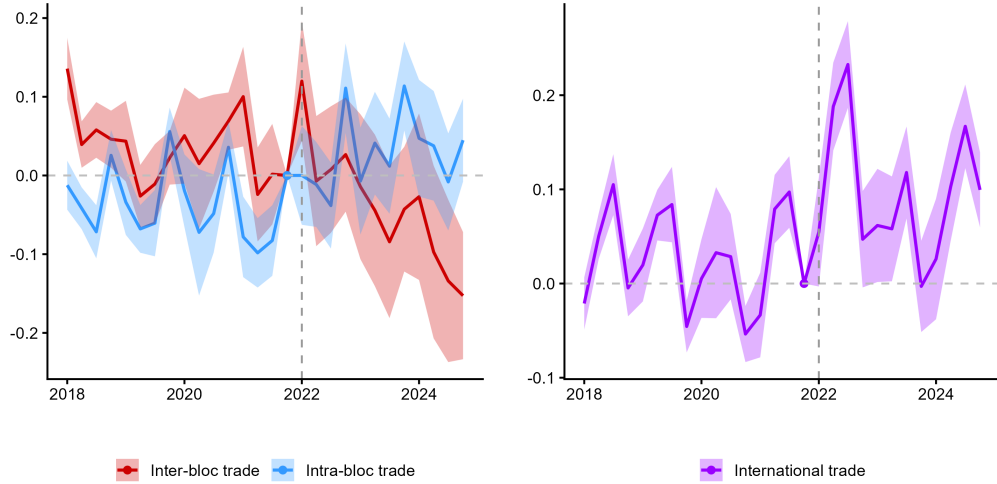
$$\tilde{Z}_{ij} := \begin{pmatrix} INTERNATIONAL_{ij} \\ INTRA_{ij} \\ INTER_{ij}^{RU} \\ INTER_{ij}^{-RU} \end{pmatrix}. \quad (5)$$

We then re-estimate equation 1 and show the coefficients in Figure 4. The right panel shows that trade with Russia accounts for a large part of the decline in inter-

¹³We assess the robustness of our results to the definition of geopolitical blocs by re-estimating our baseline specification with the bloc classification used in Gopinath et al. (2025). The results are presented in Appendix B.3 and show a clear and continued divergence between the growth of intra-trade and inter-trade growth after the beginning of the war.

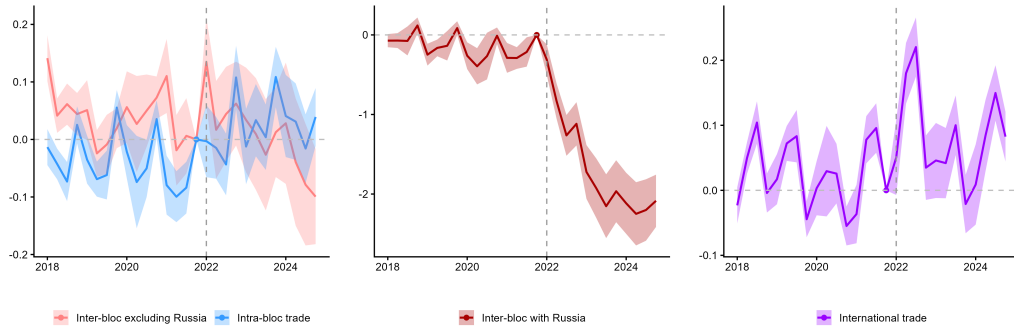
bloc trade, particularly in the first quarters after the start of the war. However, towards the end of the sample period, the estimated inter-bloc dummy remains negative even after excluding trade with Russia suggesting that inter-bloc fragmentation runs deeper than the direct sanctions effect on Russian trade.

Figure 3: Estimated Coefficients: Geopolitical Reallocation vs (De-)globalization



Notes: Estimates of β_t from Model 1, with coefficients on $INTRA_{ij}$ and $INTER_{ij}$ in the left panel and the coefficient on $INTERNATIONAL_{ij}$ in the right panel. Estimation is carried out using PPML. Shaded bands show 95% confidence intervals based on standard errors clustered by exporter $\times$ importer $\times$ sector (i.e., by bilateral-sector cell). Coefficients show the deviation of trade relative to the reference period 2021Q4.

Figure 4: Separating the Effect of Trade with Russia



Notes: Estimates of β_t from an augmented version of Model 1, where the $INTER_{ij}$ variable is split up into a component that captures trade with Russia (shown in middle panel) and a second component that captures inter-bloc trade without the involvement of Russia (left panel, together with the coefficient on $INTRA_{ij}$). The right panel shows the evolution of the coefficient on $INTERNATIONAL_{ij}$. Estimation is carried out using PPML. Shaded bands show 95% confidence intervals based on standard errors clustered by exporter $\times$ importer $\times$ sector (i.e., by bilateral-sector cell). Coefficients show the deviation of trade relative to the reference period 2021Q4.

One might worry that our reference category is itself contaminated by the war: several of the neutral countries used to define $INTER_{ij}$ and $INTRA_{ij}$ – Armenia, Kazakhstan, and Turkey in particular – have served as documented transshipment

hubs for goods rerouted around sanctions on Russia (Chupilkin et al., 2026). If this rerouted trade shows up in our data as a surge in flows to or from these connector countries, it would inflate the growth of the reference group and mechanically overstate the decline in inter-bloc trade. To check this, we augment equation 1 with a dummy for flows between these connector countries and either geopolitical bloc, letting this channel load on its own coefficient rather than being absorbed into the neutral baseline. The dynamics of $INTRA_{ij}$ and $INTER_{ij}$ are essentially unchanged from the baseline (Appendix B.4, Figure B10). The connector-trade coefficient itself displays no consistent trend before the war, then rises steadily and becomes statistically significant from the last quarter of 2022 onward – direct evidence of the rerouting channel in our own data, and reassurance that it is not driving our geopolitical reallocation estimates.

Overall, the results from this section suggest that inter-bloc trade between geopolitical rivals has declined substantially following the Russian invasion of Ukraine and that this decline is mainly driven by direct sanctions against Russia but also goes beyond them at the end of the period. At the same time, intra-trade has started to grow slightly faster than neutral trade which was not the case before the war. However, this reallocation of trade across geopolitical lines has not translated into a reduced overall openness and an increase in average trade costs as the international trade coefficient remains roughly stable relative to domestic trade. These estimates, however, cannot directly speak to welfare. The divergence between rising inter-bloc barriers and continued globalization and deepening intra-bloc integration has offsetting implications that require a structural framework to disentangle. In Section 4, we therefore compute the trade cost shocks associated with the above dynamics and turn to a quantitative general equilibrium trade model to quantify the net welfare consequences of these shifts.

4 Welfare evaluation in a trade model

Viewed through the lens of standard trade theory, what are the welfare consequences of the recent fragmentation of world trade? We derive trade cost changes from the previous gravity equation and map them to a quantitative general equilibrium trade model to solve for the implied welfare effects. Section 4.1 describes the model and Section 4.2 details the computation of trade cost shocks. Section 4.3 presents the welfare consequences of these shocks under several counterfactual scenarios.¹⁴

¹⁴An alternative approach would be to use the observed changes in the domestic share of expenditure across countries and apply a welfare formula as in Arkolakis et al. (2012). The disadvantage of that approach is that observed DSE changes may reflect productivity or demand shifts in addition

4.1 Model

We use a variant of the multi-country, multi-sector general equilibrium trade model with global value chains developed by [Serfaty and Stumpner \(2026\)](#).¹⁵ The model features N countries and S sectors, and is calibrated to the OECD ICIO 2023 input-output data ($N = 77$ countries, $S = 44$ sectors). For a survey of the quantitative general equilibrium trade framework, see [Costinot and Rodríguez-Clare \(2014\)](#).

Households. Each economy j is inhabited by L_j identical households who supply labor inelastically. Aggregate consumption is a CES composite of sectoral bundles

$$C_j = \left(\sum_s e_{js}^{\frac{1}{\kappa}} C_{js}^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}}$$

with inter-sector elasticity κ and taste shifters e_{js} . Within each sector, consumers aggregate varieties from different source countries,

$$C_{js} = \left(\sum_i d_{ijs}^{\frac{1}{\mu_s}} C_{ijs}^{\frac{\mu_s-1}{\mu_s}} \right)^{\frac{\mu_s}{\mu_s-1}}$$

with intra-sector elasticity μ_s and bilateral preference weights d_{ijs} . Household expenditure equals household income $X_j^C = w_j L_j$ and in equilibrium trade is balanced.¹⁶

Firms. Varieties are produced under perfect competition and constant returns to scale. In each sector v , output combines labor and a nested CES intermediate bundle via a Cobb-Douglas technology:

$$Q_{jv} = Z_{jv} L_{jv}^{1-\sigma_{jv}} M_{jv}^{\sigma_{jv}}, \quad M_{jv} = \left(\sum_s a_{jsv}^{\frac{1}{\epsilon_v}} M_{jsv}^{\frac{\epsilon_v-1}{\epsilon_v}} \right)^{\frac{\epsilon_v}{\epsilon_v-1}}$$

to trade cost changes. In the current exercise we want to isolate the trade cost channel and therefore use a model-based approach.

¹⁵The variant imposes a simplifying restriction: the within-sector variety aggregator for final consumption C_{js} and the within-sector variety aggregator for intermediate inputs M_{jst} share the same functional form. Concretely, this means $d_{ijs} = b_{ijst}$ and $\mu_s = \rho_{st}$, so that bilateral preference weights and substitution elasticities are common across final and intermediate use. This restriction ensures that the model delivers a structural gravity equation consistent with equation 1. We refer the reader to [Serfaty and Stumpner \(2026\)](#) for the full derivations and theoretical results.

¹⁶One challenge when matching the model to the ICIO data is that the ICIO data contain trade deficits. We treat these deficits as follows: We first generalize the model allowing for deficits D_j such that household expenditure are $X_j^C = w_j L_j + D_j$. After mapping this generalized model to the data, we neutralize the deficits within the model, implementing exogenous deficit changes $\Delta D_j = -D_j$ such that trade is balanced in a new (intermediate) equilibrium. We then implement the trade cost shocks starting from this intermediate equilibrium.

where M_{jst} aggregates varieties from different source countries within sector s , using the same bilateral weights d_{ijs} and elasticity μ_s as in final demand.

Trade costs, prices, and equilibrium. Goods are subject to iceberg transaction costs $\tau_{ijs} \geq 1$. Under perfect competition the delivered price is $p_{ijs} = \tau_{ijs} \cdot mc_{is}$, where $mc_{is} = w_i^{1-\sigma_{is}} (P_{is}^M)^{\sigma_{is}} Z_{is}^{-1}$ and P_{is}^M is the price of the intermediate bundle M_{is} . Equilibrium requires goods market clearing, $Y_{is} = \sum_j X_{ijs}$ with $X_{ijs} = X_{ijs}^C + \sum_v X_{ijsv}^M$, and labor market clearing, $L_i = \sum_s L_{is}$.

Hat algebra solution and parameters. Following Dekle et al. (2008), we solve the model in proportional changes (“hat algebra”). Let $\hat{x} \equiv x'/x$ denote the ratio of a counterfactual to a baseline equilibrium value. Given trade cost changes $\hat{\tau}_{ijs}$, the equilibrium system in $\hat{x}$ -variables is solved iteratively until convergence of wages $\hat{w}$, requiring only the initial ICIO trade flow data and the elasticity parameters. The welfare change for country j is $\hat{W}_j = \hat{w}_j / \hat{P}_j^C$. We set $\kappa = 0.9$ and $\epsilon_v = 0.2$ following Baqaee and Farhi (2019), and use sector-specific intra-sector elasticities μ_s from Fontagné et al. (2022), with a default value of 5 for sectors without estimates.

4.2 Trade cost shocks

Econometric specification. To parameterize the trade cost shocks entering the welfare analysis, we estimate a simplified version of the gravity framework from Section 3. Rather than recovering the full quarterly dynamics of the post-invasion adjustment, we collapse the post-invasion period into two representative averages that capture the *short-run* and *long-run* responses. Formally, we partition time into three periods: a pre-invasion baseline (before 2022Q1); a short-term post-period, $\mathbb{1}_t^{ST}$ (2022Q1–2023Q4, 8 quarters), capturing the initial adjustment phase when trade relationships are still in flux as firms and countries adapt to the new geopolitical environment; and a long-term post-period, $\mathbb{1}_t^{LT}$ (2024Q1–2024Q4, 4 quarters), capturing the post-adjustment state once alternative sourcing relationships have had time to consolidate. That is, we replace equation (2) by the following specification where $\tilde{Z}_{ij}$ is defined as in equation (5):

$$\epsilon_s \log(\tau_{ijst}) = \alpha_{ijs} + \sum_{p \in \{ST, LT\}} \mathbb{1}_t^p \tilde{Z}_{ij}' \beta_p + \tilde{Z}_{ij}' \delta_{q(t)} \quad (6)$$

The event-study evidence in Section 3 motivates this distinction into short-term and long-term adjustment: the inter-bloc effect involving Russia continued to amplify throughout the sample, so averaging over the full post-invasion period would conflate the initial shock with its longer-run consequences. As previously, the esti-

mation is carried out by PPML and standard errors are clustered at the exporter $\times$ importer $\times$ sector level.

