INTERNATIONAL MONETARY FUND

Fragmentation in Global Trade Accounting for Commodities

Marijn A. Bolhuis, Jiaqian Chen, and Benjamin Kett

WP/23/73

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2023 MAR



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Fragmentation in Global Trade: Accounting for Commodities* Prepared by Marijn A. Bolhuis, Jiaqian Chen, and Benjamin Kett

Authorized for distribution by Anna Ilyina March 2023

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ABSTRACT:

We construct a new database which covers production and trade in 136 primary commodities and 24 manufacturing and service sectors for 145 countries. Using this new more granular data, we estimate spillover effects from plausible trade fragmentation scenarios in a new multi-country, multi-sector, general-equilibrium model that accounts for unique demand and supply characteristics of commodities. The results show fragmentation-induced output losses can be sizable, especially for Low-Income-Countries, although the magnitudes vary according to the particular scenarios and modelling assumptions. Our work demonstrates that not accounting for granular commodity production and trade linkages leads to underestimation of the output losses associated with trade fragmentation.

RECOMMENDED CITATION: Bolhuis A. Marijn, Jiaqian Chen and Benjamin Kett (2023): Fragmentation in Global Trade: Accounting for Commodities. IMF Working Paper, No. WP 23/73

JEL Classification Numbers:	F11, F12, F14, F15, F17, F41, F42, F43, Q17, Q27, Q37, Q43
Keywords:	Commodities; international trade; sanctions; spillovers; fragmentation
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* The author(s) would like to thank Shekhar Aiyar, Jorge Alvarez, Chikako Baba, Mehdi Benatiya Andaloussi, Wenjie Chen, Stephan Danninger, Romain Duval, Christian Ebeke, Luc Eyraud, Pierre-Olivier Gourinchas, Nikolay Gueorguiev, Anna Ilyina, Petya Koeva Brooks, Ting Lan, Chiara Maggi, Papa N'Diaye, Martin Stuermer, Petia Topalova, Daria Zakharova, and Robert Zymek.

WORKING PAPERS

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1.Introduction

Following several decades of a steady increase in global economic integration, globalization has stalled and may be on the brink of a reversal. The shallow and uneven economic recovery from the Global Financial Crisis (GFC) coincided with a growing number of military conflicts around the world, a deepening skepticism about the benefits of globalization, and a growing populism and protectionism (e.g., Brexit, trade war between the United States and China). The COVID-19 pandemic has further tested international relations. The war in Ukraine served to split countries along geopolitical lines, further increasing uncertainty over the direction of globalization. Aiyar and others (2023) documents these developments and coins the term "geoeconomic fragmentation" (GEF) to describe a policy-driven reversal of global economic integration often guided by strategic considerations.

Motivated by the rising specter of GEF, a growing number of studies have attempted to gauge the potential economic effects of possible fragmentation scenarios (Aiyar and others, 2023). This paper aims to quantify the economic costs of fragmentation from an international trade perspective, with a particular focus on production and trade of commodities. More specifically, we examine how various fragmentation scenarios affect output in different country groups by applying a novel multi-country multi-sector model with input-output linkages to a newly developed dataset that accounts for granular production and trade in commodities.

To effectively account for spillovers from trade fragmentation, we construct a new dataset that covers a granular level of trade and production in commodities following Fally and Sayre (2019, FS hereafter). FS use detailed data on production and trade from various sources to construct a rich dataset covering trade, production, and prices across a range of commodities. Our dataset extends their work along several dimensions: (i) we update the data to 2019, the most recent pre-pandemic year, from 2016 in FS; (ii) we modify the list of commodities in order to reflect the most "upstream" products, which is important to ensure the characteristics of commodities (such as geographical concentration) are appropriately captured; and (iii) we reconcile our dataset with an otherwise standard input-output (IO) matrix such that the individual commodities sum up to an aggregate sector in the Eora26 database (Lenzen et al., 2012, 2013). Overall, our database contains 136 primary commodities along with 24 manufacturing and service sectors for 145 countries.

Exploiting the detail of this dataset requires an adapted model which incorporates commodities. While our model has similar building blocks, we depart from FS in several ways. Most importantly, we consider sectoral input-output linkages that allow for feedback loops in production. Intermediate inputs are shown to be important conduits for transmitting shocks across countries (e.g., Auer et al., 2019; Boehm et al., 2019) and imply substantially larger losses from increasing trade barriers (e.g., Caliendo and Parro, 2015). Moreover, to reduce the data burden we follow Cunat and Zymek (2022), making use of proportionality assumptions in the use of intermediate inputs.

We start from an otherwise standard quantitative multi-country multi-sector trade model and distinguish between two types of goods, commodities and non-commodities. The production of non-commodities uses labor, commodities, and non-commodity intermediate inputs, while the production of commodities relies on labor and non-commodity intermediate inputs. Non-commodities are also consumed as final goods. We generate a low price elasticity of demand for commodities by introducing a low elasticity of substitution between commodities and other inputs in the production of non-commodities.

We then use the model to approximate the impact of trade fragmentation on domestic prices and output. We first show that, up to a first-order approximation, fragmentation has a larger impact on prices in countries and sectors that lose access to a larger share of their pre-fragmentation supply. This impact is particularly large in sectors where the elasticity of substitution between foreign and domestic products is lower. This 'trade elasticity' is a crucial parameter measuring the response of trade to changes in trade costs which we discuss in more detail in the rest of the paper. We also show that the overall effect of fragmentation on a country's real GDP can be decomposed into the contributions of (i) the direct effect of import prices on final goods, (ii) amplification through input-output linkages, and (iii) the effect on prices of commodities.

We calibrate the key model parameters based on the latest existing literature. Our demand elasticities for commodity sectors are sourced from FS, which conducts a meta-analysis of the literature. The trade elasticities are calibrated based on recent work by Fontagné et al. (2022) and provide conservative results while being well in line with other estimates in the literature (see Data section). Notably, the two principal commodity subsectors have the lowest trade elasticities across all sectors, at 3.4 for Mining and Quarrying, and 2.9 for Agriculture (compared to an average across sectors of 6). Building on the most recent work on estimating trade elasticities, we also consider short-run trade elasticities which, due to adjustments costs, are shown by Boehm et al. (forthcoming) to be significantly lower than long-run elasticities.

Similar to FS, we find that properly accounting for trade and production in commodities (i.e., using sectoral data disaggregated into product level commodities) substantially increases the adverse economic impact of trade fragmentation compared with models which implicitly assume perfect substitutes among commodities. Comparing the baseline equilibrium (2019 global trade barriers) to global autarky, we find that the output losses more than double for Low-Income Countries (LICs), who are heavily dependent on trade in commodities, while for Advanced Economies (AEs) and Emerging Market economies (EMs) the welfare losses increase by 4 and 25 percent respectively. Intuitively, trade barriers are much more costly for products which can only be sourced from a relatively small number of countries and for which demand is relatively inelastic.

The model is used to explore several hypothetical scenarios that illustrate the cost of a more fragmentated global trade network. We make a distinction between two scenarios. In the 'mild' fragmentation scenario ('Strategic Decoupling') there is no trade between the US-EU and Russia, and no trade in high-tech sectors between the US-EU and China, but the rest of the world (RoW) are free to trade with both groups. In the 'severe' fragmentation scenario ('Geo-economic Fragmentation'), there is no trade between EU-US and Russia- China and the RoW joins one of the two groups depending on the strength of the trade link with either the US or China, resulting in zero trade with the other group.

Global output losses are estimated to fall by between 0.3 percent and 2.3 percent in the long run depending on the fragmentation scenario. Moreover, the impacts are heterogenous across income groups. Specifically, in the mild fragmentation scenario, LICs benefit from trade diversion as the trade barriers they face remain unchanged relative to the baseline; however, in the more severe fragmentation scenario, their output drops by 4.3 percent over the long run. These results underscore the vulnerability of LICs to trade barriers and the risks of forcing them to choose groups. It is, nonetheless, important to note that there is a wide range of potential estimates of the size of fragmentation-induced losses, depending on the modeling assumptions. For example, calibrating the model with different estimated trade elasticities in the literature, we find the global GDP loss ranges between 1.9 and 7.0 percent in the more severe fragmentation scenario. Moreover, these simulations do not reflect the full effects of global economic fragmentation, as some of the important channels which would imply larger economic losses are not captured. Another set of scenarios reveals the sensitivity of countries to

trade restrictions in different product groups. In particular, we find that AEs and EMEs are most vulnerable to disruption in trade in energy and high-tech manufacturing sectors, whereas LICs see the largest output loss following barriers to trade in agricultural goods.

