

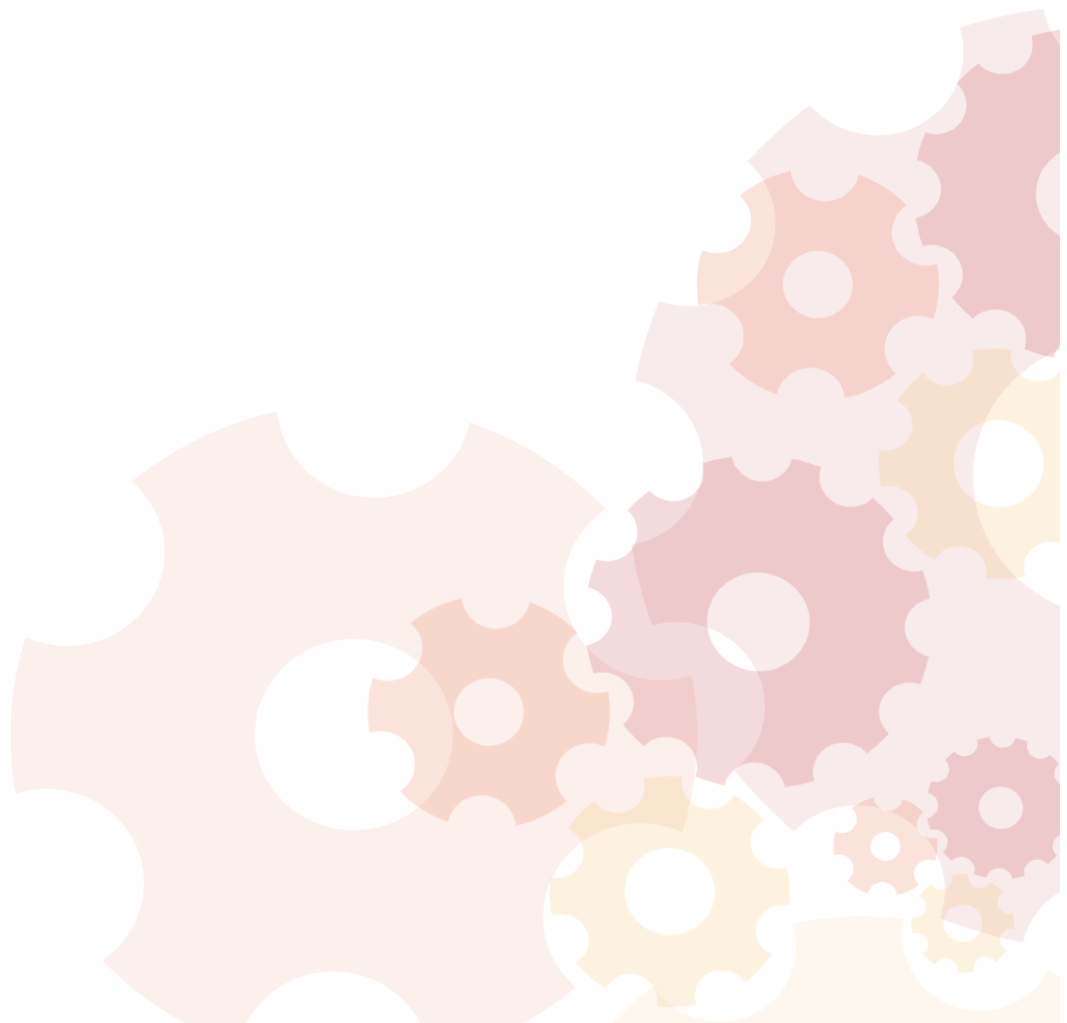


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Arnaud Persenda and Adria Rius

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Centre for Sustainable Structural Transformation

SOAS University of London

Thornhaugh Street, Russell Square, London WC1H 0XG, UK

E-mail: csst@soas.ac.uk

www.soas.ac.uk/research/research-centres/centre-sustainable-structural-transformation

Mapping hierarchical input networks: a novel method and an application to AIPNET

CSST Working Paper Number: 020

Arnaud Persenda¹ and Adria Rius²

Abstract

The recent emergence of product-level input-output datasets provides an unprecedented opportunity to model supply chains. This paper introduces the Hierarchical Inputs Network (HIN), a method to map the supply chain of any specific product at the 4- and 6-digit HS code level. The method builds on the AIPNET product-level input-output dataset (Fetzer et al., 2024) and addresses an important limitation in this dataset, namely that it does not distinguish between direct and indirect relationships between products. This distinction matters because supply chains are tiered systems, and understanding how countries engage with those supply chains means knowing not just what inputs feed into a final good, but at what stage they do so. The HIN resolves this with an algorithm that retains only direct input-output linkages and structures inputs hierarchically. The method is replicable for any product in AIPNET, and compatible with international trade data. We validate the HIN on the automotive supply chain and show its scalability to other products. We conclude by proposing avenues for further research based on the questions, old and new, that this method enables us to address.

Keywords: automotive, diversification, global supply chains, local integration, hierarchical inputs network, input-output analysis

JEL classification: C67, F14, O33, L14, L23, L62

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¹Post-doctoral fellow, Centre for Sustainable Structural Transformation, Department of Economics, SOAS University of London.

²Lecturer and affiliated researcher to the Centre for Sustainable Structural Transformation, Department of Economics, SOAS University of London.

1 Introduction

Over the past 30 years, global trade has been shaped by outsourcing and offshoring strategies and the resulting unbundling of production both vertically and horizontally (Baldwin, 2006). Understanding a country's position in such a complex web of trade has therefore been an important area of research in the past few decades. Significant efforts have been devoted to map global supply chains and identify not only a country's position in these supply chains, but also how such position conditions pathways of long-term development. Yet extant methodologies still fall short of what is needed.

An important constraint in modelling supply chain networks has been data availability. Empirical and methodological research has focused on three main approaches. First, the Global Value Chain and Global Production Network literatures have conducted thorough qualitative case-study based analysis following the seminal work of Humphrey (2000); Gereffi et al. (2005); Henderson et al. (2002). A second approach has consisted of sector-level input-output (IO) data analysis, both at the aggregate and value added levels (Antràs et al., 2012; Timmer et al., 2015; Koopman et al., 2014). Third, product-level input-output analysis is more recently emerging as a promising alternative. The latter product-level IO data bases are built leveraging different data sources such as trade (Karbevaska and Hidalgo, 2025), rules of origin (Conconi et al., 2018), firm transactions (O'Clery et al., 2025), and LLMs (Fetzer et al., 2024).

This paper addresses a limitation in the AIPNET LLM-generated product-level input-output dataset (Fetzer et al., 2024). The dataset does not distinguish between direct and indirect links between products. That means that the incoming links into a node are a mix of direct and indirect inputs, and its outgoing links similarly mix the products it feeds directly and indirectly. This is particularly critical when the goal is to analyse a specific product's supply chain, given that the obtained input list for the product of interest is not a hierarchically ordered set of products but an undifferentiated pool of every input, direct and indirect, that goes into the product of interest. This understanding of inputs, where they are not hierarchically structured, limits the use of this dataset to understand countries' participation in global supply chains.

To address this issue, the paper introduces the Hierarchical Inputs Network (HIN) method. The HIN enables the construction of ego network models for any product of choice by distinguishing between direct and indirect inputs, thereby structuring its full supply chain into a hierarchical and tiered network. The method computes a network-specific and chain-specific downstreamness measures which are then used to rank inputs based on their downstreamness from the product of choice. Subsequently, it prioritises IO relationships connecting products in sequence. As a result, we are able to construct product-specific tiered supply chain structures. The methodology is scalable across any 4- and 6-digit HS products present in AIPNET, and compatible with international trade data.

After reviewing the literature in the next section, the HIN method is presented in Section 3. Section 4 validates the HIN focusing on the automotive supply chain. The structural features of the HIN-generated automotive supply chain are compared to those of AIPNET. Then, a comparative case study across China, Japan, Morocco, and South Africa is employed to validate the HIN against existing literature about these countries' automotive supply chain dynamics. Finally, the HIN's scalability is showcased by applying it to three other products. Section 5 concludes with potential avenues for further research.

2 Literature review

Over the past three decades, global supply chains have become increasingly relevant as a result of the vertical and horizontal unbundling of economic activity across firms and locations (Baldwin, 2006). Increased integration across countries have also posed global-structural challenges related to systemic shock propagation and inflationary pressures. Similarly, they have reshaped development prospects as countries seek to participate in those supply chains while developing local linkages (Taglioni and Winkler, 2016). Yet traditional tools to analyse global value chain dynamics have often been limited. We distinguish below three approaches to the empirical mapping of supply chains and position this paper as contributing to the third approach.

The first approach is closely linked to the literature on Global Value Chains (Gereffi et al., 2005; Humphrey and Schmitz, 2002) and Global Production Networks (Henderson et al., 2002; Yeung and Cœ, 2015). These have relied on qualitative information drawn from primary and secondary sources such as interviews and industry reports. It has produced influential insights into the governance and organisational dimensions of supply chains and their territorial (dis)embeddedness. While these studies offer detailed actor-based value chain-level understanding of supply chain dynamics, they have often prioritised depth over scalability (i.e. large-scale cross-country and cross-value chain comparisons). Systematic quantitative comparative analysis enabled by progress in modelling supply chains could complement value chain analyses while enhancing scalability.

The second set of studies are affiliated to the IO framework (Leontief, 1951). They have usually relied on sector-level IO datasets at different geographical scales (Antràs et al., 2012; Bahar et al., 2019; Los et al., 2015; Johnson and Noguera, 2012). Those datasets model and quantify the interdependencies between industries. IO tables offer a comprehensive representation of production linkages and have been central to the analysis of sectoral interdependencies, revealing how seemingly unrelated industries are connected within supply chains. It is within this context that a new literature emerged aiming at modelling production networks leveraging sectoral IO data (Carvalho, 2014; Cerina et al., 2015).

The development of Global Multi-Region Input-Output models (GMRIO) (Timmer et al., 2015; MRIO, 2013; ICIO, 2026) has further expanded this perspective by enabling the study of global production networks (Carvalho, 2014; Cerina et al., 2015) and the geographic distribution of value added along global supply chains (Koopman et al., 2014). These datasets can be turned into network model of the global economy. The first being the World Input-Output Network (WION), introduced in Carvalho (2014) and formalized in (Cerina et al., 2015), which are networks where each node represent country-industry pairs and flows represent the size of the input flow from one industry to another.

Since the WIOD was the first GMRIO dataset to provide consistent yearly time series for each flow, it became possible to analyse the evolution of individual country-industries in the network between 1995 and 2011. This approach has enabled the study of shock transmission between global industries (Baqæe, 2018). Despite these advances, IO datasets are generally aggregated at the sector and country levels and provide limited granularity at the product level. This high degree of aggregation constrains their ability to capture fine production relationships and product-specific interdependencies.

A third strand of the literature has attempted to develop product-level IO linkages. These have used trade data (Karbevaska and Hidalgo, 2025), rules of origin (Conconi et al., 2018), firm-level transaction

data (O’Clery et al., 2025), and LLMs (Fetzer et al., 2024). Product-level input-output datasets offer an unprecedented opportunity to study supply chains at a fine level of disaggregation. However, focusing on the AI-generated Production Network (AIPNET) (Fetzer et al., 2024), but likely applicable to other product-level IO datasets, a key limitation is the conflation of direct and indirect inputs. This means that, when the interest is in a single product’s supply chain, the obtained input list is unstructured and does not preserve the typical tiered hierarchical system of supply chains.

Against this background, this paper addresses the above-mentioned limitation by developing a method, the HIN method, to hierarchically structure supply chains for any product across HS 4- and 6-digit codes. The next section introduces this method.

3 Modelling the hierarchical inputs network for specific supply chains

3.1 Data

The HIN is developed building on AIPNET (Fetzer et al., 2024). AIPNET is generated using a Large Language Model (LLM) which is an adapted version of GPT-4o. The LLM is asked, for each product at the 4- or at the 6-digits level, which products are used in its production. Each query is repeated roughly one hundred times to obtain a stable answer. Second, for every product pair identified as linked in the first stage, ChatGPT is again queried about one hundred times to explain the pairwise IO relationship. If the hundreds of answers consistently point in the same direction and indicate an actual use of one product as an input for another, the IO relationship is recorded. The AIPNET dataset has the major strength that it relies on BEC and HS classifications with very high granularity, at the 6-digit level.

As noted earlier, AIPNET does not distinguish direct from indirect links: for any node, both its incoming and outgoing links mix the two. This means that when a product’s input list is isolated, the list blends inputs directly used in the final good and inputs used upstream to produce other inputs of the final good. Leveraging the full dataset, we can aim to recover this structure. However, the problem is that this issue is structural: it holds for every node in the network. Because a product has more indirect than direct inputs, most of AIPNET links are therefore indirect IO linkages.

This is illustrated in Figure 1. It shows a simplified fictional version of the input list that is obtained when the goal is to map the supply chain of motor vehicles (HS 8703), or the *Car*, for simplicity. In a first instance, we are interested in obtaining the list of upstream products (its inputs). AIPNET gives us *Iron*, *Tube*, and *Motor*. However, this is an unstructured input list that does not recognise that *Iron* is not a direct input to *Car* but instead a direct input to *Tube* - thus an indirect input to *Motor* and *Car*. In a second step, we may try to leverage the full AIPNET network to recover the hierarchical structure between these inputs by looking at the links that exist between them. The result is a dataset where all inputs are mutually connected because direct and indirect input connections are conflated. Thus *Iron* will be connected to *Tube*, *Motor*, and *Car*.

This calls for a method that can hierarchically structure product-specific supply chains by retaining direct inputs only. Having presented the main issue, the next section introduces the algorithm that

id	Upstream	Downstream
1	Iron	Tube
2	Iron	Motor
3	Iron	Car
4	Tube	Motor
5	Tube	Car
6	Motor	Car

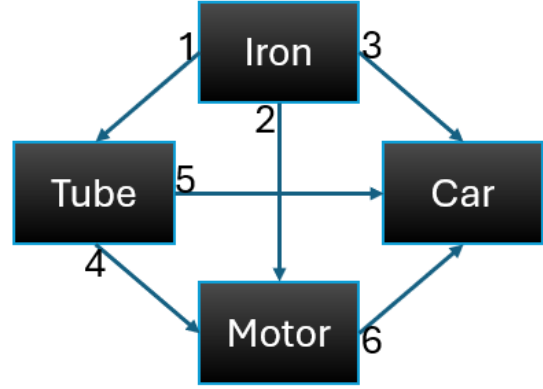


Figure 1: Simplified representation of AIPNET data for motor vehicles

Note: The table on the left is an adjacency list, that is, a list of links in which each row corresponds to a link between an upstream node and a downstream node. The figure on the right shows the corresponding network, with the id number identifying each link across the two representations.

does this.

