A risk analysis on geographical concentration of global supply chains

INSTITUTE OF DEVELOPING ECONOMIES

IDE Discussion Papers are preliminary materials circulated
to stimulate discussions and critical comments

IDE DISCUSSION PAPER No. 828

A Risk Analysis on Geographical Concentration of Global Supply Chains

Satoshi INOMATA[1] and Tesshu HANAKA[2*]

October 2021

Abstract

In this paper we present and analyze new referential statistics for risk assessment on geographical concentration of global supply chains. The study's net contribution rests on the development of a metric which indicates geographical concentration in terms of the *frequency* of supply chain engagement with the regions of analytical concerns, alongside the traditional approach based on volume measures of value-added concentration.

Japan, a country with a high propensity to encounter natural hazards, and China, under a mounting geopolitical tension with the United States, are chosen as target regions for the risk assessment. The analysis follows a line of techniques in input-output economics known as the "key sector analysis", yet with methodological augmentation by a compatible analytical framework in the network theory. Using the latest set of multi-country input-output tables constructed by the Organisation for Economic Co-operation and Development (OECD), the concentration risks of some key global supply chains such as the automotive industry and the ICT/electronics equipment industry are identified.

Keywords: risk assessment, global supply chains, choke points, input-output analysis
JEL classification: C67, F52, F60

[1] Overseas Research Fellows (the OECD), Institute of Developing Economies, JETRO.
[2] Department of Mathematical Informatics. Graduate School of Informatics, Nagoya University.
* The corresponding author (hanaka@nagoya-u.jp)

The Institute of Developing Economies (IDE) is a semigovernmental, nonpartisan, nonprofit research institute, founded in 1958. The Institute merged with the Japan External Trade Organization (JETRO) on July 1, 1998. The Institute conducts basic and comprehensive studies on economic and related affairs in all developing countries and regions, including Asia, the Middle East, Africa, Latin America, Oceania, and Eastern Europe.

INSTITUTE OF DEVELOPING ECONOMIES (IDE), JETRO
3-2-2, WAKABA, MIHAMA-KU, CHIBA-SHI
CHIBA 261-8545, JAPAN

1. Introduction

The world economy in the 21st century has given a rise to new production arrangement known as global value chains (GVCs), in which production processes are sliced and relocated to the places where the corresponding tasks are most efficiently performed.[1] Thanks to the rapid advancement of transportation modes and information & communication technology (ICT), production networks continued to expand to cover every corner of the globe; yet, at the same time, the pursuit of optimal allocation of resources often resulted in agglomeration and concentration of key production capacities in a certain region of a certain country.

This may work well in a good time, but when things start to go wrong, such production hubs can turn to "choke points" of the entire economic system. The multiple examples are found in the recent history; the Lehman Shock, the Great East Japan Earthquake, or various forms of cyber-attacks, where hyper economic interdependency rendered the production and financial system particularly vulnerable to a single point of failure.

The series of incidents has driven our attention to the systematic risk associated with geographical concentration of supply chains in global production networks. Flows of goods, money, people, and information jointly form a highly complicated nexus of economic activities, and a shock generated in one region may rapidly and extensively propagate to other regions across national borders in an unforeseeable manner.

Against this backdrop, we propose a novel approach to construct a risk indicator for firms' business operation, especially in the global context, by mapping the degree of geographical concentration of supply chains. This is done along a line of traditional techniques in input-output economics known as the "key sector analysis", yet with methodological augmentation by a compatible analytical framework in the network theory.

The novelty of the paper rests on our claim that we measure concentration risks in terms of the *frequency* that a particular supply chain passes through a high-risk region, as opposed to the conventional approach based on a *volume* concept. If the analysis is directed to the issues of supply chain disruptions (such as natural disasters or geopolitical conflicts), then the measurement will reveal the degree of supply chain vulnerability to unpredicted incidents in the region of analytical concerns.

The paper is structured as follows. The next section presents literature review with respect to the relevant methodologies, showing how our approach differs from the

[1] For an overview of GVC studies, see Inomata (2017), or, in Japanese, Inomata (2019).

previous studies. The third section introduce the basic model and the mathematical definitions of the metrics. The fourth section presents analytical examples on Japan and China using a multi-country input-output table, while the fifth section suggests some possible extensions of the research. The final section concludes.

2. Literature review

One of the strengths of the input-output analysis rests on the use of harmonized information on sectoral linkages embedded in input-output tables. The values of intermediate transaction in the table can be considered as materialization of inter-connectedness between industrial sectors, from which a multitude of linkage measures have been devised so far. The *key sector analysis* is based on these sectoral linkage metrics, as a certain sector can be regarded as a "key" if it is more connected than others and hence able to inflict a larger impact on the economy.

Consider an n-sector economy whose input-output system is represented by the following balance equation:

$$\boldsymbol{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{13} & \dots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} + \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{pmatrix}$$

$$= \boldsymbol{Ax} + \boldsymbol{y} \qquad \dots (1)$$

where $\boldsymbol{x} = (x_1, \dots, x_n)'$ is an $(n \times 1)$ vector with its elements corresponding to a total output of each sector, $\boldsymbol{y} = (y_1, \dots, y_n)'$ is an $(n \times 1)$ vector containing final demands for products of each sector, and $\boldsymbol{A}$ is an $(n \times n)$ input coefficient matrix which represents the amounts of intermediate inputs from a row sector *directly* used for a unit production by a column sector. Then, we have $\boldsymbol{x} = \boldsymbol{Ax} + \boldsymbol{y} \Leftrightarrow (\boldsymbol{I} - \boldsymbol{A})\boldsymbol{x} = \boldsymbol{y} \Leftrightarrow \boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{y}$ where $\boldsymbol{I}$ is an $(n \times n)$ identity matrix**.** Here, we denote by $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1} = \boldsymbol{I} + \boldsymbol{A} + \boldsymbol{A}^2 + \cdots$ the Leontief inverse matrix which represents the amounts of intermediate inputs from a row sector used for a unit production by a column sector, *both directly and indirectly* (i.e., through the higher-order tiers for sourcing production inputs).