The fast-growing literature on the costs of sanctions and global fragmentation has generated a wide array of quantitative estimates, reflecting the consideration of different channels as well as different assumed fragmentation scenarios. IMF (2022) investigates the effect of eliminating trade in the aggregated high-tech and energy sectors across rival blocs which are determined based on the vote to condemn Russia's invasion of Ukraine at the United Nations General Assembly (UNGA) in March 2022. The results suggest a loss of about 1.2 percent of world GDP, which increases to 1.5 percent when barriers to trade are extended to other sectors as well. Cerdeiro et al. (2021) employ a set of structural models to examine the costs of three different layers of fragmentation (trade, sectoral misallocation, and foreign knowledge diffusion), across a range of fragmentation scenarios. Their estimated welfare costs range from zero (as some countries gain from trade diversion) to 8.5 percent when accounting for all three layers of fragmentation. Bekkers and Goes (2022) focus on knowledge diffusion across countries, with the global economy divided into an Eastern bloc and a Western bloc based on UNGA voting records. The results show a range of losses from 0.4 percent of GDP for some countries in a mild fragmentation scenario to 12 percent for the most affected countries under full technological decoupling. Javorcik et al. (2022) examine fragmentation through the lens of 'friend-shoring', finding output losses of between 0.1 percent and 4.6 percent of GDP depending on the country and scenario. Our paper differs from existing papers in that we focus on the international trade channel specifically, and we account for granular trade and production of commodities, whereas previous studies assume commodities such as copper and diamond are perfect substitutes. This underestimates the cost of fragmentation for the global economy, with a particular impact on countries that are more exposed to commodity trade. Moreover, we calibrate our model with the estimated trade elasticities from the latest available literature and capture both short and long run costs of trade fragmentation.

Our paper also contributes to the literature on the effects of sanctions related to energy commodities for European countries. Bachmann et al. (2022) find a Russian gas shut-off (i.e., a 30 percent gas supply shock) would affect German Gross National Expenditure by -0.7 to -2.3 percent, depending on the elasticity of substitution used. Applying a similar framework but incorporating uncertainty and second-round effects, Lan et al. (2022) estimate that Germany's real GDP will fall by 1.4 percent in 2022 and 2.7 percent in 2023 under the assumption that households adjust consumption very little. Using a multi-sector, partial equilibrium model, DiBella et al. (2022) find an average effect of -1.8 percent on EU countries' GDP. Albrizio el al. (2022) estimate that by allowing the substitution of Russian gas with LNG from the global market, the adverse economic impacts are reduced by a factor or five, but with significant global spillovers. While the European impacts are a special case of the analysis in our paper, we go further by providing global estimates of welfare impacts and considering broader global fragmentation scenarios. We also go beyond the energy sector to consider a wide range of commodities which are key inputs to worldwide production processes.

The remainder of the paper proceeds as follows: Section 2 describes the dataset creation and calibration of elasticities; Section 3 presents the model; Section 4 discusses the fragmentation scenarios; Section 5 presents the results and the robustness checks; and Section 6 concludes.

2. Data

Production and trade data

The modelling approach used in this paper requires bilateral trade data (including self-trade) for all sectors, along with detailed disaggregation of commodity sectors, for a wide range of countries.¹ As this data is not readily available, in particular for self-trade, we combine several data sources (inspired by FS) to produce a new dataset covering 2019, the latest year prior to the start of the COVID pandemic.

The starting point for the data construction is the Eora26 multi-region input-output table (MRIO), which is a global input-output table covering 26 sectors and 190 countries. A key advantage of Eora26 is the very broad country coverage, necessary for the study of global fragmentation, whilst maintaining a uniform and relatively broad sectoral coverage. However, the sectoral breakdown is too aggregated to effectively take into account the particular properties of commodities: the two main sectors covering commodities are 'Mining and Quarrying' and 'Agriculture'. The objective of our dataset construction is therefore to break apart these two aggregate sectors to provide detailed information on individual commodities.

In order to do this, we use both international trade data and production data; self-trade is then calculated as the difference between production and total exports. The list of commodities is based on that used by FS, with a small number of modifications to ensure the list uses the most upstream commodities possible and allows the best possible mapping to both production and trade data.² We end up with 54 mining commodities and 82 agricultural commodities with the full list provided in Appendix I.

For international trade data, we use the <u>BACI</u> database produced by CEP II. This database provides bilateral trade flows for 200 countries at the harmonized system (HS) 6-digit level. While based on Comtrade, BACI incorporates various operations to improve the consistency of the data across reporters (described in the associated working paper, Gaulier & Zignago (2010)). Data is provided in both values (USD) and quantities (metric tons).

We integrate two datasets for production. For agricultural commodities, we use statistics from the Food and Agricultural Organization (FAO) which include production value data for 173 (raw and processed) agricultural products across 245 countries.³

For mining commodities, we use the World Mineral Production dataset produced by the British Geological Survey (BGS).⁴ This dataset includes production data in quantities for more than 70 mineral commodities by country worldwide. The data is compiled from a range of sources including government departments, national statistical offices, company reports etc. While FAO data is provided in value units (USD), and hence is directly compatible with both trade and Eora data, the BGS data is only provided in production quantities (with varying

¹ Self-trade is defined as the value of production consumed in the producing country (i.e., not exported).

² We develop crosswalks by hand which map products in the production data to the commodity list, as well from HS codes in the trade data to the same commodity list. Production and trade data are therefore linked through the chosen list of commodities (see Appendix). The crosswalks aim to ensure consistency between the HS code and production data aggregations whilst also ensuring the most upstream definitions of commodities possible.

³ <u>https://www.fao.org/faostat/en/#data/QV</u>

⁴ <u>https://www2.bgs.ac.uk/mineralsuk/statistics/worldStatistics.htmlS</u>

units). There are two necessary steps to derive value data from the BGS data. First, we convert all quantity units into a uniform unit, metric tons (as used in BACI), using standard conversion ratios. Second, we derive exporter-commodity specific prices using unit values from the BACI database.⁵ Values are then the product of quantities and unit values. For natural gas we take trade data from IEA, given the importance of this particular sector for the European economy and the challenges in measurement of gas exports given the usage of pipelines and complicated financial transactions.⁶

In order the ensure consistency between the production data, trade data, and Eora we employ three main strategies. First, when the sum of trade values is smaller than the aggregate sector value in Eora, we allow for a residual equal to the difference. This residual accounts for the fact that our commodity list is not exhaustive, and hence acts as an 'other' category. Second, when the sum of trade data is larger than the figure in Eora, we scale down exports or self-trade proportionately, leaving the residual at zero. Third, when export value is larger than production value, we set self-trade equal to zero. This accounts for the possibility that export product classifications may incorporate some additional value added beyond the raw commodities.

The resulting dataset contains observations in values (USD) at the exporter sector/commodity-importer level (including self-trade when the importer is also the exporter), with 24 aggregated (manufacturing and services) sectors, 82 agricultural commodities, and 54 mining commodities, for 145 countries in 2019.

Trade elasticities (short vs. long run)

One key parameter in the model is the trade elasticity, which measures how trade flows respond to trade barriers (Simonovska and Waugh, 2014). Following Boehm et al. (forthcoming), we make a distinction between long- and short-run trade elasticities in our results (discussed further below).⁷

Estimates of long-run trade elasticities in the literature vary depending on the methods and data used. Our baseline results rely on state-of-the-art estimates produced by Fontagné et al. (2022). Their paper uses bilateral tariffs for the universe of country pairs from 2001-2016 to estimate elasticities. It employs a gravity approach using a fixed effects strategy, which the authors argue benefits from generality, tractability, and transparency, while being theory-consistent. We take their estimates of elasticities at the sector-level (see Table 8 in their paper, or Annex I of this paper), for example, we use a value of -3.41 for mining commodities, and -2.91 for agricultural commodities. These two sectors represent the lowest two values across all sectors, and compare to a maximum of -10.56, further highlighting the particular nature of commodity-based sectors. Since Fontagné et al. (2022) only estimate elasticities for one services sector, for the counterfactual analysis we collapse all services trade into one sector. We also present a range of alternative trade elasticities in the Robustness section based on alternative sources from the literature.

