EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Maria-Grazia Attinasi, Lukas Boeckelmann, Bernardo de Castro Martins, Baptiste Meunier, Alessandro Borin, Francesco Paolo Conteduca, Michele Mancini

Supply chain decoupling in green products: a granular input-output analysis

No 3152

Abstract:

This paper introduces a novel methodology to enhance the granularity of Inter-Country Input-Output (ICIO) tables. While our general methodology can be applied to any products of interest, we show that the well-documented distortions caused by sectoral aggregation in ICIO tables are particularly pronounced for products with a low substitutability, such as those essential to the green transition (e.g. electric batteries, rare earths). We therefore apply our framework to construct a disaggregated ICIO table that singles out 129 products essential to the energy transition. We then simulate a hypothetical scenario of an East-West supply chain decoupling in green products through a multi-country multi-sector model calibrated with our tailored disaggregated ICIO table. Results reveal substantial economic costs: welfare losses reach 3% and trade between blocs contracts by 20%, even when accounting for trade diversion through neutral countries. We finally quantify how the green supply chain decoupling increases the intensities of greenhouse gas emissions, highlighting how trade barriers on green sectors affect both economic efficiency and climate objectives.

Keywords: Global trade, sectoral granularity, global value chains, decoupling, green transition
JEL classification: C67, F13, F18, F51, Q48

Non-technical summary

This paper examines how trade barriers, when targeted specifically at products crucial for the green transition, can affect the global macroeconomy and greenhouse gas emissions. It investigates what happens when countries impose trade restrictions on environmental-friendly products – like electric vehicles and renewable-energy equipment, thereby affecting the global supply chains of green products. This focus is particularly topical given recent policies that targeted this type of goods such as the US Inflation Reduction Act (August 2022), US tariffs on electric vehicles and batteries (May 2024) or EU tariffs on Chinese electric cars (July 2024).

But analyses typically struggle to analyse the supply chains of green products because existing input-output tables – which describe the supply-use relationships of goods and services across countries and sectors – group green products together with non-green ones. For example, standard input-output tables bundle electric and thermal cars together in a single sector ("motor vehicles"), which masks the unique features of electric cars. This limitation is particularly central in multi-country multi-sector models (e.g., Baqaee and Farhi, 2024) that are calibrated on input-output tables – and for which the lack of granularity will not allow to simulate trade shocks targeted on green products or to emulate substitution between green and non-green goods.

To address this limitation, we develop a new methodology to build tailored input-output tables that isolate specific products – which we apply to green products. This method involves breaking down broad economic sectors in input-output tables into more granular sub-categories. In our application to green products, we separate 129 green products (e.g., electric vehicles, solar panels, gallium, palladium, lithium cells, and batteries) from other (non-green) goods. For that purpose, we use detailed bilateral trade data to obtain detailed trade shares between bilateral partners. This is complemented with the use of literature on supply chain linkages and industry reports to accurately reflect the supply-use between the granular sub-categories. In the end, we construct a tailored input-output table describing the global sectoral interlinkages across green products.

Using this enhanced input-output table, we study a hypothetical scenario where two major geopolitical blocs (East and West) cease trading green products with each other, while a neutral bloc remains unaffected by restrictions. Our findings indicate significant economic consequences from such trade fragmentation with global welfare declining by as much as 3%,

and international trade in green products dropping by up to 20% – despite some trade flows being diverted through neutral countries. The restrictions lead to higher prices for green products globally, with downstream goods, such as electric vehicles, facing particularly sharp increases. This undermines the adoption of green technologies, leading to higher greenhouse gas emissions in the global economy, with cumulative additional emissions over twenty years comparable to those of large countries such as Japan or Brazil.

The analysis emphasizes that sectoral aggregation in input-output tables matters particularly when the goods that are aggregated together cannot be easily substitutable. Specifically, when the elasticities of substitution are low, we show that the impacts of a trade shock on welfare and consumer prices are significantly amplified when sectoral granularity is higher. Such detailed input-output tables are particularly essential in the context of the green transition as many green products are difficult to replace or substitute – which amplifies the economic shock when their supply chains are disrupted.

In policy terms, this research underscores the importance for policymakers to consider the high economic costs associated with trade fragmentation targeting critical green technologies. More broadly, the paper proposes a generic method to proceed to granular analysis of supply chains as the method for disaggregating input-output tables can be seamlessly applied to different categorizations beyond green products (e.g., dual-use technologies, semi-conductors). In an era of increasing geopolitical risks, the paper enriches the possibilities to run model simulations and analyse targeted trade policies. This is key to support better-informed decision-making as we show that using standard ICIO to do so might lead to an under-estimation of their impact.

Introduction

Two phenomena increasingly contribute to reshaping the world economy. One is the growing and well-documented impact of climate change, and the paramount importance of climate transition policies. The other is stark rise of trade fragmentation, with trade policies increasingly shaped by geopolitical considerations leading to an increasing array of trade restrictions. Conceptually, trade fragmentation is a policy-driven reversal of global economic integration, guided by considerations such as national security, sovereignty, autonomy, or economic rivalry. While trade fragmentation affects all trade flows, there has been an increasing number of restrictions imposed on green products such as the 2022 US Inflation Reduction Act or the EU tariffs on Chinese electric vehicles in 2024.

However, little is known on the potential impact of trade fragmentation on green products. A key challenge is that the data typically used to examine the effects of trade fragmentation scenarios – namely, Inter-Country Input-Output (ICIO) tables – are too aggregated to isolate specific green products such as electric vehicles or renewable-energy equipment. For example, the widely used TiVA ICIO tables from the OECD features 45 sectors, but “electric vehicles” are aggregated within the “motor vehicles” sector which also includes “thermal vehicles” – which electric vehicles are set to replace. This low granularity of ICIO tables across sectors makes it impossible to single out green products and does not allow to 1) calibrate a trade shock targeting only green products, 2) model substitution effects between green and non-green products, and 3) isolate the impacts of trade fragmentation on specific green sectors.

Against this background, we present a general methodology to build tailored ICIO tables that can isolate specific products, and apply it to green products. Starting from an standard ICIO table, our method expands sectoral granularity by dis-aggregating sectors into green and non-green sub-sectors. For example, the sector “motor vehicles” in a standard ICIO table is split into “electric vehicles” and “non-electric vehicles”. This dis-aggregation is performed by relying on bilateral product-level trade data and information on users of green products, hence ensuring that bilateral country linkages are accurately represented and that the supply of green products is properly allocated to the sectors (or final users) who purchase them. Using this framework, we construct a tailored ICIO table which isolate 129 green products (e.g., vehicles with both compression-ignition combustion engine and electric motor for propulsion, solar panels, gallium, palladium, lithium cells and batteries) which we group into eight homogeneous green sectors (mined rare earth, processed rare earth, chemicals for the green transition, electric batteries, renewable-energy mechanical equipment, renewable-energy electrical equipment, electric vehicles, green electricity). The resulting tailored ICIO table can be used to study the global value chains of green products.

Using our tailored disaggregated ICIO table, we quantify the impact of a hypothetical scenario where two antagonist geopolitical blocs (East and West) massively raise trade barriers on green products *vis-à-vis* each other – while a neutral bloc remains unaffected. However, one additional challenge when studying the green transition is that ICIO tables do not account for *future* transformations caused by the on-going green transition. We account for this by estimating how changes in final demand for green products will affect the outputs of green and non-green sectors by 2030 (using the Leontief inverse matrix which links output and final demand). For this, we use assumptions from the International Energy Agency on the market sizes of green sectors by 2030. In the end, we obtain an ICIO table representing a hypothetical global economy by 2030. We use this tailored disaggregated ICIO table by 2030 to calibrate the Baqaee and Farhi (2024) multi-country multi-sector model and simulate the trade fragmentation scenario on green products . Our results point to welfare losses up to 3% in the antagonist blocs and a significant (up to 20%) reduction in trade flows between geopolitical blocs. Prices of green products also increase, by up to 3% globally, with sharper price hikes for downstream products like electric vehicles. The higher prices of green products would undermine their adoption, meaning a less energy-efficient global economy. We find that our scenario of trade fragmentation on green products would lead to higher greenhouse gas emissions, with cumulative additional emissions over twenty years comparable to total emissions of large countries such as Japan or Brazil.

This paper is, to the best of our knowledge, the first to simulate the effects of a trade war across green products. In that sense, it relates to the fast-expanding literature that quantifies the macroeconomic effects of trade fragmentation (see also among others Bonadio et al., 2021; Eppinger et al., 2021; Goes and Bekker, 2022; Quintana, 2022; Attinasi et al. (2023a; 2023b), Campos et al., 2023; Javorcik et al., 2024; Attinasi, Mancini et al., 2024; Quintana, 2024; Attinasi et al., 2025a). Our study extends this literature by exploring restrictions along green products. This paper notably complements Weber et al. (2025) who studied the interplay between trade fragmentation and climate change, but without relying on model-based estimates.

We also contribute to the literature that shows that the level of aggregation in ICIO tables can affect the results of ICIO-based analysis. This issue has been identified since the 1950s (e.g., Hatanaka, 1952) and regularly poses problems to economists studying the supply chains of specific products (e.g., Michel et al., 2018; Prataviera et al., 2024). The literature generally argues that a higher granularity improves the accuracy of ICIO-based analysis (Lenzen, 2011; Steen-Olsen et al., 2013). Complementing the literature, we provide a general method – that can be applied seamlessly to any set of products – to enhance the sectoral granularity of ICIO tables, thereby offering a remedy to the distortions posed by aggregation in ICIO tables.

We further contribute to this literature by identifying *when* ICIO aggregation matters the most – specifically when the substitutability between varieties of products is low (i.e. when trade elasticities are low). This is precisely the case for many green products, where substitutability is low due to concentration of supply and limited alternative sources (Massari and Ruberti, 2013; Kowalski and Legendre, 2023). In that respect, the application of our methodology to green sectors makes the contribution particularly on point. More specifically, we study the impact of ICIO aggregation by running stylised autarky scenarios using the Baqaee and Farhi (2024) model calibrated on ICIO tables with different levels of aggregation. When elasticities of substitution are low, we find that doubling the granularity of the ICIO table doubles the impact in terms of welfare losses (9% welfare losses in a standard ICIO, 20% losses in an ICIO with twice as many sectors). Similarly, tripling the granularity also triples the effect. Importantly, the degree of ICIO aggregation matters only when the substitutability is low: this is because sub-sectors aggregated in a standard ICIO would be assumed to be perfect substitutes. Dis-aggregating these sub-sectors and assuming a low substitutability creates frictions that translates into welfare losses.

Our paper is relevant from a policy perspective as it enriches the possibilities to run simulations of targeted trade policies. It shows that the approach of using standard ICIO to simulate such targeted trade restrictions – as in, e.g., Bachmann et al. (2022) and Attinasi et al. (2023b) – might lead to under-estimating their impact. This is key as more and trade policies are weaponizing critical inputs that are notoriously hard to substitute (e.g., natural gas, advanced semi-conductors, rare earth minerals). Our framework offers a way to simulate and assess the impacts of such policies.

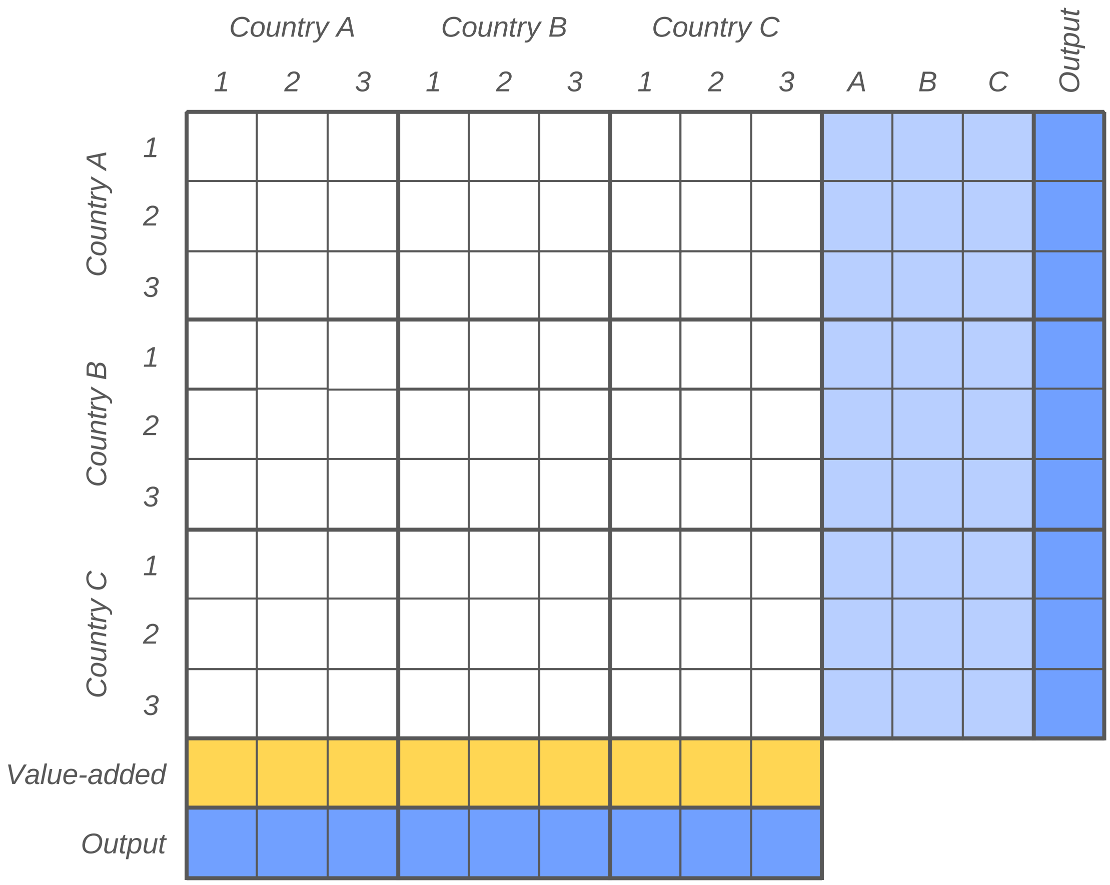
The rest of the paper is organized as follows: **section 1** reviews the literature on ICIO aggregation, **section 2** runs a stylized exercise on the importance of ICIO granularity for model simulations, **section 3** details our approach to enhance the granularity of ICIO; finally, **section 4** applies our methodology to trade barriers along green products.

1. Literature review on ICIO aggregation

ICIO tables describe the supply (sales) and use (purchases) relations between producers and consumers, both within and between countries. **Figure 1** gives a simplified example with three countries (A to C) and three producing sectors (1 to 3). White cells are flows of intermediate inputs (goods and services) from producers (1 to 3) in any country (A to C) to other producers (1 to 3) of the same or other countries. Sub-matrices on the diagonal represent *domestic* linkages (e.g., the upper left 3x3 matrix are supply-use relationships within country A) while non-diagonal matrices are *cross-country* linkages. Light blue cells are flows of final products from producers (1 to 3) to consumers (in countries A to C). Proceeding by rows, summing the sales of intermediate inputs (in white cells) and of final goods and services (in light blue cells) amounts to the gross output of a given country-sector, shown in dark blue in the rightmost column. Yellow cells represent value added (gross output minus intermediate inputs). As was the case for rows, summing over columns provides the gross output of country-sector pairs (in dark blue).

ICIO tables are central to various types of economic analysis. A first use is to calibrate multi-country multi-sector models and study the propagation of shocks through global value chains (de Backer and Miroudot, 2014; de Vries et al., 2019; Giammetti, 2020; Bonadio et al., 2021; Baqaee and Farhi, 2024). ICIO can also help tracing the flows of goods and services between industries and countries, identifying position and comparative advantages in global value chains (Borin and Mancinin, 2019; Borin et al., 2025). Third, ICIO are at the core of network analysis to identify industries or countries acting as central hubs (Blöchl et al., 2011; Acemoglu et al., 2012; Carvalho, 2014; Pasten et al., 2020). Our paper contributes by proposing a novel method to expand the granularity of ICIO tables, allowing above analysis to be run on tailored ICIO tables.

Figure 1. Example ICIO table



Source: authors.