3.2 Method

The HIN method is based on an algorithm that identifies production stages based on the idea of ranking inputs according to their downstreamness relative to the root product of choice. We then preserve only the IO linkages connecting each upstream product to its immediate downstream successor in the production sequence.

3.2.1 Notation and definitions

Let each product i be denoted by P_i . Each product is characterized by two sets:

- The **input set** $P_{P_j} = \{P_{1P_j}, \dots, P_{iP_j}, \dots, P_{nP_j}\}$ contains all products used as inputs to produce P_j .
- The **output set** $P^{P_k} = \{P^{1P_k}, \dots, P^{iP_k}, \dots, P^{nP_k}\}$ contains all products for which P_k serves as an input.

We consider a focus, or root product f , for which we will study the connection between its upstream industries. Therefore the input set P_{P_f} contains all products used as inputs to produce product f . For instance, all products within the automotive supply chain will be located within the set P_{car} .

The intersection $P_{P_f}^{P_k} = P_{P_f} \cap P^{P_k}$ represents a set of products that are both inputs of the focus product f and outputs of a specific product k . It serves to identify the products that are within a “chain of inputs”, linking products from an upstream product k to the downstream product f .

For example P_{car}^{rubber} is the input set composing the chain of inputs linking the upstream product, rubber, to the root product, car.

$$P_{car}^{rubber} = \{rubber_{car}^{rubber}, \dots, wheel_{car}^{rubber}, \dots, car_{car}^{rubber}\}$$

3.2.2 Algorithm steps

The following describes the procedure to build the HIN, also depicted in Figure 2:

- Identifying relevant products: Begin by identifying all products in the HIN P_{Pf} (e.g., motor vehicles). We identify as relevant products all products in the input set of the product P_{Pf} , to which we include P_{Pf} itself. We then subset the full AIPNET to preserve only the linkages between products from the list of relevant products. Since the focus is on intermediary inputs, we exclude all capital goods³. The resulting network is named ‘AIPNET-generated’ supply chain, which is specific to the product Pf . The AIPNET-generated supply chain of the car is modelled in Figure 4.
- Constructing product-specific subsets: Within the AIPNET-generated supply chain of Pf , for each product Pi that have been identified as input of the target product (P_{Pf}) we follow the following process: We create a subset P_{Pf}^{Pi} containing only products that are simultaneously downstream of Pi and upstream of Pf :

$$P_{Pf}^{Pi} = P_{Pf} \cap P^{Pi}$$

Each product subset P_{Pf}^{Pi} will be the basis of a chain of products from upstream product Pi to the downstream product Pf .

For example, within the motor vehicle supply chain, we denote the automotive as P_{car} . The set of all products in the automotive supply chain that are downstream of rubber is:

$$P_{car}^{rubber} = \{rubber_{car}^{rubber}, \dots, wheel_{car}^{rubber}, \dots, car_{car}^{rubber}\}$$

Where each element represents a production stage between rubber extraction and final automotive assembly.

- Computing downstreamness indicators⁴: For each product j of the subset P_{Pf}^{Pi} , calculate a downstreamness measure for every product:

$$\text{downstreamness}_j = \frac{\text{Number of Inputs}_j}{\text{Number of Outputs}_j}$$

This ratio reflects the position in the supply chain: upstream products (e.g., raw materials) have more outputs than inputs and therefore low downstreamness. Downstream products (e.g., tier 1

³Capital goods are identified using the Classification by Broad Economic Categories (BEC)

⁴Due to AIPNET’s distinct dataset structure, in particular the absence of input weights and the lack of a direct/indirect relationship distinction such as that found in Supply and Use tables, standard approaches such as that of Antràs et al. (2012) cannot be applied to measure downstreamness.

products) have more inputs than outputs and therefore high downstreamness. When a product P_f has 0 outputs, they are attributed the highest downstreamness value.

To avoid ties between downstreamness score, we generate a chain-specific upstreamness measure and a network-specific upstreamness measure:

- The network-specific downstreamness score is computed using all the products and linkages within the AIPNET-generated supply chain of product f , in our example the automobile.
 - The chain-specific downstreamness score is computed on a subset of the AIPNET-generated supply chain limited to all inputs $P_{P_f}^{P_i}$ that are simultaneously downstream of P_i and upstream of P_f .
- Order products by production stage: Rank all products in each subset $P_{P_n}^{P_i}$ by their chain-specific downstreamness score to establish a production sequence, if there is a tie we use the network-specific downstreamness ranking to identify which of the two are the most downstream:

$$P1_{P_f}^{P_i} > P2_{P_f}^{P_i} > \dots > Pk_{P_f}^{P_i} > \dots > P_f$$

Where $>$ indicates “is upstream of.” For example, within the motor vehicle supply chain:

$$rubber_{car}^{rubber} > \dots > wheel_{car}^{rubber} > \dots > car_{car}^{rubber}$$

Where each element represents a production stage between rubber extraction and final automotive assembly.

- Identify potential direct linkages: Use the ordered chains to reconstruct a simplified network showing potential direct input relationships between consecutive stages.
- Match with observed IO relationships: Through this process of creating a single chain of products from P_i to P_f , mainly unrelated products have been connected. The next step is to verify that every link is possible by matching it to an existing link in AIPNET. Links that do not exist will be rewired to other products downstream, through the following loop:
 - Validate potential linkages against the AIPNET dataset. Only IO relationships that appear both in AIPNET and as consecutive links in the ordered production chains are retained in the final simplified production network.
 - Disconnected nodes that lost their linkages, due to the IO relationship not existing are then rewired to the following downstream product.

The loop is repeated until all product pairs are part of an identified AIPNET relationship.

Figure 2 summarises this procedure, all products P_{car} that are inputs to the car value chain are first identified. For each such product $P_{i_{car}}$, we then identify the list of products that are both downstream of $P_{i_{car}}$ and upstream of car . Within each group, inputs are ordered by upstreamness, with $P_{i_{car}}$ set as the most upstream product and car set as the most downstream. Each resulting chain of products is then mapped as a list of nodes in the network. Finally, a loop is added to rewire products based on the published input list.

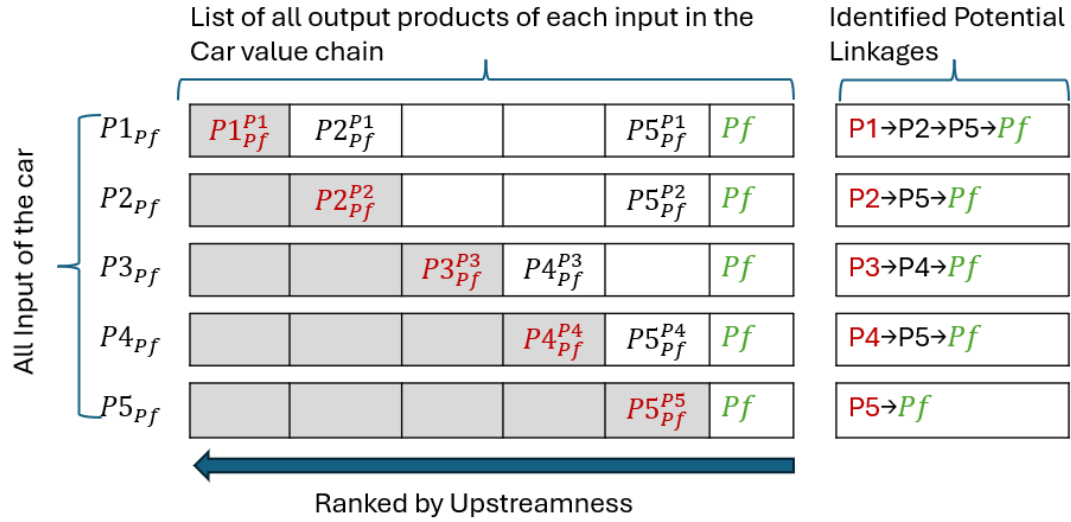


Figure 2: Identifying potential direct linkages between consecutive production stages

This procedure systematically filters the AIPNET dataset to extract direct IO relationships, removing indirect connections and revealing the sequential structure of production stages. We refer to this resulting network the 'HIN-generated' supply chain.

4 Results

In this section we present the results of the HIN algorithm. Section 4.1. discusses the general properties of the HIN-generated network in comparison to AIPNET, using the automotive supply chain as an illustration⁵. This section serves the purpose of demonstrating the advantages of the HIN algorithm. Section 4.2. showcases one of the multiple applications of the algorithm. It develops a comparative analysis of the automotive supply chain across China, Japan, Morocco, and South Africa, and compares the findings with existing evidence. This aims to validate the method by comparing its results with what we already know about these countries' automotive supply chains. Section 4.3. applies the HIN algorithm to two other final goods, bicycles (HS 8712) and refrigerators (HS 8418) and to an intermediate product, electric motors and generators (HS 8501). This showcases its scalability.

4.1 General properties of the Hierarchical Inputs Network

We begin by comparing the adjacency matrices of the automotive supply chains generated by AIPNET and HIN in Figure 3. The heatmap on the left represents the adjacency matrix for the AIPNET-generated automotive supply chain network, and the one on the right is the HIN-generated one. The x axis shows the list of inputs (upstream products) and the y axis the products in which they are used (downstream products). Products are ranked by their position in the supply chain, with the most downstream products appearing at the top of rows and to the left of columns, and the most

⁵To facilitate visualisation and understanding, the HIN is modelled at the 4-digits HS level. We use this level of disaggregation because it allows for clearer visualisation of the networks compared with the use of 6-digit codes.

upstream products at the bottom and to the right, respectively. The adjacency matrix is structured in a similar way as Figure 2, we reflect the matrix across its anti-diagonal, the diagonal running from the top-right to the bottom-left corner, so that rows become columns. Under this transformation, the element in the top-left corner moves to the bottom-right corner, following the logic of an adjacency table. The adjacency matrix is also the real representation of the simplified fictional example of the automotive supply chain developed in Figure 1.

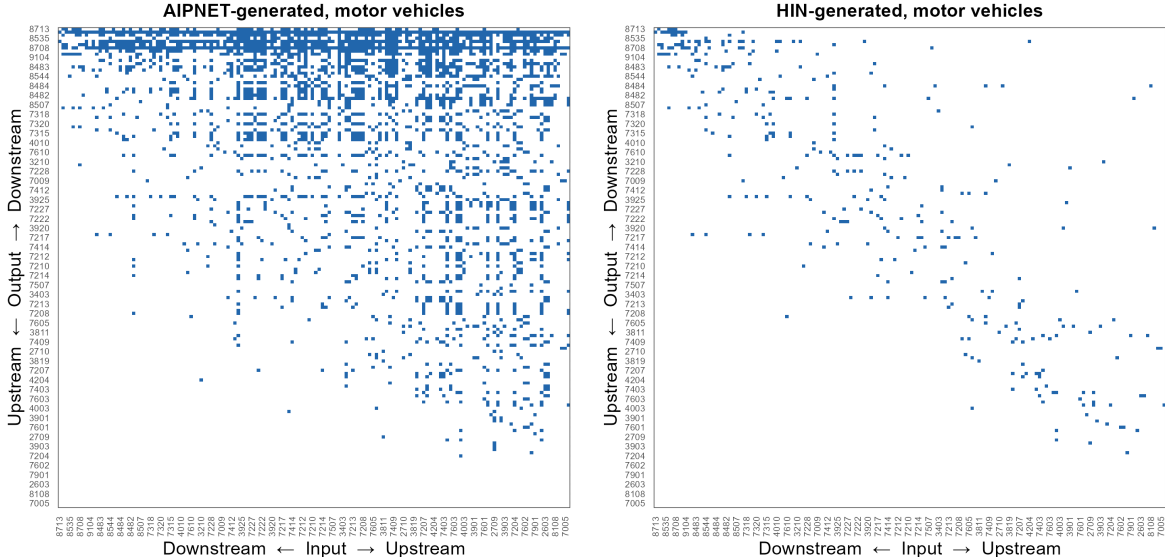


Figure 3: Comparison of AIPNET-generated and HIN-generated adjacency input-output matrices for motor vehicles

Source: author’s calculations

The Figure allows us to make two key observations. First, the triangular shape of the AIPNET-generated IO adjacency matrix is itself informative: highly downstream products are an input to only a few products, reflecting their proximity to final demand, while upstream products show a wide range of linkages. This is consistent with the long transformation chains required before inputs reach their final form. Second, the HIN-generated network simplifies the table by removing indirect links, which greatly streamlines the network while hierarchically reorganising inputs. Only links identified as direct input linkages remain. The near-diagonal shape indicates that the network connects products that are mostly at the same level of upstreamness, running from downstream (upper left corner) to upstream (lower right corner). The adjacency matrices thus point to one of the major advantages of the algorithm, namely removing indirect linkages. This is visible in the significant reduction in the number of edges when comparing HIN to AIPNET.

To compare the two network structures more formally, we rely on the network analysis description shown in Table 1. The AIPNET is considerably denser than HIN, with 2,765 links against 333, the methodology thus retaining approximately 12% of AIPNET linkages. This is reflected in an edge density of 0.12 for the AIPNET against 0.01 for HIN, where edge density denotes the ratio of observed links to the maximum number of links possible given the number of nodes. Beyond link count, the filtering also transforms network structure. Removing redundant links reveals more discrete organisational

configurations: a Louvain community detection algorithm identifies four clusters in the AIPNET and 14 in HIN. Distance-based indicators further underscore this structural divergence. The mean path length increases from 2.76 in the AIPNET to 10.28 in HIN, and the diameter, defined as the longest shortest path, rises from 12 to 48. These results indicate that nodes in the HIN are connected through considerably longer chains, reflecting a more granular articulation of production stages.