⁵ Where multiple HS codes map to a single commodity, we derive prices by dividing the total value of all 6-digit HS codes by the total quantity. To ensure reasonable bounded prices, we replace observations greater than two standard deviations above the mean with the median value. While unit values derived from trade data have known limitations such as wide cross-country variance, we argue that the result remains superior to other sources such as the US Geological Survey which only contains US-specific price data.

⁶ For a fuller discussion see http://www.cepii.fr/BLOG/en/post.asp?IDcommunique=929.

⁷ The model employed in this paper is static. However, the difference between results that use short- and long-run trade elasticities can be interpreted as the difference between the short- and long-run impact of changes in trade costs in a dynamic quantitative trade model with endogenous firm entry where firm face quadratic adjustment costs. We refer the reader to Boehm et al. (2022) for details.

Changes in trade costs result in reallocations of inputs across sectors/countries, hence modifying demand for certain inputs, or reallocation of demand to alternative suppliers. Firms may face adjustments costs, meaning that these reallocations do not happen immediately. Trade elasticities are typically estimated as long-run values which are relatively high and hence underestimate the short-run welfare losses of trade costs. Boehm et al. (forthcoming) address this concern by estimating trade elasticities at short and long horizons. They find that it can take 7 to 10 years for the elasticity point estimates to stabilize, with elasticities after one year equaling 36 percent of the long-run value. We calibrate the ratio between our short-run and long-run trade elasticities to be in line with this finding.⁸

It is also worth noting that the methodology employed by Boehm et al. (forthcoming) leads to significantly smaller long-run trade elasticity estimates than are typical in the literature (1.75 to 2.25). They argue this is a result of omitted variables in typical estimates, where multilateral resistance terms "do not absorb aggregate of product-specific bilateral taste shifters or other unobserved bilateral gravity variables" (p. 2). The authors propose time-differencing the traditional gravity specification to resolve this concern which dramatically reduces their estimates. While we acknowledge the importance of the paper's methodological innovations, we choose to use long-run estimates from Fontagné et al. (2022) to ensure conservative results while applying short-run to long-run ratio from Boehm et al. to generate short-run results.

Demand elasticities

The demand elasticities used in our model are a direct function of the elasticities of substitution between inputs in the associated production function (with the exact relationship discussed in the model section). Our model employs a Constant Elasticity of Substitution (CES) aggregator for commodities and other inputs with an elasticity of substitution equal to 0.2, taking the conservative side of the mode of the demand elasticity estimates surveyed by FS.⁹ Other sectors have a Cobb-Douglas structure which implicitly restricts the elasticity of substitution to one.

⁸ In a recent paper, Andersen and Yotov (2023) propose a new reduced-form econometric approach to short- and long-run trade elasticities that are consistent with existing theories of dynamic adjustment in trade costs. Their estimate of the short-run elasticity is about 10 percent of the long-run value. To be conservative, we apply the estimates from Boehm et al. (forthcoming) which imply a higher value of the short-run trade elasticity relative to its long-run value.

⁹ CES aggregators are standard in the trade literature, with the tractable property that elasticities of substitution between products/inputs embedded in the aggregator do not change with quantities used.

3. Modelling Framework

We develop a new multi-country, multi-sector, general equilibrium model that accounts for the unique demand and supply characteristics of commodities, as well as cross-border trade of intermediate inputs. Our starting point is the canonical input-output model of Caliendo and Parro (2015, hereafter CP). While Fally and Sayre (2019) also develop a model which accounts for commodities, we argue that their model is limited by the onedirectional production 'stream' moving from upstream commodities to downstream final goods. As highlighted by CP, accounting more fully for the input-output structure of global trade better captures the feedback loops where the output of one sector is an input to another. These feedback properties therefore capture additional gains from trade.

Model

We now highlight the main building blocks of the model (see Appendix II for full details).

Production. Consider *N* countries, indexed by *n* and *m*. There are two types of sectors: *J* commodity sectors and *K* non-commodity sectors. Commodities are used as intermediate inputs to produce non-commodities. The latter are consumed as final goods and used as intermediate inputs (Cunat and Zymek,, 2022).¹⁰ In each country and sector, there is a representative local producer. Local commodity producers use labor and intermediate inputs for production while local non-commodity producers use labor, intermediate inputs, and commodities for production.

International trade. In each country and sector, a representative trading firm acts as a wholesaler and combines local products from different countries into a composite sectoral good using a CES aggregator. The composite sectoral good is not tradable. Trade is subject to iceberg trade costs τ_{mn}^k .

The price index of a typical sectoral good k in country n can be written as

$$P_n^k = \left[\sum_m (\tau_{mn}^k p_m^k)^{-\theta_k}\right]^{-\frac{1}{\theta_k}} \quad (1),$$

where θ_k is the elasticity of substitution between local products from different countries. θ_k is a crucial model parameter that does not only govern the ease with which trading firms can substitute between foreign and domestic products, but also the sensitivity of trade flows to changes in international trade costs. To see the latter, note that this model obeys the standard gravity equation. The natural logarithm of X_{mn}^k , the value of imports by country *n* on goods from country *m* in sector *k*, is given by:

$$\ln X_{mn}^k = -\theta_k \ln \tau_{mn}^k - \theta_k \ln p_m^k + \ln D_n^k + \ln \Phi_n^k \quad (2),$$

¹⁰ Assuming that the non-commodity composite good is both consumed and used as the composite intermediate input amounts to assuming that all sectors source intermediates from other sectors with the same intensity. The overall share of expenditures on intermediate inputs varies across sectors. This assumption, used in Cunat and Zymek (2022), relaxes the data requirement substantially such that the empirical analysis does not require data on intermediate input use of detailed commodity sectors.

where p_m^k is the price of the local product in sector *k* of country *m*, excluding trade costs. D_n^k is total demand for sector *k* in country *n*, and Φ_n^k captures country *n*'s access to other supplies. θ_k is commonly referred to as the *trade elasticity*, and we discuss it in detail below and in the Data section.

Inelastic demand for commodities. For each non-commodity sector, we assume a constant elasticity production function with constant returns to scale. η denotes the elasticity of substitution between commodity inputs and other inputs, including labor and non-commodities intermediates. The total demand D_n^k for commodities by sector *k* in country *n* is given by:

$$D_n^k = \beta_n^k \left(\frac{P_n^o}{c_n^k}\right)^{1-\eta} Y_n^k \quad (3),$$

where β_n^k governs the importance of commodities in production of sector *k*, P_n^o is the price of the commodity bundle in country *n*, and c_n^k and Y_n^k are the cost function and total production value of the representative firm. If a given individual commodity accounts for a small share of total costs, and holding other input costs and demand constant, the price elasticity of demand of a given commodity *j* is approximately equal to the elasticity of substitution η :

$$\frac{\partial \ln(d_n^{kj}/p_n^j)}{\partial \ln p_n^j} \approx \eta \quad (4)$$

where d_n^{kj} is the total demand for commodity *j* by sector *k*, and p_n^j is the price of commodity *j*.

Households and income. In each country, there is a representative household that supplies labor and consumes the final good. To account for trade imbalances, households receive and send exogenous international transfers, such that household income equals labor income plus the trade balance.

Assessing the costs of fragmentation

We interpret fragmentation as policy-driven increases in trade barriers. As is standard in the quantitative trade literature, we simulate the impact of changes in trade barriers using *exact hat algebra* (Dekle et al., 2007), which allows us to study the impact of fragmentation on output without the need to estimate model fundamentals such as trade costs and productivity levels. We refer the reader to the Appendix for details, but first derive some results to highlight the role of the trade elasticity in driving the costs of fragmentation.

Impact on domestic prices. Consider two blocs of countries that erect trade barriers such that any trade between the blocs in sector *k* is eliminated. The (log) change in the local price index of country *n* in the sector *k* (commodity or non-commodity) can be approximated as:

$$d\ln P_n^k \approx \frac{1}{\theta_k} \ln \frac{1}{1 - \pi_{n,other}^k} \qquad (5),$$

where $\pi_{n,other}^k$ is the share of initial expenditures of country *n* on goods from countries that are in the other bloc. In equation (5), the first-order impact of fragmentation on domestic prices can be summarized using the exposure to the other bloc ($\pi_{n,other}^k$) and the sector-specific trade elasticity θ_k . Prices increase more in countries that lose access to a larger share of supply, which are then forced to source additional products from more expensive suppliers. This effect is scaled by the inverse of the trade elasticity, as a lower elasticity makes it more costly to switch suppliers.