The issue of aggregation in ICIO tables is a long-standing topic in the literature, which generally argues that greater granularity improves the quality of ICIO-based analysis. Aggregating data entails information losses which can lead to misleading linkages in ICIO tables, especially if heterogenous sectors are bundled together. This can lead to "aggregation bias", a term coined by Morimoto (1970) to describe differences between the outputs estimated on aggregated data and those obtained on dis-aggregated data. Various papers (Hatanaka, 1952; McManus, 1956; Theil, 1957; Fisher, 1958; and Ara, 1959) studied the necessary conditions to maintain accurate relationships after aggregating sectors, concluding in general that sectors bundled together must have a similar structure of inputs and outputs. This literature from the 1950s was later picked up by Kymn (1990), Cabrer et al. (1991), and Oksanen and Williams (1992) who show that sectoral aggregation in ICIO can induce significant differences in the outputs of the models calibrated on these ICIOs. In addition, aggregated ICIO tables can lead to misinformed decision-making, as aggregation can lead to misallocations of inventories (Bunsen and Finkbeiner, 2022). The literature generally argues that a higher granularity improves the accuracy of ICIO-based analysis (Steen-Olsen et al., 2013). This is notably important for sectoral aggregation, as the position of a sector in the value chain (upstream or downstream) affects output volatility (Koning et al., 2014; Olabisi, 2019).[1] This is supported by Flaaen et al. (2024) finding a negative bias associated with aggregation in measuring GVC activity, suggesting that higher granularity provides a better understanding of how firms adjust to shocks. Importantly, the accuracy of ICIO-based analysis is improved significantly by more granular ICIOs, even if the granularity is achieved *via* an approximation (Lenzen, 2011). We contribute to this literature in two ways: first by evaluating the impact of aggregation on model-based results, second by providing a method to dis-aggregate ICIO up to the level needed by the researcher.

Recent studies have developed techniques to enhance the granularity of ICIO tables. Borin et al. (2023) pioneered this line of work by disaggregating sectors in a standard ICIO into sub-sectors affected by Western sanctions against Russia. Their method – subsequently adopted in Conteduca et al. (2025) and Attinasi et al. (2025b) – is close to ours as they also rely on product-level bilateral trade data. However, a key limitation is their assumption that sub-sectors use inputs with the same intensity. For example, their framework would assume that electric vehicles and thermal cars (two sub-sectors of the “motor vehicles” sector in the standard ICIO) would use the same proportion of electric batteries as inputs. In contrast, our methodology accounts for heterogeneous input use, better capturing the sector-specific nature of supply chains – for instance, our framework would allow electric batteries to be used more intensively for electric vehicles than in thermal cars. This refinement yields a more accurate propagation of shocks through production networks. Another related paper is Bolhuis et al. (2023) who developed a detailed ICIO covering 136 agricultural and mining commodities. While their method is valuable for these specific sectors, our method offers broader applicability as it can be applied to any set of commodities and manufactured goods.

Beyond its methodological innovation, our paper also provides critical insights into when and how the aggregation of ICIO tables can impact model simulations of trade shocks. Using a multi-country multi-sector model, we specifically investigate which model parameters magnify the divergence between outcomes derived from aggregated *versus* disaggregated ICIO tables. This analysis highlights the conditions under which disaggregation is essential for accurate economic modelling, showing that the specific characteristics of green products – such as

1 Similarly, the level of aggregation also matters for countries / regions: see notably Blair and Miller (1983; 2009) stating that the aggregation of regions leads to some bias.

concentrated supply and limited alternative sources, which imply low trade elasticities – make results particularly sensitive to aggregation. This underscores the relevance of our contribution for analyses focused on these products.

2. The impact of ICIO aggregation on model-based results

2.1 The Baqaee and Farhi (2024) model

We rely on the Baqaee and Farhi (2024) multi-country multi-sector model to quantify economic effects from supply-chain decoupling. The model captures rich sectoral interlinkages through production networks and heterogeneities across countries, for example with respect to their endowments with factors of production.

By featuring sectoral interlinkages, the model accounts for *amplification effects* of trade shocks through production networks as well as *substitution effects* via international trade. The model response to a trade shock considers the endogenous reactions by a large variety of producers and consumers in an interconnected world economy. The transmission operates primarily through the price channel as higher barriers to trade create an import price shock. As a result, producers substitute away from more expensive foreign inputs, generating a demand shock for their upstream suppliers. The net effect of the substitution decisions by producers on the demand of each supplier may be either positive or negative depending on the latter's exposure to the shock. This also re-allocates production across countries, affecting trade along the way. It also affects demand for factors of production (capital and labour) leading to adjustments in production structures within countries. As the prices of capital and labour adjust, disposable incomes of households and their consumption patterns also change. Since consumption preferences differ by countries (e.g., type of products, provenance), demand for final products is also affected, which propagates upstream to producers. Besides these re-allocation effects, consumers also substitute across products given changes in prices for final goods. These substitution and re-allocation channels generate general equilibrium effects on prices, demand, and supply, which in turn affects trade, production, and welfare.[2]

We calibrate the Baqaee-Farhi model using the OECD ICIO TiVA table for 2018, comprising 67 countries and 45 sectors detailed in **Tables A1 and A2** in **Appendix A.** As the Baqaee-

[2] See Baqaee and Farhi (2024) for a detailed discussion of the model.

Farhi model features intensities in four primary factors (capital, low-, medium-, and high-skilled labour) that are not available in the OECD ICIO TiVA tables, we take shares from WIOD socio-economic accounts.[3] We set substitution elasticities to standard values in the literature, as detailed in **Table 1**.

Table 1. Elasticities of substitution

Across VA and inputs	0.5
Across consumption goods	0.9
Across primary factors	1.0
Across intermediate inputs	0.2
Trade elasticities	Fontagné et al. (2022)

2.2 Aggregate effects

We first investigate the consequence of calibrating multi-country multi-sector models with more granular input output matrices. We compare global welfare and consumer price effects from a trade cost shock under three different model calibrations. For the first scenario, the model is calibrated on the standard ICIO table. In the second, we split each row and column of the standard ICIO matrix into two sub-components, each accounting for 50% of the amount of the original aggregate row or column. In the third and final calibration, we split each row and column of the standard ICIO matrix into three sub-components, each accounting for 33% of the amount of the original aggregate row or column. For illustrative purposes, we apply a very large trade cost shock: a 150% increase in iceberg trade costs on each country border so that that all countries move towards autarky.[4]

We find that increasing granularity in ICIO matrices hugely increases global welfare and consumer price effects from trade cost shocks. Global welfare losses amount to -8.5% in a calibration with a standard ICIO matrix (**Figure 2**, panel a). In a calibration where we split each sector of the standard ICIO into two sub-sectors of equal size, global welfare losses would more than double and reach -19.8%. Finally, global welfare losses even increase to -43.6% in

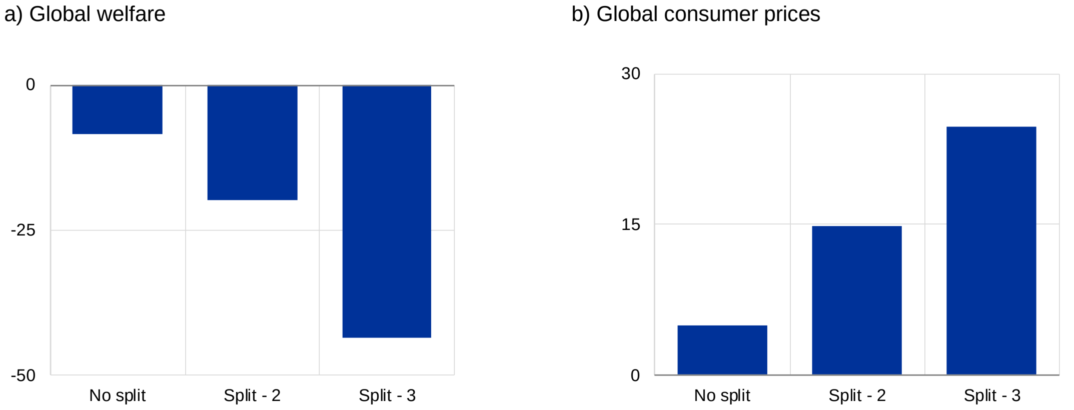
3 More specifically, for countries that are both in WIOD and OECD TiVA, we assume that the same shares apply. For countries that are not in the WIOD but in OECD TiVA, we apply the average intensities per sector based on WIOD. Such approximations are somewhat backed by the literature showing that changes in capital and labour are generally slow and structural (Saenz, 2022).

4 This exercise is similar to Bolhuis et al. (2023). While Bolhuis et al. (2023) compare global welfare effects from moving to autarky assuming traditional ICIO matrices and ICIO matrices that account for granularity in commodities, our investigation is more general as it compares welfare and price effects from trade cost shocks in scenarios with twice or three times as many sectors as in traditional ICIO matrices.

a calibration where we split each sector of the standard ICIO into three sub-sectors of equal size. In turn, increasing granularity in ICIO matrices also hugely increases global consumer price effects from trade cost shocks. We find that consumer price effects from moving to autarky would more than triple (from +4.9% to +14.9%) in a calibration where we split each sector into two sub-sectors; and fivefold (from +4.9% to +24.8%) in a calibration where we split each economic sector into three sub-sectors (**Figure 2**, panel b).

Figure 2. Global welfare (GNE) and price effects from moving to autarky

(% deviation from steady state)



Sources: Baqaee and Farhi (2024), OECD TiVA, authors' calculations.
Note: Non-linear impact simulated through 25 iterations of the log-linearized model.

Milder welfare losses and consumer price increases observed in calibrations using standard ICIO tables with aggregated sectors reflect the implicit assumption that consumers and producers can perfectly substitute between goods within the same (aggregated) sector. In contrast, calibrations employing more granular ICIO tables relax this restrictive assumption by explicitly allowing for imperfect substitutability between goods across narrower sub-sectors. When each sector is split into multiple sub-sectors, each sub-sector individually faces the same trade cost shocks previously applied to the aggregate sector as a whole. However, imperfect substitutability across these sub-sectors – consistent with empirical estimates of intermediate and final substitution elasticities – results in additional economic costs, as trade disruptions are magnified due to reduced substitution flexibility and increased frictions among narrower, more specialized sub-sectors. Consequently, calibrations based on more granular ICIO matrices yield significantly larger estimates of global welfare losses and consumer price effects from trade disruptions, highlighting the quantitative importance of sectoral disaggregation.

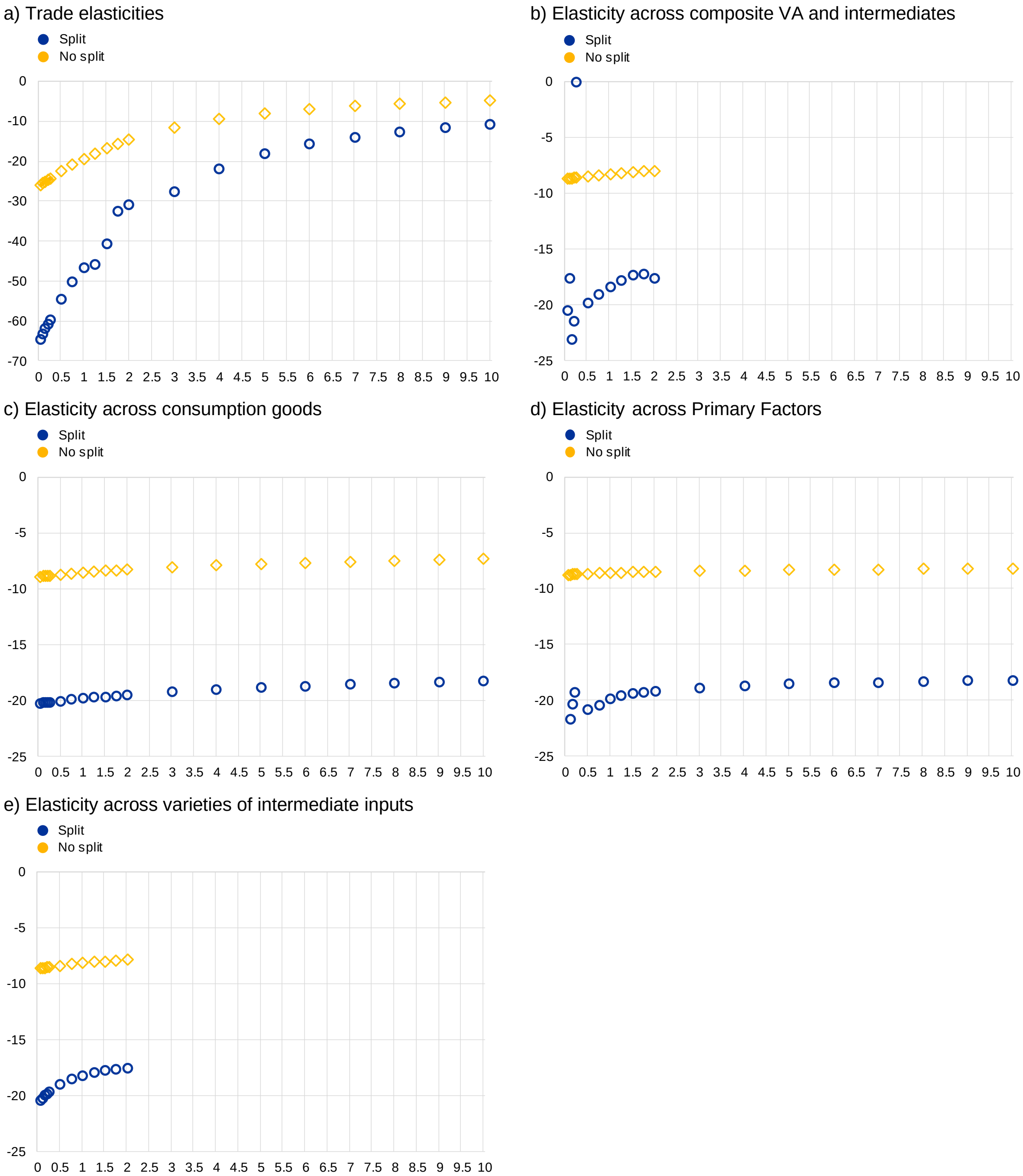
2.3 When is this important

Building on the findings of the previous section – that amid imperfect substitutability, the effects of trade shocks are amplified when multi-country multi-sector models are calibrated on more granular ICIO matrices – this section explores when the divergence between results based on aggregated versus disaggregated tables becomes particularly pronounced. Our analysis shows that granularity in ICIO matrices is especially critical when the substitutability between imported products (i.e., the trade elasticity) is low, and thus goods across sub-sectors are far from perfect substitutes. **Figure 3** plots global welfare losses from an autarky shock for different calibrations of elasticities, and for a calibration on a standard ICIO (*No split*) and a granular ICIO (*Split*) where each row and column of the standard ICIO is split into two sub-components of equal size. Each panel varies one elasticity at a time, while keeping the other elasticities at their baseline value (see **Table 1**).

Figure 3 (panel a) plots global welfare losses from an autarky shock for different trade elasticities (assumed to be homogenous across sectors). It clearly shows that at relatively high trade elasticities (7 or larger) global welfare losses in the *Split* and *No split* ICIO tables converge. Intuitively, when the trade elasticity is very high, approaching infinity, goods across sub-sectors become perfect substitutes, eliminating the additional economic costs associated with sectoral disaggregation. However, the divergence in welfare losses between the *Split* and *No split* calibrations increases substantially for trade elasticities below 2, that is when sub-sectors have lower substitutability. Other elasticities (**Figure 3**, panels b to e) appear to play a minor role. For smaller values of the substitution elasticity across composite value added and intermediates (panel b), and across primary factors (panel d) the wedge in global welfare losses also increases, albeit by a lower magnitude (while for values of the elasticity below 0.5, model results become instable). Similarly, the wedge in global welfare losses increases with smaller values for the elasticity across varieties of intermediate inputs (panel e), yet the change in the wedge remains small. Finally, different values for the elasticity across consumption goods (panel c) does not appear to affect the wedge in global welfare losses.

Figure 3. Global welfare losses from autarky under alternative elasticities

(% deviation from steady state)



Sources: Baqaee and Farhi (2024), OECD TiVA, authors' calculations.
Notes: Values for the elasticity across varieties of intermediate inputs and across composite VA and intermediates larger than 2, in combination with the baseline values for all other variables, did resulted in inconsistent welfare estimates and are hence not shown on the graphs.