Accordingly, if we look at the Leontief inverse matrix in the column-wise direction, it shows how much demands each sector is able to stimulate for the economy, while, in the row-wise direction, how much supplies are needed from each sector by the economy. So, by comparing the magnitudes of sectors' column totals (backward linkages) or row totals (forward linkages), we can identify which sector is most influential, or a key, to the economy as a whole.[2]

The key sector analysis has a long history in input-output economics, dating back to the late 1950s (Rasmussen (1957), Hirschman (1958), Chenery and Watanabe (1958)). The major advancement from the traditional approach was observed a decade later, when the Hypothetical Extraction Method (HEM) was proposed and explored. The basic idea of the method is that we consider a "hypothetical" input-output system in which a sector in question is artificially suppressed, and thereby measure the importance of this suppressed sector for the entire system by comparing the performances of the actual economy (*with* the sector) and that of the hypothetical economy (*without* the sector).

Specifically, let $\bar{\boldsymbol{A}}_{(t)}$ be a hypothetical input coefficient matrix such that its elements $\bar{a}_{(t)ij} = 0$ if either $i = t$ or $j = t$ while $\bar{a}_{(t)ij} = a_{ij}$ otherwise. The HEM impact for sector t is defined as the difference in the outputs of the actual economy and the hypothetical economy; that is,

$$HEM_{(t)} = \boldsymbol{i}'\boldsymbol{L}\boldsymbol{y} - \boldsymbol{i}'\bar{\boldsymbol{L}}_{(t)}\boldsymbol{y} = \boldsymbol{i}'(\boldsymbol{L} - \bar{\boldsymbol{L}}_{(t)})\boldsymbol{y} \quad \text{...(2)}$$

where $\bar{\boldsymbol{L}}_{(t)}$ is the Leontief inverse matrix of $\bar{\boldsymbol{A}}_{(t)}$ and $\boldsymbol{i}'$ is a row summation vector.

Early developers of the HEM are Paelinck, de Caevel, and Degueldre (1965), Strassert (1968), and Schultz (1976). Temurshoev (2009, 2010) extend the method for group-wise identification of key sectors, while Dietzenbacher and Lahr (2013) develop it in a more generalized framework.

The HEM was first brought into the international context by Dietzenbacher et al. (1993) which use a multi-country input-output tables for selected EU countries. The multi-country analysis is further elaborated in Dietzenbacher, van Burken, Kondo (2019) in which the problem of extracting one or more sectors in a closed input-output system (leading to "imports from Mars") is dealt with by explicitly considering the substitution of extracted sector's inputs with those from third countries.

Recent applications of the HEM to international trade are found in the topics of global value chains. Los et al. (2016) and Los and Timmer (2018) propose a simple yet precise interpretation of gross export decomposition into value-added sources, which shed a new light on the earlier decomposition methodologies. In this vein, Miroudot and Ye (2021) demonstrate a comprehensive HEM approach to gross export decomposition, which provides a common platform for quantifying different notions of value-added double-counting within a single accounting framework.

[2] The earliest literature in the field used input coefficient matrices, rather than the Leontief inverse matrices, to derive forward/backward linkages. Also, the Leontief inverse matrix was subsequently replaced by the Ghosh inverse matrix for the calculation of forward linkages.

Another important strand of the HEM application is seen in the field of environmental economics. The identification of key sectors which impose the largest negative impact on the environment is crucial for designing policy tools that effectively reduce greenhouse gas emissions (Lenzen, 2003). In this spirit, the HEM is applied to environmentally extended input–output models of Italy (Ali, 2015) and of China (Wang et al., 2013; Zhao et al., 2016) to measure the CO_2 emission linkages in domestic supply chains. Using a multi-country input–output model, Hertwich (2021) quantifies the levels of greenhouse gas emissions and global carbon footprint of material production.

Closer to the topic of our current interest, Dietzenbacher and Miller (2015) allude to the possibility of applying the HEM to impact assessment of natural hazards, by referring to the preceding study by Muldrow and Robinson (2014) on the 2008 Cedar Rapids Flood in the United States. Likewise, Xia et al. (2019) evaluate a specific case of IT service shutdown during the 2015 York flood in the UK using the HEM.

Our present paper is differentiated from these foregoing studies in several respects. The primary focus of the previous literature is directed either to the identification of most influential sectors for economic/environmental amelioration, to structural decomposition of production systems for an accounting diagnosis, or to posterior impact assessment of a specific natural hazard. By contrast, we aim to apply the key sector analysis to *precautionary risk management* of global supply chains. The recognition of potential "choke points" in production networks as key sectors, and the evaluation of associated risks in terms of geographical concentration of supply chains, are what distinguish this paper from others in regard to research motivation, and what necessitate the exploration of an unorthodox approach, which is unfolded below.

In the perspective of risk analyses, there are a *volume* dimension and a *frequency* dimension for risk assessment. For example, the chances that our families get infected with virus will be high, either because they go to a risky place altogether at once, or even just one of them goes, he/she visits there frequently. Or, perhaps even more straightforward analogy is that events of earthquake are reported and analyzed with respect to both the magnitude and the frequency of occurrence.

Paraphrasing it in our context, a supply chain is considered highly exposed to a specific country risk, if its product contains a significant volume of value-added sourced from the country in question, or if the production activities along the supply chain involve frequent engagement with the country's industrial sectors. The first factor is self-evident, but the second factor is also important because it relates to *the probability aspect* of how likely the supply chain is caught by contingencies in the country of concerns. The traditional key sector analysis, however, can only address the volume-wise scale of inter-sectoral spillovers, be it backward/forward linkages or the HEM. It is therefore unable to capture in isolation these dual attributes — volume and frequency — of concentration risks.

With this in mind, the following section demonstrates a method to quantify supply chain concentration in the frequency dimension, which is expected to serve as a complementary metric to the traditional volume measures of geographical concentration.

3. Basic model and the definition of the indicator

The Pass-through Frequency (PTF) presents the average number of times that a particular supply chain passes through a target sector in a given production system. It is built upon a property of the Structural Betweenness Centrality developed in Liang *et al.* (2016) as one form of key sector analyses.