From estimates to trade cost shocks. Under the structural gravity model, a change in iceberg costs $\hat{\tau}_{ijs}$ shifts the bilateral trade flow by the factor $\hat{\tau}_{ijs}^{\epsilon_s}$, where ϵ_s is the trade elasticity. We use sectoral trade elasticities estimated in [Fontagné et al. \(2022\)](#) to back out implied trade cost changes.¹⁷ For the counterfactual exercises we focus on the structural shifts in global trade that come with geopolitical fragmentation and ignore seasonal variation in trade costs. We also focus on long-term instead of short term changes in trade costs. The implied long-term trade cost change for sector-pair (i, j, s) is therefore:¹⁸

$$\hat{\tau}_{ijs} = \exp \left(\frac{1}{\epsilon_s} \left[\beta_{LT}^{RU} INTER_{ij}^{RU} + \beta_{LT}^{-RU} INTER_{ij}^{-RU} + \beta_{LT}^{intra} INTRA_{ij} + \beta_{LT}^{intl} INTERNATIONAL_{ij} \right] \right). \quad (7)$$

To characterise the trade-cost shock faced by each country, we summarise the bilateral-sector changes $\hat{\tau}_{ijs}$ into an import-weighted average for importer j :

$$\bar{\tau}_j^M = 100 \sum_{i,s} \pi_{ijs}^M \log \hat{\tau}_{ijs}, \quad (8)$$

where $\pi_{ijs}^M = X_{ijs} / \sum_{i',s'} X_{i'js'}$ is sector-pair (i, s) 's share of importer j 's total baseline expenditure, and X_{ijs} is the baseline (2019 ICIO) bilateral trade value between i and j in sector s . Beyond being a natural, model-free descriptive average, $\bar{\tau}_j^M$ is, to first order and holding wages fixed, the percent change in the consumer price index $\hat{P}_j^C$ of Section 4.1 – so it is the first-order, wage-constant prediction of the welfare change $\hat{W}_j = \hat{w}_j / \hat{P}_j^C$ that the full model solves for exactly.¹⁹

¹⁷Note that we back out gross trade cost changes $\hat{\tau}_{ijs}$, not trade cost changes of international compared to domestic flows (the change in $\tau - 1$). As mentioned in section 3, we cannot separately identify the baseline level of τ_{ijs} as it is absorbed by bilateral-sector fixed effects. However, estimates of $\hat{\tau}_{ijs}$ are sufficient to compute welfare changes within the model.

¹⁸We estimate this regression on bilateral flows involving at least one of the 43 countries with production data and on ISIC 2-digit manufacturing sectors. We map these sectors into the model's sectors and set $\hat{\tau}_{ijs}$ to 1 (i.e. no shock) for sectors outside the regression sample (mostly agriculture, mining, and services, i.e. OECD sectors 01T02, 03, 05T06, 07T08, 09, 35, 36T39, 41T43, 45T47, 49, 50, 51, 52, 53, 55T56, 58T60, 61, 62T63, 64T66, 68, 69T75, 77T82, 84, 85, 86T88, 90T93, 94T96). Note that $\hat{\tau}_{ijs}$ is also 1 for domestic pairs ($i = j$).

¹⁹Holding mc_{is} (hence wages) fixed, the hat-algebra CES sub-index for sector s in country j is $\hat{P}_{js} = (\sum_i \pi_{ijs} \hat{\tau}_{ijs}^{1-\mu_s})^{1/(1-\mu_s)}$, with $\pi_{ijs} = X_{ijs} / \sum_{i'} X_{i'js}$, and the aggregate index is $\hat{P}_j^C = (\sum_s \pi_{js} \hat{P}_{js}^{1-\kappa})^{1/(1-\kappa)}$, with $\pi_{js} = X_{js} / X_j$. To first order in $\log \hat{\tau}_{ijs}$, each CES sub-index reduces to the corresponding share-weighted average of log changes regardless of μ_s or κ (a standard envelope-theorem result), so $\log \hat{P}_{js} \approx \sum_i \pi_{ijs} \log \hat{\tau}_{ijs}$ and $\log \hat{P}_j^C \approx \sum_s \pi_{js} \log \hat{P}_{js} \approx \sum_{i,s} \pi_{js} \pi_{ijs} \log \hat{\tau}_{ijs} =$

Estimated Trade Cost Shocks. Before examining the implied bilateral trade-cost shocks, Table 1 reports the estimated coefficients underlying the construction of these shocks. The dominant driver is $INTER_{ij}^{RU}$, with a long-term coefficient of -2.05 which corresponds to an 87% decline in Russia–West trade. This effect amplifies from the short run (-1.29 or a 72% decline) to the long run, pointing to a persistent structural reorientation away from Russia–West trade, consistent with the event-study dynamics in Section 3. The analogous coefficient β_p^{-RU} is small and statistically insignificant. While the individual coefficients on $INTRA_{ij}$ and $INTERNATIONAL_{ij}$ show no significant change, the sum of the two coefficients ($\beta_{INTRA} + \beta_{INTERNATIONAL}$) equals 0.1145 and is significant at conventional levels (s.e. 0.0396), suggesting that total trade costs for intra-bloc trade fell over this period.

Table 1: Estimated trade cost changes: PPML regression coefficients

Variable	Short term		Long term	
	Est.	SE	Est.	SE
<i>Geopolitical reallocation indicators</i>				
$INTER_{ij}^{RU}$: Inter-bloc (with Russia)	-1.29	(0.14)	-2.05	(0.25)
$INTER_{ij}^{-RU}$: Inter-bloc (excl. Russia)	0.01	(0.08)	-0.08	(0.08)
$INTRA_{ij}$: Intra-bloc	0.05	(0.07)	0.05	(0.07)
<i>Globalization indicator</i>				
$INTERNATIONAL_{ij}$: International (cross-border)	0.06	(0.06)	0.06	(0.06)

Notes: PPML estimates of equation (1) with trade costs specified as in equation (6). Standard errors, three-way clustered by exporter, importer, and sector, in parentheses. All specifications include exporter $\times$ sector $\times$ time, importer $\times$ sector $\times$ time, and bilateral $\times$ sector fixed effects and seasonality controls.

Average Trade Costs and Its Components. We next use these estimates to assess the evolution of average trade cost changes and its components. Whereas $\bar{\tau}_j^M$ above aggregates bilateral-sector shocks by importer, we now aggregate across the full sample and decompose the result by source component. Given equation (7), we define aggregate trade costs as the weighted average of pair-sector trade cost changes:

$$\log(\hat{\tau}) \equiv \sum_{i,j,s} \omega_{ijs} \log(\hat{\tau}_{ijs}) = \sum_{c \in \{RU, -RU, intra, intl\}} \omega^c \frac{\beta_{LT}^c}{\epsilon^c}, \quad (9)$$

and we report each component's contribution, in percentage points of this log change, as

$$100 \omega^c \frac{\beta_{LT}^c}{\epsilon^c}. \quad (10)$$

$\sum_{i,s} \pi_{ijs}^M \log \hat{\tau}_{ijs}$, since $\pi_{js} \pi_{ijs} = X_{ijs} / X_j = \pi_{ijs}^M$.

$$\omega_{ijs} \equiv \frac{X_{ijs}}{X}, \quad \omega^c \equiv \sum_{i,j,s \in \mathcal{M}} \omega_{ijs} \mathbb{1}_{ij}^c = \frac{X^c}{X}, \quad \frac{1}{\epsilon^c} \equiv \sum_{s \in \mathcal{M}} \frac{X_s^c}{X^c} \frac{1}{\epsilon_s}, \quad (11)$$

where $\mathcal{M}$ denotes manufacturing sectors, $X^c \equiv \sum_{i,j,s \in \mathcal{M}} X_{ijs} \mathbb{1}_{ij}^c$ is the manufacturing trade weight for which the dummy c (defined in equation (7)) is active, $X \equiv \sum_{i,j,s} X_{ijs}$ is total trade weight over the same sample of country pairs used to construct $\hat{\tau}_{ijs}$ (footnote above eq. (7)), and $X_s^c \equiv \sum_{i,j} X_{ijs} \mathbb{1}_{ij}^c$ for $s \in \mathcal{M}$. The cell weights ω_{ijs} sum to 1 across all (i, j, s) ; ω^c sums only the manufacturing ω_{ijs} for which c is active and does *not* itself sum to 1 across components, both because the dummies are not mutually exclusive (a Russia–West cell has both $INTER_{ij}^{RU} = 1$ and $INTERNATIONAL_{ij} = 1$) and because domestic and non-manufacturing cells – which receive no trade-cost shock (footnote above eq. (7)) – activate none of them. ω^c is therefore, by construction, the share of total trade weight actually exposed to the shock: agriculture, services, and domestic trade are excluded from it entirely. $1/\epsilon^c$ is the trade-weighted average inverse elasticity across the manufacturing sectors where c is active: intuitively, if trade is very elastic to cost shocks ($|\epsilon_s|$ large), only a small trade cost change is needed to reconcile the model with a given change in trade flows.

We compute two versions of aggregate trade cost changes $\log(\hat{\tau})$, one where the aggregate is total trade (including domestic trade) in the entire economy (panel (a)) and one where the aggregate is international manufacturing trade only (panel (b)).²⁰ We report the relevant weights ω_c for each of these calculations in Table 2. The role of trade cost changes is naturally muted if the weights of panel (a) are applied, as international manufacturing trade only accounts for a small share of all expenditure.

Table 2: Trade-weighted activation share ω^c by component

Component	Panel (a): all pairs, manuf. (%)	Panel (b): intl. manuf. (%)
Inter-bloc, Russia–West (<i>RU</i>)	0.2	2.6
Inter-bloc, other East–West ($-RU$)	1.4	21.1
Intra-bloc (<i>intra</i>)	2.9	44.0
International (<i>intl</i>)	6.7	100.0

Notes: ω^c is the share of total trade weight $\sum_{i,j,s} X_{ijs}$ for which dummy c is active *and* the sector is manufacturing (eq. (11)); X is summed over the same sample of country pairs used to construct $\hat{\tau}_{ijs}$ (footnote above eq. (7)). Panel (a) is all pairs; panel (b) further restricts to international pairs, for which $INTERNATIONAL_{ij} = 1$ everywhere by construction, so $\omega^{intl} = 100\%$ there.

Figure 5 reports the trade-weighted average log trade cost change and its decomposition by component (from Equation (10)), under the two weighting schemes.

²⁰That is, the sum runs over all pairs and sectors, including domestic, for panel (a), or international manufacturing pairs only for panel (b). Given our assumption that trade costs do not change for domestic trade or for international trade in agriculture or services, the two calculations only differ in the applied set of weights ω_c .

Panel (a) includes domestic flows – the welfare-consistent measure, since domestic self-trade accounts for 87% of total 2019 ICIO expenditure – yielding a near-zero net change of -0.01% .²¹ Panel (b) restricts to international pairs and manufacturing sectors: common factors and intra-bloc deepening reduce average costs by 1.07% and 0.4%, while inter-bloc barriers raise them by 0.95% (Russia–West) and 0.30% (other East–West). This sums up to a net decline of -0.21% which is statistically indistinguishable from zero (95% CI: -1.47% , $+1.06\%$).²²

Table 2 shows why the components differ so much in magnitude despite comparable underlying coefficients. Russia–West pairs carry only $\omega^{RU} = 2.6\%$ of trade weight in panel (b), so the large per-pair cost increase implied by $\beta_{LT}^{RU} = -2.05$ is heavily diluted in the reported average. The international component, by contrast, is active on $\omega^{intl} = 100\%$ of the panel (b) sample by construction, so its -1.07% is reported undiluted – which is why it is the largest-magnitude component in the decomposition despite a comparatively modest coefficient.