This suggests that the aggregation of ICIO tables in general equilibrium models matter for the estimation of macroeconomic outcomes from trade shocks, as long as a researcher assumes non-zero real rigidities. Aggregation implicitly assumes perfect substitutability among products grouped within the same sector. Hence, the economic relevance of disaggregation is greatest at low trade elasticities – precisely when substitutability across imported products is limited. This is relevant for two reasons. First, recent research (Boehm et al. 2023) have shown trade elasticities to be substantially lower than previously thought, even with a long run horizon. Second, recent examples of supply disruptions (advanced semi-conductors, natural gas and oil following Western sanctions on Russia) have highlighted the importance of accounting for the criticality of trade flows in specific goods that may make up only a small share of aggregate output, but which can have disproportionate macroeconomic effects when their supply is disrupted.

3. A methodology to dis-aggregate ICIO tables

3.1 General framework

A generic Inter-Country Input-Output (ICIO) table with G countries and N sectors is represented in **Figure 4** where Z_{ij} is a $N \times N$ matrix of intermediate inputs produced in country i and used in country j; Y_{ij} is a $N \times 1$ vector of final goods and services produced in country i and absorbed in country j. X_i is the $N \times 1$ vector of gross output produced in country i. VA_i is a $1 \times N$ vector of value added generated by producers in country i. The ICIO table entails two accounting relationships that the sum of rows and columns equals the gross output X_i. Row-wise, it means that gross output is the sum what is supplied as intermediate inputs to other producers (matrix Z) and what is supplied as final products to consumers (matrix Y). Column-wise, it means that gross output is the sum of what is used as intermediate inputs from other producers (matrix Z) and the value-added (vector VA).

Figure 4. Standard ICIO table

		Output				Final Demand				Total Output
		1	2	$\cdots$	G	1	2	$\cdots$	G	
Inputs	1	$\mathbf{Z}_{11}$	$\mathbf{Z}_{12}$	$\cdots$	$\mathbf{Z}_{1G}$	$\mathbf{Y}_{11}$	$\mathbf{Y}_{12}$	$\cdots$	$\mathbf{Y}_{1G}$	$\mathbf{X}_1$
	2	$\mathbf{Z}_{21}$		$\cdots$	$\mathbf{Z}_{2G}$	$\mathbf{Y}_{21}$		$\cdots$	$\mathbf{Y}_{2G}$	$\mathbf{X}_2$
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	G	$\mathbf{Z}_{G1}$	$\mathbf{Z}_{G2}$	$\cdots$	$\mathbf{Z}_{GG}$	$\mathbf{Y}_{G1}$	$\mathbf{Y}_{G2}$	$\cdots$	$\mathbf{Y}_{GG}$	$\mathbf{X}_G$
Value Added		$\mathbf{VA}_1$	$\mathbf{VA}_2$	$\cdots$	$\mathbf{VA}_G$					
Total Output		$(\mathbf{X}_1)'$	$(\mathbf{X}_2)'$	$\cdots$	$(\mathbf{X}_G)'$					

Source: authors.

Standard ICIO tables are provided at a relatively high level of aggregation in terms of sectors, generally at 2-digit level, making it challenging to model policies targeted on selected products. For example, in the OECD TiVA ICIO table, “electric vehicles” and “thermal vehicles” are bundled together in the “motor vehicles” sector. This aggregation makes it challenging to model the effects of trade policies that target selected products instead of whole 2-digit sectors. This has been the case for most recent measures such as China-US in 2018, US export bans on semiconductors over 2020-2022, Western sanctions on Russia in 2022-2023, domestic content requirements of the Inflation Reduction Act in 2022, or the new Section 301 tariffs of 2024. Hence, standard ICIO tables do not allow for 1) simulating targeted trade policies on selected products, 2) modelling substitution effects at product-level, and 3) computing the impacts (output, prices) on selected sub-sectors.

To overcome these limitations, we propose a new data-driven methodology to disaggregate ICIO tables to isolate the relevant niche products. The idea consists in splitting the N sectors of the original ICIO into two sub-sectors: one with products subject to the targeted trade policy (*targeted* sub-sector), and one those unaffected (*non-targeted*). This dis-aggregation is run on all G countries of the original ICIO, meaning that we disaggregate $G \times N$ country-sectors. As country-sectors are both in the rows (supply side) and the columns (use side) of the ICIO, we need to disaggregate both: we proceed sequentially by first disaggregating rows (**section 3.2**) before columns (**section 3.3**).

3.2 Dis-aggregating rows (supply side of ICIO)

The disaggregation relies on splitting each row (representing one country-sector) into *targeted* and *non-targeted* rows. To do so, we build matrices Γ^Z and Γ^Y containing the share of *targeted* products in the matrices of, respectively, intermediate inputs (Z) and final products (Y). The matrix Γ^Z is of size $GN \times GN$ (the same size as the matrix Z of intermediate inputs) and its elements $\gamma_{i,j}$ indicates the share of *targeted* products in the amount of intermediate inputs sold by the country-sector corresponding to row i towards the country-sector corresponding to row j.[5] Multiplying element-by-element matrices Γ^Z and Z as in equation (1) provides the ICIO matrix Z^Γ whose elements are the amount of *targeted* products supplied and used between producers.[6] The ICIO matrix for *non-targeted* products Z^Δ is the difference between the original matrix of intermediate inputs (Z) and the matrix of *targeted* products (Z^Γ) as in equation (2).[7] We apply the same methodology for the matrix of final products (Y) with a matrix Γ^Y (of size $GN \times N$ as matrix Y).

(1) $$Z^\Gamma = \Gamma^Z \odot Z$$

(2) $$Z^\Delta = Z - Z^\Gamma$$

The disaggregation then relies on building matrix Γ^Z (and Γ^Y for final demand). More specifically, we need to estimate its elements $\gamma_{i,j}$. For clarity, we start by re-writing them with the country-sector they relate to as in equation (3) where row i relates to sector s in country c, and column j to sector t in country d.

(3) $$\gamma_{i,j} = \gamma_{\{c,s\},\{d,t\}}$$

We first use bilateral product-level trade data (BACI; Gaulier and Zigagno, 2010) to derive the share of *targeted* products in trade flows. Based on such data, we compute coefficients $\delta_{\{s,c\},d}$ which are the share of targeted products in the trade flows of country-sector $\{c, s\}$ to country d

5 The element $\gamma_{i,j}$ can be interpreted as: out of 100 products sold by country-sector i to country-sector j, how many are *targeted* products.

6 Each element $Z^\Gamma_{i,j}$ of matrix Z^Γ is the amount of *targeted* products supplied the country-sector corresponding to row i towards the country-sector corresponding to row j. The element-by-element multiplication means that $Z^\Gamma_{i,j} = \gamma_{i,j} \times Z_{i,j}$.

7 By construction, the sum of the amounts of non-targeted and targeted products must equal the amount of total products from the original ICIO matrix.

as in equation (4).[8] For example, if country-sector $\{c, s\}$ is the "motor vehicles" sector (s) in China (c) are country d is the USA, then $\delta_{\{s,c\},d}$ is the sales of Chinese electric vehicles to the US (assuming, as in **section 3.1**, that the products targeted are the "electric vehicles") divided by the total sales of Chinese motor vehicles to the USA. By working with bilateral product-level trade data, we also ensure that coefficients $\delta_{\{s,c\},d}$ will account for the specificities of the relationships across the supplying country-sector (c, s) and the using country (d).[9]

$$\delta_{\{c,s\},d} = \frac{TD_{targeted}^{\{c,s\} \to d}}{TD_{total}^{\{c,s\} \to d}} \quad (4)$$

- $TD_{targeted}^{\{c,s\} \to d}$ = flows of *targeted* products from country-sector $\{c, s\}$ to country d
- $TD_{total}^{\{c,s\} \to d}$ = total flows (*targeted* and *non-targeted* products)

The interest of using bilateral product-level trade data is to provide a necessary condition on the elements of Γ^Z as flows of *targeted* products should be consistent between the ICIO tables and the bilateral product-level trade data. This means that the proportion of *targeted* products in trade flows between a (supplying) country-sector $\{c, s\}$ and a (using) country d in trade data should be the same in the ICIO tables.[10] Formally, this translates into equation (5): the ratio computed with trade data (TD) must be the same when computed with the ICIO (Z). This equation sets conditions on the elements $\gamma_{\{c,s\},\{d,t\}}$ of matrix Γ^Z as in equation (6) which is obtained by re-writing equation (5):

- The left-hand term of equation (5) is $\delta_{\{c,s\},d}$ (see equation 4).
- $Z_{total}^{\{c,s\} \to d}$ is the amount of all products (*targeted* and *non-targeted*) sold by sector-country $\{s, c\}$ to country d. It can be obtained by summing over $Z_{\{c,s\},\{d,u\}}$ which are the amounts of products sold to each individual sector u.

8 Domestic linkages ($c = d$) are not available through trade data. Following Borin et al. (2023), we assume that domestic relations are the weighted average of exporting relations. This means the domestic coefficient $\delta_{\{c,s\},c}$ of country c is the trade-weighted average of coefficients $\delta_{\{c,s\},e}$ across foreign partners e.

9 As such bilateral product-level trade data is generally not available for services, our methodology works rather if targeted products are manufactured goods. This is the case in most of the recent trade-restrictive policies.

10 We target the same *proportion* rather than the same *amount* because there could be discrepancies in the values of trade flows in ICIO and trade data, due to different data sources or ways to clean the data.

- $Z_{targeted}^{\{c,s\}\to d}$ is the amount of *targeted* products sold by sector-country $\{s,c\}$ to country d: it is also obtained by summing over individual sectors u in country d, with the multiplication by $\gamma_{\{c,s\},\{d,u\}}$ to isolate *targeted* products.

(5)
$$\frac{TD_{targeted}^{\{c,s\}\to d}}{TD_{total}^{\{c,s\}\to d}} = \frac{Z_{targeted}^{\{c,s\}\to d}}{Z_{total}^{\{c,s\}\to d}}$$

(6)
$$\delta_{\{c,s\},d} = \frac{\sum_{u=1}^{N} \gamma_{\{c,s\},\{d,u\}} \cdot Z_{\{c,s\},\{d,u\}}}{\sum_{u=1}^{N} Z_{\{c,s\},\{d,u\}}}$$

However, estimating elements $\gamma_{\{c,s\},\{d,t\}}$ of matrix Γ^Z requires information on the using sector (t), which the bilateral product-level trade data cannot provide.[11] Bilateral product-level trade data tell the amount of any product that enters country d, but not which sectors inside country d are using it.[12] To that end, we use the economic literature (Barry et. Al, 2015; Fally and Sayre, 2018) and industry reports to get details on the sectors that use the targeted products. For example, Fally and Sayre (2018) inform that “chromium and articles thereof” (HS code 811299) are used for 62% in the sector “other non-metallic mineral products”, for 28% in “chemicals and chemical products”, for 5% in “fabricated metal products”, for 4% in “machinery and equipment, N.E.C.”, and for 1% in “motor vehicles”.[13] Formally, this means we make assumptions $\alpha_{\{s,c\},\{t,d\}}$ on the proportion of *targeted* products from country-sector $\{c,s\}$ that are used in country-sector $\{d,t\}$. Based on the example above, this means we would set $\alpha_{\{c,s\},\{d,t\}} = 0.62$ if s is the sector that produces “chromium and articles thereof” and t is the “other non-metallic mineral products” sector.[14]

11 For instance, note the absence of subscript t in equation (4).

12 A simplifying hypothesis used in Borin et al. (2023), Attinasi et al. (2025b), and Conteduca et al. (2025) is that the share of *targeted* products is the same across sectors t in country d, meaning $\gamma_{\{s,c\},\{t,d\}} = \delta_{\{s,c\},d}$ for any sector t. This allows to infer matrix Γ^Z based only on bilateral product-level trade data. But this assumption might be too naïve for highly specific products, such as green products explored in **section 4**. For example, in the case of “rare Earth”, one can suppose that they represent a portion goes to the “electronics” sector – where they are primarily employed – than in other using sectors.

13 We generally seek assumptions on the sectoral users for each product at 6-digit level.

14 This example also shows that assumptions on users of targeted products are independent of producing and using countries (c and d). This is due to the literature and industry reports not providing details by countries. Nevertheless, we end up with country-specific assumptions because the targeted sub-sector is generally composed of various HS6 products. In this case, we weight the product-level assumptions by the share of each product in trade flows between the two countries – hence computing user assumptions that are country-specific and account for the specific products that are traded between the two countries.

Such assumptions on users impose further conditions on the elements of Γ^Z which account for the using sectors (t). The definition of $\alpha_{\{c,s\},\{d,t\}}$ means that equation (7) below is verified, where the numerator of the right-hand term ($\gamma_{\{s,c\},\{t,d\}} \cdot Z_{\{s,c\},\{t,d\}}$) is the amount of *targeted* products sold by sector-country $\{s, c\}$ to sector-country $\{t, d\}$ and the denominator is the total amount of targeted products sold by sector-country $\{s, c\}$ to country d. It should be noted that setting an assumption on users in $\alpha_{\{s,c\},\{t,d\}}$ is equivalent to imposing an assumption on the corresponding element of matrix Γ^Z. Using equation (6), we can re-write equation (7) in the form of equation (8) where the element $\gamma_{\{c,s\},\{d,t\}}$ is fully identified since:

- $\alpha_{\{c,s\},\{d,t\}}$ is known, based on the literature.
- $Z_{\{c,s\},\{d,u\}}$ are known from the matrix Z in the original ICIO.
- $\delta_{\{c,s\},d}$ is obtained from bilateral product-level trade data.

$$\alpha_{\{c,s\},\{d,t\}} = \frac{\gamma_{\{c,s\},\{d,t\}} \cdot Z_{\{c,s\},\{d,t\}}}{\sum_{u=1}^{N} \gamma_{\{c,s\},\{d,u\}} \cdot Z_{\{c,s\},\{d,u\}}} \tag{7}$$

$$\gamma_{\{c,s\},\{d,t\}} = \alpha_{\{c,s\},\{d,t\}} \times \frac{\delta_{\{c,s\},d} \cdot \sum_{u=1}^{N} Z_{\{c,s\},\{d,u\}}}{Z_{\{c,s\},\{d,t\}}} \tag{8}$$

We however set assumptions only on a handful of using sectors, meaning that we still need to derive the elements $\gamma_{\{s,c\},\{t,d\}}$ for sectors t on which no assumptions are imposed. We do so by assuming coefficients $\gamma_{\{s,c\},\{t,d\}}$ are the same across all sectors for which no assumptions are imposed – which we denote $\gamma_{\{s,c\},\{*,d\}}$. Equation (6) allows us to identify this value. Concretely, suppose we have imposed an assumption on using sector t_1, meaning that we know coefficient $\gamma_{\{s,c\},\{t_1,d\}}$. Using this information in equation (6) leads to identify $\gamma_{\{s,c\},\{*,d\}}$ in equation (9). Together with the γ elements already obtained, this then provides all elements of matrix Γ^Z for the row of country-sector $\{c, s\}$ and the N columns corresponding to country d (sector-country $\{1, d\}$ to $\{N, d\}$). Running this methodology across all country-sector $\{c, s\}$ and columns yields the full matrix Γ^Z.

$$\gamma_{\{s,c\},\{*,d\}} = \frac{\delta_{\{s,c\},d} \cdot \sum_{u=1}^{N} Z_{\{s,c\},\{u,d\}} - \gamma_{\{s,c\},\{t_1,d\}} \cdot Z_{\{s,c\},\{t_1,d\}}}{\sum_{u \neq t_1} Z_{\{s,c\},\{u,d\}}} \tag{9}$$

Multiplying element-by-element matrix Γ^Z and Z as in equation (1) provides the ICIO Z^Γ which singles out the amounts of *targeted* products. The ICIO Z^Δ for *non-targeted* products is obtained by simple difference as in equation (2). The very same methodology is applied for final products to get Y^Γ and Y^Δ, respectively final demand of *targeted* and *non-targeted* products. The original ICIO is modified as in **Figure 5** where the *supply* side of the original ICIO (i.e., the rows) is separated between *targeted* (Z^Γ) and *non-targeted* (Z^Δ) parts.