Impact on domestic output. The first-order change in output in country *n* due to fragmentation can be approximated as:

$$\frac{1}{\overline{\theta_k}} \overline{\ln(1 - \pi_{n,other}^k)} + \frac{\alpha_n (1 - \mu_n)}{1 - \alpha_n} \frac{1}{\overline{\theta_k}} \overline{\ln(1 - \pi_{n,other}^k)} + \frac{\alpha_n \mu_n}{1 - \alpha_n} \frac{1}{\overline{\theta_j}} \overline{\ln(1 - \pi_{n,other}^j)}$$
(6)

where $\alpha_n(1 - \mu_n)$ is the country's average expenditure share on intermediate inputs from non-commodity sectors and $\alpha_n \mu_n$ is the country's average expenditure share on intermediate inputs from commodity sectors. $\overline{\ln(1 - \pi_{n,other}^k)}$ and $\overline{\ln(1 - \pi_{n,other}^j)}$ are the average (log) shares of initial expenditure of country *n* on non-commodity and commodity goods from countries that are in the *same* bloc.¹¹

Equation (6) shows that, up to a first order approximation (for exposition only), all the general equilibrium effects of fragmentation on welfare can be summarized by three terms. The first term captures the direct effect on prices of final goods, whereas the second term captures the indirect effect through input-output linkages. The third term then captures the effect of access to commodities. For all terms the effect is increasing in the average share of initial expenditures on countries in the same trading bloc and decreasing in the average trade elasticity.

Finally, it is useful to highlight the boundaries to the type of quantitative trade model that we use. First, the model does not account for any changes in labor productivity due to capital accumulation or technological change. Short-run disruptions to output due to fragmentation therefore do not lead to long-run losses in labor productivity. Second, although the model allows for initial aggregate trade imbalances, they are assumed to remain fixed and do not respond endogenously to changes in trade costs.¹²

¹¹ In all cases, these are weighted averages with expenditure shares as weights.

¹² However, we do exogenously vary the initial aggregate imbalances in the Robustness section to evaluate the sensitivity of the results.

4. Geo-Economic Fragmentation Scenarios

Rising geopolitical tensions have increased the specter of protectionism and fragmentation. Russia's invasion of Ukraine was followed by far-reaching sanctions by Western countries.¹³ These sanctions include measures which target both individuals (for example freezing of assets held outside Russia, or restrictions on visas for travel) and the Russian economy. Among those targeting the Russian economy, restrictions on imports and exports have been central to the policy response. For example, restricted Russia exports include (among others): crude oil (from December 2022) and refined petroleum (from February 2023), coal, steel, and gold. Both Belarus and Iran have also faced sanctions for their perceived support of the invasion. At the time of writing, it is unclear when the sanctions might be lifted and the extent to which the world will return to previous trading patterns or alternatively stabilize in a new normal with higher global trade barriers.

The intensification of US-China trade tensions in 2018 led to a surge in global trade policy uncertainty and contributed to a paralysis of the multilateral trade dispute system. The US has recently announced new measures restricting sales to China of certain high-tech goods, software, and other technology related to advanced computing and semiconductor manufacturing, as well as restricting activities of "US persons" that support the development or production of certain technologies in China.¹⁴ These recent measures—motivated by national security considerations—increase the risk of the US-China high-tech decoupling with potentially adverse implications for the global economy.

More broadly, data from the *Global Trade Alert database* shows a rising number of trade restrictions imposed by countries, notably in high-tech sectors, likely reflecting the importance of these sectors in strategic competition and national security (IMF, 2022). Furthermore, during the pandemic several countries imposed export restrictions on medical goods and foodstuffs—with exports bans accounting for about 90 percent of trade restrictions.

Against this background, this paper considers five illustrative scenarios. The first three scenarios focus on trade restrictions in key product groups with the broad objective of illustrating which country groups are most vulnerable to disruption in trade in certain types of products. Specifically, scenarios A, B and C assume the introduction of barriers that prohibit trade in energy, agricultural goods and 'high-tech' sectors respectively.¹⁵ Following Cerdeiro et. al. (2021), high-tech sectors are defined using the classification in OECD (2011), which is based on sectoral R&D intensities. This methodology highlights two high-tech sectors: *electronics and machinery*, and *transport equipment*. The last two scenarios assume the US and EU impose barriers to prohibit trade of all goods and services from Russia and vice versa. The strategic decoupling scenario additionally assumes barriers on trade in high-tech sectors between the US-EU and China but no changes in the trade relations between US, EU, China, Russia, and the rest of the world (RoW). The Geo-economic fragmentation scenario goes further by assuming barriers on all trade between the US-EU and China; at the same time,

¹³ Details of the EU response, for example, can be found here: https://www.consilium.europa.eu/en/policies/sanctions/restrictivemeasures-against-russia-over-ukraine/sanctions-against-russia-explained/

¹⁴ Details of the US response, for example, can be found here: https://www.bis.doc.gov/index.php/documents/aboutbis/newsroom/press-releases/3158-2022-10-07-bis-press-release-advanced-computing-and-semiconductor-manufacturingcontrols-final/file

¹⁵ For simplicity, all counterfactual scenarios assume the introduction of infinite trade costs for the specific sectors mentioned. This ensures zero trade occurs between the relevant countries/groups, avoids arbitrary assumptions about the finite size of trade barriers, and keeps the model from becoming too computationally heavy.

countries from the RoW are forced to choose between trading exclusively with either the US and EU or with Russia and China based on historical trade intensities. A summary of the assumptions is presented in the text table below. We also analyze the results using an alternative country grouping based on geopolitical 'closeness' in the Robustness section.

Scenario	Country Group I	Country Group II	ROW	Commodities/sectors
A	-	-	-	Trade barriers on energy sector
В	-	-	-	Trade barriers on high-tech sectors
С	-	-	-	Trade barriers on agriculture goods
Strategic	USA and EU	Russia	Free trade	Trade barriers on all sectors
decoupling		China	-Free trade	Trade barriers on high-tech sectors
	onomic USA and EU ntation	Russia and China	Join USA (China) group if country trades more (less) with USA than China, resulting in tariffs on all sectors by the other group.	Trade barriers on all sectors
Geo-economic fragmentation				Trade barriers on all sectors

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It should be stressed that these simulations do not aim to reflect the full effects of global economic fragmentation, as some of the important channels, including trade-induced technology spillovers and uncertainty, are not captured. In addition, the range of possible effects provided by the five scenarios captures some, but not all, of the possible outcomes for the magnitude and coverage of the trade barriers as well as possible policy responses. Moreover, how countries decide between joining trading blocs (if necessary), would depend on many factors that go beyond their historical trade relations. Thus, the scenarios should be viewed as illustrative.

5. Results

Main Results

Before diving into the results for each scenario, we illustrate the importance of using a more granular dataset to account for production and trade in commodities. Specifically, we compare the welfare change calculated under two experiments with and without disaggregated commodity sectors (i.e., the only difference is the input dataset, with both using the same trade model and elasticities). For simplicity, both experiments consider the output loss of moving to autarky.¹⁶ The aggregated experiment uses the standard Eora-26 IO matrix and the disaggregated experiment uses the granular commodity dataset. The estimates use the exact hat algebra summarized by the algorithm in the Annex. Figure 1 presents the ratio of the output loss incorporating granular commodity trade to the welfare loss using the standard IO matrix.¹⁷ We find that the loss more than doubles for LICs, who are heavily dependent on trade in commodities, while for AEs and EMEs the welfare losses increase by 4 and 25 percent respectively. There are two key insights here. First, aggregated commodity sectors effectively treat different commodities as being infinitely substitutable, despite the fact that products as diverse as gold and natural gas are included. In reality, commodities tend to be very specific to downstream production chains with limited substitutability (hence the low elasticities of demand). Second, aggregate sectors make it seem like commodities are produced widely across many countries when in fact the production of individual commodities tends to be geographically concentrated (hence trade barriers may greatly restrict access to particular commodity inputs).