Backward propagation of a final demand impact in a $(k-1)$ stage path is presented as follows

$$a_{s_1 s_2}\, a_{s_2 s_3}\, a_{s_3 s_4} \cdots a_{s_{k-1} s_k}\, y_{s_k} \qquad \ldots(3)$$

where $a_{s_i s_{i+1}}$ is an input coefficient from sector s_i to sector s_{i+1}, and y_{s_k} is a final demand for products of sector s_k. Suppose that the target sector t is one of intermediary sectors s_i $(i = 2,3,4,\ldots,k-1)$ along the path. Let $u_1, u_2, \ldots, u_l$ be the upstream sequence of l sectors in relation to sector t and $d_1, d_2, \ldots, d_m$ be the downstream sequence of m sectors in relation to sector t, where $l + m = k - 1$ and $u_{l+1} = d_0 = t$. Then, the $(k-1)$ stage path including sector t can be represented as $u_1, u_2, \ldots, u_l, t, d_1, d_2, \ldots, d_m$ and the Equation (3) is reformulated as

$$a_{u_1 u_2}\, a_{u_2 u_3} \cdots a_{u_{l-1} u_l}\, a_{u_l t}\, a_{t d_1}\, a_{d_1 d_2} \cdots a_{d_{m-1} d_m}\, y_{d_m} \qquad \ldots(4)$$

The structural path of the impact propagation from sector d_m to sector t is given by the right half of Equation (4), $a_{t d_1}\, a_{d_1 d_2} \cdots a_{d_{m-1} d_m}\, y_{d_m}$, and hence the total impact of all paths running up to that point is calculated as:

$$\sum_{d_1} \sum_{d_2} \cdots \sum_{d_{m-1}} \left(a_{t d_1}\, a_{d_1 d_2} \cdots a_{d_{m-1} d_m}\, y_{d_m} \right)$$
$$= \sum_{d_1,\ldots,d_{m-1}} \left(a_{t d_1}\, a_{d_1 d_2} \cdots a_{d_{m-1} d_m}\, y_{d_m} \right) \qquad \ldots(5)$$

Then, the further propagation from sector t for the remaining path up until sector u_1 is the higher-order backward propagation of Equation (5) commencing from sector t; i.e., $a_{u_1u_2}\ a_{u_2u_3} \dots a_{u_{l-1}u_l} a_{u_l t} \cdot \sum_{d_1,\dots,d_{m-1}} (a_{td_1}\ a_{d_1d_2} \dots a_{d_{m-1}d_m}\ y_{d_m})$. Accordingly, the total impact delivered along all paths running through the entire sequence from sector d_m to sector u_1 via sector t is calculated as:

$$\sum_{u_2,\dots,u_l} \left(a_{u_1u_2}\ a_{u_2u_3} \dots a_{u_{l-1}u_l}\ a_{u_l t} \cdot \sum_{d_1,\dots,d_{m-1}} \left(a_{td_1}\ a_{d_1d_2} \dots a_{d_{m-1}d_m}\ y_{d_m}\right)\right)$$

$$= \left(\sum_{u_2,\dots,u_l} \left(a_{u_1u_2}\ a_{u_2u_3} \dots a_{u_{l-1}u_l} a_{u_l t}\right)\right)\left(\sum_{d_1,\dots,d_{m-1}} \left(a_{td_1}\ a_{d_1d_2} \dots a_{d_{m-1}d_m}\ y_{d_m}\right)\right)$$

...(6)

Meanwhile, it is known that $[\boldsymbol{A}^h]_{ij}$, an element of h^{th}-power of an input coefficient matrix $\boldsymbol{A}$, indicates the total amount of impacts delivered from sector j to sector i for all paths with a length of h (i.e., with h times iteration of propagations). This property of an input coefficient matrix allows reformulation of Equation (6) as:

$$[\boldsymbol{A}^l]_{u_1 t} \cdot [\boldsymbol{A}^m]_{td_m}\ y_{d_m}.$$

...(7)

Specifically, the impact transmission through the shortest possible path, with only one-shot propagation for each of the upstream and downstream sequences (i.e., $l = m = 1$, the propagation path: $d_1 \rightarrow t \rightarrow u_1$), can be presented as follows:

$$[\boldsymbol{A}^1]_{u_1 t} \cdot [\boldsymbol{A}^1]_{td_1}\ y_{d_1}$$

$$= a_{u_1 t} \cdot a_{td_1}\ y_{d_1}$$

...(8)

Finally, we consider every possible combination of an upstream path and a downstream path with different lengths: l-stage path for the upstream sequence, and m-stage path for the downstream sequence, which leads to the following specification of total impacts delivered through all paths via sector t for respective supply chains.

$$\sum_{l=1}^{\infty}\sum_{m=1}^{\infty} \left(\boldsymbol{A}^l \boldsymbol{J}_{(t)} \boldsymbol{A}^m\ \widehat{\boldsymbol{y}}\right)$$

$$= \left(\sum_{l=1}^{\infty} \boldsymbol{A}^l\right) \boldsymbol{J}_{(t)} \left(\sum_{m=1}^{\infty} \boldsymbol{A}^m\right) \widehat{\boldsymbol{y}}$$

$$= (\boldsymbol{L} - \boldsymbol{I})\, \boldsymbol{J}_{(t)}\, (\boldsymbol{L} - \boldsymbol{I})\, \widehat{\boldsymbol{y}}$$

...(9)

where $\widehat{\boldsymbol{y}}$ is an (nxn) diagonal matrix containing final demands for its diagonal elements and zeros (0s) elsewhere, $\boldsymbol{J}_{(t)}$ is an (nxn) matrix containing 1 for (t, t)-th element and zeros (0s) elsewhere, and $\boldsymbol{L} - \boldsymbol{I} = \boldsymbol{LA} = \boldsymbol{AL} = \boldsymbol{A}^1 + \boldsymbol{A}^2 + \boldsymbol{A}^3 + \cdots$.

Now, Equation (9) shows the entire set of impact propagations along every path that goes through the target sector t. Importantly, it is possible that sector t appears multiple times along a path. This means that more than one of the sectors $u_1, u_2, \dots, u_l$, $d_1, d_2, \dots, d_m$ in Equation (4) can be sector t. When this is the case, note that Equation (9) performs multiple-counting of an impact delivered through the corresponding path by the same amount. Why? This is because each sector t along the path defines a specific pair of the upstream/downstream sequences, and each of these pairs additionally counts the identical amount of impact under Equation (9); see *Appendix A* for an illustrative example.