Figure 5. ICIO table dis-aggregated for the *supply* side (rows)

		Output				Final Demand				Total
		1	2	$\cdots$	C	1	2	$\cdots$	C	Output
Targeted Inputs	1	$\mathbf{Z}_{11}^\Gamma$	$\mathbf{Z}_{12}^\Gamma$	$\cdots$	$\mathbf{Z}_{1G}^\Gamma$	$\mathbf{Y}_{11}^\Gamma$	$\mathbf{Y}_{12}^\Gamma$	$\cdots$	$\mathbf{Y}_{1G}^\Gamma$	$\mathbf{X}_1^\Gamma$
	2	$\mathbf{Z}_{21}^\Gamma$		$\cdots$	$\mathbf{Z}_{2G}^\Gamma$	$\mathbf{Y}_{21}^\Gamma$		$\cdots$	$\mathbf{Y}_{2G}^\Gamma$	$\mathbf{X}_2^\Gamma$
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	C	$\mathbf{Z}_{G1}^\Gamma$	$\mathbf{Z}_{G2}^\Gamma$	$\cdots$	$\mathbf{Z}_{GG}^\Gamma$	$\mathbf{Y}_{G1}^\Gamma$	$\mathbf{Y}_{G2}^\Gamma$	$\cdots$	$\mathbf{Y}_{GG}^\Gamma$	$\mathbf{X}_C^\Gamma$
Non-Targeted Inputs	1	$\mathbf{Z}_{11}^\Delta$	$\mathbf{Z}_{12}^\Delta$	$\cdots$	$\mathbf{Z}_{1G}^\Delta$	$\mathbf{Y}_{11}^\Delta$	$\mathbf{Y}_{12}^\Delta$	$\cdots$	$\mathbf{Y}_{1G}^\Delta$	$\mathbf{X}_1^\Delta$
	2	$\mathbf{Z}_{21}^\Delta$		$\cdots$	$\mathbf{Z}_{2G}^\Delta$	$\mathbf{Y}_{21}^\Delta$		$\cdots$	$\mathbf{Y}_{2G}^\Delta$	$\mathbf{X}_2^\Delta$
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	C	$\mathbf{Z}_{G1}^\Delta$	$\mathbf{Z}_{G2}^\Delta$	$\cdots$	$\mathbf{Z}_{GG}^\Delta$	$\mathbf{Y}_{G1}^\Delta$	$\mathbf{Y}_{G2}^\Delta$	$\cdots$	$\mathbf{Y}_{GG}^\Delta$	$\mathbf{X}_C^\Delta$
Value Added		$\mathbf{VA}_1$	$\mathbf{VA}_2$	$\cdots$	$\mathbf{VA}_C$					
Total Output		$(\mathbf{X}_1)'$	$(\mathbf{X}_2)'$	$\cdots$	$(\mathbf{X}_C)'$					

Source: authors.

3.3 Dis-aggregating columns (use side of ICIO)

The second step consists in decomposing the columns of the ICIO matrix (i.e., the use side). The methodology employed is very close to the one used for rows (**section 3.2**). We similarly build a matrix Θ^Z which is multiplied element-by-element with $Z_{rows} = [\mathrm{Z}^\Gamma; \mathrm{Z}^\Delta]$ (obtained after dis-aggregating the rows as in **Figure 5**) to provide a matrix Z_{rows}^Γ whose elements indicate the amount of *targeted* products that are used. The ICIO matrix for *non-targeted* products Z_{rows}^Δ is the difference between Z_{rows} and the *targeted* matrix (Z_{rows}^Γ). One difference with **section 3.2** is that Θ^Z is a $2 \cdot GN \times GN$ matrix since we have twice more rows now that the ICIO has been dis-aggregated on rows. A second difference is that there is no need for a matrix Θ^Y for final demand since columns of Y are households which do not need to be dis-aggregated.

Each element $\theta_{\{c,s\},\{d,t\}}$ of matrix Θ^{Z} indicates the portion of intermediate inputs from the supplying country-sector $\{c, s\}$ towards the using country-sector $\{d, t\}$ that are used by the producers of *targeted* products. A concrete example for interpretating this element is: out of 100 products supplied by Chinese producers of electric batteries (country-sector $\{c, s\}$) to the US motor vehicles sector (country-sector $\{d, t\}$), how many go to the US producers of electric vehicles (i.e., the *targeted* products within the motor vehicles sector)?

As was the case for rows, disaggregating columns relies on building the matrix Θ^{Z}. We use the same methodology as in **section 3.2** with two main differences:

- Product-level bilateral trade data cannot be used to provide a condition.
- The dis-aggregation considers the whole column at once, while for rows we ran the dis-aggregation in G different steps corresponding to the G countries on the use side.

As regards the first difference, a condition for columns is provided by the accounting relations on gross output. Gross outputs for the *targeted* sub-sector (X^{Γ}) and the *non-targeted* sub-sectors (X^{Δ}) are known from the ICIO dis-aggregated for rows (**Figure 5**) by summing elements of the corresponding rows. As mentioned above, accounting relations in ICIO matrices means that this gross output should also match with the sum of the elements in the corresponding columns. This provides a condition on elements $\theta_{\{c,s\},\{d,t\}}$ along equation (10) where:

- $X^{\Gamma}_{\{d,t\}}$ is the gross output of the *targeted* sub-sector sector-country $\{d, t\}$, obtained from the ICIO dis-aggregated for the rows. $X^{\Delta}_{\{t,d\}}$ is gross output for *non-targeted* sub-sector.
- $VA^{\Gamma}_{\{d,t\}}$ is the value-added of the *targeted* sub-sector of sector-country $\{d, t\}$. For simplicity, we assume this is allocated proportionally to output as per equation (11).[15]

(10)
$$\sum_{c=1}^{G}\sum_{s=1}^{N}\theta_{\{c,s\},\{d,t\}} \cdot Z_{rows\,\{c,s\},\{d,t\}} + VA^{\Gamma}_{\{d,t\}} = X^{\Gamma}_{\{d,t\}}$$

15 A simplified assumption is to consider $\theta_{\{c,s\},\{d,t\}} = X^{\Gamma}_{\{d,t\}} / (X^{\Gamma}_{\{d,t\}} + X^{\Delta}_{\{d,t\}}) \quad \forall (c, s)$. This simplification is used in Borin et al. (2023), Attinasi et al. (2025b), and Conteduca et al. (2025) but means that the same proportion of inputs for producing *targeted* products and *non-targeted* products. As was the case for rows, this might not hold for very specific supply chains: for example, “electric batteries” might not be used in the same proportion by producers of electric vehicles (*targeted*) and producers of thermal vehicles (*non-targeted*).

$$VA^{\Gamma}_{\{d,t\}} = \frac{X^{\Gamma}_{\{d,t\}}}{X^{\Gamma}_{\{d,t\}} + X^{\Delta}_{\{d,t\}}} VA_{\{d,t\}} \tag{11}$$

As for rows, we set assumptions on a few coefficients $\theta_{\{c,s\},\{d,t\}}$ for which either the literature or industry reports provides information. For example, one can assume that two thirds of the production of electric batteries (country-sector $\{c, s_1\}$) is used by producers of electric vehicles (i.e., the *targeted* sub-sector of country-sector $\{d, t_1\}$). Practically, this means imposing that $\theta_{\{c,s_1\},\{d,t_1\}} = 0.67$. As was the case for rows, assumptions are available only on a few sectors. We then use equation (10) to derive θ elements for all other sectors, assuming they are the same across all sectors for which we have no assumptions. The only difference with rows is that equation (10) considers all countries at once – as shown by the summand on countries c – while the equivalent condition for rows (equation 6) was limited to one receiving country (d).

This provides matrix Θ^{Γ} from which we get the ICIO matrix Z^{Γ}_{rows} of flows of *targeted* products, as well as the ICIO matrix Z^{Δ}_{rows} for flows of *non-targeted* products. Doing so provides a fully dis-aggregated ICIO as in **Figure 6** where both *supply* and *use* sides of the original ICIO are separated between *targeted* and *non-targeted* sub-sectors. **Figure 6** further decomposes Z^{Γ}_{rows} into $Z^{\Gamma\Gamma}$, which accounts for linkages between *targeted* sub-sectors on both supply and use sides, and $Z^{\Gamma\Delta}$, which accounts for linkages between a supplying *targeted* sub-sector towards a using *non-targeted* sector. Conversely, $Z^{\Delta\Delta}$ and $Z^{\Delta\Gamma}$ decompose Z^{Δ}_{rows}.

Figure 6. Final dis-aggregated ICIO on both *supply* (rows) and *use* (columns) side

		Targeted Output			Non-Targeted Output			Final Demand			Total
		1	$\cdots$	C	1	$\cdots$	C	1	$\cdots$	C	Output
Targeted Inputs	1	$\mathbf{Z}^{\Gamma\Gamma}_{11}$	$\cdots$	$\mathbf{Z}^{\Gamma\Gamma}_{G1}$	$\mathbf{Z}^{\Gamma\Delta}_{11}$	$\cdots$	$\mathbf{Z}^{\Gamma\Delta}_{1G}$	$\mathbf{Y}^{\Gamma}_{11}$	$\cdots$	$\mathbf{Y}^{\Gamma}_{1G}$	$\mathbf{X}^{\Gamma}_{1}$
	2	$\mathbf{Z}^{\Gamma\Gamma}_{21}$	$\cdots$	$\mathbf{Z}^{\Gamma\Gamma}_{2G}$	$\mathbf{Z}^{\Gamma\Delta}_{21}$	$\cdots$	$\mathbf{Z}^{\Gamma\Delta}_{RG}$	$\mathbf{Y}^{\Gamma}_{21}$		$\mathbf{Y}^{\Gamma}_{2G}$	$\mathbf{X}^{\Gamma}_{2}$
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	C	$\mathbf{Z}^{\Gamma\Gamma}_{G1}$	$\cdots$	$\mathbf{Z}^{\Gamma\Gamma}_{GG}$	$\mathbf{Z}^{\Gamma\Delta}_{G1}$	$\cdots$	$\mathbf{Z}^{\Gamma\Delta}_{GG}$	$\mathbf{Y}^{\Gamma}_{G1}$	$\cdots$	$\mathbf{Y}^{\Gamma}_{GG}$	$\mathbf{X}^{\Gamma}_{C}$
Non-Targeted Inputs	1	$\mathbf{Z}^{\Delta\Gamma}_{11}$	$\cdots$	$\mathbf{Z}^{\Delta\Gamma}_{1G}$	$\mathbf{Z}^{\Delta\Delta}_{11}$	$\cdots$	$\mathbf{Z}^{\Delta\Delta}_{1G}$	$\mathbf{Y}^{\Delta}_{11}$	$\cdots$	$\mathbf{Y}^{\Delta}_{1G}$	$\mathbf{X}^{\Delta}_{1}$
	2	$\mathbf{Z}^{\Delta\Gamma}_{21}$	$\cdots$	$\mathbf{Z}^{\Delta\Gamma}_{2G}$	$\mathbf{Z}^{\Delta\Delta}_{11}$	$\cdots$	$\mathbf{Z}^{\Delta\Delta}_{2G}$	$\mathbf{Y}^{\Delta}_{21}$		$\mathbf{Y}^{\Delta}_{2G}$	$\mathbf{X}^{\Delta}_{2}$
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	C	$\mathbf{Z}^{\Delta\Gamma}_{G1}$	$\cdots$	$\mathbf{Z}^{\Delta\Gamma}_{GG}$	$\mathbf{Z}^{\Delta\Delta}_{G1}$	$\cdots$	$\mathbf{Z}^{\Delta\Delta}_{GG}$	$\mathbf{Y}^{\Delta}_{G1}$	$\cdots$	$\mathbf{Y}^{\Delta}_{GG}$	$\mathbf{X}^{\Delta}_{C}$
Value Added		$\mathbf{VA}^{\Gamma}_{1}$	$\cdots$	$\mathbf{VA}^{\Gamma}_{C}$	$\mathbf{VA}^{\Delta}_{1}$	$\cdots$	$\mathbf{VA}^{\Delta}_{C}$				
Total Output		$(\mathbf{X}^{\Gamma}_{1})'$	$\cdots$	$(\mathbf{X}^{\Gamma}_{C})'$	$(\mathbf{X}^{\Delta}_{1})'$	$\cdots$	$(\mathbf{X}^{\Delta}_{C})'$				

Source: authors.

4. An application to green industrial policies

4.1 Identifying green sectors

To design a scenario of trade fragmentation affecting green sectors, the first task consists in identifying green products at HS6 level. We do so by relying on two complementary sources. The first is the list of products that were targeted in the US Inflation Reduction Act of 2022. It provides 92 products at a highly granular level, such as “Turbines; hydraulic turbines and water wheels, of a power not exceeding 1000kW” (HS 841011) or “Poly(ethylene terephthalate); in primary forms, having a viscosity of 78ml/g or higher” (HS 390769). We complement this by the list of EU critical dependencies from which we isolate 17 products related to the green transition – and that were not in the IRA list. Finally, we add 20 products to cover some green products that were not included in the two lists above, notably for hydraulic power generation and heat pumps. The detailed list of 129 products is available in **Table A3** in **Appendix A**.

For tractability in the Baqaee-Farhi model, we merge these products into 7 homogenous sub-groups in terms of sectoral classification and product class. They are “mined rare earths”, “processed rare earths”, “green-related chemicals”, “mechanical renewable-energy components", "electric batteries", "electrical renewable-energy components", and "electric vehicles". This accounts for the entire supply chain of green products, from very upstream (mined rare Earth) to very downstream (electric vehicles). To represent the changes in electricity consumption, we also add an eight sub-sector "green electricity" (i.e., that is produced from renewables) which is obtained by dis-aggregating the utilities sector in the ICIO matrix.[16]

4.2 Accounting for green transition

Another limitation is that the available ICIO tables reflect the state of value chains with a significant lag – typically around five years.[17]. However, green product markets have grown rapidly and are expected to evolve even more dramatically in the near future. For this reason, we simulate growth in green sectors to account for future sectoral linkages.

For this, we rely on the Leontief inverse matrix that links final demand (Y) and output (X) as in equation (12). This relationship comes from the accounting relation on supply side of the ICIO: when summing rows as in **Figure 4**, $Z + Y = X$. We then construct a matrix of technical coefficients A by dividing each row of Z by output (X).[18] It follows that $Z = AX$, and therefore $AX + Y = X$. Re-writing this equation provides equation (14) where $B = (I - A)^{-1}$ is the Leontief inverse matrix.

$$X = BY \quad (12)$$

We obtain a future ICIO by applying assumptions from the International Energy Agency (IEA) as regards the final demand for green products and the production of green electricity by 2030. Detailed assumptions are provided in **Appendix B**. We proceed in two steps.

- The first step consists in reflecting the growth of the final demand of green products by 2030, through a modification of Y. This is done by simply applying the IEA assumptions on the corresponding countries: for example, if the IEA assumes that demand for

16 For this dis-aggregation, we apply a simpler method for dis-aggregating rows by using the ratio of green electricity in total utilities (see **Table B3** in **Appendix B**). This is akin to Conteduca et al. (2025) and assumes implicitly that all using sectors are consuming green and non-green electricity in the same proportion. For the split on the column, we apply the method described in **section 3.3** to effectively account for the fact that the inputs are different to produce green and non-green electricity. Concretely, our method ensures that the production of solar panels, wind turbines, and other renewable-energy equipment is primarily geared towards the green electricity sub-sector.