Figure 1. Relative Output Loss in Model with and without Disaggregated Commodities Sectors

¹⁶ This counterfactual involves two changes in exogenous variables. We increase all international trade barriers such that there is no international trade in the new equilibrium. We also set trade imbalances to zero.

¹⁷ Throughout the paper, we present impacts in terms of changes in output, or real GDP. In the model these are equivalent to changes in real factor income. We aggregate to group-level and global impacts using real GDP (PPP) weights from 2019.

Turning to the scenarios, Figure 2 shows the results of the simulations. The charts show the weighted average impact on real GDP for AEs, EMs and LICs in each scenario. The effects are differentiated by the 'short-run', corresponding to one year after the increase in trade barriers with a low associated trade elasticity, and 'long-run', corresponding to 10 years (shown by Boehm et al. (forthcoming) to be the time required for the elasticity to stabilize) after the barrier increase and a higher trade elasticity. To be conservative, we only lower the short-run trade elasticity for strategic sectors (commodities and high-tech) to 36 percent of the long-run value.¹⁸

Under Scenario A, the elimination of energy trade has a significant negative short-run impact on all countries, ranging from a 10.1 percent decrease in output for EMs to a 7.8 percent decrease for AEs and a 6.3 percent decrease for LICs. This reflects the different degrees of reliance on energy for production as well as fewer energy exporters among LICs. Over the long run, the impacts are significantly lower for all country groups, ranging from 1.1 to 2.1 percent, as countries reallocate inputs to other sectors and find other substitutes for internationally traded energy.

Scenario B shows the outcome of zero high-tech trade, with AEs experiencing the largest output loss. The result reflects the broader representation of high-tech trade for AEs. Scenario C underscores the importance of international trade in agriculture for the global living standards and especially for LICs that are highly dependent on agricultural goods imports.

In the <u>Strategic Decoupling</u> scenario (SD), the increase in trade barriers between the US/EU and Russia/China groups reduces output for AEs and EMs by 0.7 and 0.8 percent in the short run respectively, but only by 0.3 percent in the long run. LICs, however, benefit slightly due to trade diversion over both time periods, as demand and supply from trading partners in the two groups move to countries that still trade freely. Overall, we estimate a fall in global output of 0.3 percent in the long-run, and 0.8 percent in the short run with our baseline elasticities.

In the <u>Geo-economic Fragmentation</u> scenario (GEF), when countries in the ROW are forced into exclusive trade relations with one of the groups and trade barriers are applied across all sectors, the negative impact across all country groups increases dramatically. In the aggregate, there is a long run reduction in real GDP of 2.3 percent, and a short-run reduction of 4.8 percent. Losses for AEs and EMs are 4.2 and 5.2 percent in the short run and 2.1 and 2.5 percent in the long run, respectively. LICs would come under significant pressure, experiencing output losses of 10.8 percent in the short run and 4.3 percent in the long-run. LICs lose most because they are most exposed to commodity trade, i.e., they import and export commodities at a higher rate than AEs and EMs. This is because (i) LICs are more commodity intensive (especially in agriculture), (ii) LICs tend to be small and therefore rely more on commodity imports, and (iii) LICs tend to specialize in the exports of key commodities, especially metals and energy.

The last panel of Figure 3 provides a breakdown of results by key regions under the SD and the GEF scenarios (using the baseline, long-run elasticities). Under the SD scenario, we see positive impacts across several regions due to the diversion of trade that previously occurred between blocs. The largest positive impact occurs for Middle East and Central Asia, while the largest negative impact occurs for Emerging Market Europe (losses reduce from 3.8 percent of GDP to 3.0 percent if Russia and Turkey are excluded). As before, the GEF produces negative impacts across all regions with Latin American and the Caribbean showing the smallest

¹⁸ 36 percent is the ratio of the 1-year elasticity to the 10-year elasticity in Boehm et al. (forthcoming). See the Data section for more details.

negative impact and Emerging Market Europe showing the biggest losses. The losses depend largely on the regions' pre-fragmentation trade exposure to the other bloc, their overall trade openness, and the concentration of trade exposure in sectors with low elasticities of substitution.



Figure 2. Estimated Output Losses under Different Scenarios

Sources: Fund staff calculations.

Scenario B: Tariffs on High-tech Sectors



Sources: Fund staff calculations.



Scenario C: Tariffs on Agriculture Goods

Figure 3. Estimated Output Losses under Different Scenarios (continued)



Sources: Fund staff calculations.

Geo-economic Fragmentation Scenario (percent deviation from baseline)



Sources: Fund staff calculations.



Robustness checks

Trade Elasticities

While our welfare loss estimates are based on trade elasticities sourced from the most recent literature, it is also important to recognize that the literature has produced a range of different estimates which vary based on differences in data and methodology used. Table 2 below provides an overview of recent papers providing such estimates.

	Deint estimate	Denge	Nata
	Point estimate	Range	Note
Caliendo and Parro (2015)	4.55	0.49 ~ 69.31	Range over agriculture, mining and 18 manufacturing sectors
Amiti et. al. (2019)	5.89	5.89	
de Bromhead et. al. (2019)		1.47 ~ 23.47	Range over 9 products including agriculture goods, minerals and food
Boehm et. al. (2020)	2.12	0.75 ~ 5	Range over 10 HS product groups
Ossa (2014)	3.42	1.91 ~ 10.07	Range over 33 products including wheat, rice, etc.
Cerderio et al. (2021)		2.5 ~ 19	Based on Caceres et al (2019)
Fajgelbaum et al. (2020)	2.53	2.53	
Broda and Weinstein (2006)	6.6	6.6 ~ 12.6	the tariff line (13972 categories) level
Simonovska and Waugh (20	4.12	4.12	
Goes and Bekkers (2022)		2.8 ~ 10.09	Range over 6 sectors based on Hertel et al (2007)
Fontagne et al. (2022)		2.91 ~ 10.56	Range over 21 TiVA 2016 sectors
Giri et. al. (2021)	4.51	2.97 ~ 8.94	Range over 19 ISIC sectors
Kee et. al. (2008)	3.12	3.12	
Soderbery (2018)	3.4	3.4	
Romalis 2007	6.25	6.25	Based on US/EU imports from Canada data

Table 2: Selected Trade Elasticity Estimates in the Literature 1/

1/ in absolute value



Figure 4: Range of estimated output losses (percent deviation from baseline)

In this section we present additional results to test the robustness of our results to variations in the choice of trade elasticities. To do this, we take the variance in long-run trade elasticities by sector from Fontagné (2022) and scale them up and down based on the ratio of their mean value to the mean value (or point estimate) from other papers in the literature. We therefore take a maximum value of 6.6 from Broda and Weinstein (2006), and a minimum value of 2.12 from Boehm et at. (forthcoming). This places our mean value of 6.00 towards the conservative end of the spectrum of possibilities as higher elasticities, all else equal, lead to smaller welfare costs.

Figure 4 presents the results for both the strategic decoupling and geo-economic fragmentation scenarios. In both cases, our baseline results sit on the lower end of the range of results and hence represent conservative estimates relative to other possibilities in the literature (see the Data section for further explanation of this choice for baseline elasticities). For example, in the geo-fragmentation scenario welfare costs range from 1.9 percent of GDP for the global economy in the high elasticity case to 7.0 percent of GDP in the low elasticity case (with a baseline estimate of 2.3 percent of GDP).

Inter-bloc aggregate imbalances

As discussed in the modelling section, our model allows for endogenous bilateral trade imbalances, but aggregate trade imbalances are assumed to be exogenous and remain unchanged in the various counterfactuals (as commonly done in the literature, see Costinot and Rodriguez-Clare, 2014). As a robustness check, we rerun the baseline results with scaled imbalances such that all surpluses and deficits cancelled out within each bloc by construction (i.e., inter-bloc imbalances are zero).

The results are presented in Table 3, and remain very close to those from the baseline analysis. There are several explanations for this. First, inter-bloc imbalances are relatively low when countries are assigned to

blocs largely based on economic interests (i.e., trading relationships), the resulting scaling factors are also therefore relatively small (on the order of 15 percent). Second, nominal wages and prices tend to move together in the model as country deficits/surpluses are scaled meaning that even though changes in nominal GDP can be sizable, changes to real GDP are more muted.¹⁹ Third, the model assumes full employment which also minimizes output changes. Fourth, the model does not contain capital flows or technology impacts and hence differences in imbalances do not lead to corresponding differences in equilibrium capital stocks or productive capacity through differences in technology.