In general, multiple emergences of target sector t along a path result in multiple-counting of the identical amounts of impacts by the number of sector's emergence. Upon this ground, and in light of the definition given in Liang et al. (2016),[3] Equation (9) can be expressed as

$$\sum_{k=3}^{\infty} \sum_{s_{2,\dots,}s_{k-1}} \left(c_{(t)} \cdot a_{s_1 s_2}\, a_{s_2 s_3}\, a_{s_3 s_4} \dots a_{s_{k-1} s_k}\, y_{s_k} \right) \qquad \dots(10)$$

where $c_{(t)}$ is the number of times that the sector t appears on a particular backward linkage path $s_k \to s_{k-1} \to \cdots \to s_3 \to s_2 \to s_1$ specified by the multiplicand on the right, i.e., $c_{(t)} = |\{ j \,|s_j = t\} \setminus \{1, k\}|$. The summation $\sum_{s_{2,\dots,}s_{k-1}}(\cdot)$ is to embrace every combination of intermediary sectors s_i $(i = 2,3,4, \dots, k-1)$ for a path with the length of $(k-1)$, and $\sum_{k=3}^{\infty}(\cdot)$ is to consider every path with a different length of more than 2 (i.e., $k \geq 3$).

Capitalizing on this property, we propose and define the Pass-through Frequency of an (i, j) supply chain for sector t as:

$$f_{(t)_{ij}} = \frac{\left[\boldsymbol{L}\boldsymbol{J}_{(t)}\boldsymbol{L} - \boldsymbol{J}_{(t)}\right]_{ij}}{[\boldsymbol{L} - \boldsymbol{I}]_{ij}} \qquad \dots (11)$$

Note that, unlike Structural Betweenness Centrality, we use $\boldsymbol{L}$ instead of $\boldsymbol{L} - \boldsymbol{I}$ in the numerator; this is to allow for the emergence of target sector t at either/both of the terminal points of a path, i.e., $c_{(t)} = \left|\{ j \mid s_j = t \}\right|$ (Tokito, et al. 2021). Also, the terms $\boldsymbol{J}_{(t)}$ and $\boldsymbol{I}$ are respectively subtracted from the numerator and the denominator in order to negate the values corresponding to the initial final demands, which are analytically irrelevant to identifying the structure of the networks.

[3] The specification in Liang *et al.* (2016) uses a different notational system.

By analogy to Equation (10), the PTF can be alternatively expressed in the form of a structural path such that:

$$f_{(t)_{s_1 s_k}} = \frac{c_{(t)} a_{s_1 s_k} + \sum_{k=3}^{\infty} \sum_{s_2,\ldots,s_{k-1}} \left(c_{(t)} \cdot a_{s_1 s_2}\, a_{s_2 s_3}\, a_{s_3 s_4} \ldots a_{s_{k-1} s_k} \right)}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1 s_k}}$$

$$= c_{(t)} \cdot \frac{a_{s_1 s_k}}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1 s_k}} + \sum\nolimits_{k=3}^{\infty} \sum\nolimits_{s_2,\ldots,s_{k-1}} \left(c_{(t)} \cdot \frac{a_{s_1 s_2}\, a_{s_2 s_3}\, a_{s_3 s_4} \ldots a_{s_{k-1} s_k}}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1 s_k}} \right).$$

... (12)

Since the denominator $[\boldsymbol{L}-\boldsymbol{I}]_{s_1 s_k}$ is the total amount of impact propagations from s_k to s_1, the multiplicands $a_{s_1 s_k}/[\boldsymbol{L}-\boldsymbol{I}]_{s_1 s_k}$ and $\left(a_{s_1 s_2}\, a_{s_2 s_3}\, a_{s_3 s_4} \ldots a_{s_{k-1} s_k}\right)/[\boldsymbol{L}-\boldsymbol{I}]_{s_1 s_k}$ give a *share* of the impact delivered through a particular backward path $s_k \to s_1$ (single-stage path) or $s_k \to s_{k-1} \to \cdots \to s_3 \to s_2 \to s_1$(multi-stage path).

Accordingly, Equation (12) shows that the PTF is equivalent to a *weighted average* of $c_{(t)}$, an integer indicating the number of times that the target sector t appears in a particular (s_1, s_k) path, using the aforementioned impact shares as weights. In effect, the metric indicates the frequency that a particular supply chain engages with the target sector through the operation of a given production system.[4]

The above specification of the indicator offers the following analytical benefits:

i) It is possible to calculate a value for a supply chain connecting any two sectors,

ii) The value can be calculated from only one data source: an input-output table,

iii) Given the Leontief inverse matrix of an input-output table, the value can be computed in a constant time, and hence the computational cost is low.[5]

iv) The indicator has a set of weights as a built-in decay parameter in an economically meaningful way, so that the value will converge.

Regarding point iv), let us consider a pair of (s_1, s_k) paths with different lengths yet with the same number of times that the target sector appears along the way. Apparently, the longer path has lower density of target emergence than the shorter path, and hence it should be assigned with a smaller weight in calculating the value of the indicator. The impact shares as weights serve for this purpose since an impact becomes smaller as it goes along a path for higher-order propagations, thanks to the property of an input coefficient ($a_{ij} < 1$).

---

[4] The PTF has a similar structure to the *Average Propagation Lengths* (APL) proposed by Dietzenbacher et al. (2005). The APL measures a length of a supply chain connecting a pair of industrial sectors, and defined as a weighed average of the number of propagations using impact shares as weights. Specifically, $APL_{ij} = [\boldsymbol{LAL}]_{ij}/[\boldsymbol{L}-\boldsymbol{I}]_{ij} = [1\boldsymbol{A}^1 + 2\boldsymbol{A}^2 + 3\boldsymbol{A}^3 + \cdots]_{ij}/[\boldsymbol{L}-\boldsymbol{I}]_{ij} = [\sum_{h=1}^{\infty} h\boldsymbol{A}^h]_{ij}/[\boldsymbol{L}-\boldsymbol{I}]_{ij} = \sum_{h=1}^{\infty}\{h \cdot ([\boldsymbol{A}^h]_{ij}/[\boldsymbol{L}-\boldsymbol{I}]_{ij})\}$, where h is the number of impact propagations from sector j to sector i.

[5] Since $\boldsymbol{J}_{(t)}$ is an (nxn) matrix containing 1 for $(t,\, t)$-th element and zeros (0s) elsewhere, we can explicitly denote each (i,j)-element of $\boldsymbol{LJ}_{(t)}\boldsymbol{L}$ as $l_{it} l_{tj}$.