17 In this study, the base ICIO table is the OECD TiVA table for year 2018.

18 Each coefficient $A_{i,j}$ of matrix A can be interpreted as the quantity of inputs needed from the country-sector i to produce one unit of output in country-sector j.

electric vehicles will grow 10-fold in China, we multiply the corresponding cells in matrix Y by 10.[19] Doing so across all countries and green sectors provides an updated matrix of final demand Y^{2030}.[20]

- The second step consists in reflecting changes in the use of renewable *vs.* non-renewable electricity in the matrix of technical coefficients A. We rely on IEA assumptions for electricity mix in 2030. Thanks to the dis-aggregation of the ICIO along green sectors (see **section 4.1**), the ICIO contains sectors "green electricity" and "non-green electricity". To reflect the green transition, we impose that the ratio of *green* to *non-green* electricity follows IEA assumptions. Formally, elements $A_{\{c,s\},\{d,t\}}$ in matrix A are the quantity of inputs needed from country-sector $\{c, s\}$ to produce one unit of output in country-sector $\{d, t\}$. We update these coefficients $A_{\{c,s\},\{d,t\}}$ for sector s being "green electricity" and "non-green electricity" following equations (13) and (14) in which $\beta^{2030}_{green\ elec.,c}$ is the proportion of green electricity in the electricity mix in of country c derived from IEA scenarios. Doing so provides a matrix A^{2030} which accounts for a higher usage of green electricity by 2030.[21] By changing A^{2030}, it also implies that gross outputs of *green* and *non-green* electricity will change accordingly. Most notably, *green* electricity will have a higher output, leading to higher demand towards its suppliers of intermediate inputs, like producers of solar panels or wind turbines which will also see their output increase significantly. For instance, the world output of renewable-energy equipment (solar panels, wind turbines, etc.) increases by 118% after accounting for green transition.

$$A^{2030}_{\{c,green\ elec.\},\{d,t\}} = \beta^{2030}_{c,green\ elec.}(A_{\{c,green\ elec.\},\{d,t\}} + A_{\{c,non-green\ elec.\},\{d,t\}}) \tag{13}$$

$$A^{2030}_{\{c,non-green\ elec.\},\{d,t\}} = (1 - \beta^{2030}_{c,green\ elec.})(A_{\{c,green\ elec.\},\{d,t\}} + A_{\{c,non-green\ elec.\},\{d,t\}}) \tag{14}$$

In equation (12), we then replace Y by Y^{2030} and take the Leontief inverse matrix B^{2030} obtained by inverting $I - A^{2030}$. It provides X^{2030}, the vector of gross output by 2030. This then

19 In more details, we proceed in two steps because Y in equation (12) is a vector obtained as the row-wise sum of the full matrix Y (as represented in **Figure 4**). We first use the full matrix Y (with countries on the columns) to apply IEA country-specific assumptions. Second, we collapse it into a vector Y for use in equation (12).

20 As assumptions are available only for green products, we do not modify the final demand in other sectors.

21 Coefficients for *green* and *non-green* electricity in A^{2030} are obtained by a re-scaling of coefficients in A, this ensures that the ICIO remain consistent – notably that accounting relationships on the ICIO are still verified.

gives $Z^{2030} = A^{2030}X^{2030}$. With Y^{2030} already constructed, it is then sufficient to derive value added VA^{2030}. [22] Hence, we get an ICIO matrix accounting for green transition by 2030.[23]

4.3 Scenario design

Rival countries are increasingly crafting industrial policies aimed at favouring their domestic production of green products. This includes trade-restrictive measures such as the 2022 US Inflation Reduction Act, whose domestic content requirements incentivize US consumers and producers to buy from North America, or the 2024 Section 301 tariffs set by the Biden administration which set higher import duties on green products such as electric vehicles and solar panels. At the same time, the EU is imposing anti-dumping tariffs on Chinese electric vehicles and is fostering its domestic production of green products through the European Green Deal and the Critical Raw Materials Act. China also provides ample industrial subsidies to green sectors (Bickenbach et al., 2024) which entail major spillovers (Attinasi et al., 2024).

Against this background, we simulate a *Green War* scenario where two geopolitical blocs (East and West) impose trade barriers to imports of green products from the other bloc, while a third neutral group of countries continue to trade freely. Country allocation relies on Attinasi, Mancini et al. (2024):[24] as shown in **Figure 7**, the West bloc includes advanced economies (e.g., US, EU, Japan) while the East bloc encompasses China, Russia, and their allies. Most emerging economies in Africa, Latin America, and South-East Asia are deemed neutral. Our scenario entails a 150% increase in non-tariff barriers on trade of the green products (detailed in **section**

22 $VA^{2030}$is obtained by using the accounting relationship on the columns of the ICIO (*use* side): value-added is gross output (X^{2030}) minus intermediate inputs (column-wise sum of Z^{2030}). The underlying assumption is that the proportion of value added per unit of output remains unchanged.

23 Changes in final demand will affect the demand in intermediate inputs of producers because, as producers of *final* green goods will face a higher demand, they will mechanically increase their demand for *intermediate* green inputs. This means that in the end, our method modifies the full input-output table – both for intermediate and final products. Nevertheless, one limitation of our approach of exogenously changing final demand is that the proportion of inputs that each sector uses for production will remain the same – apart from the specific case of green electricity which is tackled in step 2. This would under-estimate the extent of the impact of the green transition on the economy.

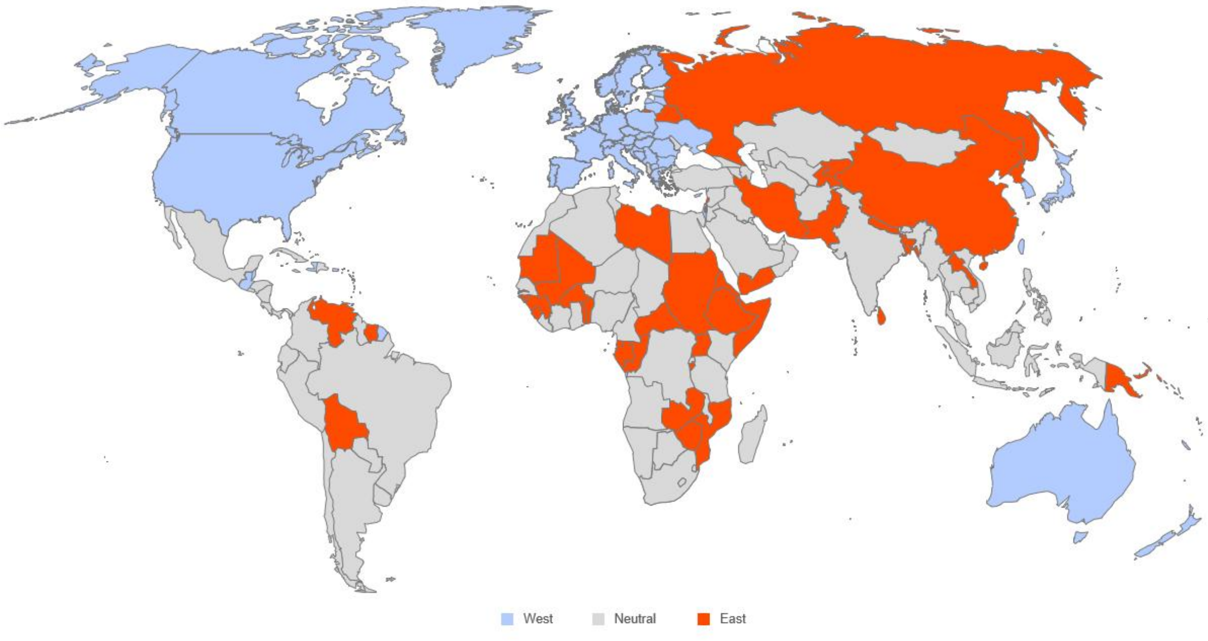
24 In Attinasi, Mancini et al. (2024), each country is allocated mechanically based on political alignment and economic ties. Contrary to most of the literature (e.g., Goes and Bekkers, 2022; Campos et al., 2023; Javorcik et al., 2024) the allocation does not rely only on voting patterns at the UN General Assembly but also on a broader set of additional metrics for political alignments (historical sanctions, military imports, official lending from China, security alliances, territorial disputes, public opinion about China and the US) and economic ties (FDI from and exports to China and the US, participation to the Belt and Road Initiative). More precisely, the geopolitical index relies on an index developed in the spirit of den Besten et al. (2023) for 63 countries covering 87% of global GDP. Since this index is not available for all countries, the allocation of the remaining 166 smallest countries covering 13% of global GDP relies on Capital Economics (2023).

4.1) between the two antagonist blocs, *de facto* halting trade flows of green products between blocs.[25]

Following Attinasi et al. (2025a) Scenarios are run under two alternative model setups, a rigid and a flexible setup which differ by the degree of nominal rigidities. The rigid setup entails sticky wages and a reduced substitutability across suppliers, reflecting difficulties for producers to adjust swiftly their network of suppliers. Trade elasticities in this setup are calibrated based on Boehm et al. (2023). It reflects empirical findings in the literature that nominal wages are usually sticky (Le Bihan et al., 2012; Taylor, 1980) and supply chains inflexible (Barkema et al., 2019), at least in the short- to medium-term. The flexible setup allows for fully flexible wages and a higher substitutability of suppliers through larger trade elasticities from Fontagné et al. (2022). It represents effects as rigidities dissipate and the economy gradually adjusts.

Figure 7. Country (mechanical) allocation

(mechanical allocation based on political and economic linkages)



Sources: Attinasi, Mancini et al. (2024) based on den Besten et al. (2023) and Capital Economics (2023)
Notes: Countries are allocated mechanically to a geopolitical bloc based on political alignment and economic ties with China (East bloc) and the US (West bloc).

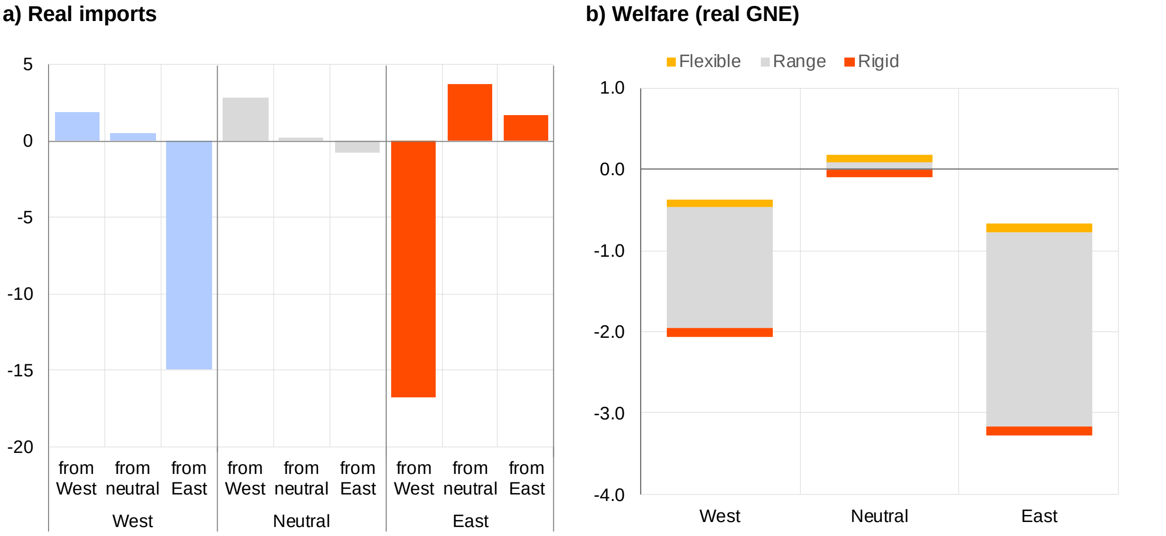
25 A scenario in which trade between blocs is zeroed is in line with Campos et al. (2024) and Gopinath et al. (2024) providing evidence that trade between East and West has been almost non-existent during episodes of heightened geopolitical tensions (e.g., Cold War).

4.4 Economic impact

Higher barriers to trade create an import price shock that affect imports and welfare. As a result, producers and consumers substitute away from more expensive products from the antagonist bloc towards products from either the same bloc or the neutral bloc, creating a positive demand shock for the latter. This is shown in **Figure 8** (panel a) where trade between West and East decreases sharply by 15-20% while trading more within the same bloc and with the neutral bloc by 2 to 3%, suggesting that trade diversion takes place. In terms of welfare, both antagonist blocs would lose as trade barriers increase the prices of green products and reduce the trade opportunities for their domestic production (**Figure 8**, panel b). Welfare losses are higher in the East bloc where they reach 3% in the rigid set-up, while only amounting to -2% in the West. This reflects the fact that the East bloc is reliant on the West for their exports of green products. In a rigid set-up, the Neutral bloc experiences a slight decrease in welfare that reflects the indirect effects from large welfare losses in the West and the East blocs. In a flexible set-up, welfare increases slightly in the Neutral bloc as the world economy adjusts and the absence of trade barriers on the Neutral bloc opens them additional trade opportunities.

Figure 8. Higher losses in the East, trade diversion towards neutral countries

(percentage deviation from steady state)



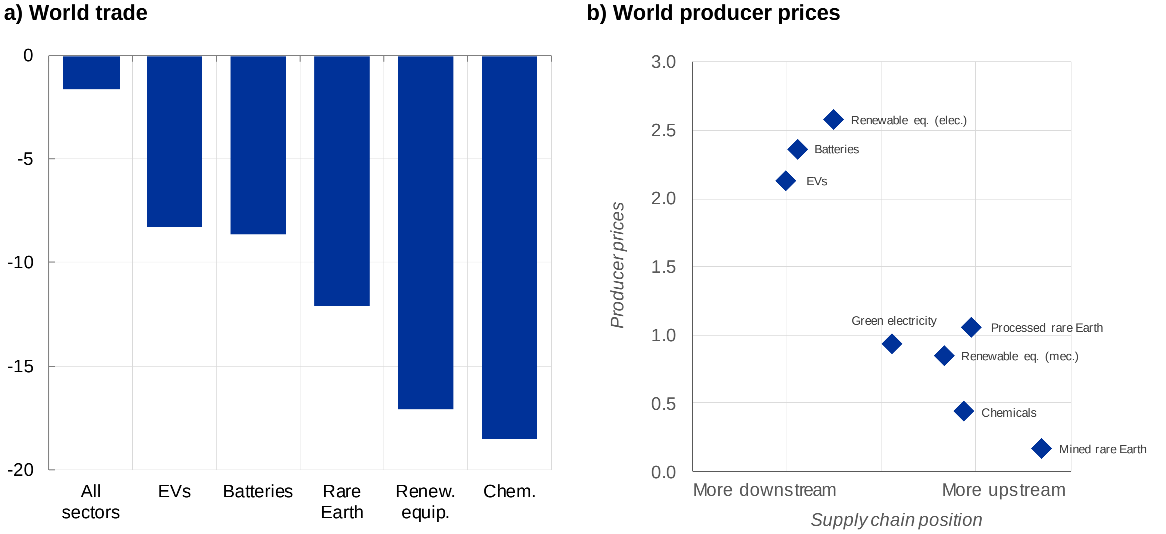
Sources: Baqaee and Farhi (2024); Attinasi, Mancini et al. (2024); OECD TiVA; International Energy Agency; BACI; and authors' calculations
Notes: GNE = Gross National Expenditures. Non-linear impact simulated through 25 iterations of the log-linearized model. Panel a) includes intra-bloc imports. Panel a) relates to the flexible set-up.

Due to model limitations, our estimates of a decoupling along green products likely represent a lower bound. Several other channels may be at play and amplify the losses such as impaired knowledge diffusion (Cai et al., 2022), financial amplification (Berthou et al., 2018), frictions to migration and demography (Banerjee and Duflo, 2007), and macroeconomic uncertainty (Caldara et al., 2020). In addition, the substitution effects across green and brown sectors might be under-estimated as producers and consumers in the Baqaee-Farhi model can substitute freely across all products (e.g., faced with an increase of the relative price of electric vehicles, they can substitute it by textile). A more accurate representation should consider substitution at a more granular level (e.g., electric vehicles *versus* thermal cars, green electricity *versus* brown electricity). This would however be a substantial change to the model, and we leave it for future research.

Splitting the IO table also allows to uncover sector-specific effects. World trade in the product groups targeted by the *Green War* declines by 10 to 20% (**Figure 9**, panel a) led by a drastic drop of trade between the two antagonist blocs. Most affected product groups are chemicals and renewable-energy equipment since these products were largely traded between East and West prior to fragmentation. As trade barriers are introduced, producer prices for these sectors increase (**Figure 9**, panel b). While prices rise across all green products, they rise more for products with downstream positions such as electric vehicles. This reflects the fact the *Green War* scenario targets the entire supply chain of green products, magnifying the impact on those products that depend on upstream green products.