Table 1: Properties of the AIPNET- and HIN-generated automotive supply chain networks

	AIPNET	HIN		AIPNET	HIN
Number of nodes	152	152	Mean distance	2.76	10.28
Number of links	2765	333	Reciprocity	0.12	0.31
Average in/out-degree	18.19	2.19	Edge density	0.12	0.01
Max in-degree	151	17	Avrg. clustering coefficient	0.66	0.36
Max out-degree	49	12	Homophily (degree)	-0.29	0.05
Diameter	12	48	No. of clusters (Louvain)	4	14

Source: author’s calculations

Under the new structure, the inputs network is rewired to enable the re-positioning of nodes into different stages of production. This also ranks them based on product complexity, in the sense of the sub-system of components they are made of. This sorting is illustrated in Table 2, which lists the five highest and five lowest ranked products in the HIN-generated automotive supply chain by downstreamness. The products with the highest downstreamness value correspond to the first-tier components used directly as inputs to motor vehicles, while the least downstream are raw materials and minimally processed products. It is worth noting that HS 8713, *Carriages for disabled persons*, emerges as the most downstream product in the network. This is driven by the way AIPNET is built, which results in *Carriages for disabled persons* as drawing heavily on inputs from HS 8703, *Motor cars and other motor vehicles*, and carriages being retrofitted into cars, creating a circular linkage between the two products.

Finally, we compare both networks visually in figures 4 and 5. The properties of each network as depicted in Table 1 now become clearer as the density and lack of clear clutsering of the AINPET-generated network compared to HIN become clear. In the latter, products are arranged in a tree-like structure, with raw materials at the periphery progressively combined and transformed into more complex intermediates, culminating in car assembly at the centre. Inputs are also clustered, each cluster corresponding to a distinct production stage and grouping products at similar levels of processing. These clusters fall into two broad types: material processing clusters and assembly and manufacturing clusters.

Material processing clusters occupy the periphery of the network. They transform raw materials into processed inputs, with distinct clusters identifiable for aluminium, copper, iron and steel, plastics, rubber, glass, and zinc⁶. Each of these feed into clusters that convert materials into single-material components, which are in turn assembled into parts - car body parts, electronic components, vehicle engines - and ultimately into the finished automotive product. Assembly and manufacturing clusters occupy the centre of the network, with the closest nodes being bodies (HS 8707), carriages for

⁶A closer view of the car assembly nodes, with labels, is presented in Figure A1 in Appendix

Table 2: Five highest and five lowest products by network-specific downstreamness

Downstreamness	Code	Product
27.5	8713	Carriages for disabled persons, whether or not motorised
25.2	8703	Motor cars and other motor vehicles for the transport of persons
21.8	8707	Bodies (including cabs) for motor vehicles of headings 8701 to 8705
19.7	8535	Electrical apparatus for switching or protecting circuits
18.1	8714	Vehicles; parts and accessories of headings 8711 to 8713
...		
0.0	7801	Lead; unwrought
0.0	7901	Zinc; unwrought
0.0	8001	Tin; unwrought
0.0	8108	Titanium; articles thereof, including waste and scrap
0.0	8111	Manganese; articles thereof, including waste and scrap

Note: product names have been shortened for simplicity.

Source: author's calculations

disabled persons (HS 8713), chassis (HS 8706), electrical apparatus for electrical circuits (HS 8535), lightning and visual equipment (HS 8512), engines and engine parts (HS 8408, HS 8409), and vehicle and machinery parts (HS 8714, HS 8472).

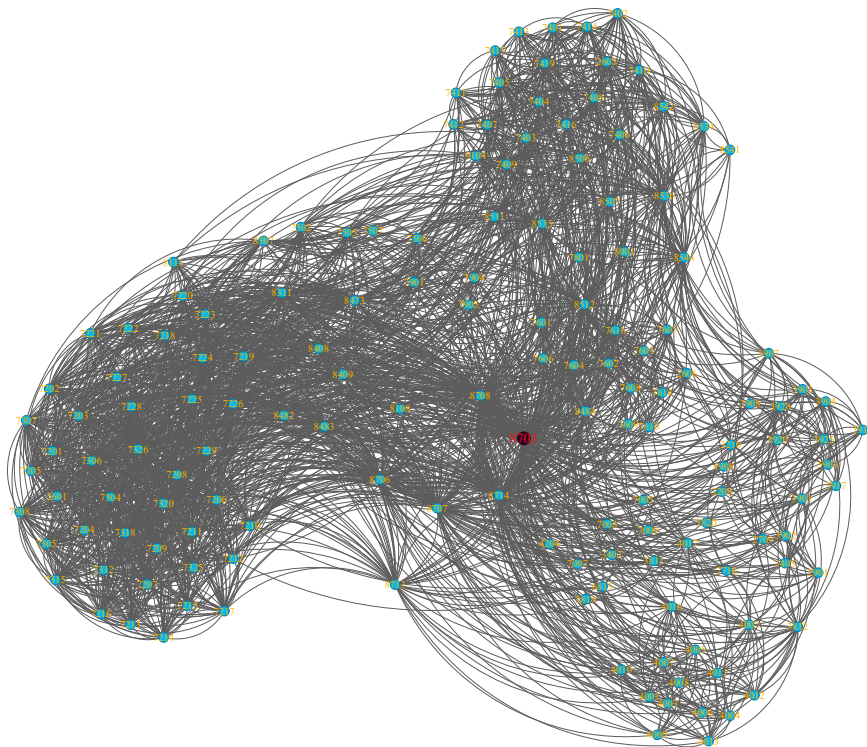


Figure 4: AIPNET-generated automotive supply chain network

Note: the red label indicates the root product, motor vehicles (HS 8703), while its inputs appear in orange.

Source: author's calculations

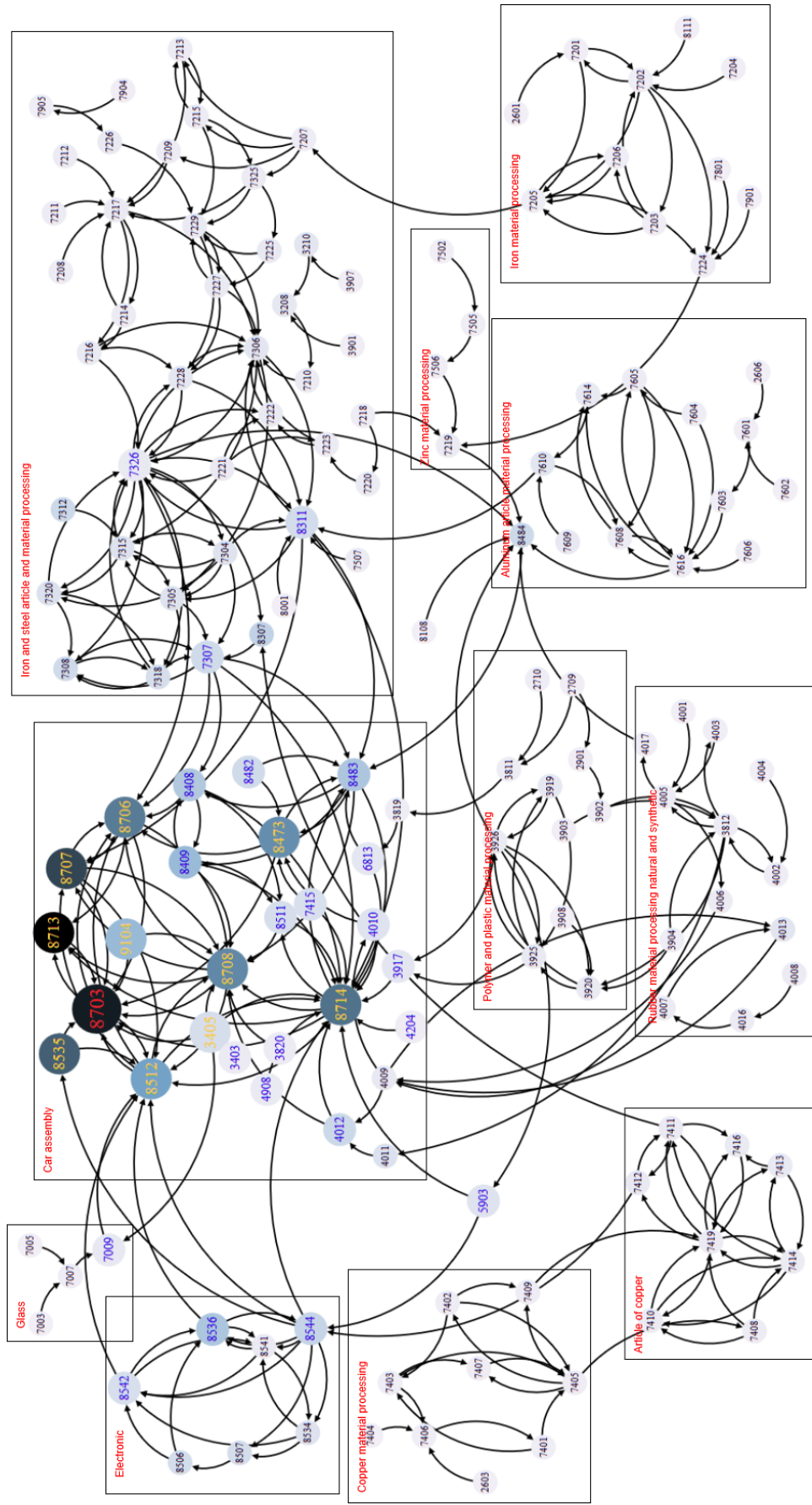


Figure 5: HIN-generated automotive supply chain network

Note: Product 8703 (Motor vehicles) is written in red and represents the main product of interest. Labels follow a three-tier colour and size scheme: red for the final good (the largest), yellow for tier 1 suppliers, and blue for tier 2 suppliers. Node colours reflect global downstream position: the darkest grey nodes are the most upstream.

Source: author's calculations

4.2 The automotive supply chain under globalisation: a comparative analysis of China, Japan, Morocco and South Africa

4.2.1 Measuring local supply chain integration

In this section we highlight one of the multiple applications of the HIN method. Extending our focus on the automotive supply chain, we explore the extent to which the HIN-generated motor vehicle supply chain can help us understand local integration patterns, meaning how countries build local capabilities across different segments of the supply chain. To do this, we first match the HIN with trade data at the product level using the BACI database (Gaulier and Zignago, 2010) for 2002-2022, capturing a period of fully-fledged globalisation. The start year is selected to align with the HS 2002 nomenclature, the end year is selected to allow the study of a 20-year period. This allows to draw three benchmark years at equal ten-year intervals: 2002, 2012, 2022. From the matched HIN-trade dataset, we construct three measures to conduct the analysis: an Integration Coefficient (IC), a trade-weighted IC, and a Centre of Gravity.

The Integration Coefficient ($IC_{i,c,t}$) is an input-level measure based on the relative importance of exports versus imports for that component. It is measured as the share of exports over total trade for that specific component c , year t , and country i , so that:

$$IC_{i,c,t} = \frac{X_{i,c,t}}{X_{i,c,t} + M_{i,c,t}}.$$

The IC allows us to identify whether a country is a net exporter of component c ($IC > 0.5$) or a net importer ($IC < 0.5$). This is interpreted as signalling whether component c is more likely to be produced domestically and competitively or abroad. The lower the IC is, the more import-dependent a country is in that component. Therefore, the IC is a simple but useful proxy for local integration of supply chain production. Countries with a net export position in a specific component are expected to produce locally more than what they import and not simply engage in re-exporting.

However, the IC cannot distinguish between countries that, for the same component, share the same IC value but differ in trade volumes. When trade volumes are large, both imports and exports are substantial because the sector is highly globalised. When trade volumes are small, this can be the result of two sub-cases: local capabilities exist but output is directed towards the domestic market, or local capabilities do not exist and that country has no meaningful activity in that segment of the supply chain. While the distinction between these latter two situations remains unresolved, a straightforward way to differentiate the first case from the second is to weight IC by trade volumes.

Applied at the country-level, the trade-weighted IC ($\overline{IC}_{i,t}$) uses the IC computed above and aggregates product-level IC across all components in the HIN, weighting each by its share of the country's total trade in the supply chain of interest:

$$\overline{IC}_{i,t} = \frac{\sum_{c \in \mathcal{C}_{i,t}^{(r)}} IC_{i,c,t} \cdot T_{i,c,t}}{\sum_{c \in \mathcal{C}_{i,t}^{(r)}} T_{i,c,t}}$$

Where $\mathcal{C}_{i,t}^{(r)}$ is the set of components linked to root product r (motor vehicles, in this case) and

observed for country i in year t , and $T_{i,c,t} = X_{i,c,t} + M_{i,c,t}$ is total trade in component c , used as the weight. This ensures that heavily traded components contribute more to the average.

A third useful measure, complementary to $\overline{IC}_{i,t}$, is developed at the country level to capture where in the supply chain a country's trade integration is concentrated: the Centre of Gravity ($CG_{i,t}$). Building on $\overline{IC}_{i,t}$, the CG is defined as a weighted average of network position across all components, where each component's weight reflects its share of total IC-weighted trade. Formally:

$$CG_{i,t} = \sum_{c \in \mathcal{C}_{i,t}^{(r)}} s_c \cdot w_{i,t,c}$$

where s_c is the network position of component c (measured by its upstream distance from the root product)⁷, and $w_{i,t,c}$ is defined as:

$$w_{i,t,c} = \frac{IC_{i,c,t} \cdot T_{i,c,t}}{\sum_{c' \in \mathcal{C}_{i,t}^{(r)}} IC_{i,c',t} \cdot T_{i,c',t}}$$

The denominator normalises across all components so that weights sum to one. Components with both high IC and large trade volume contribute more to the weighted average. A low $CG_{i,t}$ indicates that a country's local integration is concentrated in components close to the root product, while a high value indicates concentration in components far from the root product.

4.2.2 Four cases of local integration in the automotive sector: China, Japan, Morocco, South Africa

These three simple measures are used alongside the shortest path length to root and the automotive network visualisation, to compare patterns of local integration in the automotive supply chain across China, South Africa, Morocco, and Japan. These four country cases have been selected because of the extensive literature on their automotive sector and available value added sector-level evidence through the $\text{\textcircled{C}}\text{E}\text{C}\text{D}$ TiVA database⁸, which allows the HIN findings to be validated against existing knowledge. Given the complexity of most of these countries' historical engagement with the sector, the analysis below focuses on overall trends in the local build-up of supply chain capacity.