Analogously to the PTF for a sector, we can also consider the *Pass-through Frequency for a transaction*, which indicates the frequency that a particular supply chain engages in the target *transaction* through the operation of a given production system. The definition is similar to the one for the sectoral model, i.e., the average number of times that a supply chain passes through a target transaction specified by a particular element in an input-output matrix. Based on the Structural Betweenness Centrality for a transaction proposed by Hanaka *et al.* (2017), the PTF for a transaction can be formulated as follows:

$$f_{(t_1,t_2)_{s_1 s_k}} = \frac{\left[a_{t_1 t_2} \boldsymbol{L} \boldsymbol{J}_{(t_1,t_2)} \boldsymbol{L}\right]_{s_1 s_k}}{[\boldsymbol{L} - \boldsymbol{I}]_{s_1 s_k}},$$

... (13)

where $\boldsymbol{J}_{(t_1,t_2)}$ is an (nxn) matrix containing 1 for (t_1, t_2)-th element and zeros (0s) elsewhere; see *Appendix B* for a detailed exposition of the transactional model.

Using this transactional model, we further demonstrate that impact propagations of a particular supply chain can be decomposed in accordance with the number of times that the transaction (t_1, t_2) appears on each propagation path. Define $\sigma^{(r)}(s_1, t_1, t_2, s_k)$ as the total amount of impact propagations from s_k to s_1 such that transaction (t_1, t_2) appears *exactly r times* along the paths. Also, let $\boldsymbol{A}_{(t_1,t_2)}$ be a matrix such that its elements $a_{(t_1,t_2)ij} = a_{ij}$ if $i = t_1$ and $j = t_2$ while $a_{(t_1,t_2)ij} = 0$ otherwise, and $\bar{\boldsymbol{A}}_{(t_1,t_2)} = \boldsymbol{A} - \boldsymbol{A}_{(t_1,t_2)}$ be a hypothetical input coefficient matrix with respect to (t_1, t_2). Then, $\sigma^{(r)}(s_1, t_1, t_2, s_k)$ can be formulated as:

$$\sigma^{(r)}(s_1, t_1, t_2, s_k) = \begin{cases} \left[\bar{\boldsymbol{L}}_{(t_1,t_2)} - \boldsymbol{I}\right]_{s_1 s_k} & r = 0 \\ \left[\left(\bar{\boldsymbol{L}}_{(t_1,t_2)} \boldsymbol{A}_{(t_1,t_2)}\right)^r \bar{\boldsymbol{L}}_{(t_1,t_2)}\right]_{s_1 s_k} & r \geq 1 \end{cases}$$

... (14)

where $\bar{\boldsymbol{L}}_{(t_1,t_2)} = \left(\boldsymbol{I} - \bar{\boldsymbol{A}}_{(t_1,t_2)}\right)^{-1}$ is the Leontief inverse matrix of $\bar{\boldsymbol{A}}_{(t)}$.

Now, because $\bar{\boldsymbol{L}}_{(t_1,t_2)}$ is derived from the hypothetical input-output system extracting (t_1, t_2) transaction, an element $\left[\bar{\boldsymbol{L}}_{(t_1,t_2)} - \boldsymbol{I}\right]_{s_1 s_k}$ represents the total amount of impact propagations from s_k to s_1 which do *not* pass through the transaction (t_1, t_2); i.e., the case of $r = 0$.

For $r \geq 1$, by contrast, $\boldsymbol{A}_{t_1 t_2}$ appears exactly r times in the matrix multiplication of $\left[\left(\bar{\boldsymbol{L}}_{(t_1,t_2)} \boldsymbol{A}_{t_1 t_2}\right)^r \bar{\boldsymbol{L}}_{(t_1,t_2)}\right]_{s_1 s_k}$. This is equivalent to saying that the input coefficient $a_{t_1 t_2}$, which corresponds to the target transaction (t_1, t_2), appears r times in each (s_1, s_k) path under $\left[\left(\bar{\boldsymbol{L}}_{(t_1,t_2)}\boldsymbol{A}_{t_1t_2}\right)^r \bar{\boldsymbol{L}}_{(t_1,t_2)}\right]_{s_1s_k}$, given the properties of $\boldsymbol{A}_{(t_1,t_2)}$ and $\bar{\boldsymbol{L}}_{(t_1,t_2)}$.

Accordingly, $\sigma^{(r)}(s_1, t_1, t_2, s_k)$ as defined above presents the total amount of impact propagations from s_k to s_1 such that transaction (t_1, t_2) appears exactly r times, for both cases of $r = 0$ and $r \geq 1$; see *Appendix C* for the calculation result of a case study on China's ICT/electronics industry.

4. Analytical example (Japan and China)

In this section, we present two analytical examples, on Japan and China, using the preliminary data of the forthcoming Inter-Country Input-Output Tables, the 2021 release, constructed by the Organisation for Economic Co-operation and Development (OECD). The database is chosen because of its high degree of harmonization and consistency among the constituent national input-output tables, which are sourced only from the official statistics of individual countries. The latest version, to be published in 2021, is based on 36 industries (concordant with ISIC Rev.4), covering 67 countries/regions for the years from 1995 to 2018, allowing comprehensive time and geographical coverage for GVC analyses; see *Appendix D* for the description of the data, industrial sector classification and countries of reference.

[Japan]

Japan is well-recognized as a country prone for natural hazards. Earthquake in Japan accounts for 17.9% of all cases (larger than magnitude 6.0) reported all over the world during 2011-2020, even though its national territory occupies less than 1% of the total land area on the globe (River Databook, 2021).

In particular, the Great East Japan Earthquake in 2011 caused unprecedented economic and social damages to the country, exacerbated by the multiple chained disasters of tsunami as well as the breakdown of nuclear power stations. Not to mention the tragic loss of human lives, the disaster's economic impact on global supply chains has equally gathered world-wide attention. For example, the devastating physical damage on local factories of Renesas Electronics, a car parts supplier, led to a critical shortage of micro-computers for cars and abruptly disactivated production lines of the automotive industries, both in Japan and foreign countries alike.

It is not only about the scale but also the scope of natural disasters that reveals Japan's vulnerable position: earthquake, tsunami, volcanic eruption, typhoon, flood, rainfall and snow damages …, caused by a very complex interaction of geophysical and meteorological conditions that the country rests on. Accordingly, we chose Japan as one of the target regions for the supply chain risk analysis.

[China]

Mounting geopolitical tension between the United States and China adds another aspect to supply chain risks. China has achieved remarkable economic growth in the last few decades and became a global manufacturing center, dubbed as "the Factory of the World". Its economic influence was vividly demonstrated by a bitter experience in the wake of the Covid-19 outbreak when production activities in many countries came to a halt as parts supplies from the country were suddenly suspended.