Figure 9. Sectoral impacts

(percentage deviation from steady state)



Sources: Baqaee and Farhi (2024); Attinasi, Mancini et al. (2024); OECD TiVA; International Energy Agency; BACI; and authors' calculations
Notes: "Renew. equip." = renewable-energy equipment, mechanical (e.g., wind turbines) and electrical (e.g., solar panels). "Chem." = chemicals for the green transition. Non-linear impact simulated through 25 iterations of the log-linearized model. In panel a) trade relates to real exports. Both panels relate to the "flexible" set-up.

4.5 Impact on greenhouse gas emissions

The rise in prices of green goods – particularly those downstream the supply chain, closer to final consumption – weighs on their global demand, which falls by 2.2%. This decline is driven primarily by the Western bloc, where consumption drops by 9.5% due to reduced access to cheaper imports from Eastern economies. This suggests that, following the shock, the global economy may become more polluting, as higher costs and reduced access to affordable green goods discourage their consumption and lead to a shift back toward more emission-intensive alternatives.

To quantify the impact on greenhouse gas emissions, we start by calculating the emission intensity of production at country-sector level. This is defined as the amount of CO2-equivalent emitted per US dollar of output produced, computed by dividing total emissions (from OECD; Yamano et al., 2024) by the gross output from our ICIO table, for each country-sector pair. We use 2018 emissions data to ensure consistency with the 2018 ICIO table throughout our analysis.[26]

To project emission intensities to 2030, we exploit the strong correlation (nearly 80%) between a country-sector's emission intensity ($EI_{c,s}$) and the share of its inputs sourced from the "coke and refined petroleum products" sector ($A_{c,s}$). Specifically, we estimate the following regression on 2018 data, including country (γ_c) and sector (γ_s) fixed effects:[27]

$$EI_{c,s}^{2018} = \beta_0 + \beta_1 \cdot A_{c,s}^{2018} + \gamma_c + \gamma_s + \epsilon_{c,s}. \quad (15)$$

Using this estimated relationship, we calculate projected emission intensities for 2030 based on the "coke and refined petroleum products" shares from pre- and post-shock ICIO tables.

[26] We rely on *scope 1* emissions (caused directly by a firm) to avoid any double counting that could occur when using *scope 2* emissions (caused indirectly or coming from the production of the energy purchased by the firm) or *scope 3* emissions (caused by suppliers and consumers in the value chain). For green sectors constructed through our methodology – where OECD emissions data are not available – we assume their emission-intensity is the same as their parent sector. The only exception is the "green energy" sector (comprising wind, solar, and hydro energy) for which we assume zero emissions. To preserve consistency with total CO2 emissions in the aggregated "energy" sector (combining green non- and green sources), we infer the emission-intensity of the "non-green energy" sub-sector by dividing total CO2 emissions of the aggregated "energy" sector by the share of non-green energy in the sector's output.

[27] The regression is estimated on a sample of approximately 680 country-sector pairs. The R^2 is 0.56, and the estimated coefficient $A_{c,s}$ is positive and statistically significant at the 1% level. Results are available upon request.

We then multiply these intensities by gross output to estimate total production-based emissions in 2030.

To account for households' emissions, we use households' final demand for thermal vehicles (obtained from the ICIO tables) as a proxy.[28] We first calculate country-specific households' emission-intensity by dividing household CO2-equivalent emissions – sourced from the OECD – for 2018 by household spending on thermal vehicles in the same year. We then apply this coefficient to household purchases of thermal vehicles in 2030 before and after the trade shock. Lastly, we compute total emissions by summing production and household components and derive pre- and post-shock emission intensities by dividing total emissions by global GDP.

The East-West decoupling in green products would lead to higher CO2-equivalent emissions per US dollar of output, threatening hard-won progress toward global climate goals. According to our estimates, supply chain decoupling in green sectors reduces global energy efficiency, with each additional USD billion of output generating 544 more tonnes of CO2-equivalent emissions. This corresponds to roughly 50 million tonnes of additional emissions annually comparable to the yearly emissions of countries such as Bulgaria or Finland. Over two decades, the cumulative increase would approach one gigatonne of CO2-equivalent greenhouse gas emission, equivalent to adding a new emitter the size of Japan or Brazil to the global economy, according to OECD data. In the end, green supply chain decoupling not only affects macroeconomic outcomes but also undermine the energy efficiency of the global economy.

4.6 Comparison with other methods

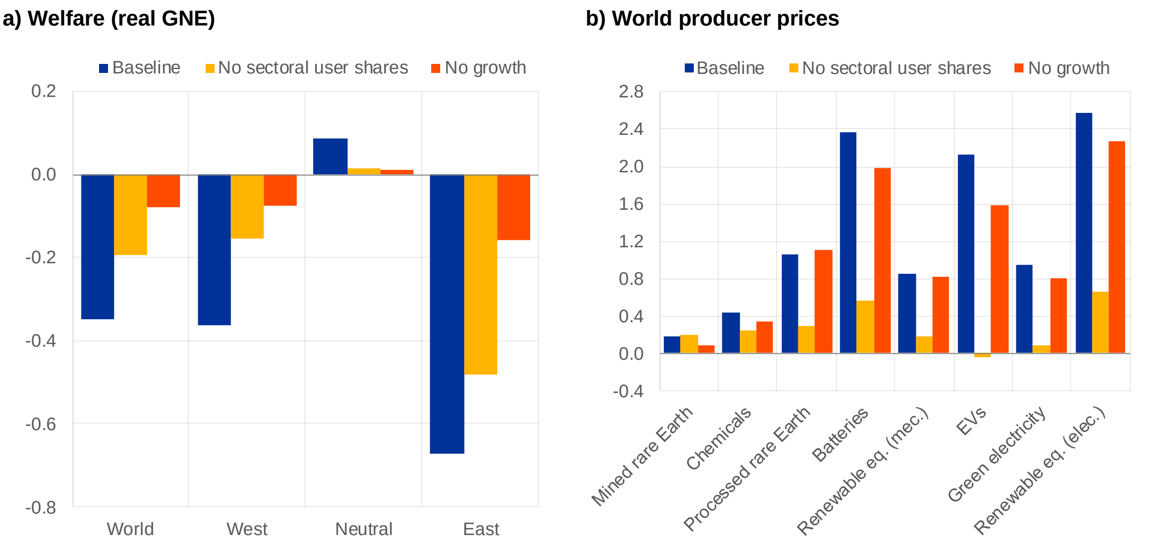
Finally, we compare how results using our methodology differ from results using alternative methods. **Figure 10** (panel a) depicts the welfare impact. The impact under our (baseline) method is larger than under the alternative where no growth is applied to the demand of green products. This is expected and somewhat mechanical as this alternative method do not account for the growth of the green sectors by 2030, hence the relative size of green sectors in the global economy is much smaller. Our (baseline) method also produces larger impacts than the alternative where no sector-specific user shares are used – as in Borin et al. (2023).

[28] Due to lack of sector-specific data on household emissions in the OECD database, we use consumption of thermal vehicles as a proxy for overall emission-intensity. This approach is supported by empirical literature showing a strong correlation between electric vehicle ownership and broader household energy-efficiency (Dai et al., 2023) notably as EVs owners are more likely to invest in green energy sources like solar panels (Sharda et al., 2024).

This is because our method allows to properly account for the sectoral linkages between green products, therefore enabling larger amplification effects through global production chains. The discrepancies are significant, with our baseline method multiplying the impact by around 2. As regards sectoral producer prices (**Figure 10**, panel b), impacts under our baseline method and the alternative "no sectoral user shares" are large, reflecting how accounting for sectoral inter-linkages along the value chain of green products magnifies the effect on producer prices – notably for downstream products like EVs, batteries, and renewable-energy equipment. By contrast, differences between our baseline method and the "no growth" alternative are marginal. This is expected since the relative changes in producer prices should be little influenced by growing the IO matrix – as doing so will not affect the linkages between sectors, but only the size of these sectors in the total output.[29]

Figure 10. Comparison with other approaches

(percentage deviation from steady state)



Sources: Baqaee and Farhi (2024); Attinasi, Mancini, et al. (2024); OECD TiVA; International Energy Agency; BACI; and authors' calculations
Notes: "GNE" = Gross National Expenditures. Non-linear impact simulated through 25 iterations of the log-linearized model. "No sectoral user shares" refers to an alternative method for splitting rows without accounting for user shares, as in Borin et al. (2023). "No growth" refers to the alternative where no sectoral growth is applied to the IO (only the splitting).

[29] Differences between the baseline and the "no growth" alternative stems from the fact that not all sectors are grown by the same proportion when growing the IO matrix. It results that the weight of the different sectors in the proportion of inputs / outputs of the sectors will change, modifying to some extent the impact of changes in upstream suppliers and/or downstream consumers.

Conclusion

We provide a general methodology to build highly granular ICIO tables, giving researchers a tool to enhance standard ICIO and isolate specific products of interest. We study the impact of dis-aggregation and find that granularity in ICIO tables matters even more when products cannot be easily substituted through trade with other countries (i.e. low trade elasticities) – as is the case for most goods essential to the green transition (e.g., electric batteries, rare earths). We then apply our method to study a hypothetical Green War scenario where East and West blocs stop trading green products. To do so, we also enhance the ICIO to account for the growth potential of green sectors by 2030, based on assumptions of the International Energy Agency. We show that a Green War lowers welfare by up to 3%, while leading to a significant (up to 20%) reduction of bilateral trade flows. Such decoupling in green supply chains also raises greenhouse gas emission intensity per unit of GDP, as reduced access to efficient and affordable low-carbon technologies leads to a less energy-efficient allocation of production and consumption across countries.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, 80(5), 1977-2016

Aiyar, S., Chen, J., Ebeke, C., Garcia-Saltos, R., Gudmundsson, T., Ilyina, A., Kangur, A., Kunaratskul, T., Rodriguez, S., Ruta, M., Schulze, T., Soderberg, G., & Trevino, J. (2023). Geoeconomic Fragmentation and the Future of Multilateralism. *Staff Discussion Notes*, No 2023/1, International Monetary Fund

Ara, K. (1959). The aggregation problem in input-output analysis. *Econometrica*, 27(2), 257-262

Attinasi, M. G., Boeckelmann, L., & Meunier, B. (2023a). Friend-shoring global value chains: a model-based assessment. *Economic Bulletin Boxes*, 2

Attinasi, M. G., Boeckelmann, L., & Meunier, B. (2023b). Unfriendly friends: Trade and relocation effects of the US Inflation Reduction Act. *VoxEU. org*

Attinasi, M. G., Boeckelmann, L., de Castro Martins, B., & Meunier, B. (2024). A model-based assessment of the spillovers of Chinese subsidies to electric vehicles. Box 2 in Al-Haschimi, A., and Spital, T., *The evolution of China's growth model: challenges and long-term growth prospects*, Economic Bulletin Articles, 1. European Central Bank

Attinasi, M. G., Mancini, M., Boeckelmann, L., Bottone, M., Conteduca, F. P., Giordano, C., Meunier, B., and Panon, L., et al. (2024). Navigating a fragmenting global trading system: Some lessons for central banks. *Occasional Paper Series,* No 365, European Central Bank

Attinasi, M. G., Boeckelmann, L., & Meunier, B. (2023b2025a). The economic costs of supply chain decoupling. *Working Paper SeriesThe World Economy*, No 283948(3), European Central Bank598-627

Attinasi, M. G., Boeckelmann, L., Gerinovics, R., & Meunier, B. (2025b). Steeling losses: sectoral strains from the return of tariffs on steel and aluminium. *Econbrowser*

Bachmann, R., Baqaee, D., Bayer, C., Kuhn, M., Löschel, A., Moll, B., Peichl, A., Pittel, K., & Schularick, M. (2022). What if? The Economic Effects for Germany of a Stop of Energy Imports from Russia. *Policy Brief*, No 28

Banerjee, A. V., & Duflo, E. (2007). The Economic Lives of the Poor. *Journal of Economic Perspectives*, 21(1), 141-168

Baqaee, D. R., & Farhi, E. (2024). Networks, barriers, and trade. *Econometrica*, 92(2), 505-541

Barkema, J., Bayoumi, T., & Cerdeiro, D. (2019). The Inflexible Structure of Global Supply Chains. *Working Paper*, No 2019/193, International Monetary Fund

Barry, J. J., Matos, G. R., & Menzie, W. D. (2015). *A Crosswalk of Mineral Commodity End Uses and North American Industry Classification System (NAICS) codes*, US Geological Survey

Berthou, A., Jardet, C., Siena, D., & Szczerbowicz, Z. (2018). Costs and consequences of a trade war: a structural analysis. *Rue de la Banque*, 72, Banque de France

Bickenbach, F., Dohse, D., Langhammer, R. J., & Liu, W. H. (2024). *Foul play? On the scale and scope of industrial subsidies in China*. Kiel Policy Brief, No 173

Blair, P., & Miller, R. E. (1983). Spatial aggregation in multiregional input-output models. *Environment and Planning A*, 15(2), 187-206

Blöchl, F., Theis, F. J., Vega-Redondo, F., & Fisher, E. O. N. (2011). Vertex centralities in input-output networks reveal the structure of modern economies. *Physical Review E—Statistical, Nonlinear, and Soft Matter Physics*, 83(4)

Boehm, C. E., Levchenko, A. A., & Pandalai-Nayar, N. (2023). The Long and Short (Run) of Trade Elasticities. *American Economic Review*, 113(4), 861-905

Bolhuis, M. A., Chen, M. J., & Kett, B. R. (2023). Fragmentation in global trade: Accounting for commodities. *Working Paper*, No 2023/073, International Monetary Fund

Bonadio, B., Huo, Z., Levchenko, A. A., & Pandalai-Nayar, N. (2021). Global supply chains in the pandemic. *Journal of international economics*, 133

Borin, A., Conteduca, F. P., Di Stefano, E., Gunnella, V., Mancini, M., & Panon, L. (2023). Trade decoupling from Russia. *International Economics*, 175, 25-44

Borin, A., & Mancini, M. (2019). Measuring what matters in global value chains and value-added trade. *Policy research working paper*, No 8804, The World Bank

Borin, A., Mancini, M., & Taglioni, D. (2025). Economic Consequences of Trade and Global Value Chain Integration. *World Bank Economic Review*, forthcoming

Bunsen, J., & Finkbeiner, M. (2022). An introductory review of input-output analysis in sustainability sciences including potential implications of aggregation. *Sustainability*, 15(1), 46

Cabrer, B., Contreras, D., & Miravete, E. (1991). Aggregation in input–output tables: how to select the best cluster linkage. *Economic Systems Research*, 3(2), 99-110

Cai, J., Li, N., & Santacreu, A. M. (2022). Knowledge Diffusion, Trade, and Innovation across Countries and Sectors. *American Economic Journal: Macroeconomics*, 14(1), 104-145

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., & Raffo, A. (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, 109, 38-59

Capital Economics (2023). *China Economics Focus: Mapping decoupling*

Campos, R. G., Estefanía-Flores, J., Furceri, D., & Timini, J. (2023). Geopolitical fragmentation and trade. *Journal of Comparative Economics*, 51(4), 1289-1315

Campos, R. G., Heid, B., & Timini, J. (2024). The economic consequences of geopolitical fragmentation: Evidence from the Cold War. *CESifo Working Paper Series*, No 11057

Carvalho, V. M. (2014). From Micro to Macro via Production Networks. *Journal of Economic Perspectives*, 28(4), 23-48

Conteduca, F. P., Mancini, M., Romanini, G., Borin, A., Di Stefano, E., Giglioli, S., Attinasi, M.-G., Boeckelmann, L., & Meunier, B. (2025). Fragmentation and the future of GVCs. *Occasional Papers*, No 932, Bank of Italy

Dai, Z., Rodgers, M. O., & Guensler, R. (2023). Hybrid EV and BEV Owners: A Comparative Analysis of Household Demographics, Travel Behavior, and Energy Use. *Technical Report*, National Center for Sustainable Transportation

de Backer, K., & Miroudot, S. (2014). Mapping global value chains. *Working Paper Series*, No 1677, European Central Bank de Vries, G., Chen, Q., Hasan, R., & Li, Z. (2019). Do Asian countries upgrade in global value chains? A novel approach and empirical evidence. *Asian Economic Journal*, 33(1), 13-37

den Besten, T., Di Casola, P., & Habib, M. (2023). Geopolitical fragmentation risks and international currencies. *The international role of the euro*, European Central Bank

Eppinger, P., Felbermayr, G., Krebs, O., & Kukharskyy, B. (2021). Decoupling Global Value Chains. *Working Paper Series*, No 9079, CESifo

Fally, T., & Sayre, J. (2018). Commodity trade matters. *NBER Working Papers*, No 24965, National Bureau of Economic Research

Fisher, W. D. (1958). Criteria for aggregation in input-output analysis. *The review of Economics and Statistics*, 250-260

Flaaen, A., Kamal, F., Lee, E., & Yi, K. M. (2024). Aggregation Bias in the Measurement of US Global Value Chains. *AEA Papers and Proceedings*, 114, 136-142

Fontagné, L., Guimbard, H., & Orefice, G. (2022). Tariff-based product-level trade elasticities. *Journal of International Economics*, 137

Gaulier, G., & Zignago, S. (2010). BACI: International Trade Database at the Product-Level. The 1994-2007 Version. *Working Papers*, No 2010-23, CEPII research center

Giammetti, R. (2020). Tariffs, domestic import substitution and trade diversion in input-output production networks: an exercise on Brexit. *Economic Systems Research*, 32(3), 318-350

Góes, C., & Bekkers, E. (2022). The impact of geopolitical conflicts on trade, growth, and innovation. *WTO Staff Working Papers*, No ERSD-2022-9, World Trade Organization

Gopinath, G., Gourinchas, P. O., Presbitero, A., & Topalova, P. B. (2024). Changing Global Linkages: A New Cold War? *Working Paper*, No 2024/076, International Monetary Fund.