Dispersion of Trade Cost Shocks. Figure 6 decomposes the cross-sectional dispersion of bilateral log trade cost shocks into each component’s contribution to the total variance, complementing the mean decomposition above. Denoting log trade cost shocks by $g_{ijs} = \log(\hat{\tau}_{ijs})$, component c ’s contribution to that trade cost shock is

$$g_{ijs}^c = \mathbb{1}_{ij}^c \frac{\beta_{LT}^c}{\epsilon_s}, \quad g_{ijs} = \sum_c g_{ijs}^c, \quad (12)$$

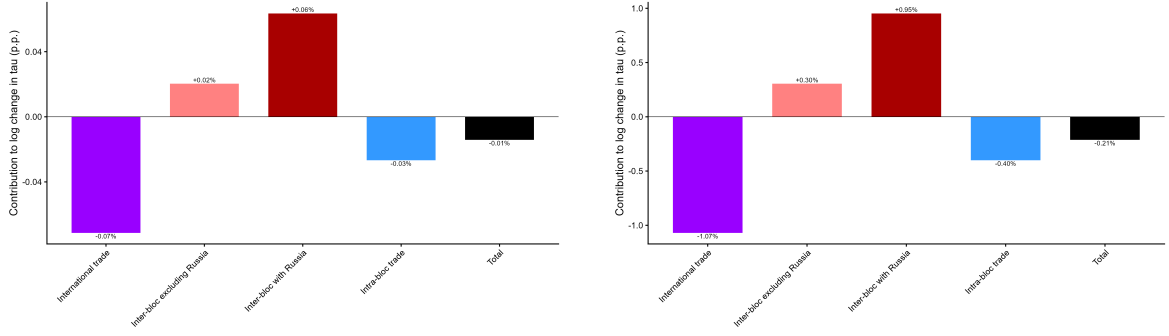
$$s^c = \frac{\text{Cov}_\omega(g_{ijs}^c, g_{ijs})}{\text{Var}_\omega(g_{ijs})}, \quad \text{Cov}_\omega(x, y) = \sum_{i,j,s} \omega_{ijs} (x_{ijs} - \bar{x}_\omega) (y_{ijs} - \bar{y}_\omega), \quad \sum_c s^c = 1, \quad (13)$$

where Var_ω , $\bar{x}_\omega$, and the weights ω_{ijs} are as in equation (11). $INTER_{ij}^{RU}$ accounts for $s^{RU} = 97.5\%$ of total variance in panel (b) despite its modest contribution to the mean ($+0.95\%$, Section 4.2): the mean scales linearly in β_{LT}^c , the variance quadratically, and $|\beta_{LT}^{RU}| = 2.05$ is 25–40 times larger than the other components’ (Table 1), which swamps its comparatively modest incidence disadvantage ($\omega^{RU}(1 - \omega^{RU}) = 2.5\%$, the same order as $-RU$ ’s and intra’s, Table 2). $INTERNATIONAL_{ij}$ shows the mirror case: it is the largest mean contributor (-1.07%) but contributes essentially nothing to variance, since $\omega^{intl} = 100\%$ in panel (b) leaves it with no cross-sectional variation to explain.

²¹Panel (a) of Table 2 shows the shares of international trade in manufactured goods only, leaving out trade in agriculture and services for which we lack data. This also explains why domestic self-trade and international manufacturing trade do not add up to 100%.

²²Standard errors of aggregate trade cost changes are computed using Equation 9, where we treat c and ϵ^c as fixed.

Figure 5: Trade-weighted mean trade cost change: decomposition by component

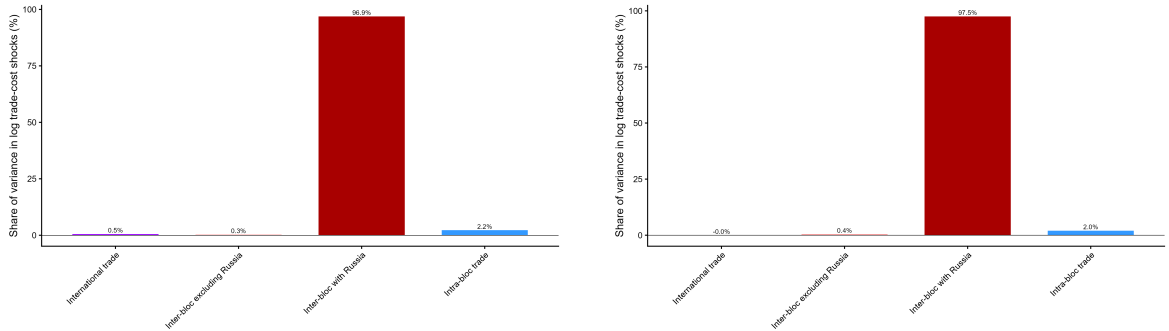


(a) All flows (domestic and international, all sectors)

(b) International manufacturing pairs only

Notes: Trade-weighted average contribution of each component c to the log change in trade costs, in percentage points, $100 \omega^c \beta_{LT}^c / \epsilon^c$ (equations (10)–(11)); bars sum exactly to the Total. Panel (a) weights all bilateral pairs and all sectors, including domestic self-trade and non-manufacturing sectors, which receive no shock; Panel (b) restricts the weights to international, manufacturing pairs, i.e. the observations that actually receive a shock. *International trade*: the cross-border (globalization) indicator common to all international flows. *Inter-bloc with Russia*: East–West pairs involving Russia. *Inter-bloc excluding Russia*: other East–West pairs. *Intra-bloc trade*: within-West and within-East pairs. *Total*: sum of all components. Long-run coefficients from Table 1, ϵ_s from Fontagné et al. (2022). Source: authors’ calculations.

Figure 6: Variance decomposition of bilateral log trade cost shocks



(a) All flows (domestic and international, all sectors)

(b) International manufacturing pairs only

Notes: Each component’s share of the total variance of the estimated long-run bilateral-sector log trade-cost shock $\log \hat{\tau}_{ijs}^c$, s^c (equations (12)–(13)); shares sum to 100% by construction. Panel (a) weights all bilateral country pairs and sectors by their baseline trade value, including domestic flows and non-manufacturing sectors, which receive no trade-cost shock. Panel (b) restricts the weights to international manufacturing flows, i.e. the observations that are directly affected by the estimated trade-cost shocks. *International trade* denotes the cross-border (globalization) component common to all international flows; *Inter-bloc with Russia* captures East–West trade involving Russia; *Inter-bloc excluding Russia* captures all other East–West trade; and *Intra-bloc trade* captures within-West and within-East trade. Long-run coefficients from Table 1, ϵ_s from Fontagné et al. (2022). Source: authors’ calculations.

4.3 Welfare effects

Scenario definitions. We construct three counterfactual scenarios by selectively including components of (7):

- (a) **Full scenario:** all components— $INTERNATIONAL_{ij}$, $INTER_{ij}$, and $INTRA_{ij}$. This captures the full estimated trade cost change.
- (b) **Globalization and inter-bloc fragmentation:** $INTERNATIONAL_{ij}$, and $INTER_{ij}$ (excluding $INTRA_{ij}$). This adds the East–West geopolitical barrier on top of the common globalization trend.
- (c) **Globalization:** $INTERNATIONAL_{ij}$ only. This captures the non-geopolitical component: the shift in the relative cost of cross-border versus domestic trade.

We additionally consider two welfare differences between scenarios. Scenario (b) – (c) isolates the welfare effect of rising inter-bloc trade costs (inter-bloc fragmentation) while scenario (a) – (c) captures the full geopolitical effect (inter-bloc fragmentation plus intra-bloc integration – referred to interchangeably below as intra-bloc deepening or, informally, friendshoring). Note that scenario (b) is labelled “globalization and inter-bloc fragmentation” because it bundles both components; the inter-bloc fragmentation effect itself is isolated only in the difference (b) – (c), which nets out the common globalization trend. Table 3 summarizes the three primitive scenarios and the two derived differences, together with the label used for each throughout the paper.

Table 3: Welfare scenarios: components and labels

Scenario	Components included (Z_{ij})	Reported as
(a)	$INTERNATIONAL_{ij} + INTER_{ij}^{RU} + INTER_{ij}^{-RU} + INTRA_{ij}$	Full scenario
(b)	$INTERNATIONAL_{ij} + INTER_{ij}^{RU} + INTER_{ij}^{-RU}$	Globalization and inter-bloc fragmentation
(c)	$INTERNATIONAL_{ij}$	Globalization
(b)–(c)	$INTER_{ij}^{RU} + INTER_{ij}^{-RU}$	Inter-bloc fragmentation
(a)–(c)	$INTER_{ij}^{RU} + INTER_{ij}^{-RU} + INTRA_{ij}$	Geopolitical reallocation

Notes: (a), (b), and (c) are the three primitive scenarios, constructed by selectively including components of the trade-cost shock (7); $INTER_{ij}^{RU}$ and $INTER_{ij}^{-RU}$ are estimated with separate coefficients in Table 1 (see Appendix B.5 for the Russia-specific decomposition of the inter-bloc fragmentation result). (b)–(c) and (a)–(c) are welfare differences between primitive scenarios, isolating the inter-bloc fragmentation and full geopolitical effects, respectively, net of the common globalization trend. The “Reported as” column gives the label used consistently in the text, figure titles, and figure notes throughout Section 4.3 and Appendix B.5.

For each scenario, the corresponding bilateral trade cost changes $\hat{\tau}_{ijs}$ are fed into the hat-algebra system, which is solved iteratively until convergence. Welfare outcomes are reported as percentage changes $100 \times (\hat{W}_j - 1)$ relative to the 2019 ICIO baseline.

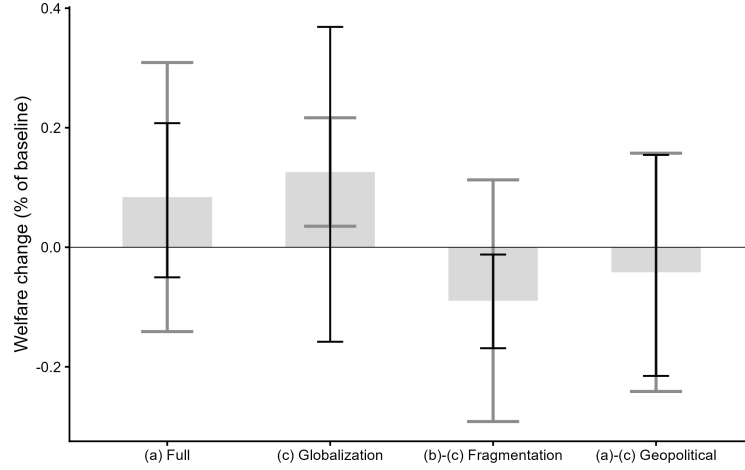
To account for estimation uncertainty in trade cost shocks we implement a procedure following [Krinsky and Robb \(1986\)](#): We draw $R = 200$ coefficient vectors $\beta^{(r)}$ from the estimated asymptotic distribution $N(\hat{\beta}, \hat{V})$, compute the implied trade cost shocks $\hat{\tau}(\beta^{(r)})$ for each draw, and solve the model to obtain the corresponding welfare changes $\hat{W}^{(r)}$. This procedure delivers a distribution of welfare changes for each country.

Aggregate effects. The bars in Figure 7 report the expenditure-weighted average welfare change for each scenario. We add two error bars for each scenario. The wide error bars show the expenditure-weighted standard deviation of individual country welfare changes around the mean, capturing cross-country heterogeneity rather than estimation uncertainty, while the narrow bars show the 95% confidence interval from the sampling uncertainty of $\hat{\beta}$.²³ The full scenario (a) delivers an average welfare change of 0.08% of the baseline with an expenditure-weighted standard deviation of 0.23% – almost three times the mean. The first key result is therefore that the observed trade cost changes are primarily redistributive: aggregate welfare effects are modest (well under one tenth of a percent on average) while cross-country heterogeneity is several times larger. Russia’s loss under scenario (a) is –1.1%, roughly fourteen times the mean, illustrating the wide dispersion the aggregate conceals. Second, sampling uncertainty in our empirical estimates introduces uncertainty in average welfare gains, so that the confidence interval for the average welfare change overlaps with zero.

Decomposing the aggregate reveals two partially offsetting forces. Globalization, scenario (c), is the dominant, positive component, delivering +0.13% on its own: the estimated *INTERNATIONAL*_{ij} coefficient is positive (Table 1), implying that cross-border trade continued to expand relative to domestic activity even after the Russian invasion. The inter-bloc fragmentation component, scenario (b) – (c), is negative on average (–0.09%) and offsets part of this gain. This loss is only partially attenuated by intra-bloc reorientation, as the geopolitical scenario (a) – (c) yields a smaller but still negative average (–0.04%).