In the post-pandemic world, the US-China confrontation is considered to escalate, and government intervention into business activities is likely to be modus operandi in China, as precedented in the form of export controls on key strategic materials or forced technological transfers from foreign affiliates operating within the country. Global firms should be well prepared for its geopolitical implication on their supply chain management.

Table 1 juxtaposes metrics of the PTF and Trade in Value-Added (TiVA: see below) for 50 cross-border supply chains ranked by the PTF index, with Japan and China (inclusive of "Hong Kong, China") being set as a target region, respectively.[6]

The PTF index is derived from the elements in the aggregate PTF matrix, benchmarked against the sample average. The aggregate matrix is a linear sum of 36 PTF matrices, each of which is individually calculated for one of 36 sectors in Japan/China, using a multi-country input-output table. The index therefore indicates how frequent the corresponding supply chains may engage with *any* of the 36 industrial sectors located in the target region.

[6] Here in this table, we only consider the supply chains that do not have a target region at either terminal point of a path, in order to highlight the region's position as an indirect influencer of supply chains. Also, the supply chains carrying less than 500 million USD of value-added have been truncated from the sample set.

Table 1: Top 50 PTF index ranking of individual cross-border supply chains: 2018

[1-a: target region = Japan]

Rank	Final product producer (j)	Value-added source (i)	PTF index Japan	TiVA_ij (million USD)
1	CHN_41T43	MYS_05T06	1.37	640
2	CHN_27	AUS_05T06	1.26	523
3	CHN_28	AUS_05T06	1.18	1,027
4	CHN_41T43	AUS_05T06	1.13	2,440
5	KOR_41T43	AUS_05T06	0.92	698
6	CHN_41T43	IDN_05T06	0.73	1,145
7	CHN_26	USA_69T82	0.52	1,423
8	CHN_28	RUS_05T06	0.52	847
9	CHN_26	USA_64T66	0.51	577
10	KOR_41T43	AUS_07T08	0.49	618
11	IND_41T43	AUS_07T08	0.47	708
12	CHN_26	AUS_07T08	0.47	1,143
13	KOR_41T43	RUS_05T06	0.45	542
14	CHN_27	USA_69T82	0.43	735
15	CHN_41T43	IDN_45T47	0.42	652
16	CHN_41T43	SGP_45T47	0.40	852
17	CHN_28	USA_69T82	0.40	1,335
18	CHN_29	CHL_07T08	0.38	561
19	CHN_26	SGP_45T47	0.38	538
20	CHN_41T43	RUS_05T06	0.37	2,936
21	IND_41T43	AUS_05T06	0.37	1,525
22	CHN_29	USA_69T82	0.37	968
23	USA_84	RUS_05T06	0.36	507
24	CHN_41T43	CAN_07T08	0.34	778
25	CHN_28	USA_64T66	0.33	679
26	CHN_20T21	USA_69T82	0.33	514
27	CHN_28	USA_20T21	0.33	533
28	CHN_41T43	CHL_07T08	0.32	2,305
29	CHN_26	USA_49T53	0.32	532
30	CHN_41T43	USA_69T82	0.31	3,820
31	USA_29	CHN_13T15	0.31	839
32	CHN_41T43	GBR_69T82	0.30	715
33	CHN_41T43	AUS_45T47	0.30	1,542
34	CHN_41T43	USA_05T06	0.29	709
35	KOR_29	USA_69T82	0.29	508
36	CHN_28	AUS_45T47	0.28	744
37	CHN_41T43	AUS_69T82	0.28	918
38	CHN_41T43	USA_20T21	0.27	1,567
39	CHN_28	CHL_07T08	0.27	1,452
40	CHN_26	USA_45T47	0.27	2,112
41	TWN_26	CHN_45T47	0.26	511
42	IND_41T43	CHL_07T08	0.26	778
43	CHN_41T43	USA_64T66	0.26	1,962
44	IDN_41T43	MYS_05T06	0.26	567
45	CHN_10T12	RUS_05T06	0.25	530
46	CHN_41T43	AUS_35T39	0.25	507
47	USA_41T43	CHN_13T15	0.25	722
48	CHN_20T21	RUS_05T06	0.25	618
49	CHN_49T53	RUS_05T06	0.25	560
50	CHN_27	USA_45T47	0.25	1,016

[1-b: target region = China]

Rank	Final product producer (j)	Value-added source (i)	PTF index China	TiVA_ij (million USD)
1	USA_41T43	KOR_26	5.65	516
2	USA_29	TWN_26	5.58	572
3	USA_84	TWN_26	5.34	685
4	USA_84	KOR_26	5.00	910
5	USA_29	KOR_26	4.74	842
6	MEX_26	TWN_26	4.42	590
7	USA_29	SAU_05T06	3.28	640
8	MEX_26	KOR_26	3.11	1,037
9	IND_41T43	AUS_07T08	2.27	708
10	TWN_26	KOR_26	2.12	664
11	KOR_41T43	AUS_07T08	1.88	618
12	KOR_26	TWN_26	1.63	940
13	USA_84	JPN_45T47	1.60	855
14	MYS_26	TWN_26	1.53	620
15	USA_84	RUS_05T06	1.45	507
16	USA_29	KOR_45T47	1.37	539
17	USA_41T43	SAU_05T06	1.26	2,156
18	USA_86T88	JPN_45T47	1.26	547
19	CAN_41T43	SAU_05T06	1.20	550
20	USA_45T47	SAU_05T06	1.14	739
21	USA_41T43	JPN_45T47	1.12	1,309
22	IND_41T43	JPN_45T47	1.11	595
23	KOR_41T43	RUS_05T06	0.93	542
24	USA_86T88	SAU_05T06	0.91	1,253
25	VNM_26	KOR_26	0.89	849
26	MEX_26	USA_69T82	0.89	571
27	USA_29	JPN_69T82	0.86	520
28	USA_29	JPN_45T47	0.85	1,657
29	JPN_41T43	AUS_07T08	0.85	938
30	IDN_41T43	SAU_05T06	0.84	1,178
31	IND_29	SAU_05T06	0.83	572
32	JPN_28	AUS_07T08	0.82	509
33	KOR_26	USA_26	0.80	511
34	MEX_29	JPN_45T47	0.74	647
35	USA_90T96	SAU_05T06	0.72	582
36	KOR_29	SAU_05T06	0.70	734
37	KOR_28	SAU_05T06	0.69	540
38	KOR_41T43	USA_45T47	0.66	852
39	TWN_26	JPN_45T47	0.64	559
40	IND_41T43	USA_45T47	0.64	1,109
41	FRA_41T43	SAU_05T06	0.64	773
42	USA_10T12	SAU_05T06	0.63	790
43	USA_84	JPN_69T82	0.63	708
44	IND_13T15	SAU_05T06	0.62	604
45	USA_41T43	JPN_69T82	0.62	728
46	TWN_26	SAU_05T06	0.61	734
47	JPN_41T43	RUS_05T06	0.60	687
48	USA_41T43	DEU_45T47	0.60	619
49	IDN_41T43	JPN_45T47	0.59	720
50	IND_41T43	SAU_05T06	0.57	2,764