Hatanaka, M. (1952). Note on consolidation within a Leontief system. *Econometrica*, 301-303

Javorcik, B. S., Kitzmüller, L., Schweiger, H., & Yildirim, M. A. (2024). Economic Costs of Friend-Shoring. *The World Economy*, 47(7), 2871-2908

Kowalski, P., & Legendre, C. (2023). Raw materials critical for the green transition: Production, international trade and export restrictions. *OECD Trade Policy Papers*, No 269

Kymn, K. O. (1990). Aggregation in input–output models: a comprehensive review, 1946–71. *Economic Systems Research*, 2(1), 65-93

Le Bihan, H., Montornès, J., & Heckel, T. (2012). Sticky Wages: Evidence from Quarterly Microeconomic Data. *American Economic Journal: Macroeconomics*, 4(3), 1-32

Lenzen, M. (2011). Aggregation versus disaggregation in input–output analysis of the environment. *Economic Systems Research*, 23(1), 73-89

Massari, S., & Ruberti, M. (2013). Rare earth elements as critical raw materials: Focus on international markets and future strategies. *Resources policy*, 38(1), 36-43

Morimoto, Y. (1970). On aggregation problems in input-output analysis. *The Review of Economic Studies*, 37(1), 119-126

McManus, M. (1956). General Consistent Aggregation in Leontief Models. *Bulletin of Economic Research*, 8(1), 28-48

Michel, B., Hambÿe, C., & Hertveldt, B. (2018). The Role of Exporters and Domestic Producers in GVCs: Evidence for Belgium based on Extended National Supply-and-Use Tables Integrated into a Global Multiregional Input-Output Table. *NBER Working Paper*, No 25155, National Bureau of Economic Research

Miller, R. E., & Blair, P. D. (2009). *Input-output analysis: foundations and extensions*. Cambridge university press.

Oksanen, E. H., & Williams, J. R. (1992). An alternative factor-analytic approach to aggregation of input–output tables. *Economic Systems Research*, 4(3), 245-256

Olabisi, M. (2020). Input–output linkages and sectoral volatility. *Economica*, 87(347), 713-746

Pasten, E., Schoenle, R., & Weber, M. (2020). The propagation of monetary policy shocks in a heterogeneous production economy. *Journal of Monetary Economics*, 116, 1-22

Prataviera, L. B., Bosio, D., and Koliousis, I. (2024). Can we increase the granularity in understanding global value chains? An integration of academic and practice perspectives to enhance future developments. *Global Business and Economics Review*, 31(1)

Quintana, J. (2022). Economic Consequences of a Trade Embargo between Russia and EU. *Analytical Article*, No. 2/22, Banco de España

Quintana, J. (2024). The Dynamics of Trade Fragmentation: a Network approach. *Working Paper Series*, forthcoming, Banco de España

Saenz, L. F. (2022). Time-varying capital intensities and the hump-shaped evolution of economic activity in manufacturing. *Journal of Macroeconomics*, 73

Sharda, S., Garikapati, V. M., Goulias, K. G., Reyna, J. L., Sun, B., Spurlock, C. A., & Needell, Z. (2024). The electric vehicles-solar photovoltaics Nexus: Driving cross-sectoral adoption of sustainable technologies. *Renewable and Sustainable Energy Reviews*, 191, 114172

Steen-Olsen, K., Owen, A., Hertwich, E. G., & Lenzen, M. (2014). Effects of sector aggregation on CO2 multipliers in multiregional input–output analyses. *Economic Systems Research*, 26(3), 284-302

Taylor, J. (1980). Aggregate Dynamics and Staggered Contracts. *Journal of Political Economy*, 88(1), 1-23

Theil, H. (1957). Linear aggregation in input-output analysis. *Econometrica*, 111-122

Weber, P. F., et al. (2025). The intersection between climate transition policies and geoeconomic fragmentation. *Occasional Paper Series*, No 366, European Central Bank

Yamano, N., Lioussis, M., & Cimper, A. (2024). Measuring greenhouse gas footprints in global production networks: New perspectives on emissions embodied in production chains and final demand patterns. *OECD Science, Technology and Industry Working Papers*, No. 2024/12

Appendix A: complementary tables and charts

Table A1. List of sectors

SECTORS IN THE STANDARD OECD TiVA ICIO TABLE
Manufacturing
Food products, beverages, and tobacco
Textiles, textile products, leather, and footwear
Wood and products of wood and cork
Paper products and printing
Coke and refined petroleum products
Pharmaceuticals, medicinal chemical, and botanical products
Chemicals and chemical products; rubber and plastics products
Other non-metallic mineral products
Basic metals
Fabricated metal products
Computer, electronic and optical equipment; electrical equipment
Machinery and equipment, not elsewhere classified (n.e.c.)
Motor vehicles, trailers, and semi-trailers
Other transport equipment
Manufacturing, n.e.c.; repair and installation of machinery and equipment
Services
Wholesale and retail trade; repair of motor vehicles
Land transport and transport via pipelines
Water transport
Air transport
Warehousing and support activities for transportation
Postal and courier activities
Accommodation and food service activities
Publishing, audiovisual and broadcasting activities
Telecommunications
IT and other information services
Financial and insurance activities
Real estate activities
Professional, scientific, and technical activities
Administrative and support services
Public administration and defence; compulsory social security
Education
Human health and social work activities
Arts, entertainment, and recreation
Other service activities

Activities of households as employers; activities of households for own use
Others
Agriculture, hunting, forestry
Fishing and aquaculture
Mining and quarrying, energy producing products
Mining and quarrying, non-energy producing products
Mining support service activities
Electricity, gas, steam, and air conditioning supply
Water supply; sewerage, waste management and remediation activities
Construction
ADDITIONAL GREEN SECTORS
Mined rare earths
Processed rare earths
Chemicals for green transition
Electric batteries
Renewable-energy equipment (mechanical)
Renewable-energy equipment (electrical)
Electric vehicles
Green electricity

Sources: OECD and authors.
Note: Some sectors (out of the 45 in the original OECD TiVA table) are aggregated for tractability reasons in the Baqaee-Farhi simulations.

Table A2. List of countries

Country	Share in world GDP PPP
Argentina	0.75
Australia	1.00
Austria	0.37
Belgium	0.45
Brazil	2.34
Brunei Darussalam	0.02
Bulgaria	0.12
Cambodia	0.06
Canada	1.38
Chile	0.34
China, People's Republic of	18.58
Colombia	0.58
Costa Rica	0.08
Croatia	0.09
Cyprus	0.03
Czech Republic	0.32
Denmark	0.25
Estonia	0.04
Finland	0.20
France	2.28
Germany	3.29
Greece	0.24
Hong Kong	0.32
Hungary	0.25
Iceland	0.02
India	7.21
Indonesia	2.49
Ireland	0.41
Israel	0.31
Italy	1.87
Japan	3.78
Kazakhstan	0.37

Korea	1.71
Lao, People’s Democratic Republic	0.04
Latvia	0.05
Lithuania	0.08
Luxembourg	0.06
Malaysia	0.68
Malta	0.02
Mexico	1.80
Morocco	0.22
Myanmar	0.03
Netherlands	0.76
New Zealand	0.16
Norway	0.26
Peru	0.32
Philippines	0.71
Poland	0.99
Portugal	0.27
Romania	0.45
Russia	2.87
Saudi Arabia	1.30
Singapore	0.43
Slovak Republic	0.13
Slovenia	0.07
South Africa	0.57
Spain	1.37
Sweden	0.42
Switzerland	0.46
Taiwan	1.00
Thailand	0.91
Tunisia	0.09
Türkiye	2.05
United Kingdom	2.33
United States	15.47
Viet Nam	0.80

Rest of the World	11.28

Sources: OECD and authors.
Note: Some countries (out of the 67 in the original OECD TiVA table) are aggregated for tractability reasons when running the Baqaee-Farhi model.

Table A3. List of green products at HS6 level

Source	HS code	Description	ISCI4	Green sector
IRA	870220	Vehicles; public transport type (carries 10 or more persons, including driver), with both compression-ignition internal combustion piston engine (diesel or semi-diesel) and electric motor for propulsion, new or used	D29	Electric vehicles
IRA	870230	Vehicles; public transport type (carries 10 or more persons, including driver), with both compression-ignition internal combustion piston engine (diesel or semi-diesel) and electric motor for propulsion, new or used	D29	Electric vehicles
IRA	870240	Vehicles; public transport type (carries 10 or more persons, including driver), with only electric motor for propulsion, new or used	D29	Electric vehicles
IRA	870340	Vehicles; with both spark-ignition internal combustion reciprocating piston engine and electric motor for propulsion, incapable of being charged by plugging to external source of electric power	D29	Electric vehicles
IRA	870350	Vehicles; with both compression-ignition internal combustion piston engine (diesel or semi-diesel) and electric motor for propulsion, incapable of being charged by plugging to external source of electric power	D29	Electric vehicles
IRA	870360	Vehicles; with both spark-ignition internal combustion reciprocating piston engine and electric motor for propulsion, capable of being charged by plugging to external source of electric power	D29	Electric vehicles
IRA	870370	Vehicles; with both compression-ignition internal combustion piston engine (diesel or semi-diesel) and electric motor for propulsion, capable of being charged by plugging to external source of electric power	D29	Electric vehicles
IRA	870380	Vehicles; with only electric motor for propulsion	D29	Electric vehicles
IRA	850650	Cells and batteries; primary, lithium	D27	Electric batteries
IRA	850680	Cells and batteries; primary, (other than manganese dioxide, mercuric oxide, silver oxide, lithium or air-zinc)	D27	Electric batteries
IRA	850690	Cells and batteries; primary, parts thereof	D27	Electric batteries
IRA	850710	Electric accumulators; lead-acid, of a kind used for starting piston engines, including separators, whether or not rectangular (including square)	D27	Electric batteries
IRA	850760	Electric accumulators; lithium-ion, including separators, whether or not rectangular (including square)	D27	Electric batteries

IRA	850780	Electric accumulators; other than lead-acid, nickel-cadmium, nickel-iron, nickel-metal hydride and lithium-ion, including separators, whether or not rectangular (including square)	D27	Electric batteries
IRA	850790	Electric accumulators; parts n.e.c. in heading no. 8507	D27	Electric batteries
IRA	854519	Carbon electrodes; with or without metal, of a kind used for other than furnaces	D27	Electric batteries
IRA	841919	Heaters; instantaneous or storage water heaters, non-electric, other than instantaneous gas water heaters	D27	Renewable energy components (electrical)
IRA	850231	Electric generating sets; wind-powered, (excluding those with spark-ignition or compression-ignition internal combustion piston engines)	D27	Renewable energy components (electrical)
IRA	850239	Electric generating sets; (excluding those with spark-ignition or compression-ignition internal combustion piston engines), other than wind powered	D27	Renewable energy components (electrical)
Other	850240	Electric rotary converters	D27	Renewable energy components (electrical)
Other	850300	Electric motors and generators; parts suitable for use solely or principally with the machines of heading no. 8501 or 8502	D27	Renewable energy components (electrical)
Critical	853400	Circuits; printed	D26	Renewable energy components (electrical)
IRA	854140	Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light-emitting diodes (LED)	D26	Renewable energy components (electrical)
IRA	854190	Electrical apparatus; parts for diodes, transistors and similar semiconductor devices and photosensitive semiconductor devices	D26	Renewable energy components (electrical)
IRA	841011	Turbines; hydraulic turbines and water wheels, of a power not exceeding 1000kW	D28	Renewable energy components (mechanical)
IRA	841012	Turbines; hydraulic turbines and water wheels, of a power exceeding 1000kW but not exceeding 10000kW	D28	Renewable energy components (mechanical)
Other	841013	Turbines; hydraulic turbines and water wheels, of a power exceeding 10000kW	D28	Renewable energy components (mechanical)
Other	841090	Turbines; parts of hydraulic turbines and water wheels, including regulators	D28	Renewable energy components (mechanical)

Other	841221	Engines; hydraulic power engines and motors, linear acting (cylinders)	D28	Renewable energy components (mechanical)
Other	841229	Engines; hydraulic power engines and motors, other than linear acting (cylinders)	D28	Renewable energy components (mechanical)
IRA	841290	Engines; parts, for engines and motors of heading no. 8412	D28	Renewable energy components (mechanical)
Other	841350	Pumps; reciprocating positive displacement pumps, n.e.c. in heading no. 8413, for liquids	D28	Renewable energy components (mechanical)
Other	841360	Pumps; rotary positive displacement pumps, n.e.c. in heading no. 8413, for liquids	D28	Renewable energy components (mechanical)
Other	841381	Pumps and liquid elevators; n.e.c. in heading no. 8413	D28	Renewable energy components (mechanical)
Other	841391	Pumps; parts thereof	D28	Renewable energy components (mechanical)
IRA	841861	Heat pumps; other than air conditioning machines of heading no. 8415	D28	Renewable energy components (mechanical)
IRA	841950	Heat exchange units; not used for domestic purposes	D28	Renewable energy components (mechanical)
IRA	280450	Boron; tellurium	D20	Chemical products for EV batteries or solar panels
IRA	280461	Silicon; containing by weight not less than 99.99% of silicon	D20	Chemical products for EV batteries or solar panels
Other	280469	Silicon; containing by weight less than 99.99% of silicon	D20	Chemical products for EV batteries or solar panels
IRA	280480	Arsenic	D20	Chemical products for EV batteries or solar panels
IRA	280519	Alkali or alkali-earth metals; other than sodium and calcium	D20	Chemical products for EV batteries or solar panels
IRA	280530	Earth-metals, rare; scandium and yttrium, whether or not intermixed or interalloyed	D20	Chemical products for EV batteries or solar panels

Critical	281410	Ammonia; anhydrous	D20	Chemical products for EV batteries or solar panels
IRA	281910	Chromium trioxide	D20	Chemical products for EV batteries or solar panels
IRA	281990	Chromium oxides and hydroxides; excluding chromium trioxide	D20	Chemical products for EV batteries or solar panels
IRA	282010	Manganese dioxide	D20	Chemical products for EV batteries or solar panels
IRA	282090	Manganese oxides; excluding manganese dioxide	D20	Chemical products for EV batteries or solar panels
IRA	282200	Cobalt oxides and hydroxides; commercial cobalt oxides	D20	Chemical products for EV batteries or solar panels
IRA	282520	Lithium oxide and hydroxide	D20	Chemical products for EV batteries or solar panels
IRA	282530	Vanadium oxides and hydroxides	D20	Chemical products for EV batteries or solar panels
IRA	282560	Germanium oxides and zirconium dioxide	D20	Chemical products for EV batteries or solar panels
IRA	282580	Antimony oxides	D20	Chemical products for EV batteries or solar panels
IRA	283324	Sulphates; of nickel	D20	Chemical products for EV batteries or solar panels
IRA	283327	Sulphates; of barium	D20	Chemical products for EV batteries or solar panels
IRA	283691	Carbonates; lithium carbonate	D20	Chemical products for EV batteries or solar panels
Critical	284011	Borates; disodium tetraborate (refined borax), anhydrous	D20	Chemical products for EV batteries or solar panels
Critical	284019	Borates; disodium tetraborate (refined borax), other than anhydrous	D20	Chemical products for EV batteries or solar panels