Turning first to the root product, Figure 6 shows the IC for motor vehicles (HS 8703). The heterogeneity of the pattern observed across the four countries considered provides grounds for comparative analysis. It shows how China has imported more motor vehicles than it has exported until the upward trend experienced since 2020. Japan has remained a global export hub of finished motor vehicles while experiencing a subtle declining trend. Morocco's car exports relative to imports have increased significantly since 2012. With a long history of car production, South Africa's IC coefficient remains above 0.5, with an upward (but volatile) trend since the early 2010s.

⁷We use the reverse of the downstream measure presented in Section 3 to improve intuition, so that low values are now associated with products closer to the root product - thus the name change towards an *upstream* measure.

⁸See the country highlights for 2023 in $\text{\textcircled{C}}\text{E}\text{C}\text{D}$ (2023b,c,a,d).

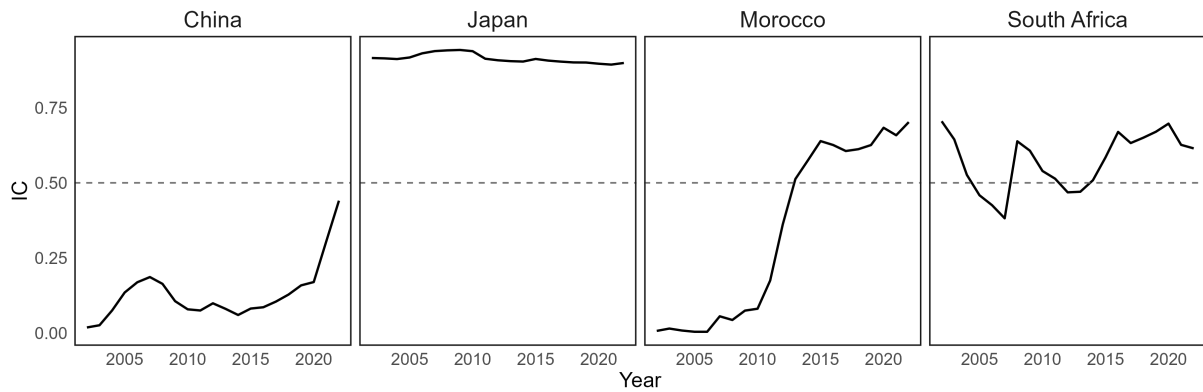


Figure 6: Integration coefficient by year and country

Source: author's calculations

The above is consistent with existing knowledge about these countries' automotive sector, where China is rapidly emerging as a global automotive leader - especially due to its leadership in the electric vehicle market (Altenburg et al., 2022). Japan is the country with the highest level of integration, while key Japanese OEMs responded to globalisation by opening plants abroad and severing ties with local suppliers, contributing to a process of 'hollowing out' of the Japanese automotive industry (Schæde, 2010). Morocco and South Africa have sought to boost automotive sector exports by localising motor vehicle assembly processes and exporting the finished good, and both have experienced reasonable success in that endeavour, especially from the mid-2010s onwards (Monaco and Schröder, 2026).

Beyond these initial insights, what the HIN allows us to do is to analyse the supply chain dynamics that underpin each country's IC position in the final product. A first insight can be gained by looking at the cumulative distribution function of products' distance from the final product including only components for which countries have an $IC > 0.5$ (Figure 7). Therefore, the plot indicates in which segments of the supply chain countries are net exporters and how that has evolved over time by comparing three points in time: 2002, 2012, 2022. The dark line shows the cumulative distribution function including all products regardless of their IC, serving as a benchmark. If all supply chain components of a country had an $IC > 0.5$, the country's cumulative distribution function would match the benchmark.

The first insight is that Japan is the country with a CDF that is closest to the benchmark, suggesting that the country is competitive in virtually all segments of the supply chain. This result confirms existing knowledge about Japan's tightly domestically integrated automotive sector. It has been argued that Japanese OEMs moved away from the traditional *keiretsu* production model and embarked in a hybridisation model combining arms-length governance relations with low-tier suppliers and the introduction of global benchmarking practices (Aoki and Lennerfors, 2013). This data shows that while some degree of 'hollowing out' of low-tier suppliers due to global competition and changes in domestic value chain governance models might be in force, it is generally slow and Japan remains competitive across virtually all stages of the supply chain.

China has come closer to Japan over time, although its distribution is slightly biased towards downstream products. This suggests that the country has locally integrated more tier 1 and tier 2 com-

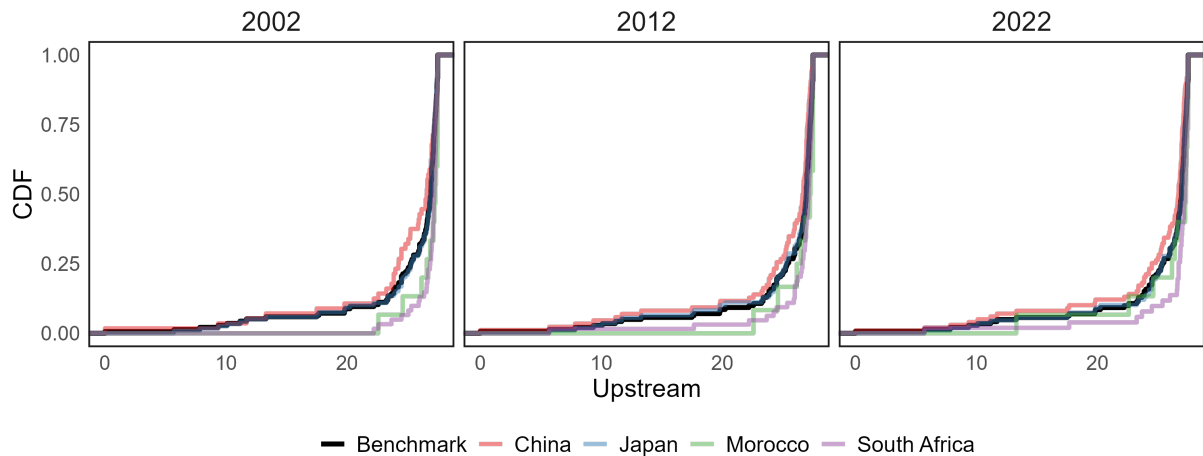


Figure 7: Cumulative distribution function of distance by country. For each country, it includes only products for which $IC > 0.5$. A benchmark CDF is introduced, which includes all products irrespective of their IC . Components closer to the root are assigned downstream values closer to one. Source: author's calculations

ponents in relation to lower-level supply chain inputs. Morocco and South Africa show a significantly different pattern. The case of Morocco is more difficult to analyse using this figure as big jumps in its CDF reflect the fact that the country's number of components with a net export position remains small. In the case of South Africa, the plot shows that the country has become more competitive in upstream segments than in stages closer to the root product.

As mentioned earlier, a key issue related to the IC measure, particularly in the case of Japan and its evolving *keiretsu* system, is that if local suppliers tend to have domestic OEMs as their main clients, the IC would not reflect the fact that both exports and imports are considerably low in absolute terms because most production remains within a country's borders. The trade-weighted IC adjusts for this and highlights whether a country's automotive supply chain is both locally integrated and globally competitive. This issue can be further addressed by considering the degree to which a country is stronger in upstream or downstream segments of the supply chain using the CG coefficient. Figure 8 shows, for each country, the average annual IC, trade-weighted IC, and the Centre of Gravity.

Starting with Japan, the plot shows a sustained decline in the IC coefficient, suggesting that Japan is indeed losing competitiveness across the supply chain. This said, it is also the case that Japan is the country with the highest IC coefficient. The trade-weighted IC shows a more volatile trend, suggesting that despite the decrease in the IC coefficient trade volumes are (at times) concentrated in those bins where IC is higher. The increase in the centre of gravity has also been gradual and positive, meaning that its strength in the value chain is moving from high- to low-tier positions. Overall, this is consistent with the fact that as local tier-1 firms have increased exports, local OEMs now rely more on foreign imports of certain inputs (Schæde, 2010).

In contrast, China has consistently increased its IC to the extent that since the early 2010s the country has a net export position in most components. The trade-weighted IC, which remains below 0.5, suggests that despite the increase in component competitiveness, a significant share of trade volumes remains concentrated in products with a lower IC. Yet the increase in this coefficient

over time also indicates that China’s growing export competitiveness in supply chain components is reflected in large trade volumes, not just marginal products. The increase in the CG coefficient is coherent with this trend, indicating an increase in background linkage development (Lee et al., 2021). This is consistent with the relatively low increase in intermediate imported inputs used for exports depicted in OECD (2023a) for the sector as a whole.

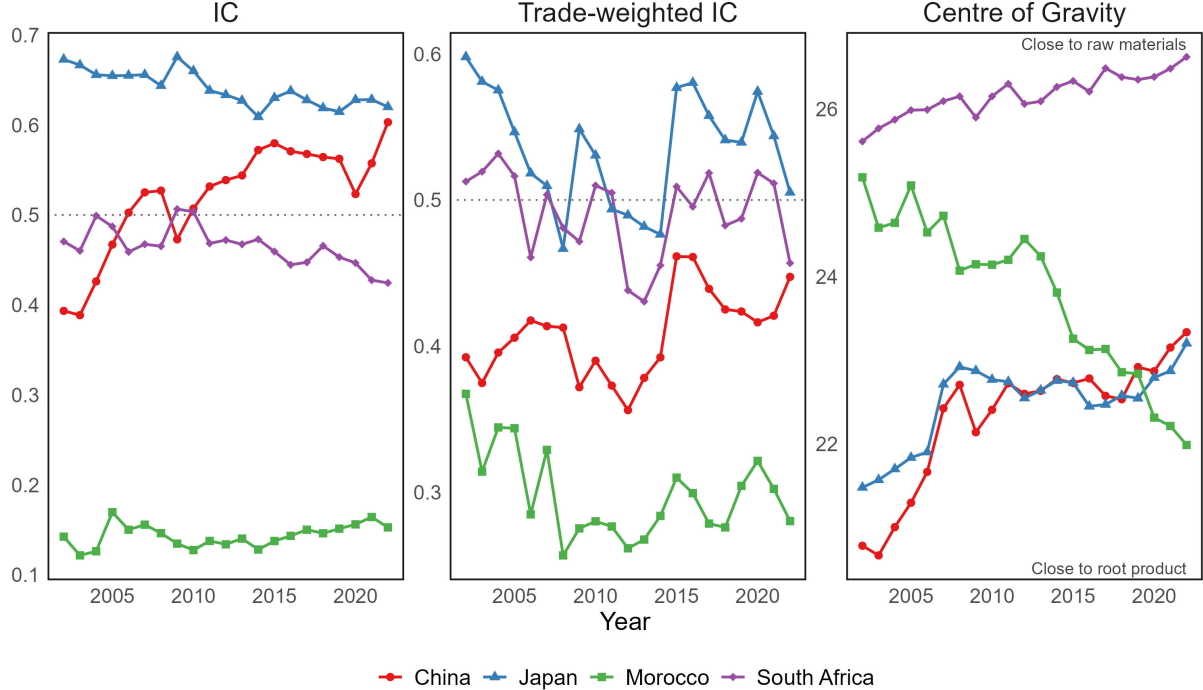


Figure 8: Evolution of IC, trade-weighted IC and Centre of Gravity.

Source: author’s calculations

The trends in Morocco and South Africa reflect these countries’ industrial policy strategies to boost exports of the finished good by prioritising assembly processes over local supply chain integration. Both governments targeted finished good exports by leveraging special economic zones, foreign market access, and foreign direct investment from automotive firms operating in the most downstream segments of the supply chain. A key difference between both countries is that while South Africa’s automotive sector has a long history, Morocco only started exporting cars at scale in the mid-2000s and early 2010s (Hahn and Auktor, 2017).

Extant analyses of the automotive sector in South Africa indicate that while the industrial policy instruments deployed by the government contributed to the successful increase in car exports, they also contributed to hollowing out the supplier base (Barnes et al., 2021). Partly, this is because of the follow-sourcing strategy of large OEMs, which contributes to localising assembly and tier 1 processes through FDI, while relying on imports for the supply of lower-tier segment components (Sturgeon et al., 2008). This translates into a decline of both the IC and trade-weighted IC over time, and an increase in the centre of gravity - which was already significantly high, showing that South Africa’s strength is much closer to raw materials than to the root product⁹.

⁹This could, of course, also be related to high trade volumes in extraction and early-stage processing of raw materials relevant to other sectors.

In Morocco, the challenge has been to link local firms with foreign automotive tier-1 and OEM firms which have established plants in the country’s SEZs. After becoming majority shareholder of the local car manufacturer Somaca in 2003, Renault started exporting cars from Morocco in 2007 and made a significant investment in a new plant in 2012, which marked a turning point in the sector (Hahn and Auktor, 2017). Yet the reliance on foreign firms combined with the lack of a pre-existing indigenous supply chain, likely underpins the low level, although increasing, IC as well as low and decreasing level of the trade-weighted IC. Yet the ex-novo creation of the tier-1 segment through FDI has moved the sector’s centre of gravity towards downstream segments.

To add nuance to the patterns above, Figure 9 plots the change in each product’s IC relative to 2002, for 2012 and 2022. Products are organised based on how far they are from the root using the shortest path length. Products that are between 1-3 links away from the root can be interpreted as tier 1 and tier 2 products, and semi-assemblies are captured by path lengths between 3-6. Those nodes that are at greater lengths consist of processed, semi-processed, and raw material goods¹⁰. While trends are largely consistent with Figure 8, decomposing the IC by path length provides greater detail about where specifically countries have gained control over certain parts of the supply chain, or alternatively have become import-dependent.