Source: Calculated by the authors

By contrast, TiVA metric presents the amounts and sources of value-added embodied in final products, which are consumed in various locations in the world through international trade. In a matrix form based on a multi-country input-output table, it maps out flows of value-added, both within and across the borders, as formulated as $\hat{\boldsymbol{v}}\boldsymbol{L}\hat{\boldsymbol{y}}$ where $\hat{\boldsymbol{v}}$ is a diagonal matrix of value-added coefficients (the amount of value-added generated by a unit production), $\boldsymbol{L}$ is a multi-country Leontief inverse matrix, and $\hat{\boldsymbol{y}}$ is a diagonal matrix of final demands with a country dimension.

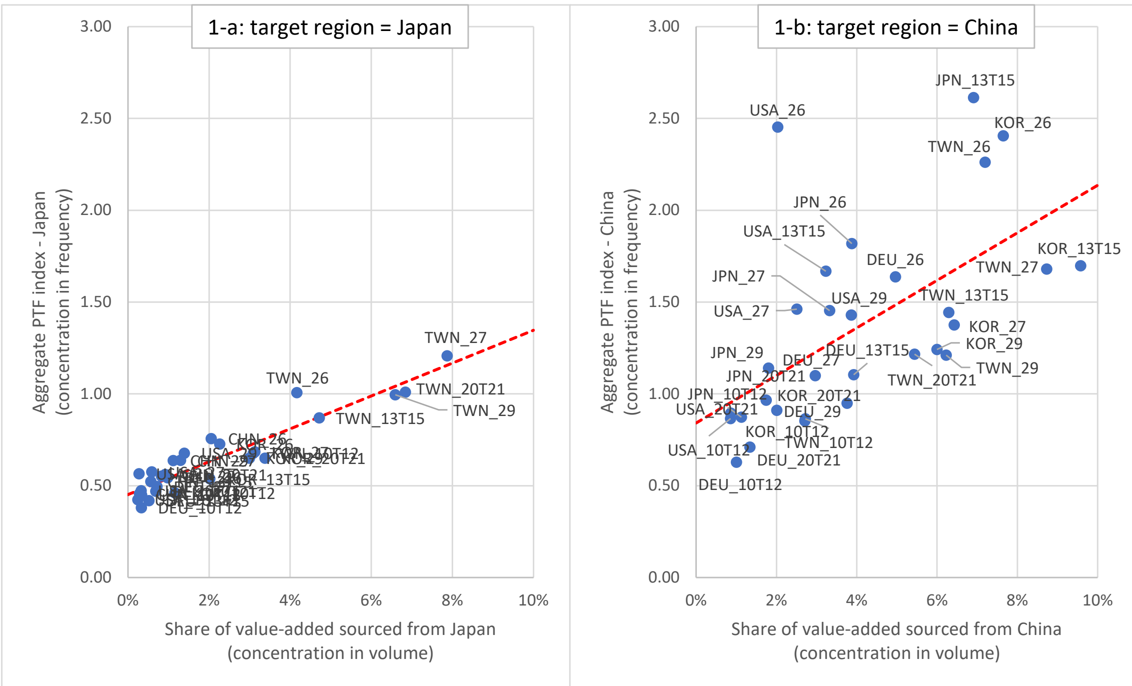
The shaded entry in Table 1-b, for example, shows that the US car supply chain (USA_29) engages with industrial sectors of China in the frequency of 5.58 times higher than the average, in order to source 572 million USD of value-added from the ICT/electronics equipment industry of Chinese Taipei (TWN_26). Likewise, just below the shaded entry, it may deserve a sharp attention of the US policy makers that "Public administration and defence; compulsory social security" of the United States (USA_84), the-sector-in-charge for the US national security, exhibits high presence of China's industrial sectors in its supply chains for sourcing value-added from the ICT/electronics equipment sectors of Chinese Taipei and Korea (TWN_26, KOR_26).

Figure 1 presents relative risk positions of GVC-oriented manufacturing sectors in selected industrialized economies. The horizontal axis gives the share of value-added sourced from the target region, calculated from the corresponding subset of elements in $\hat{\boldsymbol{v}}\boldsymbol{L}$ from the TiVA matrix, while the vertical axis is the industry's total PTF for all branches of its supply chains, given by the column sums of the aggregate PTF matrix, and indexed against the sample average.[7] Dotted lines indicate simple regressions.

From the perspective of final product producers, TiVA presents how much value of their products is attributable to the value-added origin of which country, showing the ultimate form of supply chain dependence in volume term. Therefore, the diagram depicts the nature of supply chain concentration/dependence of each country-sector pair along the volume and frequency dimensions.

[7] Note that, unlike Table 1, the selected supply chains here include those which have a target sector at an end point of a path.

Figure 1 Relative risk positions of GVC-oriented manufacturing sectors: 2018



CHN	People's Republic of China	10T12	Food products, beverages and tobacco
DEU	Germany	13T15	Textiles, wearing apparel, leather and related products
JPN	Japan	20T21	Chemicals and pharmaceutical products
KOR	Republic of Korea	26	Computer, electronic and optical products
TWN	Chinese Taipei	27	Electrical equipment
USA	The United States	29	Motor vehicles, trailers and semi-trailers

Source: Drawn by the authors.

The key findings are as follows.

- By comparing the two panels, the data is more dispersed for China's case [1-b], especially towards the top-right corner of the diagram. This shows that the supply chains of the selected economies are generally more concentrated in China than in Japan, but also the variation therein is larger among individual economies and industries.