²³Denoting by $\hat{W}_0$ the welfare change implied by the point estimate $\hat{\beta}$ and by $q_{2.5}$ and $q_{97.5}$ the 2.5th and 97.5th percentiles of $\{\hat{W}^{(r)}\}_{r=1}^R$, we report the 95% confidence interval $[2\hat{W}_0 - q_{97.5}, 2\hat{W}_0 - q_{2.5}]$, i.e., the basic (reverse-percentile) interval of [Davison and Hinkley \(1997\)](#). This interval allows for asymmetry in the distribution of welfare changes and reduces to $\hat{W}_0 \pm 1.96 \hat{SE}$ when that distribution is symmetric.

Figure 7: Aggregate welfare effects of trade cost changes



Notes: Expenditure-weighted average welfare change ($100 \times (\hat{W}_j - 1)$, percentage of baseline) for each counterfactual scenario. Grey (wide) whiskers: ± 1 expenditure-weighted standard deviation of individual country welfare changes around the mean, measuring cross-country heterogeneity. Black (narrow) whiskers: 95% CI from the sampling uncertainty of β_{LT} . Weights: 2019 consumer expenditure shares from OECD ICIO ($N = 77$ countries). (a) *Full scenario*: all components. (c) *Globalization*: $INTERNATIONAL_{ij}$ component. (b) – (c) *Inter-bloc fragmentation*: $INTER_{ij}$ component only. (a) – (c) *Geopolitical reallocation*: $INTER_{ij}$ and $INTRA_{ij}$ components. Source: authors' calculations.

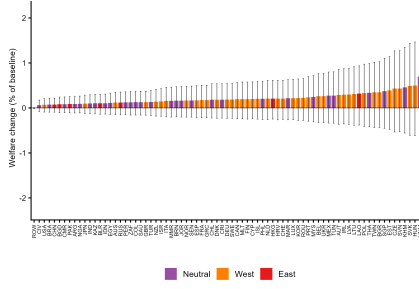
Globalization (scenario (c)). Common, non-geopolitical trade cost changes benefit almost every country – by 0.13% on average, the dominant force behind the aggregate result. The gains are largest for countries with a high share of imported manufacturing in total expenditure such as Vietnam and Cambodia or Hungary and Slovakia (Figure 8, panel (b)), since the $INTERNATIONAL_{ij}$ shock lowers the relative cost of cross-border manufacturing trade while leaving domestic trade unaffected.²⁴

However, countries with higher average welfare gains also tend to have wider confidence intervals. Since countries that gain more in the globalization scenario are countries that are generally more open, they can also lose more when average trade costs increase, which is not excluded by our estimates. For some countries, such as Vietnam, the role of sampling uncertainty can be quite large, so that welfare changes between -1% and +2% are within the 95% confidence bands.

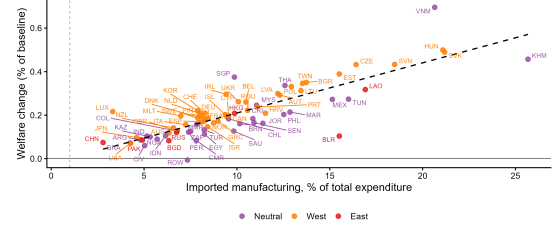
Inter-bloc fragmentation (scenario (b) – (c)). Isolating the rise in inter-bloc (East–West) barriers ($INTER_{ij}^{RU}$ and $INTER_{ij}^{-RU}$), lowers welfare by –0.09% on average. The confidence band is tighter than for the globalization shock only so that fragmentation alone leads to clear welfare losses on average (Figure 7). The losses

²⁴The very largest gains accrue to economies where manufacturing is an outsized share of activity, led by Vietnam – where manufacturing accounts for over half of both absorption and output, the highest in the sample – and the other East-Asian assembly hubs (Taiwan, Thailand, Cambodia). Because the shock lowers *only* manufacturing trade costs, it raises real income most where manufacturing represents a large share of value added in the economy.

Figure 8: Welfare effects of globalization (scenario (c))



(a) Welfare change by country

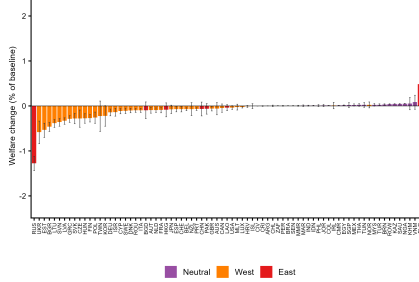


(b) Welfare vs. imported-manufacturing share

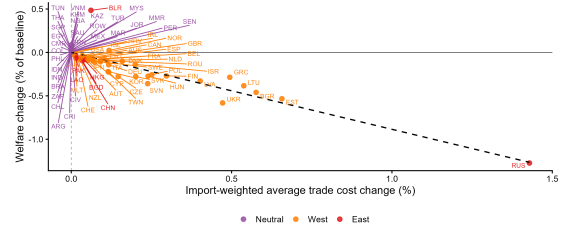
Notes: Welfare change $100 \times (\hat{W}_i - 1)$ (% of baseline) under scenario (c) ($INTERNATIONAL_{ij}$ components): common, non-geopolitical trade cost changes that benefit almost all countries. Panel (a) orders countries by welfare change; its error bars are the 95% confidence interval from the sampling uncertainty of the long-term gravity coefficients β_{LT} (parametric bootstrap, $R = 200$ draws). Panel (b) plots welfare against imported manufacturing as a share of total expenditure – the gains rise with this demand-side exposure to the manufacturing shock. Source: authors' calculations.

are overwhelmingly concentrated on Russia, whose trade with the West is sharply curtailed by the large estimated Russia–West barrier (Table 1). To a first order, each country's welfare change tracks its import-weighted average trade cost change (Figure 9, panel (b)). Many Western countries lose from fragmentation, even after taking into account sampling uncertainty, while neutral countries tend to gain, although welfare changes are very small. Belarus emerges as the clearest beneficiary, since it gains larger access to the Russian market. Appendix B.5 details this trade diversion mechanism by running counterfactual scenarios treating Russia's East–West barrier like that of any other cross-bloc pair. Once Russia is no longer isolated from Western supply and demand, the diversion windfall disappears and Belarus drops out of the right tail of winners.

Figure 9: Welfare effects of inter-bloc fragmentation (scenario (b) – (c))



(a) Welfare change by country

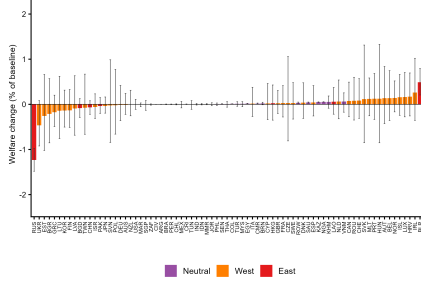


(b) Welfare vs. average trade cost change

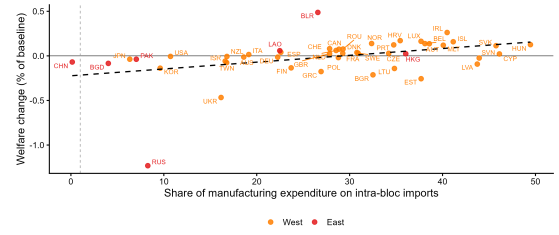
Notes: Welfare change $100 \times (\hat{W}_i - 1)$ (% of baseline) under (b) – (c) ($INTER_{ij}$ component only): the rise in East–West inter-bloc barriers. Panel (a) orders countries by welfare change – Russia is the main loser and Belarus the main winner; its error bars are the 95% confidence interval from the sampling uncertainty of the long-term gravity coefficients β_{LT} (parametric bootstrap, $R = 200$ draws). Panel (b) plots welfare against the import-weighted average change in bilateral trade costs attributable to inter-bloc fragmentation alone (eq. (8)), which captures the first-order welfare effect. Source: authors' calculations.

Geopolitical reallocation (scenario (a) – (c)). The full geopolitical effect – the gap between the full scenario and globalization – averages -0.04% (Figure 10). It combines the direct cost of inter-bloc fragmentation (-0.09%) with a partially offsetting intra-bloc reorientation, or friendshoring, dividend ($+0.05\%$): as inter-bloc barriers rise, countries deepen trade within their own bloc at costs that have themselves fallen. Western countries in particular come out slightly ahead on this margin, as the decline in intra-bloc trade costs deepens trade among aligned partners and broadly offsets their exposure to higher inter-bloc barriers. This pattern also holds across countries: among the 47 bloc-aligned economies, those with a higher initial share of manufacturing expenditure on intra-bloc imports gain significantly more in this scenario (Figure 10, panel (b); $R^2 = 0.16$, $p = 0.005$). The relationship is specific to bloc-aligned countries – neutral countries are excluded from this comparison because the intra-bloc shock does not apply to their trade: $INTRA_{ij}$ is defined only for pairs within the same West or East bloc, so a neutral country’s share of intra-bloc imports is mechanically zero, regardless of its actual trade pattern.

Figure 10: Welfare effects of geopolitical reallocation (scenario (a) – (c))



(a) Welfare change by country



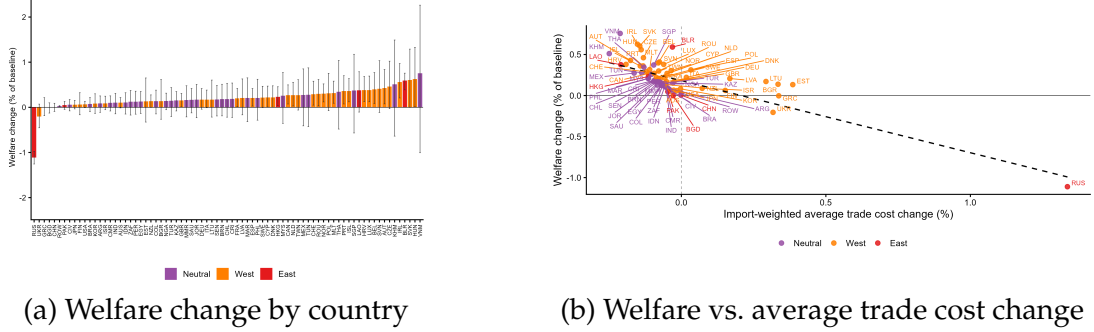
(b) Welfare vs. share of manufacturing expenditure on intra-bloc imports

Notes: Welfare change $100 \times (\hat{W}_j - 1)$ (% of baseline) under (a) – (c) ($INTER_{ij}$ and $INTRA_{ij}$ components): the full geopolitical effect, combining inter-bloc fragmentation with intra-bloc reorientation. Western countries gain on balance from the friendshoring (intra-bloc) channel. Panel (a)’s error bars are the 95% confidence interval from the sampling uncertainty of the long-term gravity coefficients β_{LT} (parametric bootstrap, $R = 200$ draws). Panel (b) plots welfare against the share of manufacturing expenditure on intra-bloc imports, excluding neutral countries (whose intra-bloc share is mechanically zero). Source: authors’ calculations.

Full scenario (a). Combining all components, most countries gain: the average welfare change is $+0.08\%$ with an expenditure-weighted standard deviation of 0.23% , confirming the predominantly redistributive character of the shock. Once sampling uncertainty in estimates is taken into account, Russia is the only country with a clear welfare loss in the full scenario. While Neutral countries tend to have positive point estimate welfare gains, uncertainty around the empirical estimates is too large, so that none of these countries exhibits welfare gains that are statistically different from zero. Beyond Belarus, the few countries with positive and statisti-

cally significant welfare gains tend to be small and open Western countries such as Ireland, Austria, Iceland, and Portugal, that are characterized by relatively high intra-bloc integration and relatively small direct trade relationships with Russia.²⁵ Figure 11, panel (b) shows that countries' welfare outcomes are highly correlated with their individual average trade cost change.²⁶

Figure 11: Welfare effects of the full scenario (a)



Notes: Welfare change $100 \times (\hat{W}_j - 1)$ (% of baseline) under the full scenario (a) (all components). Panel (a) orders countries by welfare change, with error bars showing the 95% confidence interval from the sampling uncertainty of the long-term gravity coefficients β_{LT} (parametric bootstrap, $R = 200$ draws): most gain, the largest winners are large manufacturing importers and Belarus, and Russia is the largest loser. Panel (b) plots welfare against the import-weighted average change in bilateral trade costs (eq. (8)); each point is a country ($N = 77$), line is an OLS fit. Source: authors' calculations.