Alternative country blocs

The specific grouping of countries in different fragmentation scenarios is fundamentally assumptions driven. In our baseline, we choose a politically neutral approach by focusing largely on pre-pandemic trading relationships. Aside from the EU and Russia, who are grouped with the US and China, respectively, countries are assigned to the US group if they trade more with the US, and to the China group if they trade more with China.

However, it is reasonable to consider a different approach to assigning countries to different trading blocs based on political ties (or foreign policy similarities) rather than economic interests. In order to do this, we employ the 'Ideal Point Distance' (IPD) from Bailey et al. (2017).²⁰ The IPD is based on historical voting patterns at the UN Generally Assembly and allows calculation of bilateral political 'distances' between two countries based on how similar their voting patterns have been.

The bilateral IPD scores (averaged over 2017-2021) are calculated for all countries with respect to both the US and China. Then every country is ranked based on their closeness to each of the two pole countries. If a country is more highly ranked for the US than China, then it is "assigned" to the US bloc (and vice versa). We make two manual reassignments, moving Russia and Mali from the US group into the China group. For Russia, the justification is self-evident. For Mali, we note that this is the only country that would have been placed in the US group based on the IPD measure that voted against the United Nations General Assembly Resolution on Ukraine (A/ES-11/L. 7).²¹

The last column in Table 3 presents the output loss estimates for the IPD-based country groupings (Geopolitical blocs). Aggregate losses amount to 3.2 percent of global GDP, significantly more than under the baseline scenario in which blocs are based on trade intensities. It is intuitive that the economic costs would be larger under the geopolitical bloc formation, as inherently this implies choosing exclusive trading relations not solely based on economic interests (i.e., trade intensities). LICs fair somewhat similarly under the robustness exercise, as their economic and geopolitical preferences are appear to be more aligned. AEs see the largest

¹⁹ The small impact of changes in trade imbalances on output is in line with Dekle et al. (2007, 2008) who find that in a counterfactual world with all current accounts balancing, large changes in nominal variables (wages, nominal GDP), large changes translate into muted changes in real GDP. The reason for this is that the more a country's relative wage (and hence nominal GDP) needs to decline to make exports competitive abroad, the lower its domestic price index.

²⁰ A similar approach is also used in Chapter 3 of the IMF April 2023 WEO (IMF, 2023) except that (i) we assign all countries to one or other of the blocs based on relative rankings as opposed to allowing for a non-assigned group, and (ii) we assign all countries individually rather than grouping them together in regions.

²¹ Our model also has a small number of economies for which no IPD is available, in these cases we manually assigned: New Caledonia to the US group; Palestine to the US group; Hong Kong SAR to the China group. We also dropped Serbia from the sample given an absence of a corresponding IPD.

difference, moving from 2.1 percent in losses to 3.4 percent under geopolitical bloc formation. EMs also see increase in losses from 2.5 percent to 3 percent.

Country Grouping	Baseline - GEF	No inter-bloc imbalances	Geopolitical blocs
AE	-2.14	-2.09	-3.40
EM	-2.48	-2.36	-3.03
LIC	-4.25	-4.12	-4.17
Global	-2.34	-2.25	-3.20

Table 3: GDP Losses for Robustness Checks

6.Conclusion

This paper estimates output losses for a range of potential global trade fragmentation scenarios using a newly constructed dataset that provides detailed trade and production data for commodities, and a novel model which incorporates the key features of production and trade in commodities. We use trade and demand elasticities which are both conservative and based on the most up to date literature.

First, we show that not accounting for granular commodity production and trade linkages leads to underestimation of the output losses associated with trade fragmentation. LICs face losses that are more than twice compared to a model using aggregate commodity sectors, while AEs and EMs face costs that are 4 percent and 25 percent larger respectively.

Second, we show that output losses tend to be larger the deeper the fragmentation scenario and that LICs experience larger losses than AEs or EMs. Trade barriers that are limited to specific countries or specific sectors, whilst allowing the RoW to trade freely, lead to relatively contained GDP losses in the long run as production processes and source countries adjust and trade diversion provides a boost to countries outside of the main trade blocs. In contrast, a severe fragmentation scenario leads to larger losses, particularly for low-income countries that are forced to choose between one bloc or the other. Moreover, we illustrate the estimated output loss varies widely depending on the assumption on trade elasticities. Formation of blocs by geopolitical allegiances as opposed to economic interests also increases the losses, while closing inter-bloc trade imbalances does not materially impact the results.

Third, we exploit recent work on the variation in trade elasticities over time to estimate the potential short run costs of fragmentation. With trade elasticities as a fraction of their long run values we see costs of 10.8 percent for LICs in the short run as countries faced adjustment costs which reduce their ability to adapt quickly. Furthermore, we run robustness checks that use a range of reasonable trade elasticities from the literature to demonstrate that our loss estimates sit on the conservative side of the spectrum.

Future research will concentrate on several elements. The difference between short and long-run elasticities can be micro founded by introducing quadratic adjustment costs in a dynamic system. The model could be additionally extended to introduce endogenous capital formation and technological progress which would induce long-run welfare effects from short-run adjustment costs. Furthermore, the model currently assumes exogenous overall trade imbalances, an assumption that could be relaxed in future research. There is also scope for algorithm of endogenous bloc formation where countries choose their bloc in an iterative process on the basis of which other countries choose to join and their potential welfare benefits depending on the evolving bloc composition.

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Annex I. Data

Commodity list

Agriculture Commodity		Mineral Product		
Almonds	Lettuce	Antimony	Rare Earths	
Apples	Linseed	Arsenic	Salt	
Apricots	Maize	Asbestos	Selenium	
Asparagus	Mandarins	Barytes & Strontium	Sillimanite	
Avocados	Mangoes	Bauxite	Silver	
Bananas	Mate	Beryl	Talc	
Barley	Melons	Bismuth	Tellurium	
Beans	Millet	Borates	Tin	
Berries	Mushrooms	Bromine	Titanium	
Brazil nuts	Mustard seeds	Cadmium	Tungsten	
Buckwheat	Natural rubber	Chromium	Uranium	
Canary seed	Nutmeg	Coal	Vermiculite	
Carrots	Oats	Cobalt	Wollastonite	
Cashews	Onions	Copper	Zinc	
Cassava	Oranges	Crude Oil	Zirconium	
Cauliflowers	Papayas	Diamond	Other minerals	
Cherries	Peaches	Diatomite		
Chestnuts	Pears	Feldspar		
Chickpeas	Peas	Fluorspar		
Cinnamon	Pineapples	Gallium, indium, rhenium,	thallium	
Cloves	Pistachios	Germanium		
Сосоа	Plums	Gold		
Coconuts	Poppy seeds	Graphite		
Coffee	Potatoes	Gypsum		
Cotton seeds	Rapeseed	lodine		
Cucumbers	Rice	Iron & Steel		
Dates	Rye	Lead		
Eggplants	Sorghum	Lithium		
Figs	Soy beans	Magnesium		
Flax	Spinach	Manganese		
Garlic	Sugar	Mercury		
Ginger	Sunflower seeds	Mica		
Grapefruit	Sweet potatoes	Molybdenum		
Grapes	Теа	Natural Gas		
Hazelnuts	Tobacco	Nickel		
Hops	Tomatoes	Niobium, tantalum, vanad	lium	
Jute	Vanilla	Palladium		
Leeks	Walnuts	Phosphate		
Lemons	Wheat	Platinum		
Lentils	Other agriculture goods	Potash		

Trade Elasticities

Sector – TiVA 2016	Sector(s) - Eora	Trade elasticity
Agriculture, hunting, forestry and	Agriculture, Fishing	-2.91
fishing		
Mining and quarrying	Mining and Quarrying	-3.41
Food products, beverages and tobacco	Food & Beverages	-4.17
Textiles, textile products, leather and	Textiles and Wearing Apparel	-4.71
footwear		
Wood and products of wood and cork	Wood and Paper	-8.80
Pulp, paper, paper products, printing		-8.21
and publishing		
Coke, refined petroleum products and	Petroleum, Chemical and Non-	-3.67
nuclear fuel	Metallic Mineral Products	
Chemicals and chemical products		-10.56
Rubber and plastics products		-6.75
Other non-metallic mineral products		-4.79
Basic metals	Metal Products	-7.39
Fabricated metal products		-4.22
Machinery and equipment, nec	Electrical and Machinery	-5.01
Computer, electronic and optical		-5.14
equipment		
Electrical machinery and apparatus,		-4.11
nec		
Motor vehicles, trailers and semi-	Transport Equipment	-8.92
trailers		
Other transport equipment		-8.99
Manufacturing nec; recycling	Other Manufacturing, Recyling	-4.06
Other community, social and personal	Construction-Education	-8.35
services		

Notes: Adapted from Fontagné et al. (2022), Table 8. For Eora sectors that comprise multiple TiVA sectors, we assign the unweighted average estimate. Wood and Paper, for example, is assigned a trade elasticity of -8.505 (the average of -8.8 and -8.21). We assign an elasticity of -8.35 for all services sectors. Trade elasticities are defined as the change in trade in response to a change in trade costs.