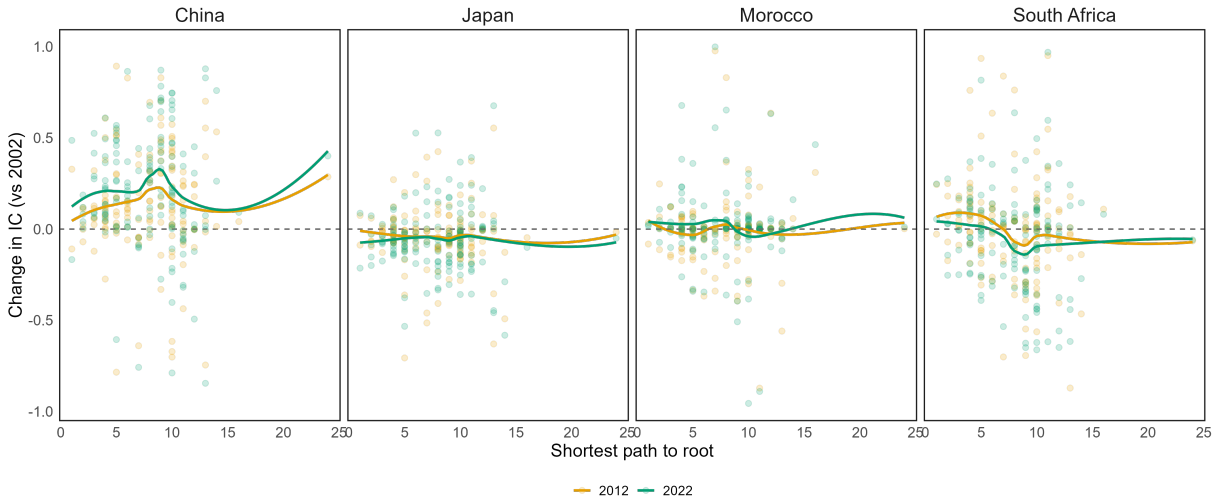


Figure 9: Where in the supply chain countries gained IC relative to 2002. Smoothed profiles for 2012 and 2022.

Source: author’s calculations

China has, overall, gained competitiveness and localised production across all supply chain segments. Yet the highest gains are concentrated in low-upstream components, where the IC has risen significantly since 2002 and in particular between 2002 and 2012. Gains have also been made in the tier 1 and tier 2 segments. The insights gained about Japan’s automotive supply chain are also well illustrated in this plot. Each year the country is farther from the 2002 baseline. Yet while most of the decrease in IC is concentrated in the top tiers, it is overall not significantly large. Thus, it corroborates the gradual decline in the local degree of integration across top-tier stages of the supply chain highlighted above, but also the qualification that the decrease in competitiveness should not be over-stated.

¹⁰See Appendix B for the list of products and their associated shortest path length value.

The case of Morocco shows an increase in the top-tier segments of the supply chain and a decrease in mid-upstream segments. While this evidence is only suggestive, the decrease in the mid-upstream segments of the value chain might align with the observation in the literature that developing linkages between foreign tier-1 firms and local low-tier firms remains a challenge (Hahn and Auktor, 2017). The increase in the top tiers is considerable but moderate considering the significant increase in the exports of the finished good. This suggests that those exports remain dependent on imports.

The case of South Africa shows, similar to Morocco, an improvement in the IC coefficient of top tier segments, especially between 2002 and 2012. At the same time, there is sustained weakening of mid-upstream components. This could indicate the de-linking of local low-tier component manufacturers as a result of increased imports for first and second-tier parts of the value chain by foreign CEMs operating in South Africa (Wuttke, 2023; Barnes et al., 2021). The disparity with Figure 8 reflects the fact that a significant part of trade, in absolute value terms, has shifted to upstream segments, which compensates for a decrease in these components IC values.

Finally, we look at these dynamics using the HIN-generated motor vehicle network visualisation. Figure 10 displays the evolution in IC between 2002 and 2022 for each of the selected countries. For each country, we highlight in blue the components for they have $IC > 0.5$. In short, the plot indicates in which segments of the supply chain countries are (or have become) net exporters. The use of an $IC > 0.5$ threshold makes the interpretation less fine-grained in comparison to the above, but it has the advantage of providing a clear binary signal making structural shifts easier to identify, and being able to directly identify specific inputs and their tiered-clusters.

Starting with China (Figure 10a, 10b), it displays one of the densest 2022 networks among the four countries. It indeed holds a net export positions across most products in the network, except for the final product. This reflects China's role as a supply-side hub and not just a downstream assembler. The electronics cluster at the top-left of each panel, corresponding to electrical and electronic components (HS 85), is heavily activated across both years. Notably, 8542 (electronic integrated circuits and microassemblies) stands as the one product for which China remains a net importer, pointing to a general sectoral position of Chinese industries as a net importer of microchips.

Between 2002 and 2022, China's network undergoes a marked densification. Active nodes increase, edge density in the electronics cluster rises, and the expansion of blue nodes signals an improvement in net export positions across additional product lines. It is significant how tier 1 nodes, those that connect directly with the root product (motor vehicles, HS 8703) have become activated. At mid-upstream levels, the expansion occurred mainly in two clusters, "polymer and plastic" and "iron and steel". Indeed, by 2022 the supply chain in China had come to converge with Japan's far more closely than it did two decades earlier. The copper material processing cluster remains, however, even in 2022, in a net importer position.

Japan presents a similarly dense and interconnected network in both years (Figure 10c and 10d), consistent with what has been discussed so far. The change between 2002 and 2022 is, therefore, more limited than China's: while export positions in the final assembly section receded in relative terms (Figure 9), it remained a net exporter. In the final assembly, only heading 8473 "Parts and accessories suitable for use solely or principally with machines" saw Japan become a net importer. On the other hand, Japan lost its net exporter position in some upstream nodes, mainly in material

processing.

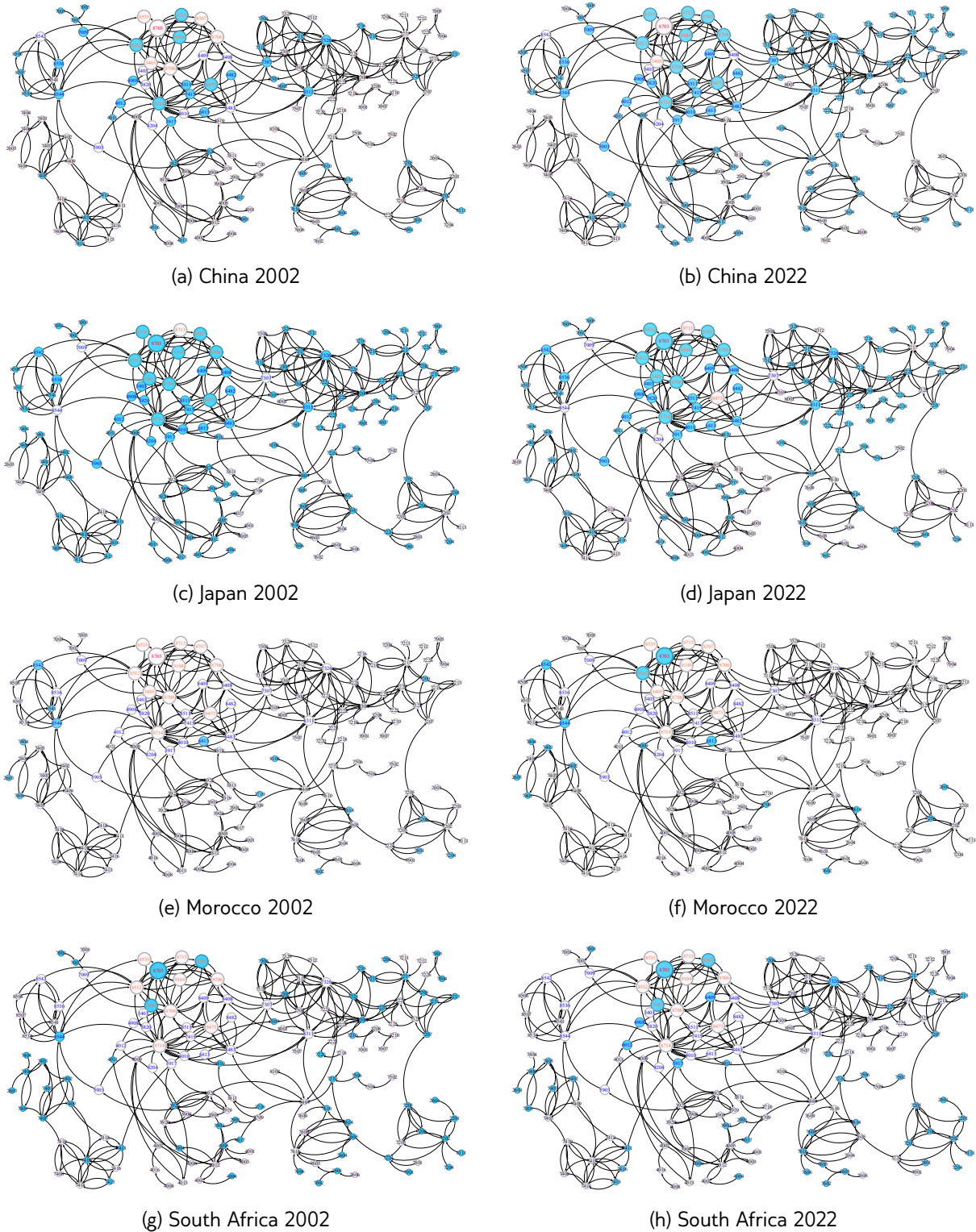


Figure 10: Automotive supply chain networks across China, Japan, Morocco and South Africa

Note: Product 8703 (motor vehicles) is written in red and represents the main product of interest. Node colours reflect the IC level: $IC \geq 0.5$ is shown in blue, corresponding to a net export position, while $IC < 0.5$ is shown in white, corresponding to a net import position. Labels follow a three-tier colour and size scheme: red for the final good (the largest), yellow for tier 1 suppliers, and blue for tier 2 suppliers.

Source: author's calculations

Aligned with the analysis so far, Morocco (Figure 10e and 10f) presents a much sparser network in 2002, with a large share of nodes carrying net import positions across a wide range of products. Changes between 2002 and 2022 show an export position in the final good, yet a limited increase in the number of net export components. This supports the literature's finding, as well as the evidence presented so far, about how Morocco has become an automotive export hub with a significant reliance on imported components. Components that become 'activated' are concentrated in the copper material processing cluster and in lighting or visual signalling equipment.

South Africa (Figure 10g and 10h) presents, in 2002, a structurally richer network than Morocco, with more activated nodes across both the mechanical and materials clusters, as well as the most upstream segments of the value chain. Yet, it clearly falls short of China and Japan. In terms of its trajectory between 2002 and 2022, South Africa's is the most ambiguous of the four. Products that held net exporter positions in 2002 appear to have weakened by 2022, particularly in the steel clusters that underpinned the country's upstream integration. The assembly core remains present, however, with some products gaining a net export position.

4.3 Scalability: alternative HIN-generated supply chains

Before concluding, we show that the HIN algorithm is scalable and can be applied to any product present in the AIPNET dataset. To do that, we select three products of increasing complexity but all less complex than motor vehicles: the bicycle (HS 8712), the electric motors and generators (HS 8501), and the refrigerator (HS 8418). By including electric motors and generators, we seek to include an intermediary product. We begin by identifying structural features common to all three networks before turning to their respective specificities.

The plots below (Figure 11) show the difference between the AIPNET and the HIN-generated input matrices. The comparison shows how the HIN algorithm prunes surplus inputs appropriately, as it did for the automotive supply chain: HIN-generated adjacency matrices are significantly simpler than the AIPNET-generated ones. By comparing across the three products, it also becomes clear that each has a different degree of complexity. The refrigerator is the product with the highest number of inputs, while the electric motors and generators and the refrigerator both have a similar number of inputs despite one being a final good and the other an intermediary product.

The following figures display their respective networks (Figures 12 - 14). The colour of the node is based on the input's upstreamness coefficient, where darker the colour the closer the component is to the root. The root product is labelled in red. In each case, the periphery is occupied by simple, clustered sets of virtually unprocessed upstream goods, while downstream products are concentrated at the centre of the network. Products are organised into clusters of compositionally similar products. Those clusters range from clusters of raw materials to clusters in which components are assembled into more complex products.

While some noise is inevitable, the components show an adequate hierarchical sorting of the inputs. The case of the bicycle reveals several peripheral clusters of raw materials such as iron, steel, aluminium, and rubber. This segmentation reflects not only the complexity of bicycle manufacturing but also the plurality of production methods and material pathways. The products closer to the final

good are generally the most direct input into it: transmission shafts, bearings, pneumatics, tubes, and cloth.

The electric motors and generators network similarly succeeds in identifying a clear manufacturing sequence. Several distinct clusters can be identified, each dedicated to the processing of a specific material (aluminium, copper, nickel, zinc), which are subsequently connected through assembly into the electric motor. The electric motor is therefore directly linked to direct inputs such as transmission shafts, electrical apparatus for switching. While some noise is still present, both the pruning and structuring is highly satisfactory.

Finally, the refrigerator supply chain is the most complex of the three cases. While it likewise exhibits peripheral clusters dedicated to material processing (aluminium, copper, plastic, glass, steel), it differs from the bicycle and electric motors and generators networks in the prominence of a cluster dedicated to complex intermediate manufacturing. A substantial portion of this cluster is specifically concerned with the elaboration of electrical components, including cables, printed circuits, and electricity distribution boards and panels. A final set of direct inputs include plastic articles, glass, switching electrical apparatus, insulating fittings, or boards for electricity control.

5 Discussion and conclusions

This paper introduces the Hierarchical Inputs Network method. The HIN maps product-specific supply chains as hierarchically structured sets of inputs. It addresses a limitation in AIPNET whereby direct and indirect inputs are conflated. By retaining direct IO linkages between consecutive production stages, the HIN resolves this issue, with the added advantage of scalability, as the approach can be applied to systematically model all products' supply chains in the product network of 5000 products at the 4 to 6 digit of the HS classification available in AIPNET. This is particularly useful when the goal of the analysis is to study product-specific supply chains.

The validation exercise on the automotive supply chain demonstrates that the HIN successfully recovers the sequential logic of manufacturing, organising products into interpretable clusters that range from raw material processing to final assembly. Its application to examine the evolution of the automotive supply chain in China, Japan, Morocco, and South Africa, to a significant extent concurs, and matches, the overall dynamics of these four cases as we know them from extant research. The extension to the bicycle, electric motors and generators, and refrigerator supply chains demonstrates the reproducibility of the method across products of varying complexity and material composition.