5 Concluding remarks

This paper asks whether the recent surge in geopolitical tensions has given rise to a fragmentation of global trade, or even led to a broad retreat of globalization. Due to data constraints, previous discussions of (de-)globalization have largely relied on the aggregate trade-to-GDP ratio, which may be driven by compositional changes across countries and sectors, potentially concealing any trend in cross-border trade relative to economic activity. We build a novel quarterly sector-level production database from public sources, and combine it with international trade data to estimate a structural gravity equation including domestic trade flows in a panel from 2017 to 2024.

²⁵Some other examples are Belgium, Luxembourg, Croatia, Malta, and Norway. On average across these nine countries, the share of manufacturing imports from Russia in total manufacturing expenditure is 0.5%, while it is 1.34% for other Western countries. For manufacturing exports to Russia relative to manufacturing output, the respective numbers are 0.54% and 0.96%. The share of intra-West manufacturing imports in total manufacturing imports is 82% for these nine countries, while it is 67% for the remaining Western countries.

²⁶Some countries such as Vietnam and Cambodia lie above the line: as in scenario (c), their high share of imported manufacturing in total expenditure amplifies the gains from the common decline in cross-border manufacturing trade costs, beyond what their average bilateral trade-cost change implies.

We find that inter-bloc fragmentation is real but largely geographically concentrated: inter-bloc trade costs rose substantially after the Russian invasion of Ukraine, dominated by disintegration between Western countries and Russia, while fragmentation between the West and other Eastern bloc countries, though widening toward the end of the sample, remain small and imprecisely estimated. Deglobalization, however, has not materialized: on a trade-weighted basis, the net change in average bilateral trade costs was -0.21% , as rising inter-bloc barriers were more than offset by declining common trade costs and, to a lesser extent, by intra-bloc deepening.

The welfare consequences of this episode are primarily redistributive rather than aggregate: the average total welfare effect is only $+0.08\%$, compared to a standard deviation of 0.23% . Russia bears the largest individual loss, at -1.1% , while Belarus benefits from more exclusive access to the Russian market. Among Western and neutral countries, gains accrue particularly to countries with a large share of imported manufacturing goods in total expenditure, such as Vietnam, Hungary, and Slovakia, that benefit disproportionately from the decline in common trade costs.

The trade cost changes we document combine two distinct forces. Some reflect observable policies adopted for strategic or security reasons, such as sanctions, export controls, or discriminatory tariffs, which are the objects that the IMF definition of geoeconomic fragmentation has in mind (Aiyar et al., 2023). Others reflect how firms respond to a riskier environment, e.g. by diversifying suppliers in anticipation of future disruptions. Our approach is deliberately agnostic between the two, backing out trade costs from observed trade flows. This is a strength for measurement, since it captures frictions no policy database records, but it limits interpretation: the same estimated change in trade costs may warrant very different policy conclusions depending on its origin.

The welfare exercise is correspondingly stylized. We treat all frictions as iceberg transaction costs regardless of their true origin, and we abstract from the possibility that lowering trade frictions with a partner may require investment, so that intra-bloc deepening is not costless. While addressing these limitations is beyond the scope of this paper, it opens up questions for future work. Separating policy-driven from response-driven frictions would sharpen both the welfare accounting and the calibration of the theoretical models of fragmentation now emerging (Clayton et al., 2026), as would direct evidence on how countries and firms mitigate exposure, e.g. through stockpiling, diversification among existing suppliers, or investments in new trade relationships. What our estimates provide is the benchmark such work needs to match: between 2017 and 2024, the geography of world trade was redrawn without the average level of trade barriers rising.

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A Data Appendix

A.1 Representativeness relative to BACI

This appendix reports two complementary measures of coverage relative to BACI. First, in Table A1 we evaluate the coverage of the underlying TDM reporting base by restricting BACI to flows whose destination country is one of our 65 TDM reporting countries. These flows account for roughly 90% of total trade in BACI, and this share is stable over time. Second, in Table A2, we evaluate the coverage of the final estimation sample after applying the mirroring procedure and the restrictions required to construct positive domestic expenditure. While we lose some trade flows that are included in Table A1 by restricting ourselves to trade from 43 instead of 65 countries, we also gain some flows by including mirror flows. The final sample also accounts for roughly 90% of the total trade volume observed in BACI.

Table A1: Coverage of TDM reporting countries in BACI

Year	Share of BACI manufacturing trade
2017	90.28
2018	89.52
2019	89.38
2020	89.93
2021	89.59
2022	88.85
2023	88.66
2024	89.24

Table A2: Coverage of the final estimation sample in BACI

Year	Share of BACI manufacturing trade
2017	91.59
2018	90.96
2019	90.82
2020	90.41
2021	90.11
2022	89.85
2023	90.54
2024	90.74

A.2 Quarterly Production Series

In this section we now provide details of the production of the domestic production data: formulas and sources. We also provide an exercise that show that the extrapolated series represent the actual series well.

A.2.1 Extrapolation formula

We start with three sets of data:

- P_{ism} : producer price indices rebased to January 2015.
- Q_{ism} : monthly index of real (volumes) industrial production.
- V_{isy} : nominal output in current EUR

Step 1 — Monthly nominal output index. Reflate the volumes indices:

$$IY_{ism} = P_{ism} Q_{ism}. \quad (14)$$

Step 2 — Annual benchmarking For every year y with observed output, distribute the annual level V_{isy} across months in proportion to the index (14):

$$Ye_{ism} = \frac{IY_{ism}}{\sum_{m' \in y} IY_{ism'}} V_{isy}, \quad m \in y. \quad (15)$$

By construction this allocation reproduces the annual total exactly:

$$\sum_{m \in y} Ye_{ism} = V_{isy}. \quad (16)$$

Step 3 — Extrapolation We extrapolate to years with no annual volumes, using the nominal index scaled by the *annual* ratio of the last year with available data (here: $\text{Dec}(T_{is}^*)$):

$$Ye_{ism} = IY_{ism} \frac{V_{is, T_{is}^*}}{\sum_{m' \in T_{is}^*} IY_{ism'}}, \quad m > \text{Dec}(T_{is}^*). \quad (17)$$

The extrapolated series depends on the last point with available annual data, not on any single month's index value.

Step 4 — Quarterly aggregation and domestic expenditure. Monthly output is summed to quarters,

$$Ye_{isq} = \sum_{m \in q} Ye_{ism}, \quad (18)$$

and domestic expenditure and total expenditure follow as

$$\text{DomExp}_{isq} = Ye_{isq} - \text{Exports}_{isq}, \quad \text{TotExp}_{isq} = \text{DomExp}_{isq} + \text{Imports}_{isq}. \quad (19)$$

Country–sector–quarter cells with $\text{DomExp}_{isq} \leq 0$ are dropped.

A.2.2 Data sources

Table A3: Main data blocks used to construct monthly production values

Sources	Coverage and Classification	Use	Preprocessing
Annual nominal output			
UNIDO INDSTAT Revision 4, series <i>Output</i> .	Annual country–industry data. The retained vintage covers 2010–2022. It contains 120 countries and uses the 2-digit ISIC level of aggregation, covering manufacturing divisions 10–33 as well as divisions in sections B, D, and E of the ISIC classification.	Provides the annual nominal production level used to anchor the monthly production series.	Output values are reported in current U.S. dollars and in national currency. They are converted to current euros using annual EUR/USD exchange rates. The national-currency value is retained to compute and check the implicit exchange rate. Observations are kept for manufacturing industries only.
Monthly real production index			
UNIDO Indices of Industrial Production (IIP). We use the original, non-seasonally-adjusted index.	Monthly country–industry observations, starting in 2005 where available. Industries are reported at the 2-digit ISIC manufacturing level, sectors 10–33, and 72 countries are available.	Provides the monthly real production evolution.	The monthly IIP is combined with producer price indices to construct a monthly nominal production index by country and industry.
Exchange rates			
IMF Exchange Rates, series Representative Rates by currencies.	Daily exchange rates based on USD, starting in 2005 when available, for 41 currencies.	Allows production values to be expressed in current euros.	Rates are converted to monthly averages and harmonized to EUR per local currency unit where necessary. When both IMF and ECB rates are available, the ECB rate is preferred. Currency changes are treated explicitly.
ECB Euro foreign exchange reference rates, historical time series file.	Daily euro reference rates for 41 currencies covered by the ECB, available since 2000.		
Datastream exchange rates	EUR/local-currency exchange rates from 2010 at a daily frequency for countries requiring additional coverage: ARM, BIH, COL, CRI, EGY, JOR, KGZ, LKA, MDA, PAK, RWA, SEN, SRB, TUN, TWN, and UKR.		
Producer price indices			
Sector-level producer price indices from national statistical institutes where available; aggregate producer price indices from IMF and Datastream otherwise. See Table A4.	Monthly country–industry observations where detailed sector PPIs are available; monthly country-level aggregate PPI otherwise. Source classifications include ISIC, NACE, NAICS and other national product classifications.	Used to transform real monthly production indices into nominal monthly production indices.	Sector PPIs are rebased to January 2015 and the sector classification is harmonized. When detailed sector PPIs are unavailable, aggregate country PPIs are combined with U.S. sector-relative PPI dynamics to approximate industry-level nominal price movements.

Table A4: Producer price indices data sources and preprocessing

Countries and Sources	Coverage and Classification	Preprocessing and Use
United States U.S. Bureau of Labor Statistics: PPI All Commodities (series <i>PPIACO</i>), PPI Delivery and Warehouse Industries (<i>PCUADLVWRADLVWR</i>), PPI by Industry (series <i>PCU1133–1133–</i>)	Monthly aggregate, manufacturing, and industry-level PPI series from 2005. Industry-level series use 6-digit NAICS-based categories.	Keep only series that have complete data for the retained period, with the exception of the Tobacco series, which starts at the end of 2011 and is the only NAICS code in ISIC sector 12. Detailed NAICS series are mapped to 2-digit ISIC manufacturing sectors using a concordance table. Within each 2-digit ISIC sector, matched NAICS series are aggregated using an unweighted geometric mean. The resulting U.S. sector PPI is used directly for the United States and as the sector-relative inflation reference in fallback cases.
European countries Eurostat: PPI dataset <i>STS_INPP_M</i> . European countries covered in Eurostat, excluding country aggregates and series with insufficient coverage.	Monthly indices using NACE sectors, from 2005, for countries covered in Eurostat and with sufficient coverage, : AT, BE, BG, CH, CZ, DE, DK, EL, ES, FI, FR, HR, HU, IE, IT, LT, MK, NL, NO, PL, PT, RO, SE, SI.	Sector codes are kept for manufacturing sectors C10–C33 and selected aggregate manufacturing groupings such as C10–C12. Missing detailed sectors are filled, when possible, using the closest available aggregate manufacturing grouping. Countries with no usable sector PPI coverage are excluded.

Continued on next page

Countries and Sources	Coverage and Classification	Preprocessing and Use
Canada Statistics Canada, Industrial Product Price Index, by industry, table 18-10-0267-01.	Monthly NAICS-based industry price indices from 2005.	Detailed NAICS industries are mapped to 2-digit NACE sectors using a NAICS–NACE concordance. When multiple NAICS industries map to the same 2-digit NACE sector, their price indices are averaged.
China National Bureau of Statistics of China, Producer Price Indices for Industrial Products.	Monthly producer price indices, with different raw source vintages for 2012–2013, 2014–2017, and 2018 onward, using the national classification.	Raw sector labels or product codes are harmonized across source vintages where necessary and mapped to 2-digit ISIC manufacturing sectors using manually created concordance tables. All resulting sector series are rebased to January 2015. For cases in which one national sector maps into two NACE sectors, new rows are created to accommodate multiple NACE industries. For cases in which two national sectors map into one NACE sector, the national price indices are averaged. Country-specific transformations are then applied where needed. For China, because the raw data are year-on-year price indices, monthly sector indices are reconstructed by chaining the year-on-year price indices.
India Office of the Economic Adviser, Wholesale Price Index, 2011–12 series.	Monthly price indices based on WPI product categories, from 2012.	

Continued on next page

Countries and Sources	Coverage and Classification	Preprocessing and Use
Japan Bank of Japan, Corporate Goods Price Index, Producer Price Index component.	All products belonging to the <i>Manufacturing industry products group</i> in the BOJ classification.	
South Korea Bank of Korea Economic Statistics System, 4.1.1.1 <i>Producer Price Indices (Basic Groups)</i> .	Monthly PPI series at level 4 of the BOK classification for items included in level 2 Manufacturing products, from 2012.	
Mexico National Institute of Statistics and Geography, <i>Índice Nacional de Precios Productor</i> .	Monthly manufacturing price-index series in the Mexican source classification.	