IRA	284290	Salts; of inorganic acids or peroxoacids, other than double or complex silicates, including aluminosilicates, whether or not chemically, excluding azides	D20	Chemical products for EV batteries or solar panels
IRA	284610	Cerium compounds	D20	Chemical products for EV batteries or solar panels
IRA	284690	Compounds, inorganic or organic (excluding cerium), of rare-earth metals, of yttrium, scandium or of mixtures of these metals	D20	Chemical products for EV batteries or solar panels
IRA	381800	Chemical elements; doped for use in electronics, in the form of discs, wafers or similar forms; chemical compounds doped for use in electronics	D20	Chemical products for EV batteries or solar panels
IRA	390761	Poly(ethylene terephthalate); in primary forms, having a viscosity of 78ml/g or higher	D20	Chemical products for EV batteries or solar panels
IRA	390769	Poly(ethylene terephthalate); in primary forms, having a viscosity of less than 78ml/g	D20	Chemical products for EV batteries or solar panels
Other	392010	Plastics; plates, sheets, film, foil and strip (not self-adhesive), of polymers of ethylene, non-cellular and not reinforced, laminated, supported or similarly combined with other materials	D22	Chemical products for EV batteries or solar panels
IRA	392062	Plastics; plates, sheets, film, foil and strip (not self-adhesive), of poly(ethylene terephthalate), non-cellular and not reinforced, laminated, supported or similarly combined with other materials	D22	Chemical products for EV batteries or solar panels
IRA	392099	Plastics; plates, sheets, film, foil and strip (not self-adhesive), of plastics n.e.c. in heading no. 3920, non-cellular and not reinforced, laminated, supported or similarly combined with other materials	D22	Chemical products for EV batteries or solar panels
Other	392111	Plastics; plates, sheets, film, foil and strip, of polymers of styrene, cellular	D22	Chemical products for EV batteries or solar panels
Other	392112	Plastics; plates, sheets, film, foil and strip, of polymers of vinyl chloride, cellular	D22	Chemical products for EV batteries or solar panels
Other	392113	Plastics; plates, sheets, film, foil and strip, of polyurethanes, cellular	D22	Chemical products for EV batteries or solar panels
Other	392114	Plastics; plates, sheets, film, foil and strip, of regenerated cellulose, cellular	D22	Chemical products for EV batteries or solar panels
Other	392119	Plastics; plates, sheets, film, foil and strip, of plastics n.e.c. in heading no. 3921, cellular	D22	Chemical products for EV batteries or solar panels

Other	392190	Plastics; plates, sheets, film, foil and strip, other than cellular	D22	Chemical products for EV batteries or solar panels
IRA	262091	Slag, ash and residues; (not from the manufacture of iron or steel), containing antimony, beryllium, cadmium, chromium or their mixtures	D24	Processed rare Earth
IRA	711011	Metals; platinum, unwrought or in powder form	D24	Processed rare Earth
IRA	711019	Metals; platinum, semi-manufactured	D24	Processed rare Earth
IRA	711021	Metals; palladium, unwrought or in powder form	D24	Processed rare Earth
IRA	711029	Metals; palladium, semi-manufactured	D24	Processed rare Earth
IRA	711031	Metals; rhodium, unwrought or in powder form	D24	Processed rare Earth
IRA	711039	Metals; rhodium, semi-manufactured	D24	Processed rare Earth
IRA	711041	Metals; iridium, osmium, ruthenium, unwrought or in powder form	D24	Processed rare Earth
IRA	711049	Metals; iridium, osmium, ruthenium, semi-manufactured	D24	Processed rare Earth
Other	720221	Ferro-alloys; ferro-silicon, containing by weight more than 55% of silicon	D24	Processed rare Earth
IRA	720241	Ferro-alloys; ferro-chromium, containing by weight more than 4% of carbon	D24	Processed rare Earth
IRA	720249	Ferro-alloys; ferro-chromium, containing by weight 4% or less of carbon	D24	Processed rare Earth
IRA	720280	Ferro-alloys; ferro-tungsten and ferro-silico-tungsten	D24	Processed rare Earth
IRA	720292	Ferro-alloys; ferro-vanadium	D24	Processed rare Earth
IRA	720293	Ferro-alloys; ferro-niobium	D24	Processed rare Earth
IRA	740200	Copper; unrefined, copper anodes for electrolytic refining	D24	Processed rare Earth
IRA	740311	Copper; refined, unwrought, cathodes and sections of cathodes	D24	Processed rare Earth
IRA	740500	Copper; master alloys of copper	D24	Processed rare Earth
Critical	740620	Copper; powders of lamellar structure, flakes	D24	Processed rare Earth

Critical	740990	Copper; plates, sheets and strip, of a thickness exceeding 0.15mm, of copper alloys (other than copper-zinc base alloys, copper-tin base alloys, copper-nickel base alloys or copper-nickel-zinc base alloys)	D24	Processed rare Earth
Critical	741021	Copper; foil, backed with paper, paperboard, plastics or similar backing material, of a thickness (excluding any backing) not exceeding 0.15mm, of refined copper	D24	Processed rare Earth
Critical	750400	Nickel; powders and flakes	D24	Processed rare Earth
Critical	750120	Nickel; oxide sinters and other intermediate products of nickel metallurgy	D24	Processed rare Earth
IRA	750210	Nickel; unwrought, not alloyed	D24	Processed rare Earth
Critical	760320	Aluminium; powders of lamellar structure, flakes	D24	Processed rare Earth
IRA	780191	Lead; unwrought, unrefined, containing by weight antimony as the principal other element	D24	Processed rare Earth
Critical	780199	Lead; unwrought, unrefined, not containing by weight antimony as the principal other element	D24	Processed rare Earth
IRA	810411	Magnesium; unwrought, containing at least 99.8% by weight of magnesium	D24	Processed rare Earth
Critical	810419	Magnesium; unwrought, containing less than 99.8% by weight of magnesium	D24	Processed rare Earth
Critical	810490	Magnesium; articles n.e.c. in heading no. 8104	D24	Processed rare Earth
Critical	810820	Titanium; unwrought, powders	D24	Processed rare Earth
IRA	810920	Zirconium; unwrought, powders	D24	Processed rare Earth
IRA	811010	Antimony and articles thereof; unwrought antimony, powders	D24	Processed rare Earth
Critical	811100	Manganese; articles thereof, including waste and scrap	D24	Processed rare Earth
IRA	811212	Beryllium and articles thereof; unwrought beryllium, powders	D24	Processed rare Earth
IRA	811219	Beryllium and articles thereof; wrought other than waste and scrap	D24	Processed rare Earth
IRA	811221	Chromium and articles thereof; unwrought chromium, powders	D24	Processed rare Earth
IRA	811292	Gallium, germanium, hafnium, indium, niobium (columbium), rhenium and vanadium; articles	D24	Processed rare Earth

		thereof, unwrought, including waste and scrap, powders		
IRA	811299	Gallium, germanium, hafnium, indium, niobium (columbium), rhenium and vanadium; articles thereof, other than unwrought including waste and scrap and powders	D24	Processed rare Earth
IRA	250410	Graphite; natural, in powder or in flakes	D08	Mined rare earth
IRA	251110	Barium sulphate (barytes); natural	D08	Mined rare earth
Other	252921	Fluorspar; containing by weight 97% or less of calcium fluoride	D08	Mined rare earth
IRA	252922	Fluorspar; containing by weight more than 97% of calcium fluoride	D08	Mined rare earth
IRA	260200	Manganese ores and concentrates, including ferruginous manganese ores and concentrates with a manganese content of 20% or more, calculated on the dry weight	D07	Mined rare earth
IRA	260400	Nickel ores and concentrates	D07	Mined rare earth
IRA	260500	Cobalt ores and concentrates	D07	Mined rare earth
Critical	260600	Aluminium ores and concentrates	D07	Mined rare earth
IRA	260800	Zinc ores and concentrates	D07	Mined rare earth
IRA	260900	Tin ores and concentrates	D07	Mined rare earth
IRA	261000	Chromium ores and concentrates	D07	Mined rare earth
IRA	261100	Tungsten ores and concentrates	D07	Mined rare earth
Critical	261390	Molybdenum ores and concentrates; other than roasted	D07	Mined rare earth
IRA	261400	Titanium ores and concentrates	D07	Mined rare earth
IRA	261510	Zirconium ores and concentrates	D07	Mined rare earth
IRA	261590	Niobium, tantalum, vanadium ores and concentrates	D07	Mined rare earth
IRA	261710	Antimony ores and concentrates	D07	Mined rare earth

Sources: US administration, European Commission, and authors.
Note: HS (Harmonized commodity description and coding System) codes refer to the 2017 version. International Standard Industrial Classification of all economic activities (ISIC) codes refer to revision 4.

Appendix B: Assumptions on green transition

Assumptions are based on International Energy Agency (IEA) scenarios. **Tables B1 and B2** presents assumptions as growth factor: i.e., a value of 3 means that final demand will be 3 times higher in 2030 compared to now.

B1. Demand of electric vehicles and electric batteries

As assumptions for electric batteries are not directly available, we take the same as for electric vehicles. We derive them the number of electric vehicles projected to be sold in each country or region by 2030 under the *"announced policies"* scenario of the IEA's Global EV Data Explorer, compared with 2020.[30] We further multiply these sales by the ratio of electric vehicles sold in the *"net zero"* scenario of the IEA's Net Zero by 2050.[31] As projections in *"net zero"* are global – instead of by countries / regions in the *"announced policies"* – the same ratio is applied to every region. This provides growth factors in **Table B1**.

Table B1. Growth of final demand in electric vehicles and batteries	
Country / region	**Growth factor**
European countries	10.6
USA	40.1
China	19.4
Other countries	18.9

B2. Demand of renewable-energy equipment

We use similar assumptions for electrical (e.g., solar panels) and mechanical (e.g., wind turbines) components, as assumptions separating the two are not available. We derive them from the total capacity in renewables projected in each country or region by 2030 under the *"accelerated case"* of the IEA's Renewables Data Explorer, compared with 2020.[32] We further multiply these capacities to account for the *"net zero"* scenario of the IEA's Net Zero by 2050.

30 The *"announced policy"* scenario projects the growth of EV adoption based on current government policies and commitments, without any new or additional policy interventions.

31 The *"net zero by 2050"* scenario assumes policies needed to achieve a balance between the amounts of greenhouse gases emitted into the atmosphere and removed from it. The ratio are world EV sales in 2030 under the *"net zero"* (available here) on the world EV sales in 2030 under the *"announced policy"* scenario (available here).

32 The *"accelerated case"* envisions a faster deployment of renewable energy technologies than currently planned, driven by enhanced policy support and technological advancements.

As projections in *"net zero"* are global – instead of by countries in the *"accelerated case"* – the same ratio is applied to every region.[33] This provides growth factors in **Table B2**.

Table B2. Growth of final demand of renewable-energy equipment	
Country / region	**Growth factor**
Argentina	2.7
Australia	4.8
Belgium	3.2
Brazil	3.2
Canada	2.2
China	5.1
Denmark	4.1
France	3.4
Germany	3.7
India	4.7
Indonesia	4.4
Italy	2.9
Japan	2.8
Korea	4.6
Mexico	2.7
Netherlands	6.5
Philippines	4.4
Poland	8.5
Russia	2.0
South Africa	5.6
Spain	4.5
Sweden	3.0
Thailand	2.7
Turkey	3.8
UK	3.7
USA	4.2
Vietnam	3.6

33 The ratio is the world capacity in 2030 under the *"net zero"* (available here) on the world capacity in 2030 under the *"accelerated case"* (available here).

Other countries	4.1

B3. Share of renewables in electricity

We start from the share of renewables (hydro, wind, and solar) in energy consumption use in 2020 from the IEA's Modern Renewables page. As projections are not available by country, we use the world assumptions on the share of renewables in energy consumption under the *"net zero"* scenario: compared with world's energy consumption in 2020, this provides a ratio of increase in the use of renewables. We apply this ratio to all countries, which provides the share of renewables in energy consumption projected in 2030 for individual countries.[34] But we need to use this in ICIO table where the relevant sector (D35 in ISIC4) is not limited to electricity but includes all utilities (gas, steam, and air conditioning), so we rescale this share by the share of electricity in utilities. Using US BEA's ICIO (which are granular enough to decompose utilities in its different constituents), electricity is found to account for 85% of utilities. Using the figures from 2020 and 2030 then provides assumptions of **Table B3**.

Table B3. Share of renewable (solar, wind, hydro) in utilities consumption

Country / region	**2020**	**2030**
Argentina	0.115	0.212
Australia	0.134	0.248
Austria	0.442	0.808
Belgium	0.152	0.280
Brazil	0.574	0.808
Bulgaria	0.260	0.480
Cambodia	0.281	0.518
Canada	0.295	0.543
Chile	0.330	0.608
China	0.137	0.253
Colombia	0.287	0.529
Costa Rica	0.426	0.784
Croatia	0.400	0.737
Cyprus	0.186	0.342

34 For some countries with high shares of renewables, this can however push the share of renewables to unreachable values – we set a maximum of 95% to reflect this.

Czech Republic	0.210	0.386
Denmark	0.491	0.808
Estonia	0.494	0.808
Finland	0.587	0.808
France	0.208	0.384
Germany	0.230	0.423
Greece	0.248	0.457
Hungary	0.182	0.336
Iceland	0.808	0.808
India	0.219	0.403
Indonesia	0.161	0.297
Ireland	0.169	0.311
Israel	0.069	0.128
Italy	0.231	0.425
Japan	0.104	0.192
Kazakhstan	0.022	0.041
Korea	0.045	0.082
Laos	0.297	0.546
Latvia	0.541	0.808
Lithuania	0.392	0.721
Luxembourg	0.257	0.473
Malaysia	0.072	0.133
Malta	0.113	0.209
Morocco	0.097	0.179
Myanmar	0.080	0.147
Mexico	0.152	0.281
Netherlands	0.133	0.246
New Zealand	0.354	0.651
Norway	0.758	0.808
Peru	0.238	0.438
Philippines	0.128	0.235
Poland	0.199	0.367
Portugal	0.386	0.710
Romania	0.297	0.547

Russia	0.046	0.085
Singapore	0.011	0.021
Slovakia	0.218	0.402
Slovenia	0.277	0.510
South Africa	0.048	0.089
Spain	0.239	0.440
Sweden	0.722	0.808
Switzerland	0.326	0.600
Taiwan	0.137	0.253
Thailand	0.212	0.391
Turkey	0.169	0.312
UK	0.167	0.307
USA	0.138	0.254
Vietnam	0.196	0.361
Other countries	0.156	0.287

Acknowledgements

We are very grateful to R. Giacomini, one anonymous referee, and participants of the IRC Network on Climate Change for useful comments. We thank L. Hespert and E. Olsson Kaalhus for excellent research assistance. The authors do not have any competing interest to declare.
The views expressed in this paper are those of the authors and do not necessarily represent those of the European Central Bank or Banca d'Italia.

Maria-Grazia Attinasi
European Central Bank, Frankfurt am Main, Germany; email: maria_grazia.attinasi@ecb.europa.eu

Lukas Boeckelmann
European Central Bank, Frankfurt am Main, Germany; email: lukas.boeckelmann@ecb.europa.eu

Bernardo de Castro Martins
European Central Bank, Frankfurt am Main, Germany; email: bernardocfmartins@gmail.com

Baptiste Meunier
European Central Bank, Frankfurt am Main, Germany; email: baptiste.meunier@ecb.europa.eu

Alessandro Borin
Bank of Italy, Rome, Italy; email: alessandro.borin@bancaditalia.it

Francesco Paolo Conteduca
Bank of Italy, Rome, Italy; email: francescopaolo.conteduca@bancaditalia.it

Michele Mancini
Bank of Italy, Rome, Italy; email: michele.mancini@bancaditalia.it

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

PDF ISBN 978-92-899-7510-0 ISSN 1725-2806 doi:10.2866/6396260 QB-01-25-258-EN-N