A key limitation is that the HIN inherits the constraints of the existing product-level input-output datasets. For example, while the overall performance of the HIN is satisfactory, the ranking of some specific products can be inaccurate, and difficult to resolve, if it stems from the way AIPNET itself is constructed. From this perspective, we see HIN as a powerful tool to be used in combination with qualitative supply chain analysis, while it also enables to address questions that existing tools have been unable to address - at least at the scale that HIN allows.

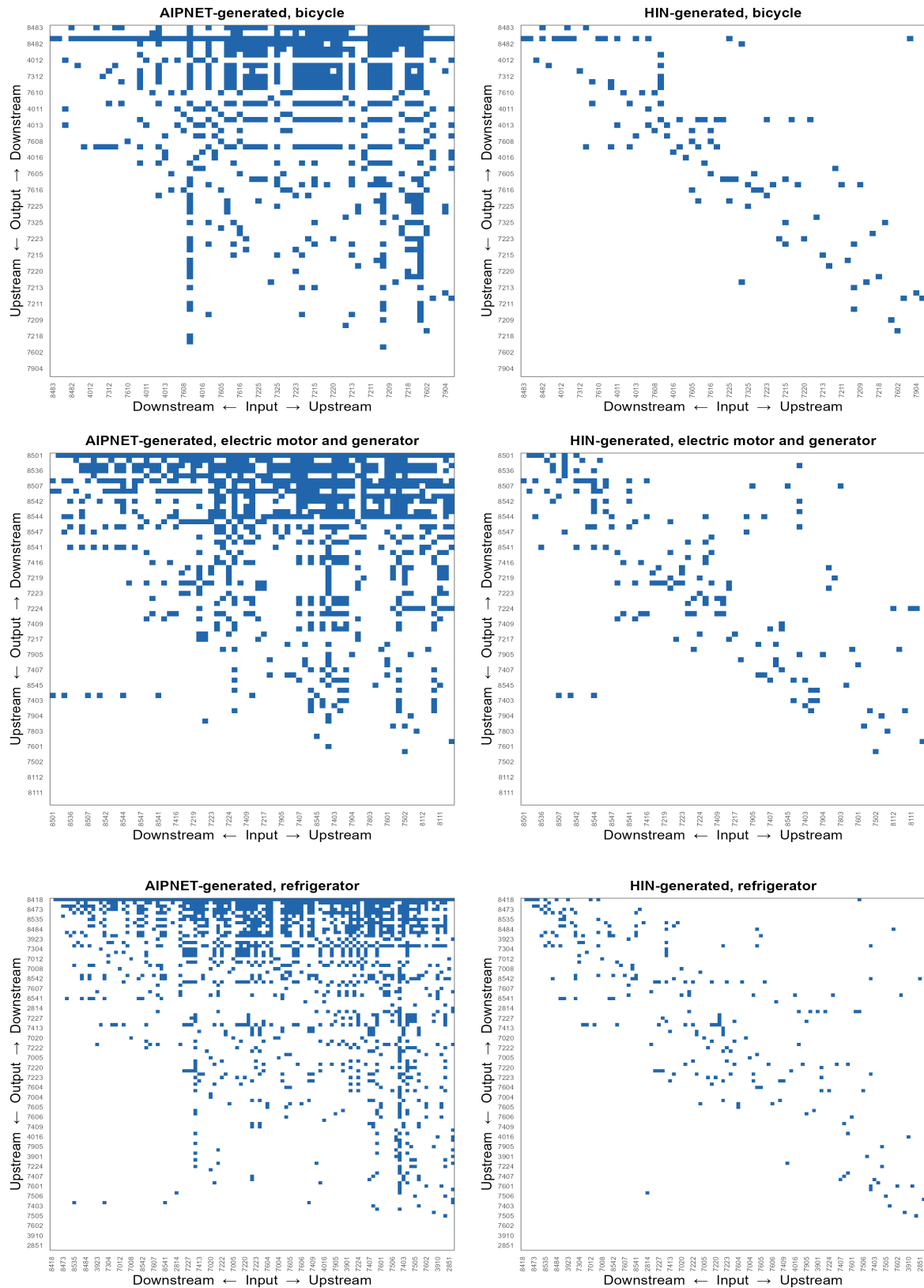


Figure 11: Comparison of AIPNET-generated and HIN-generated adjacency input-output matrices for the bicycle, electric motor and generator, and refrigerator.

Source: author's calculations

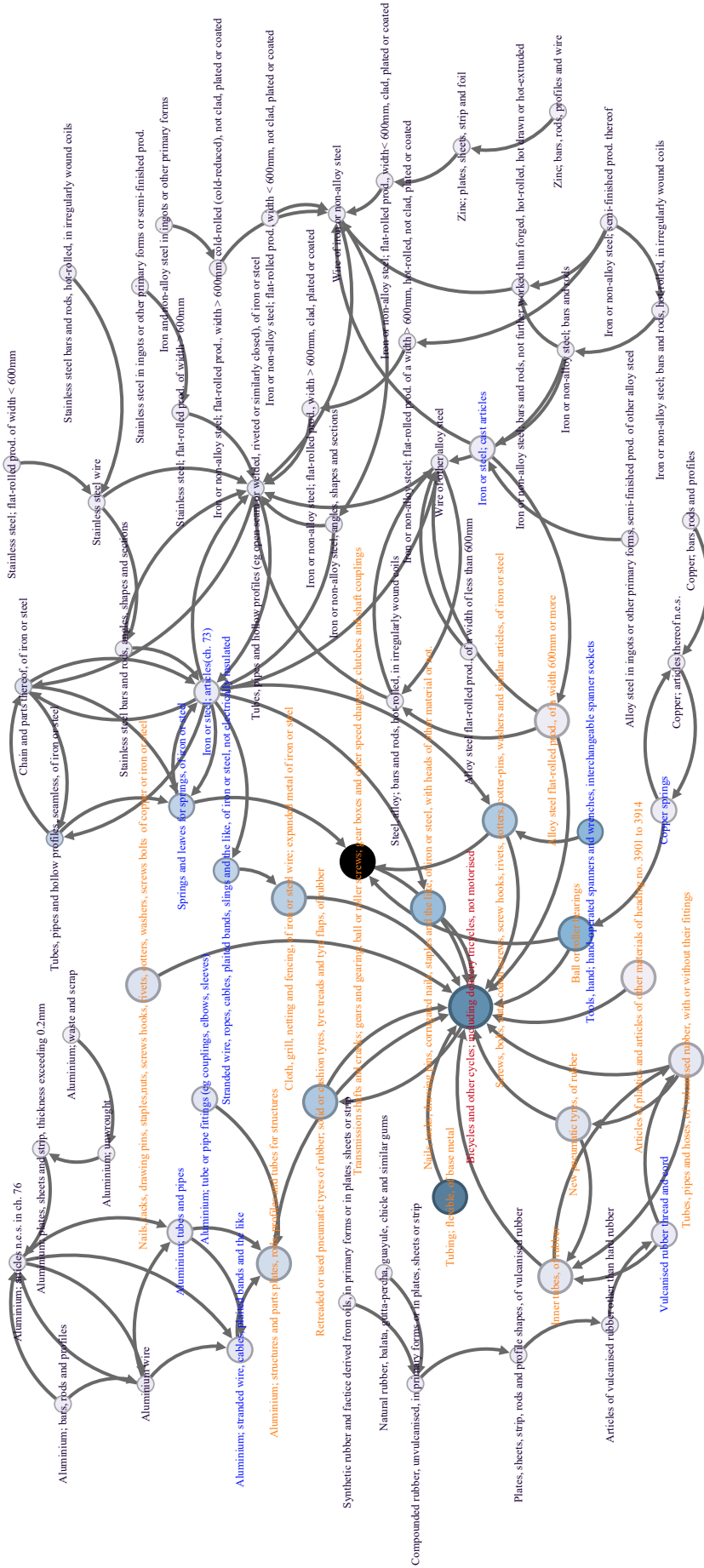


Figure 12: HIN-generated bicycle (8712) inputs networks

Note: Bicycle (HS code: 8712 *Bicycles and other cycles*) is written in red and represents the main product of interest. Node colours reflect global downstream position: the darkest nodes are the most downstream, while the lightest grey colour and size scheme: red for the final good (the largest), yellow for tier 1 suppliers, and blue for tier 2 suppliers.
 Source: author's calculations

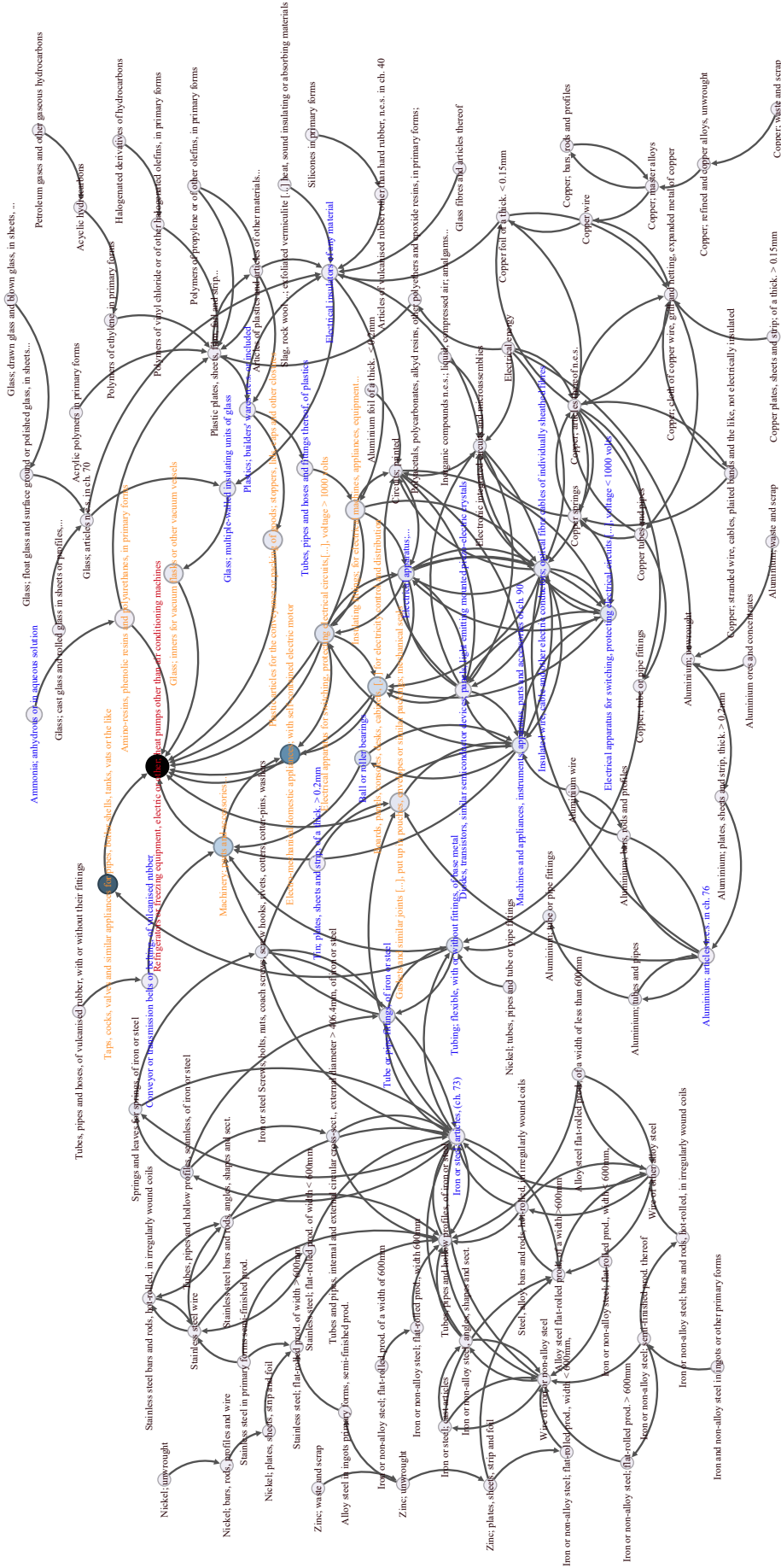


Figure 14: HIN-generated refrigerator (8418) inputs networks

Note: Refrigerator (HS code: 8418 Refrigerators or freezing equipment) is written in red and represents the main product of interest. Node colours reflect global downstream position: the darkest nodes are the most downstream, while the lightest grey nodes are the most upstream. Labels follow a three-tier colour and size scheme: red for the final good (the largest), yellow for tier 1 suppliers, and blue for tier 2 suppliers.

Source: author's calculations

From that perspective, in the comparative case analysis across China, Japan, Morocco, and South Africa, we have used HIN in one of many possible ways. The goal was to analyse the extent to which countries have developed domestic capabilities, proxied by their net export position in each component of the supply chain. We have therefore used a simple measure, the 'integration coefficient', because the goal was to showcase the use of HIN. There are a series of limitations that follow from the use of such a simple measure, pointing to the opportunity to develop more sophisticated analyses of local integration pathways by leveraging the structure of HIN-generated supply chain networks.

Beyond assessing local integration, HIN can be matched with 'complexity' and 'relatedness' measures of the product space literature (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009) to learn about how countries' existing capabilities influence supply chain positions and trajectories. Also, the role of intermediate production stages in transmitting shocks across borders can also more easily be characterised. There is also potential to advance knowledge in the identification of strategic bottlenecks within global supply chains. We regard these as amongst the most productive avenues for future research building on the present contribution.

Finally, the issue addressed through the HIN is unlikely to be unique to AIPNET and may arise across a broader range of product-level input-output datasets such as O'Clery et al. (2025) and Conconi et al. (2018). While this manuscript does not systematically compare AIPNET with these datasets on the direct-indirect input conflation specifically, the structural and network-level similarities amongst these datasets, documented in O'Clery et al. (2025), suggests that the HIN could potentially be used to distinguish direct and indirect inputs and analyse product-specific supply chains across this growing set of product-level IO datasets. Therefore, the HIN holds promise owing to both its diverse analytical applications and its potential deployment across different emerging datasets.