Continued on next page

Countries and Sources	Coverage and Classification	Preprocessing and Use
Turkey Turkish Statistical Institute, Domestic Producer Price Index, historic series by sections, divisions, and groups of CPA 2008.	Monthly domestic PPI series by NACE Rev. 2 sections, divisions, and groups from 1994.	Manufacturing divisions are retained and harmonized to the 2-digit manufacturing sector level. The raw index is reshaped to a sector-month panel and rebased to January 2015.
IMF Producer Price Index dataset	Aggregate PPI for 78 countries at a monthly frequency from 2005.	The IMF aggregate PPI is used only when detailed country-sector PPIs are unavailable.
Datastream aggregate PPI for the manufacturing sector when available, or for the entire economy otherwise.	40 countries requiring additional aggregate PPI coverage. Monthly country-level aggregate PPI at the manufacturing or aggregate level.	These series are used to extend aggregate PPI coverage beyond the IMF source. When no detailed country-sector PPI is available, the aggregate country PPI is combined with U.S. sector-relative PPI dynamics to approximate sector-level nominal price movements. Countries with missing coverage or missing production values are dropped.

A.2.3 Validation of the extrapolation procedure

The construction of the domestic production dataset uses the extrapolation method detailed in Section A.2.1 for years in which official data is unavailable. In order to confirm that the constructed series represent the true values well we perform the following exercise: we apply the extrapolation procedure using 2018 as the last year with data, and we generate extrapolated data for 2019-2021. We then compare the constructed data to the true one. The sample used for these exercises is the balanced panel described in Section 2.

Figure A1 plots the value of the extrapolated series for 2021 against their true values. The predicted annual output aligns closely with the observed values, the scatter plot is concentrated around the 45-degree line, indicating no systematic departures between the extrapolated values and the true ones.

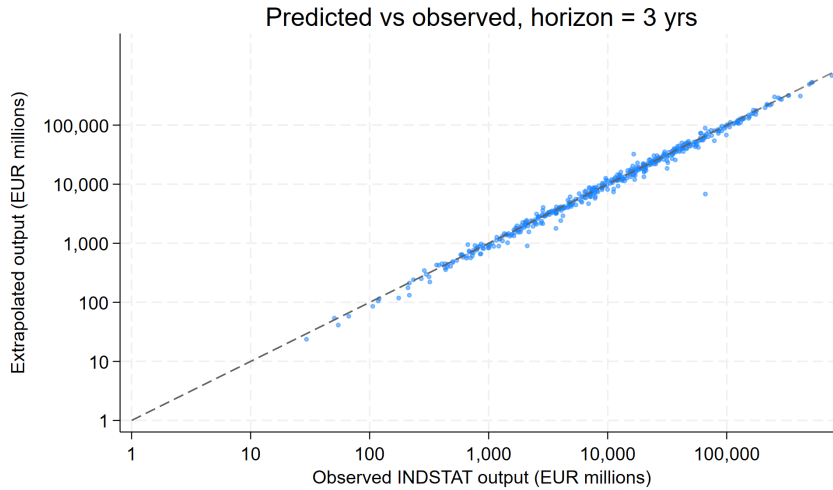


Figure A1: Predicted versus observed annual output. Annual output predicted using information available up to 2018 is compared with subsequently observed INDSTAT values. The dashed line denotes the 45-degree line.

To look more closely we report some moments of the deviations, defined as the difference between the extrapolated values and the true ones. Define the cumulative log prediction error as $e_i = \ln(\hat{Y}_i) - \ln(Y_i)$, where $\hat{Y}_i$ denotes predicted annual output and Y_i the observed value. Percentage prediction errors are $PE_i = 100(\exp(e_i) - 1)$. These are reported below in Table A5. Signed prediction errors remain close to zero at each extrapolation horizon. There is no evidence of monotonic upward or downward drift as the extrapolation horizon increases.

Table A5: Mean and median changes by years after the benchmark

Years after benchmark	Mean	Median
1	1.81%	0.76%
2	4.73%	0.12%
3	−2.81%	−2.49%

Note: The table reports mean and median percentage values of extrapolation errors expressed in percentage, by extrapolation length. The year of observed data is 2018, thus a 1-year horizon is 2019, two-year 2020 and three-year 2021.

A.3 Allocation of countries into geopolitical blocs

The geopolitical index used as baseline is developed in [Attinasi et al. \(2024\)](#), as a combination of two sources. The first one is an index inspired by [Den Besten et al. \(2023\)](#) that combines four different proxies of political alignment between countries, measured for 2013-2023. Each variable is scaled and normalized to vary from zero to one, and averaged out to create an index for which increasing values indicate closer geopolitical alignment with China and Russia compared with the United States.

1. # was sanctioned by Russia/China - # sanctioned by the US (Global Sanctions Database)
2. % military imports from Russia and China - % military imports from the US (SIPRI database)
3. Whether it participates in the *Belt and Road Initiative* (BRI)
4. country voting on the resolution of the Eleventh Emergency Special Session of the United Nations General Assembly adopted on 2 March 2022 on Russia's invasion of Ukraine

Data are available for 63 countries covering 87% of global GDP. For the remaining smaller countries, the allocation is supplemented by [Capital Economics \(2023\)](#), which allocates countries on a broader set of indicators, as it considers additional geopolitical and economic variables such as public opinion about China and the US, security alliances, territorial disputes, FDI from China and the United States and exports to China and the US, as well as participation to the Belt and Road Initiative. [Capital Economics \(2023\)](#) represents a close match to the index of [Den Besten et al. \(2023\)](#) for countries covered in both classifications, the implied allocations are highly correlated.

Figure [A2](#) reports the bloc allocation for all countries in the sample and the value share of trade flows by geopolitical bloc. Figure [A3](#) reports the bloc allocation for countries with production data and the value share of domestic flows by geopolitical bloc.

Figure A2: Bloc composition of countries and trade flows

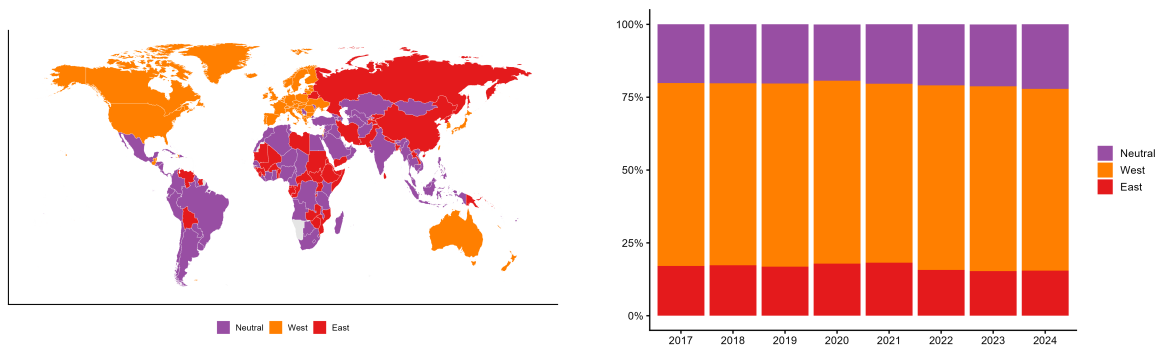
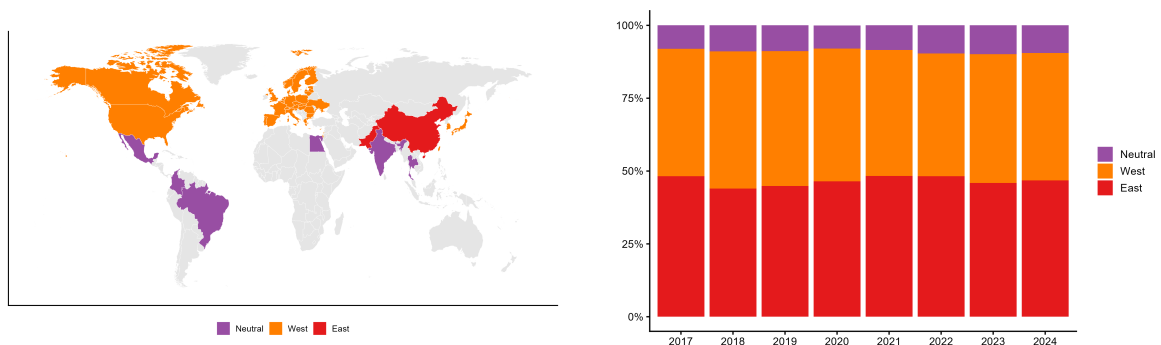


Figure A3: Bloc composition of countries with production data and domestic flows



A.4 Sector composition

Table A6 reports the distribution of country-pair-sector observations and trade value across the 24 manufacturing sectors used in our sample.

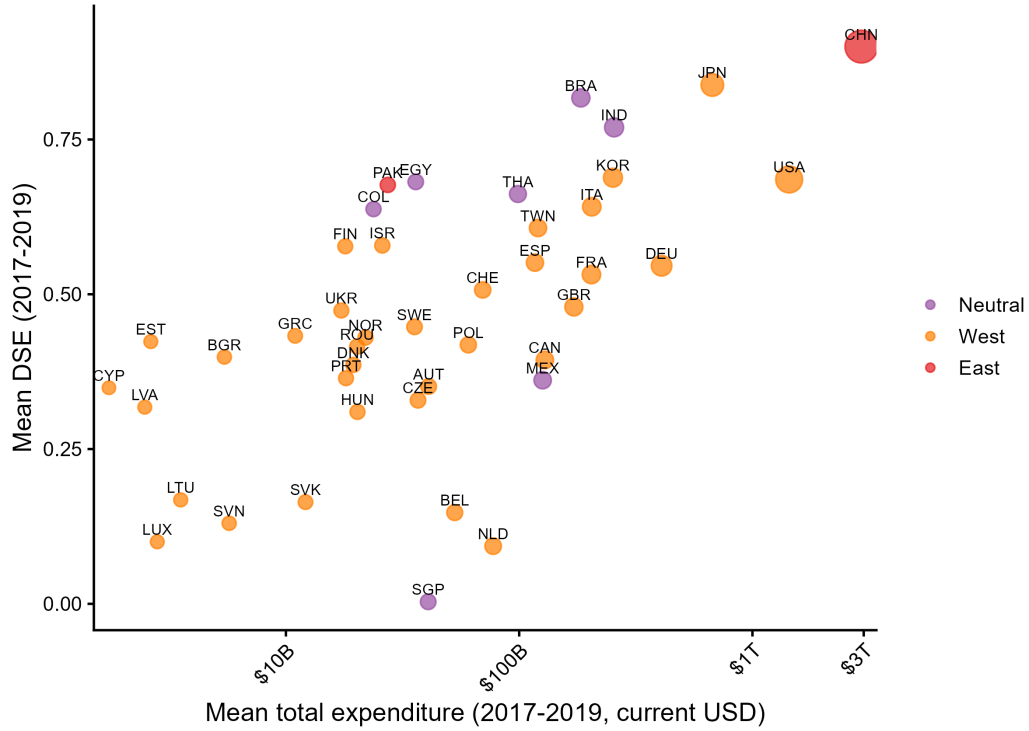
Table A6: Sector composition of the final sample

Sector code	Description	Number of country pairs	Share of total flows value
10	Food products	12995	10.93
11	Beverages	8776	1.85
12	Tobacco products	2208	0.68
13	Textiles	7900	1.71
14	Wearing apparel	4013	1
15	Leather and related products	4335	0.7
16	Wood products, excluding furniture	10370	1.34
17	Paper and paper products	9976	2.05
18	Printing and reproduction of recorded media	8693	0.82
19	Coke and refined petroleum products	5352	6.29
20	Chemicals and chemical products	7781	8.86
21	Pharmaceuticals, medicinal chemicals, etc.	4272	2.87
22	Rubber and plastics products	11060	3.57
23	Other non-metallic mineral products	12142	3.61
24	Basic metals	5575	9.6
25	Fabricated metal products, except machinery	13670	4.96
26	Computer, electronic and optical products	3702	10.69
27	Electrical equipment	6967	5.38
28	Machinery and equipment n.e.c.	9194	7.5
29	Motor vehicles, trailers and semi-trailers	8825	10.68
30	Other transport equipment	3721	1.98
31	Furniture	8907	0.92
32	Other manufacturing	4816	1.58
33	Repair and installation of machinery/equipment	23	0.44