Annex II. Modelling framework details

Full Model

Environment. There are *N* countries, denoted by *m* (exporter) and *n* (importer). There are *K* non-commodity sectors, denoted by *k*, and *J* commodity sectors, denoted by *j*.

Production. In each country, a representative retailer produces composite final good that is aggregated from *K* non-tradable non-commodity goods, solving:

$$\max P_n Q_n - \sum_k P_n^k \tilde{Q}_n^k \quad (A.1).$$

subject to

$$Q_n = \prod_k \left(\frac{\tilde{Q}_n^k}{\sigma_n^k}\right)^{\sigma_n^k} \quad (A.2)$$

where Q_n is total output of the composite final good, \tilde{Q}_n^k are non-commodity inputs, and $\sum_k \sigma_n^k = 1$.

In each non-commodity sector,

• a representative wholesaler combines varieties from different countries into composite, solving:

$$\max P_n^k Q_n^k - \sum_m p_m^k \tau_{mn}^k x_{mn}^k \quad (A.3),$$

subject to

$$Q_n^k = \left[\sum_m (\omega_{mn}^k)^{\frac{1}{1+\theta_k}} (x_{mn}^k)^{\frac{\theta_k}{1+\theta_k}}\right]^{\frac{1+\theta_k}{\theta_k}} \quad (A.4),$$

where x_{mn}^k are inputs from countries m, θ_k is the sector's trade elasticity, and $\sum_m \omega_{mn}^k = 1$. τ_{mn}^k are trade costs, which we describe in more detail below.

 a representative variety producer combines labor with intermediate inputs from the composite final good and a composite commodity good, solving

$$\max p_{n}^{k} q_{n}^{k} - P_{n}^{o} O_{n}^{k} - P_{n} M_{n}^{k} - w_{n} L_{n}^{k} \quad (A.5),$$

subject to

$$q_{n}^{k} = z_{n}^{k} \left[(\alpha_{n}^{k} \mu_{n}^{k})^{\frac{\eta-1}{\eta}} (O_{n}^{k})^{1-\eta} + (1 - \alpha_{n}^{k} \mu_{n}^{k})^{1/\eta} \left((M_{n}^{k})^{\frac{\alpha_{n}^{k}(1-\mu_{n}^{k})}{\alpha_{n}^{k}(1-\mu_{n}^{k})+1-\alpha_{n}^{k}} \cdot L^{k} \frac{1 - \alpha_{n}^{k}}{\alpha_{n}^{k}(1-\mu_{n}^{k})+1-\alpha_{n}^{k}} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$
(A.6),

where L_n^k , O_n^k , and M_n^k are labor, composite commodity goods, and intermediate inputs. z_n^k is a productivity term. η is the elasticity of substitution between composite commodities and other inputs.

In each country, the commodity retailer aggregates a composite from J commodities, solving

$$\max P_n^o Q_n^o - \sum_j P_n^j \tilde{Q}_n^j \quad (A.7),$$

subject to

$$Q_n^o = \prod_j \left(\frac{\tilde{Q}_n^j}{\sigma_n^j}\right)^{\sigma_n^j} \quad (A.8),$$

where Q_n^o is total output of the composite commodity good, \tilde{Q}_n^j are commodity inputs, and $\sum_j \sigma_n^j = 1$.

In each commodity sector,

 a representative commodity wholesaler combines varieties from different countries into a composite, solving

$$\max P_{n}^{j}Q_{n}^{j} - \sum_{m} p_{m}^{j}\tau_{mn}^{j}x_{mn}^{j} \quad (A.9),$$

$$Q_n^j = \left[\sum_m \left(\omega_{mn}^j\right)^{\frac{1}{1+\theta_j}} \left(x_{mn}^j\right)^{\frac{\theta_j}{1+\theta_j}}\right]^{\frac{1+\theta_j}{\theta_j}} \quad (A.10),$$

where x_{mn}^{j} are inputs from countries m, θ_{j} is the sector's trade elasticity, and $\sum_{m} \omega_{mn}^{j} = 1$.

 a representative commodity variety producer combines labor with intermediate inputs from the composite final good, solving

$$\max p_n^j q_n^j - P_n^o O_n^k - w_n L_n^j$$
 (A.11),

subject to

$$q_n^j = z_n^j \left(\frac{L_n^j}{1-\alpha_n^j}\right)^{1-\alpha_n^j} \left(\frac{M_n^j}{\alpha_n^j}\right)^{\alpha_n^j} \quad (A.\,12),$$

where L_n^j and M_n^j are labor and intermediate inputs. z_n^j is a productivity term.

Household. In each country there is a measure of L_n representative households that supply labor, consume the final good, and receive an exogenous deficit. The budget constraint reads

$$P_n C_n = w_n L_n + D_n \qquad (A.13),$$

where $\sum_{n} D_{n} = 0$.

Trade. Trade between countries is subject to iceberg trade costs where one unit of a tradable good in sector *k* shipped from country *m* to country *n* requires producing $\tau_{mn}^k \ge 1$ units in *m*, with $\tau_{nn}^k = 1$. The triangular inequality holds such that $\tau_{mn}^k \tau_{nh}^k \ge \tau_{mn}^k$ for all *n*, *m*, *h*.

Equilibrium. Given L_n , D_n , z_n^k , z_n^j , and τ_{mn}^k , τ_{mn}^j , an equilibrium is a set of wages w_n , prices P_n , P_n^o , P_n^k , P_n^j , p_n^k , p_n^j , and allocations Q_n , C_n , M_n^k , M_n^j , Q_n^k , \tilde{Q}_n^j , \tilde{Q}_n^j , L_n^k , L_n^j , q_n^k , q_n^j , O_n^k such that

$$\begin{split} Q_n &= C_n + \sum M_n^k + \sum M_n^j \quad (A.22), \\ Q_n^k &= \tilde{Q}_n^k \quad (A.23), \\ Q_n^j &= \tilde{Q}_n^j \quad (A.24), \\ L_n &= \sum L_n^k + \sum L_n^j \quad (A.25), \\ \sum p_n^k q_n^k + \sum p_n^j q_n^j + D_n &= w_n L_n + \sum (P_n M_n^k + P_n^o O_n^k) + \sum (P_n M_n^j) \end{split}$$

• in each country, the representative retailer solves the problem summarized by (A1)-(A2) such that

$$Q_{n}^{k} = \sigma_{n}^{k} \frac{\sum P_{n}^{k'} Q_{n}^{k'}}{P_{n}^{k}}$$
 (A. 14),

and

$$P_n = \prod_k (P_n^k)^{\sigma_n^k} \quad (A.\,15),$$

 in each country and each non-commodity sector, the representative wholesaler solves the problem summarized by (A.3)-(A.4) such that

$$\pi_{mn}^{k} \equiv \frac{p_{m}^{k} \tau_{mn}^{k} x_{mn}^{k}}{\sum_{m'} p_{m'}^{k} \tau_{m'n}^{k} x_{m'n}^{k}} = \frac{(\tau_{mn}^{k} p_{mn}^{k})^{-\theta_{k}}}{\sum_{m'} (\tau_{m'n}^{k} p_{m'n}^{k})^{-\theta_{k}}} \quad (A.16),$$

and

$$P_n^k = \left[\sum_m (\tau_{mn}^k p_m^k)^{-\theta_k}\right]^{-\frac{1}{\theta_k}} \quad (A.17),$$

 in each country and each non-commodity sector, the representative producer solves the problem summarized by (A.5)-(A.6) such that

$$L_{n}^{k} = \frac{(1 - \alpha_{n}^{k})p_{n}^{k}q_{n}^{k}}{w_{n}} \quad (A. 18),$$

$$P_{n}^{o}O_{n}^{k} = \alpha_{n}^{k}\mu_{n}^{k} \cdot \left(\frac{P_{n}^{o}}{p_{n}^{k}}\right)^{1-\eta}p_{n}^{k}q_{n}^{k} \quad (A. 19),$$

$$M_{n}^{k} = \frac{\alpha_{n}^{k}(1 - \mu_{n}^{k})p_{n}^{k}q_{n}^{k}}{P_{n}} \quad (A. 20),$$

and

$$p_n^k = (z_n^k)^{-1} \left[\alpha_n^k \mu_n^k (P_n^o)^{1-\eta} + (1 - \alpha_n^k \mu_n^k) \left((P_n)^{\frac{\alpha_n^k (1-\mu_n^k)}{\alpha_n^k (1-\mu_n^k)+1-\alpha_n^k}} \cdot w_n^{\frac{1-\alpha_n^k}{\alpha_n^k (1-\mu_n^k)+1-\alpha_n^k}} \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}$$
(A.21),