References

- Altenburg, T., N. Corrocher, and F. Malerba (2022, October). China's leapfrogging in electromobility. A story of green transformation driving catch-up and competitive advantage. *Technological Forecasting and Social Change* 183, 121914.
- Antràs, P., D. Chor, T. Fally, and R. Hillberry (2012, May). Measuring the Upstreamness of Production and Trade Flows. *American Economic Review* 102(3), 412–416.
- Aoki, K. and T. T. Lennerfors (2013, January). Whither Japanese keiretsu? The transformation of vertical keiretsu in Toyota, Nissan and Honda 1991–2011. *Asia Pacific Business Review* 19(1), 70–84.
_eprint: <https://doi.org/10.1080/13602381.2011.652832>.
- Bahar, D., S. Rosenow, E. Stein, and R. Wagner (2019, May). Export take-offs and acceleration: Unpacking cross-sector linkages in the evolution of comparative advantage. *World Development* 117, 48–60.
- Baldwin, R. (2006). Globalisation: the great unbundling(s).
- Baqæe, D. R. (2018). Cascading failures in production networks. *Econometrica* 86(5), 1819–1838.
- Barnes, J., A. Black, and L. Monaco (2021, August). Government Policy in Multinational-Dominated Global Value Chains: Structural Transformation within the South African Automotive Industry. In A. Andreoni, P. Mondliwa, S. Roberts, and F. Tregenna (Eds.), *Structural Transformation in South Africa: The Challenges of Inclusive Industrial Development in a Middle-Income Country*, pp. 0. Oxford University Press.
- Carvalho, V. M. (2014, November). From Micro to Macro via Production Networks. *Journal of Economic Perspectives* 28(4), 23–48.
- Cerina, F., Z. Zhu, A. Chessa, and M. Riccaboni (2015). World input-output network. *PloS one* 10(7), e0134025.
- Conconi, P., M. García-Santana, L. Puccio, and R. Venturini (2018, August). From Final Goods to Inputs: The Protectionist Effect of Rules of Origin. *American Economic Review* 108(8), 2335–2365.
- Fetzer, T., P. Lambert, B. Feld, and P. Garg (2024). AI-Generated Production Networks: Measurement and Applications to Global Trade. Technical report, SSRN.
- Gaulier, G. and S. Zignago (2010, October). BACI: International Trade Database at the Product-Level. The 1994-2007 Version. Working Papers 2010-23, CEPII.
- Gereffi, G., J. Humphrey, and T. Sturgeon (2005, February). The governance of global value chains. *Review of International Political Economy* 12(1), 78–104.
- Hahn, T. and G. V. Auktor (2017). The effectiveness of Morocco's industrial policy in promoting a national automotive industry. Working Paper 27/2017, Deutsches Institut für Entwicklungspolitik (DIE).

- Henderson, J., P. Dicken, M. Hess, N. Coe, and H. W.-C. Yeung (2002, January). Global production networks and the analysis of economic development. *Review of International Political Economy* 9(3), 436–464. _eprint: <https://doi.org/10.1080/09692290210150842>.
- Hidalgo, C. A. and R. Hausmann (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences* 106(26), 10570–10575. _eprint: <https://www.pnas.org/content/106/26/10570.full.pdf>.
- Hidalgo, C. A., B. Klinger, A.-L. Barabási, and R. Hausmann (2007). The Product Space Conditions the Development of Nations. *Science* 317(5837), 482–487. _eprint: <https://www.science.org/doi/pdf/10.1126/science.1144581>.
- Humphrey, J. (2000, September). Assembler-Supplier Relations in the Auto Industry: Globalisation and National Development. *Competition & Change* 4(3), 245–271.
- Humphrey, J. and H. Schmitz (2002, December). How does insertion in global value chains affect upgrading in industrial clusters? *Regional Studies* 36(9), 1017–1027.
- ICIO, O. (2026). inter-country input-output tables.
- Johnson, R. C. and G. Noguera (2012, March). Accounting for intermediates: Production sharing and trade in value added. *Journal of International Economics* 86(2), 224–236.
- Karbevaska, L. and C. A. Hidalgo (2025, March). Mapping global value chains at the product level. *EPJ Data Science* 14(1), 21.
- Koopman, R., Z. Wang, and S.-J. Wei (2014, February). Tracing Value-Added and Double Counting in Gross Exports. *American Economic Review* 104(2), 459–494.
- Lee, K., D. Qu, and Z. Mao (2021, April). Global Value Chains, Industrial Policy, and Industrial Upgrading: Automotive Sectors in Malaysia, Thailand, and China in Comparison with Korea. *The European Journal of Development Research* 33(2), 275–303.
- Leontief, W. W. (1951). Input-Output Economics. *Scientific American* 185(4), 15–21.
- Los, B., M. P. Timmer, and G. J. de Vries (2015). How Global Are Global Value Chains? A New Approach to Measure International Fragmentation. *Journal of Regional Science* 55(1), 66–92. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/jors.12121>.
- Monaco, L. and M. Schröder (Eds.) (2026). *Emerging Auto Industries in a World of Global Value Chains: Actors, Policies and Structural Issues*. Palgrave Studies of Internationalization in Emerging Markets. Cham: Springer Nature Switzerland.
- MRIO, W. (2013). Eora: a global multi-region input-output database.
- O’Clery, N., B. Radcliffe-Brown, T. Spencer, and D. Tarling-Hunter (2025, November). Deciphering the global production network from cross-border firm transactions. arXiv:2508.12315 [econ].
- OECD (2023a). ICIO-TiVA highlights: GVC indicators for China. Trade in Value Added. <https://www.oecd.org/content/dam/oecd/en/topics/policy-sub-issues/trade-in-value-added/tiva-2023-MAR.pdf>.

- OECD (2023b). ICIO-TiVA highlights: GVC indicators for Japan. Trade in Value Added. <https://www.oecd.org/content/dam/oecd/en/topics/policy-sub-issues/trade-in-value-added/tiva-2023-JPN.pdf>.
- OECD (2023c). ICIO-TiVA highlights: GVC indicators for Morocco. Trade in Value Added. <https://www.oecd.org/content/dam/oecd/en/topics/policy-sub-issues/trade-in-value-added/tiva-2023-MAR.pdf>.
- OECD (2023d). ICIO-TiVA highlights: GVC indicators for South Africa. Trade in Value Added. <https://www.oecd.org/content/dam/oecd/en/topics/policy-sub-issues/trade-in-value-added/tiva-2023-ZAF.pdf>.
- Schæde, U. (2010). Globalisation and the reorganisation of Japan's auto parts industry. *International Journal of Automotive Technology and Management* 10, 270–288.
- Sturgeon, T., J. Van Biesebrœck, and G. Gereffi (2008, February). Value chains, networks and clusters: reframing the global automotive industry. *Journal of Economic Geography* 8(3), 297–321.
- Taglioni, D. and D. Winkler (2016). Making Global Value Chains Work for Development. Technical report, World Bank.
- Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer, and G. J. de Vries (2015). An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. *Review of International Economics* 23(3), 575–605. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/roie.12178>.
- Wuttke, T. (2023, February). Global Value Chains and Local Inter-Industry Linkages: South Africa's Participation in the Automotive GVC. *The Journal of Development Studies* 59(2), 153–169.
- Yeung, H. W.-c. and N. M. Cœ (2015, January). Toward a Dynamic Theory of Global Production Networks. *Economic Geography* 91(1), 29–58. _eprint: <https://www.tandfonline.com/doi/pdf/10.1111/ecge.12063>.

Appendix A Motor vehicles, zooming into the most downstream components

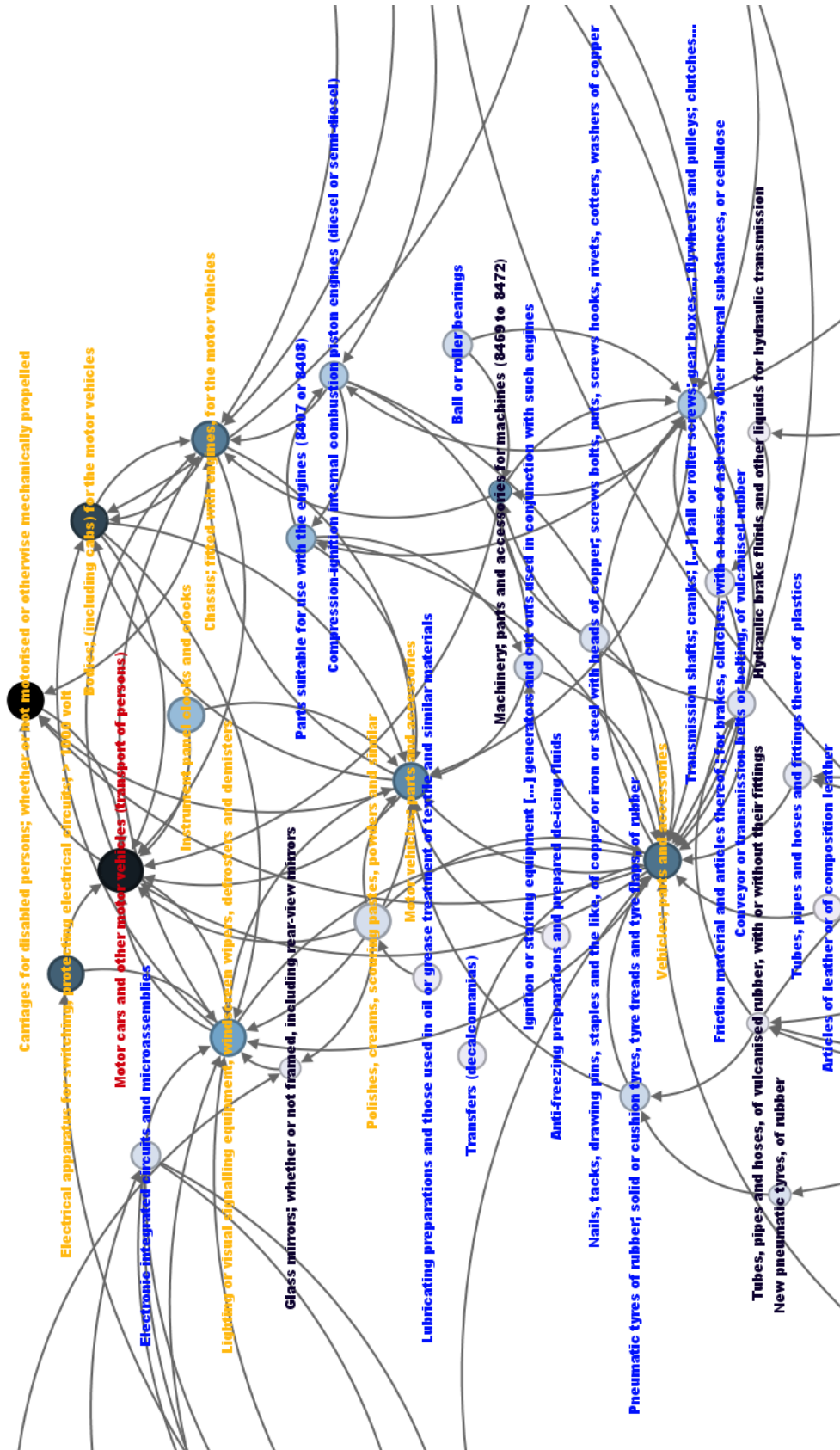


Figure A1: Zoom on the Automotive assembly

Source: author's calculations

Appendix B Automotive supply chain: upstream and shortest path measures

The table below shows the list of products sorted by shortest path distance in ascending order. Some noise is expected given the structure of the AIPNET network, and a small number of products appear at positions inconsistent with their role in the automotive supply chain. However, results remain valid at the aggregate level, given individual misclassification shall not systematically bias the overall ordering. Despite some anomalies, the ordering is overall consistent as finished vehicles and direct electric and electronic components appear at low distances (shortest path distances 1-2), followed by mechanical parts and sub-assemblies (3-6), raw materials (7-11), and ores and concentrates (12-24). Alternative measures could be explored, such as binning the Upstream variable by quartiles, or deciles. However, the highly skewed distribution of this variable presents its own challenges when interpreting those bins.

Table B1: Products by upstream position in the automotive value chain.