B Additional Results

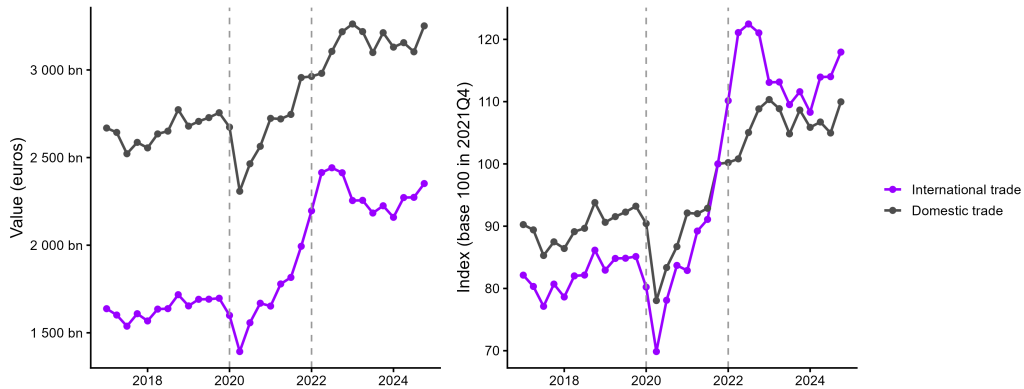
B.1 Detailed Results on Domestic Expenditure

Figure B1: Share of Domestic Expenditure and Total Expenditure by country



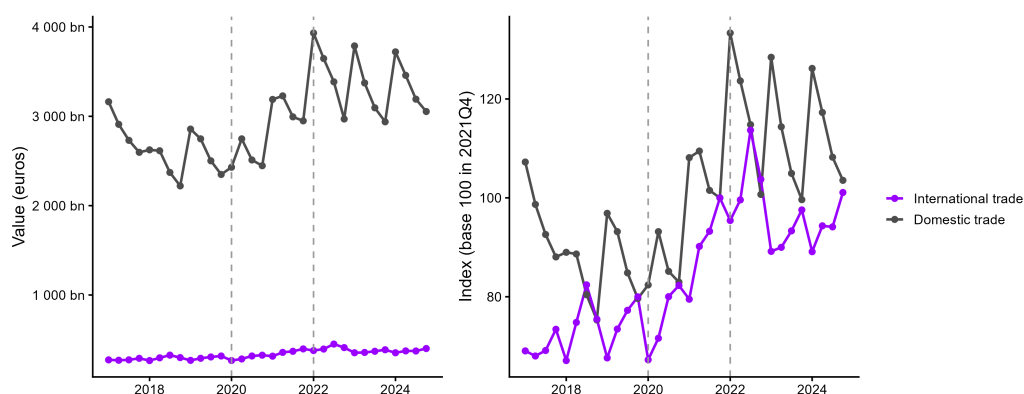
Notes: The figure plots the average domestic share of expenditure against average total expenditure over 2017–2019 for each of the 43 countries with positive domestic expenditure. Marker size is proportional to total expenditure. The horizontal axis is displayed on a pseudo-logarithmic scale. Source: Authors' calculations based on data from TDM, UNIDO, and national statistical institutes.

Figure B2: Aggregate Domestic Expenditure and Aggregate Imports: Western Countries



Notes: Domestic Expenditure and Imports for the aggregate of Western countries in the data. Domestic expenditure computed as production minus exports. Source: Authors' calculations based on data from TDM, UNIDO, and national statistical institutes.

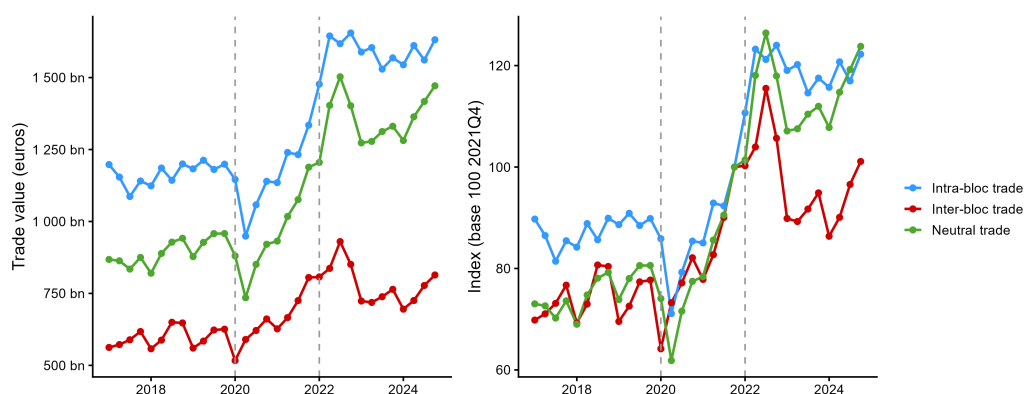
Figure B3: Aggregate Domestic Expenditure and Aggregate Imports: China



Notes: Domestic Expenditure and Imports for China. Domestic expenditure computed as production minus exports. Source: Authors' calculations based on data from TDM, UNIDO, and the National Bureau of Statistics of China.

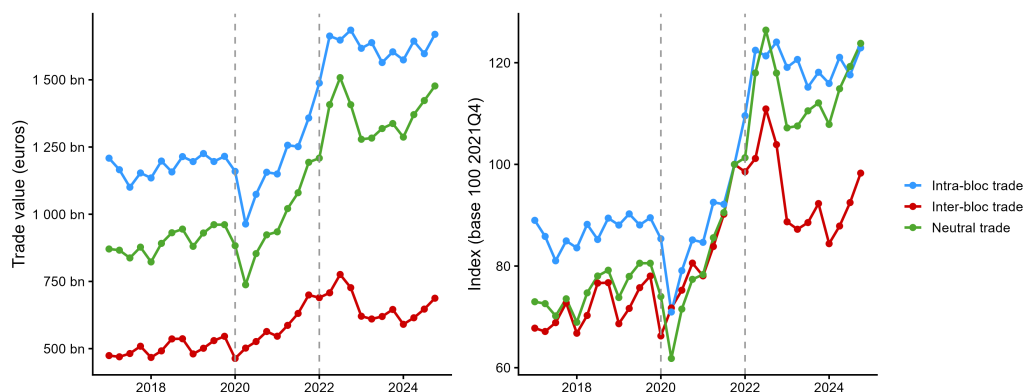
B.2 Detailed Time Series of Trade flows

Figure B4: Aggregate Trade Flows: Intra-Bloc, inter-bloc, and neutral trade: Excluding Trade with Russia



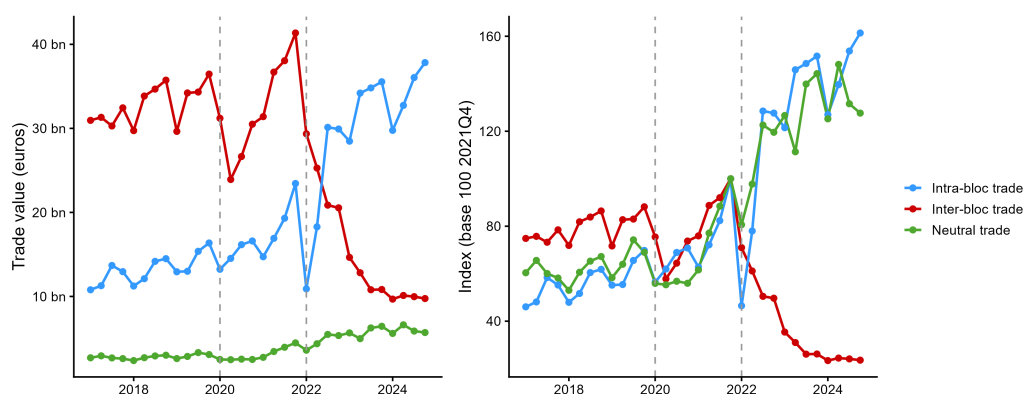
Notes: Intra-Bloc, inter-bloc, and neutral trade for the aggregate of international trade flows, excluding all trade with Russia. Source: Authors' calculations based on data from TDM.

Figure B5: Aggregate Trade Flows: Intra-Bloc, inter-bloc, and neutral trade: Excluding US-China Trade



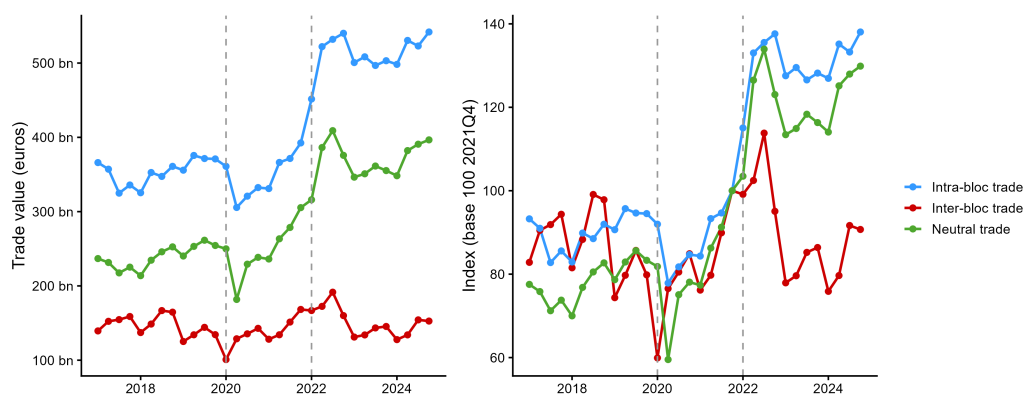
Notes: Intra-Bloc, inter-bloc, and neutral trade for the aggregate of international trade flows, excluding all US-China trade. Source: Authors' calculations based on data from TDM.

Figure B6: Aggregate Trade Flows: Intra-Bloc, inter-bloc, and neutral trade: Russia Only



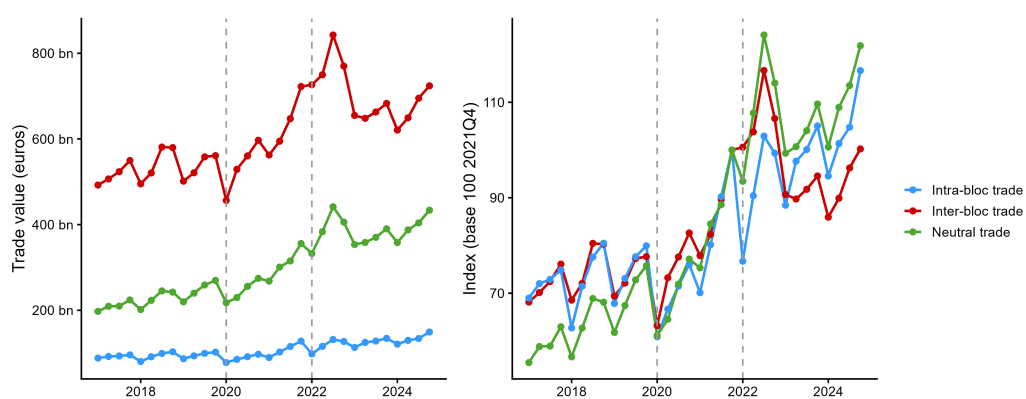
Notes: Intra-Bloc, inter-bloc, and neutral trade for Russia. Source: Authors' calculations based on data from TDM.

Figure B7: Aggregate Trade Flows: Intra-Bloc, inter-bloc, and neutral trade: US Only



Notes: Intra-Bloc, inter-bloc, and neutral trade for the US. Source: Authors' calculations based on data from TDM.

Figure B8: Aggregate Trade Flows: Intra-Bloc, inter-bloc, and neutral trade: China Only

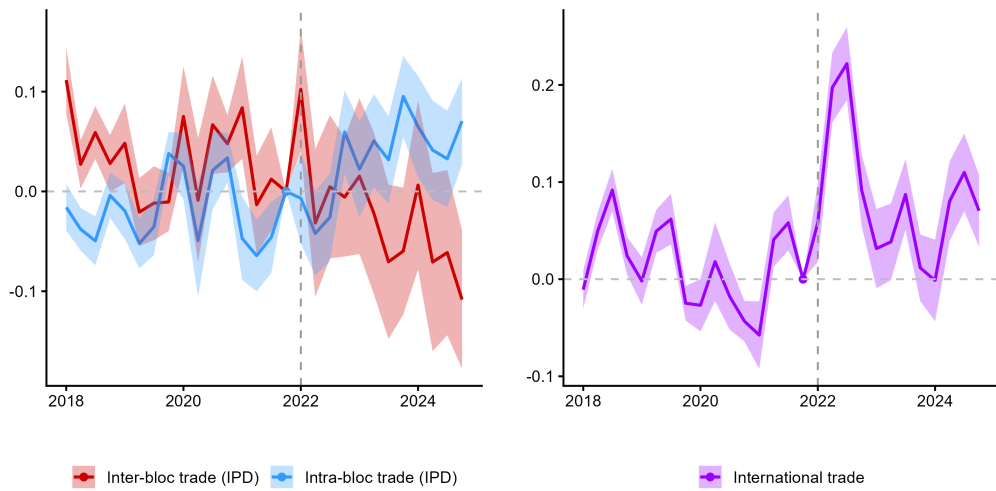


Notes: Intra-Bloc, inter-bloc, and neutral trade for China. Source: Authors' calculations based on data from TDM.