• in each country, the representative commodity retailer solves the problem summarized by (A7)-(A8) such that

$$Q_n^j = \sigma_n^j \frac{\sum P_n^{j'} Q_n^{j'}}{P_n^j}$$
 (A.22),

and

$$P_n^o = \prod_j \left(P_n^j \right)^{\sigma_n^j} \quad (A.\,23),$$

• in each country and each commodity sector, the representative wholesaler solves the problem summarized by (A.9)-(A.10) such that

$$\pi_{mn}^{j} \equiv \frac{p_{m}^{j} \tau_{mn}^{j} x_{mn}^{j}}{\sum_{m'} p_{m'}^{j} \tau_{m'n}^{j} x_{m'n}^{j}} = \frac{\left(\tau_{mn}^{j} p_{mn}^{j}\right)^{-\theta_{j}}}{\sum_{m'} \left(\tau_{m'n}^{j} p_{m'n}^{j}\right)^{-\theta_{k}}} \quad (A.16),$$

and

$$P_n^j = \left[\sum_m \left(\tau_{mn}^j p_m^j\right)^{-\theta_j}\right]^{-\frac{1}{\theta_j}} \quad (A.17),$$

• in each country and each commodity sector, the representative producer solves the problem summarized by (A.11)-(A.12) such that

$$L_{n}^{j} = \frac{(1 - \alpha_{n}^{j})p_{n}^{j}q_{n}^{j}}{w_{n}} \quad (A.18),$$
$$M_{n}^{j} = \frac{\alpha_{n}^{j}p_{n}^{j}q_{n}^{j}}{P_{n}} \quad (A.20),$$

and

$$p_n^j = (z_n^j)^{-1} P_n^{\alpha_n^j} w_n^{1-\alpha_n^j}$$
 (A.21),

markets clear in all countries and sectors:

$$Q_{n} = C_{n} + \sum M_{n}^{k} + \sum M_{n}^{j} \quad (A.22),$$

$$Q_{n}^{k} = \tilde{Q}_{n}^{k} \quad (A.23),$$

$$Q_{n}^{j} = \tilde{Q}_{n}^{j} \quad (A.24),$$

$$L_{n} = \sum L_{n}^{k} + \sum L_{n}^{j} \quad (A.25),$$

$$\sum p_{n}^{k} q_{n}^{k} + \sum p_{n}^{j} q_{n}^{j} + D_{n} = w_{n} L_{n} + \sum (P_{n} M_{n}^{k} + P_{n}^{o} O_{n}^{k}) + \sum (P_{n} M_{n}^{j} + P_{n}^{o} O_{n}^{j}) \quad (A.26).$$

Equilibrium using exact hat algebra.

A variable with a hat represents the relative change of the variable between the counterfactual and observed equilibrium. Given changes in trade costs $\hat{\tau}_{mn}^k, \hat{\tau}_{mn}^j$, changes in prices \hat{w}_n and prices $\{\{\hat{P}_n^j, \hat{P}_n^k\}_{n=1}^N$ solve:

•
$$\hat{p}_{n}^{k} = \left[\zeta_{n}^{k} (\hat{P}_{n}^{o})^{1-\eta} + (1-\zeta_{n}^{k}) \left((\hat{P}_{n})^{\frac{\alpha_{n}^{k}(1-\mu_{n}^{k})}{\alpha_{n}^{k}(1-\mu_{n}^{k})+1-\alpha_{n}^{k}}} \cdot \hat{w}_{n}^{\frac{1-\alpha_{n}^{k}}{\alpha_{n}^{k}(1-\mu_{n}^{k})+1-\alpha_{n}^{k}}} \right)^{1-\eta} \right]^{1-\eta}$$
 for all non-commodity sectors,

• where ζ_n^k is a non-commodity sector's initial expenditure share on commodities.

- $\hat{p}_n^j = \hat{w}_n^{1-\alpha_n^j} (\hat{P}_n)^{\alpha_n^j}$ for all commodity sectors,
- $\hat{P}_n^k = \left[\sum_m \pi_{mn}^k (\hat{\tau}_{mn}^k \hat{p}_m^k)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}$ for all non-commodity sectors,
- $\hat{P}_n^j = \left[\sum_m \pi_{mn}^j (\hat{\tau}_{mn}^j \hat{p}_m^j)^{-\theta_j}\right]^{-\frac{1}{\theta_j}}$ for all commodity sectors, $\hat{P}_n = \prod_k (\hat{P}_n^k)_k^{\sigma_n^k}$

•
$$\hat{P}_n^o = \prod_j (\hat{P}_n^j)^{\sigma_j^o}$$

- $\hat{\pi}_{mn}^{k} = \left[\frac{\hat{r}_{mn}^{k} \hat{p}_{m}^{k}}{\hat{p}_{n}^{k}}\right]^{-\theta_{k}}$ for all non-commodity sectors,
- $\hat{\pi}_{mn}^{j} = \left[\frac{\hat{r}_{mn}^{j}\cdot\hat{p}_{m}^{j}}{\hat{p}_{n}^{j}}\right]^{-\theta_{j}}$ for all commodity sectors, $\hat{E}_{n} = \frac{D_{n}}{E_{n}} + \frac{w_{n}L_{n}}{E_{n}}\hat{w}_{n}$ \circ where $E_{n} \equiv w_{n}L_{n} + D_{n}$ denotes total income

•
$$\hat{E}_n^M = \sum_k m_n^k \hat{Y}_n^k + \sum_j m_n^j \hat{Y}_n^j$$
o where:
•
$$E_n^M \equiv +\sum_k P_n M_n^k + \sum_k P_n M_n^j$$
•
$$m_n^k \equiv \frac{P_n M_n^k}{\sum_k P_n M_n^{kr}}, m_n^j \equiv \frac{P_n M_n^j}{\sum_k P_n M_n^{jr}}$$

• $\hat{Y}_{m}^{k} = \sum_{n} \frac{X_{mn}^{k}}{Y_{m}^{k}} \cdot \hat{\pi}_{mn}^{k} \cdot \left(\frac{E_{n}}{E_{n} + E_{n}^{M}} \cdot \hat{E}_{n} + \left(1 - \frac{E_{n}}{E_{n} + E_{n}^{M}}\right) \cdot \hat{E}_{n}^{M}\right)$ \circ Where Y_{m}^{K} denotes production

•
$$\hat{E}_n^o = \sum_k o_n^k \cdot \left(\frac{\hat{p}_n^o}{\hat{p}_n^k}\right)^{1-\eta} \hat{Y}_n^k$$

•
$$\hat{Y}_m^J = \sum_n \frac{X_{mn}}{Y_m^j} \cdot \hat{\pi}_{mn}^J \cdot \hat{E}_n^o$$

• $\sum_{k} Y_n^k \hat{Y}_n^k + \sum_{j} Y_n^j \hat{Y}_n^j + D_n = E_n \cdot \hat{E}_n + \sum_{j} (P_n M_n^k + P_n^o O_n^k) \hat{Y}_n^k + \sum_{j} P_n M_n^j \hat{Y}_n^j$



Fragmentation in Global Trade: Accounting for Commodities Working Paper No. WP/2023/075