HS code	Description	Upstream	SP dist
8703	Motor cars and other motor vehicles; principally designed for the transport of persons (other than those of heading no. 8702), including station wagons and racing cars	2.33	0
8535	Electrical apparatus for switching, protecting electrical circuits, for making connections to or in electrical circuits; for a voltage exceeding 1000 volts	7.83	1
3405	Polishes, creams, scouring pastes, powders and similar; in any form, (including articles impregnated, coated or covered with such), for furniture, footwear, floors, coachwork, glass or metal	24.50	1
8713	Carriages for disabled persons; whether or not motorised or otherwise mechanically propelled	0.00	2
8544	Insulated wire, cable and other electric conductors, connector fitted or not; optical fibre cables of individually sheathed fibres, whether or not assembled with electric conductors or fitted with connectors	22.59	2
8473	Machinery; parts and accessories (not covers, carrying cases and the like) suitable for use solely, principally with machines of heading no. 8469 to 8472	11.70	2
9104	Instrument panel clocks and clocks of a similar type for vehicles, aircraft, spacecraft or vessels	17.50	2
3403	Lubricating preparations and those used in oil or grease treatment of textile and similar materials; excluding preparations containing 70% or more (by weight) of petroleum or bituminous mineral oils	27.06	2
8706	Chassis; fitted with engines, for the motor vehicles of heading no. 8701 to 8705	10.10	3
8708	Motor vehicles; parts and accessories, of heading no. 8701 to 8705	11.17	3
8714	Vehicles; parts and accessories of heading no. 8711 to 8713	9.36	3
8536	Electrical apparatus for switching, protecting electrical circuits, for making connections to or in electrical circuits, for a voltage not exceeding 1000 volts	19.79	3
4010	Conveyor or transmission belts or belting, of vulcanised rubber	25.50	3

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Table B1 – continued from previous page

HS code	Description	Upstream	SP dist
7415	Nails, tacks, drawing pins, staples (not those of heading no. 8305) and the like, of copper or iron or steel with heads of copper; screws bolts, nuts, screws hooks, rivets, cotters, washers of copper	24.83	3
7412	Copper; tube or pipe fittings (eg couplings, elbows, sleeves)	26.58	3
8511	Ignition or starting equipment; used for spark-ignition or compression-ignition internal combustion engines; generators and cut outs used in conjunction with such engines	24.50	4
8409	Parts suitable for use solely or principally with the engines of heading no. 8407 or 8408	17.67	4
8408	Compression-ignition internal combustion piston engines (diesel or semi-diesel engines)	20.25	4
8512	Lighting or visual signalling equipment (excluding articles of heading no. 8539), windscreen wipers, defrosters and demisters; electrical, of a kind used for cycles or motor vehicles	13.30	4
8506	Cells and batteries; primary	24.25	4
4009	Tubes, pipes and hoses, of vulcanised rubber (other than hard rubber), with or without their fittings (eg joints, elbows, flanges)	26.40	4
6813	Friction material and articles thereof (eg sheets, rolls, strips, segments, discs, washers, pads) not mounted; for brakes, clutches, with a basis of asbestos, other mineral substances, or cellulose	26.17	4
5903	Textile fabrics impregnated, coated, covered or laminated with plastics, other than those of heading no. 5902	25.50	4
7307	Tube or pipe fittings (eg couplings, elbows, sleeves), of iron or steel	23.86	4
8482	Ball or roller bearings	23.86	4
7326	Iron or steel; articles, n.e.s. in chapter 73	26.63	4
8311	Wires, rods, tubes, plates, electrodes of base metal or metal carbides; of a kind used for soldering, brazing, welding; wires and rods for metal spraying	24.00	4
3917	Tubes, pipes and hoses and fittings thereof (for example, joints, elbows, flanges), of plastics	26.00	4
4908	Transfers (decalcomanias)	26.83	4
7419	Copper; articles thereof n.e.s.	27.06	4
4204	Articles of leather or of composition leather, of a kind used in machinery or mechanical appliances or for other technical uses	27.30	4
3820	Anti-freezing preparations and prepared de-icing fluids	27.00	4
4013	Inner tubes, of rubber	25.88	5
4006	Unvulcanised rubber in other forms (eg rods, tubes and profile shapes) and articles (eg discs and rings)	26.95	5
8542	Electronic integrated circuits and microassemblies	24.61	5
8541	Diodes, transistors, similar semiconductor devices; including photovoltaic cells assembled or not in modules, panels, light emitting mounted piezo-electric crystals	26.88	5
7318	Screws, bolts, nuts, coach screws, screw hooks, rivets, cotters, cotter-pins, washers (including spring washers) and similar articles, of iron or steel	24.50	5
7320	Springs and leaves for springs, of iron or steel	25.00	5

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Table B1 – continued from previous page

HS code	Description	Upstream	SP dist
7304	Tubes, pipes and hollow profiles, seamless, of iron (other than cast iron) or steel	25.38	5
3925	Plastics; builders' wares n.e.s. or included	26.64	5
3926	Articles of plastics and articles of other materials of heading no. 3901 to 3914, n.e.s. in chapter 39	26.93	5
7221	Stainless steel bars and rods, hot-rolled, in irregularly wound coils	26.90	5
7416	Copper springs	26.71	5
7409	Copper plates, sheets and strip; of a thickness exceeding 0.15mm	27.18	5
3819	Hydraulic brake fluids and other prepared liquids for hydraulic transmission, not containing or containing less than 70% by weight of petroleum oils or oils obtained from bituminous minerals	27.25	5
7411	Copper tubes and pipes	26.85	5
7507	Nickel; tubes, pipes and tube or pipe fittings (eg couplings, elbows, sleeves)	27.00	5
8001	Tin; unwrought	27.50	5
4012	Retreaded or used pneumatic tyres of rubber; solid or cushion tyres, tyre treads and tyre flaps, of rubber	23.25	6
4007	Vulcanised rubber thread and cord	26.94	6
8483	Transmission shafts (including cam and crank) and cranks; bearing housings and plain shaft bearings; gears and gearing; ball or roller screws; gear boxes and other speed changers; flywheels and pulleys; clutches and shaft couplings	19.83	6
8534	Circuits; printed	25.23	6
7308	Structures of iron or steel and parts thereof; plates, rods, angles, shapes, sections, tubes and the like, prepared for use in structures	23.68	6
7305	Tubes and pipes (eg welded, riveted or similarly closed), internal and external circular cross-sections, external diameter of which exceeds 406.4mm, of iron or steel	25.31	6
7315	Chain and parts thereof, of iron or steel	25.25	6
7610	Aluminium; structures (excluding prefabricated buildings of heading no. 9406) and parts (eg bridges and sections, towers, lattice masts, etc) plates, rods, profiles and tubes for structures	25.93	6
3919	Self-adhesive plates, sheets, film, foil, tape, strip and other flat shapes, of plastics, whether or not in rolls	26.38	6
3811	Anti-knock preparations, oxidation and gum inhibitors, viscosity improvers, anti-corrosive preparations and the like, for mineral oils (including gasoline) or other liquids used for the same purposes	27.17	6
7009	Glass mirrors; whether or not framed, including rear-view mirrors	26.50	7
8484	Gaskets and similar joints of metal sheeting combined with other material or of two or more layers of metal; sets or assortments of gaskets and similar joints, dissimilar in composition, put up in pouches, envelopes or similar packings; mechanical seals	23.39	7
7312	Stranded wire, ropes, cables, plaited bands, slings and the like, of iron or steel, not electrically insulated	23.38	7
7614	Aluminium; stranded wire, cables, plaited bands and the like, (not electrically insulated)	26.60	7

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Table B1 – continued from previous page

HS code	Description	Upstream	SP dist
7414	Copper; cloth (including endless bands) of copper wire, grill and netting, expanded metal of copper	26.93	7
7410	Copper foil (whether or not printed or backed with paper, paperboard, plastics or similar backing materials) of a thickness (excluding any backing) not exceeding 0.15mm	27.00	7
7405	Copper; master alloys	27.28	7
2709	Petroleum oils and oils obtained from bituminous minerals; crude	27.44	7
7402	Copper; unrefined, copper anodes for electrolytic refining	27.25	7
4017	Hard rubber (eg ebonite) in all forms, including waste and scrap; articles of hard rubber	27.23	8
8307	Tubing; flexible, with or without fittings, of base metal	22.21	8
7306	Tubes, pipes and hollow profiles (eg open seam or welded, riveted or similarly closed), of iron or steel	26.00	8
7609	Aluminium; tube or pipe fittings (eg couplings, elbows, sleeves)	26.50	8
7616	Aluminium; articles n.e.s. in chapter 76	27.18	8
7608	Aluminium; tubes and pipes	27.15	8
3920	Plastic plates, sheets, film, foil and strip; non-cellular and not reinforced, laminated, supported or similarly combined with other materials, n.e.s. in chapter 39	26.83	8
7216	Iron or non-alloy steel, angles, shapes and sections	26.72	8
7219	Stainless steel; flat-rolled products of width of 600mm or more	27.02	8
7413	Copper; stranded wire, cables, plaited bands and the like, not electrically insulated	26.57	8
7408	Copper wire	27.08	8
7403	Copper; refined and copper alloys, unwrought	27.33	8
7401	Copper mattes; cement copper (precipitated copper)	27.31	8
8108	Titanium; articles thereof, including waste and scrap	27.50	8
4005	Compounded rubber, unvulcanised, in primary forms or in plates, sheets or strip	27.15	9
3812	Prepared rubber accelerators; compound plasticisers for rubber or plastics, n.e.s. or included; anti-oxidising preparations and other compound stabilisers for rubber or plastics	27.15	9
7210	Iron or non-alloy steel; flat-rolled products, width 600mm or more, clad, plated or coated	26.95	9
7605	Aluminium wire	27.15	9
7604	Aluminium; bars, rods and profiles	27.26	9
7606	Aluminium; plates, sheets and strip, thickness exceeding 0.2mm	27.31	9
7603	Aluminium; powders and flakes	27.35	9
3904	Polymers of vinyl chloride or of other halogenated olefins, in primary forms	27.38	9
7228	Alloy steel bars, rods, shapes and sections; hollow drill bars and rods, of alloy or non-alloy steel	26.37	9
7217	Wire of iron or non-alloy steel	26.88	9
7229	Wire of other alloy steel	26.82	9
7227	Steel, alloy; bars and rods, hot-rolled, in irregularly wound coils	26.71	9
7223	Stainless steel wire	26.95	9

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Table B1 – continued from previous page

HS code	Description	Upstream	SP dist
7224	Alloy steel in ingots or other primary forms, semi-finished products of other alloy steel	27.18	9
7506	Nickel; plates, sheets, strip and foil	27.41	9
2710	Petroleum oils and oils from bituminous minerals, not crude; preparations n.e.c. containing by weight 70% or more of petroleum oils or oils from bituminous minerals; these being the basic constituents of the preparations; waste oils	27.23	9
3908	Polyamides in primary forms	27.50	9
4011	New pneumatic tyres, of rubber	25.07	10
7007	Safety glass, consisting of toughened (tempered) or laminated glass	27.21	10
4001	Natural rubber, balata, gutta-percha, guayule, chicle and similar gums; in primary forms or in plates, sheets or strip	27.50	10
7214	Iron or non-alloy steel; bars and rods, not further worked than forged, hot-rolled, hot drawn or hot-extruded, but including those twisted after rolling	27.00	10
7225	Alloy steel flat-rolled products, of a width 600mm or more	26.70	10
7222	Stainless steel bars and rods, angles, shapes and sections	26.77	10
7325	Iron or steel; cast articles	27.00	10
7215	Iron or non-alloy steel; bars and rods, n.e.s. in chapter 72	27.10	10
7226	Alloy steel flat-rolled products, of a width of less than 600mm	26.67	10
7213	Iron or non-alloy steel; bars and rods, hot-rolled, in irregularly wound coils	27.09	10
7212	Iron or non-alloy steel; flat-rolled products, width less than 600mm, clad, plated or coated	26.95	10
7208	Iron or non-alloy steel; flat-rolled products of a width of 600mm or more, hot-rolled, not clad, plated or coated	27.11	10
7211	Iron or non-alloy steel; flat-rolled products, width less than 600mm, not clad, plated or coated	27.10	10
7209	Iron or non-alloy steel; flat-rolled products, width 600mm or more, cold-rolled (cold-reduced), not clad, plated or coated	27.15	10
7205	Granules and powders, of pig iron, spiegeleisen, iron or steel	27.34	10
7220	Stainless steel; flat-rolled products of width less than 600mm	26.94	10
7218	Stainless steel in ingots or other primary forms; semi-finished products of stainless steel	27.19	10
3208	Paints, varnishes; (enamels and lacquers) based on synthetic polymers or chemically modified natural polymers, dispersed or dissolved in a non-aqueous medium	26.25	10
3903	Polymers of styrene, in primary forms	27.45	10
7202	Ferro-alloys	27.37	10
7505	Nickel; bars, rods, profiles and wire	27.47	10
7901	Zinc; unwrought	27.50	10
3902	Polymers of propylene or of other olefins, in primary forms	27.40	10
7801	Lead; unwrought	27.50	10
7207	Iron or non-alloy steel; semi-finished products thereof	27.26	11
3901	Polymers of ethylene, in primary forms	27.39	11

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Table B1 – continued from previous page

HS code	Description	Upstream	SP dist
3210	Paints and varnishes (including enamels, lacquers and distempers), excluding those of heading no. 3209, prepared water pigments of a kind used for finishing leather	26.00	11
7201	Pig iron and spiegeleisen in pigs, blocks or other primary forms	27.43	11
7204	Ferrous waste and scrap; remelting scrap ingots of iron or steel	27.48	11
7407	Copper; bars, rods and profiles	27.29	11
7406	Copper; powders and flakes	27.35	11
7502	Nickel; unwrought	27.50	11
7203	Ferrous products obtained by direct reduction of iron ore and other spongy ferrous products, in lumps, pellets or the like; iron having a minimum purity of 99.94%, in lumps, pellets or similar forms	27.44	11
2901	Acyclic hydrocarbons	27.44	11
7003	Glass; cast glass and rolled glass in sheets or profiles, whether or not having an absorbent, reflecting or non-reflecting layer, but not otherwise worked	27.50	11
7005	Glass; float glass and surface ground or polished glass, in sheets, whether or not having an absorbent, reflecting or non-reflecting layer, but not otherwise worked	27.50	11
8111	Manganese; articles thereof, including waste and scrap	27.50	11
4003	Reclaimed rubber in primary forms or in plates, sheets or strip	27.38	12
7601	Aluminium; unwrought	27.43	12
7905	Zinc; plates, sheets, strip and foil	27.38	12
2601	Iron ores and concentrates; including roasted iron pyrites	27.50	12
2603	Copper ores and concentrates	27.50	12
7404	Copper; waste and scrap	27.50	12
3907	Polyacetals, other polyethers and epoxide resins, in primary forms; polycarbonates, alkyd resins, polyallyl esters and other polyesters, in primary forms	27.45	12
8707	Bodies; (including cabs) for the motor vehicles of heading no. 8701 to 8705	5.70	13
4002	Synthetic rubber and factice derived from oils, in primary forms or in plates, sheets or strip; mixtures of heading no. 4001 and 4002, in primary forms or in plates, sheets or strip	27.24	13
7206	Iron and non-alloy steel in ingots or other primary forms (excluding iron of heading no. 7203)	27.36	13
7602	Aluminium; waste and scrap	27.50	13
2606	Aluminium ores and concentrates	27.50	13
7904	Zinc; bars, rods, profiles and wire	27.44	13
8507	Electric accumulators, including separators therefor; whether or not rectangular (including square)	24.28	14
4004	Waste, parings and scrap of rubber (other than hard rubber) and powders and granules obtained therefrom	27.50	14
4016	Articles of vulcanised rubber other than hard rubber, n.e.s. in chapter 40	27.00	16
4008	Plates, sheets, strip, rods and profile shapes, of vulcanised rubber other than hard rubber	26.97	24



**Centre for Sustainable
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SOAS UNIVERSITY OF LONDON

SOAS University of London
Thornhaugh Street, Russell Square, London WC1H 0XG, UK
E-mail: csst@soas.ac.uk

www.soas.ac.uk/research/research-centres/centre-sustainable-structural-transformation