B.3 Quarterly Dynamics of Geopolitical Reallocation and Deglobalization Coefficients with Alternative Bloc Allocation

As a robustness check, we re-estimate equation 1 using an alternative geopolitical classification based on the Ideal Point Distance (IPD) measure of Bailey et al. (2017), which is constructed from voting patterns in the United Nations General Assembly and adopted by Gopinath et al. (2025). Figure B9 reports the resulting estimates of the fragmentation and deglobalization coefficients. Table B1 summarizes the differences between our baseline ECB classification and the IPD classification.

Figure B9: Estimated Coefficients under the IPD Bloc Classification: Geopolitical Reallocation vs Deglobalization



Notes: Estimates of β_t from Model 1, with coefficients on $INTRA_{ij}$ and $INTER_{ij}$ in the left panel and the coefficient on $INTERNATIONAL_{ij}$ in the right panel. Estimation is carried out using PPML. Shaded bands show 95% confidence intervals based on standard errors clustered by exporter $\times$ importer $\times$ sector (i.e., by bilateral-sector cell). The $INTRA_{ij}$ and $INTER_{ij}$ dummies are defined using the IPD bloc classification. Coefficients show the deviation of trade relative to the reference period 2021Q4.

Table B1: Differences between the ECB and IPD bloc classifications

ECB	IPD	N countries	Share of trade value (%)	Countries
Neutral	East	33	7.3	ATG, BHS, BRB, BTN, BWA, CHL, CIV, CPV, DOM, ECU, GHA, JAM, KAZ, KNA, LCA, LSO, MAR, MDV, MNG, MWI, NGA, PHL, SAU, SEN, SGP, SLV, SYC, THA, TLS, TTO, URY, UZB, ZAF
West	Neutral	6	6.4	CYP, GTM, HTI, JPN, NRU, PLW
West	Missing	34	6.2	ABW, AIA, ANT, ASM, BES, BLM, BMU, CCK, COK, CUW, CXR, CYM, FLK, GIB, GRL, GUM, IOT, LIE, MCO, MNP, MSR, NCL, NFK, NIU, PCN, PYF, SHN, SPM, SXM, TCA, TKL, TWN, VGB, WLF
East	Missing	5	3.5	HKG, MAC, PRK, PSE, SSD
East	Neutral	32	1.3	BDI, BGD, BOL, CAF, COG, COM, ERI, GIN, GNO, IRN, KGZ, LAO, LBN, LBY, LKA, MLI, MOZ, MRT, NPL, PAK, PNG, SDN, SLB, SLE, SOM, TGO, TJK, TON, UGA, VEN, YEM, ZWE
Neutral	Missing	4	0.3	COD, CUB, SRB, TUV
Neutral	West	4	0.1	AND, FSM, GEO, MDA
West	East	1	0.0	BLZ
Same classification		108	75.5	–
Reclassified (rows above, net of double counting)		76	15.1	–
Unmeasurable under IPD (rows above, net of double counting)		43	9.4	–
Total		227	100.0	–

Notes: Countries are classified West/East/Neutral under our baseline ECB classification (Den Besten et al. (2023)) and the alternative IPD classification of Bailey et al. (2017); “Missing” denotes countries with no IPD classification (non-UN members, for which no voting-based measure exists). Each of the eight upper rows is a case where the two measures disagree, reporting the number of countries and the share of trade value whose bilateral classification ($INTER_{ij}$ / $INTRA_{ij}$ /neutral) actually differs (or becomes unmeasurable, for Missing rows). The bottom panel gives the exact decomposition of the full sample, not a row sum: the three Missing rows alone add to 10.0%, 0.6 percentage points above the 9.4% reported below, because 0.57% of trade value is between a pair of countries in two different Missing rows (almost entirely West/Missing $\times$ East/Missing, e.g. Taiwan–Hong Kong-type trade) and so is counted in both rows but only once in the total.

B.4 Robustness to Trade Rerouting through Connector Countries

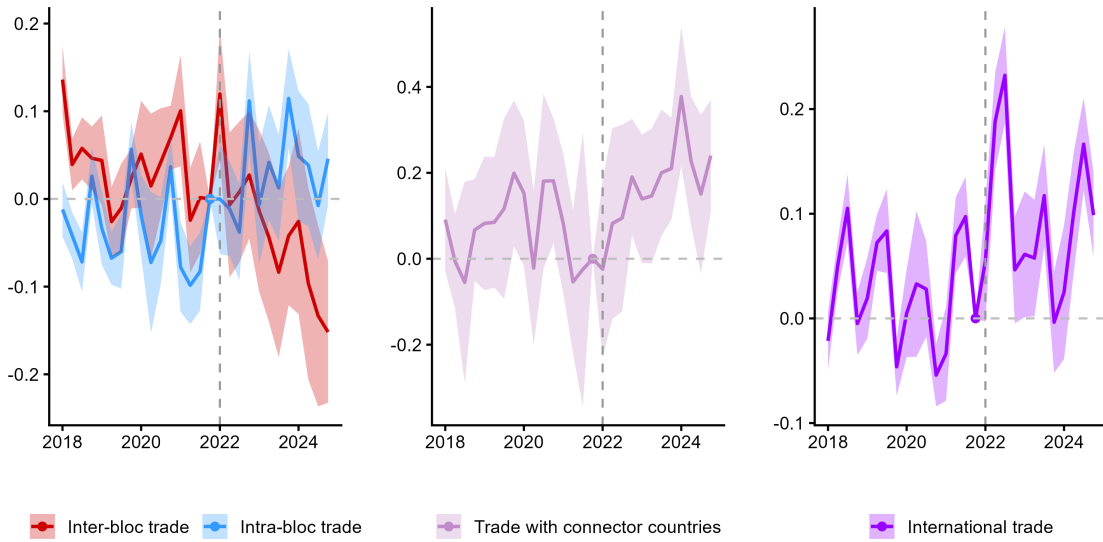
The neutral countries that anchor our reference category include some of the best-documented transshipment hubs for goods rerouted around sanctions on Russia. Chupilkin et al. (2026) show that European exports to Armenia, Kazakhstan, and the Kyrgyz Republic surged after 2022, disproportionately so for sanctioned products, and that a meaningful share of these goods still reaches Russia in spite of sanctions. Turkey has played a similar role as an intermediary for EU-Russia trade. If flows through these connector countries inflate the growth of our neutral reference group, the estimated decline in inter-bloc trade would partly reflect rerouted trade rather than a genuine increase in bilateral trade costs.

To assess this, we augment our baseline event-study specification (equation 1) with an additional dummy, $CONNECTOR_{ij}$, equal to one whenever Armenia, Kazakhstan, or Turkey is the exporter or importer and the trade partner belongs to either geopolitical bloc, and zero otherwise. This lets any differential growth in bloc-facing trade with these three countries load on its own coefficient rather than being absorbed into the neutral baseline used to identify $INTRA_{ij}$ and $INTER_{ij}$.

Figure B10 reports the results. The dynamics of $INTRA_{ij}$ and $INTER_{ij}$ (left

panel) are virtually identical to the baseline estimates in Figure 3, indicating that trade intermediated through these connector countries is not responsible for the estimated geopolitical reallocation pattern. At the same time, the connector-trade coefficient (middle panel) provides a validity check on the specification itself: it fluctuates around zero with no consistent trend before the war, then rises steadily and becomes statistically significant from 2022Q4 onward, reaching its highest values in 2024. This is precisely the pattern one would expect if trade with Armenia, Kazakhstan, and Turkey increasingly reflects rerouted trade following the invasion, and it confirms that our specification is capturing this channel separately rather than folding it into the geopolitical reallocation estimates.

Figure B10: Estimated Coefficients with a Connector-Country Rerouting Dummy



Notes: Estimates of β_t from an augmented version of Model 1, including an additional dummy $CONNECTOR_{ij}$ equal to one when Armenia, Kazakhstan, or Turkey is the exporter or importer and the counterpart belongs to either geopolitical bloc. Left panel: coefficients on $INTRA_{ij}$ and $INTER_{ij}$. Middle panel: coefficient on $CONNECTOR_{ij}$. Right panel: coefficient on $INTERNATIONAL_{ij}$. Estimation is carried out using PPML. Shaded bands show 95% confidence intervals based on standard errors clustered by exporter $\times$ importer $\times$ sector (i.e., by bilateral-sector cell). Coefficients show the deviation of trade relative to the reference period 2021Q4.

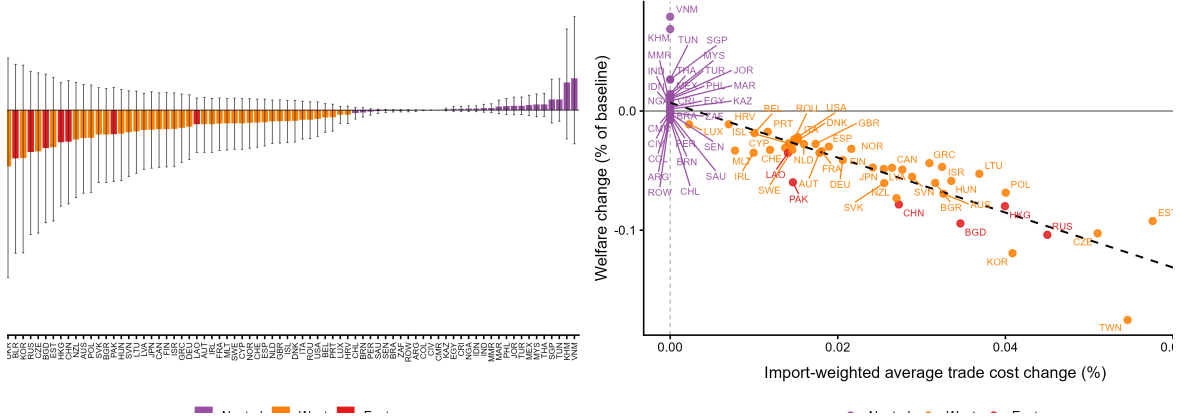
B.5 The role of trade diversion: a Russia counterfactual

The welfare effects of inter-bloc fragmentation are driven almost entirely by the large, Russia-specific rise in East–West trade costs ($INTER_{ij}^{RU}$, a long-run coefficient of -2.05 , against a small and insignificant non-Russia inter-bloc estimate). To show that the cross-country redistribution operates through the *trade diversion* this barrier induces, we re-run the inter-bloc fragmentation scenario (b) under a counterfactual that strips out the Russia-specific component: we set the Russia–West coefficient equal to the non-Russia inter-bloc coefficient ($INTER^{RU} := INTER^{-RU}$), so that

Russia is treated like any other cross-bloc trading partner. All other shocks are unchanged; as in the main text, the inter-bloc fragmentation effect is read off the difference $(b) - (c)$.

Figure B11 reports the result, and the message is simple: when Russia no longer bears an outsized loss, Belarus no longer enjoys an outsized gain. Under inter-bloc fragmentation alone, scenario $(b) - (c)$, Russia's welfare change rises from -1.3% to -0.1% (compare the -1.1% loss reported for Russia under the full scenario (a) in Section 4.3, which also nets in the common globalization and intra-bloc components). Belarus—the single largest winner in the baseline $(+0.49\%)$ —drops out of the winners entirely, to -0.12% (panel (a)). The reason is that Belarus's baseline gain was never a gain from its own cost changes: it captured the Western demand priced out of the Russian market as Russia's closest partner. Once Russia is no longer isolated, that windfall vanishes, and Belarus and Russia—which lie far off the first-order welfare-exposure line in the baseline—return to it, their welfare now matching their own modest trade-cost exposure (panel (b)).

Figure B11: Counterfactual inter-bloc fragmentation, scenario $(b) - (c)$ (Russia treated as other inter-bloc)



Notes: As in the main-text inter-bloc fragmentation figure, but with the Russia–West inter-bloc coefficient set to the non-Russia inter-bloc estimate. Panel (a): welfare change $100 \times (\hat{W}_j - 1)$ by country, with error bars showing the 95% confidence interval from the sampling uncertainty of the long-term gravity coefficients β_{LT} (parametric bootstrap, $R = 200$ draws); panel (b): welfare against the import-weighted average change in bilateral trade costs. With Russia's loss neutralized, Belarus is no longer a major winner. Source: authors' calculations.