- For Japan's case [1-a], the industries of Chinese Taipei stand out for being dependent on the country, especially with regard to the shares of value-added origins.

- China's case reveals that the nature of concentration risks differs between advanced economies (Germany, Japan, the United States) and emerging economies (Korea, Chinese Taipei). The industrial sectors of the former group tend to be clustered in the area above the regression line (volume < frequency), while those of the latter group are mostly found below the line (volume > frequency), except for the ICT/electronics equipment sectors of Korea and Chinese Taipei (KOR_26, TWN_26). Namely, the advanced economies are more prone for facing the concentration risks in terms of frequency rather than volume.

The last observation can be explained by two simple factors. First, because domestic markets and industrial base of advanced economies are sufficiently large, the share of foreign value-added in their production activities tends to be small. Second, advanced economies accommodate many global firms that organize long and sophisticated supply chains with substantial foreign exposure, which is considered to increase their engagement frequency with the target region.[8]

- Focusing on the ICT/electronics equipment industry, which is now widely recognized as a strategic sector in the domain of national security, the supply chains of Korea and Chinese Taipei (KOR_26, TWN_26) are most exposed to the concentration risks in China, both in terms of volume and frequency. The various diplomatic efforts by the US government to "de-couple" the ICT supply chains away from China's influence reflect its bare recognition of such risks through the lens of real-world geopolitics.[9]

The US supply chains of the ICT/electronics equipment industry (USA_26) presents an interesting case, which is positioned at the top-left corner of the diagram. The low concentration of its value-added origin in China may be straightforward reflection of the sheer size of the US economy, as well as a classic offshoring practice that only low value-added segments of supply chains are transferred abroad. By contrast, the high positioning along the vertical axis indicates the frequent exposure of its supply chains to the production networks within China's geographic territory, raising the likelihood of getting caught by (natural or human-driven) contingencies in the country.

In general, the two metrics of geographic concentration in volume term and frequency term seem to be positively correlated. However, the above case of the US ICT/electronics sector vis-à-vis China suggests that only looking at the volume side may lead to significant underestimation of the overall risk in supply chain management.

[8] See, however, the point raised in Section 5, (3).

[9] In 2020, the US government successfully persuaded TSMC, the world's dominant foundry of semiconductors from Chinese Taipei, to build a plant in the State of Arizona, while keeping the company away from its bilateral transaction with Huawei, a major Chinese mobile phone manufacturer.

5. Some extensions

The current research can be developed and extended in several directions. What follows is not an exhaustive list of ideas but intended to give an insight for its application possibility in the areas of high policy relevance.

(1) “Choke point map”

In Table 1, we presented a pair of PTF index and TiVA for respective supply chain, setting Japan and China as target regions. By doing the same calculation for all other countries covered in the multi-country input-output table, it is possible to identify a choke point for each supply chain by cross-country comparison of the PTF/TiVA values. Such a “choke point map” can be drawn in much higher resolution if the PTF is referred to in individual target-sector matrices rather than the aggregate matrix, which enables us to define a choke point at the country-sectoral level.

(2) Subregional analyses

Natural hazards are generally associated with a specific area/subregion of a country. More detailed and accurate risk analyses will be possible if we use the information of input-output table at the sub-national level. Several efforts have been made in the past to construct multi-country input-output tables with subregional extensions. For example, Inomata and Meng (2013) introduce the *Transnational Interregional Input-Output Table for China, Japan, and Korea*, constructed by the Institute of Developing Economies, JETRO, which links the interregional input-output tables of respective countries into a single matrix to account for regional heterogeneity within a country in a multi-country framework. The table allows for disaster impact analyses across the borders on a region-to-region basis—for example, between Tohoku in Japan and Huanan in China. See also Cherubini and Los (2013) for Italy, Dietzenbacher, et al. (2013) for Brazil, and Meng, et al. (2013) for China, which embed the respective country’s interregional input-output table in the European Commission–funded World Input-Output Database (Timmer et al. 2015).

(3) Supply chain lengths and risk exposure

Against the backdrop of the pandemic and geopolitical tensions, there is an increasing concern that a long cross-border supply chains may translate into high exposure to foreign disturbances, calling for withdrawal and internalization of supply chains by facilitating reshoring of production activities. However, this is a conjecture that should be empirically tested. A metric of supply chain lengths, notably Average Propagation Lengths developed by Dietzenbacher et al. (2005), and the PTF can be compared for cross-border supply chains to see if there is a significant correlation between the two; see *Footnote 4*.

6. Conclusion

In this paper we presented and analyzed new referential statistics for risk assessment on geographical concentration of global supply chains. The study's net contribution rests on the development of a metric which indicates geographical concentration in terms of the *frequency* of supply chain engagement with the regions of analytical concerns, alongside the traditional approach based on volume measures of value-added concentration.

Japan, a country with a high propensity to encounter natural hazards, and China, under a mounting geopolitical tension with the United States, were chosen as target regions for the risk assessment. The analysis followed a line of techniques in input-output economics known as the "key sector analysis", yet with methodological augmentation by a compatible analytical framework in the network theory. Using the latest set of multi-country input-output tables constructed by the OECD, the following findings were presented.

The supply chains of the selected industrialized economies are generally more concentrated in China than in Japan. The study on China as a target region reveals that the nature of concentration risks differs between advanced economies and emerging economies, such that the former is more prone for facing frequency risks than volume risks, while the opposite is observed for the latter. For Japan as a target region, the industries of Chinese Taipei stand out for being dependent on the country, especially with regard to the shares of value-added origins.

Focusing on the ICT/electronics equipment industry, the supply chains of Korea and Chinese Taipei are most exposed to the concentration risks in China, both in volume and frequency terms. By contrast, the US supply chains presents an interesting case; the low concentration of its value-added origin in China may be straightforward reflection of the sheer size of the US economy, while its high pass-through frequency indicates its frequent exposure to China's geographic territory, raising the likelihood of getting caught by (natural or human-driven) contingencies in the country.

In general, the two metrics of geographic concentration in volume term and frequency term are positively correlated. However, the above US case suggests that only looking at the volume side may lead to significant underestimation of the overall risk in supply chain management.

References

Ali, Y. 2015. "Measuring CO2 Emission Linkages with the Hypothetical Extraction Method (HEM)," *Ecological Indicators*, 54, 171-183.

Chenery, H.B., Watanabe, T. 1958. "International Comparisons of the Structure of Productions," *Econometrica*, 4, 487–521.

Cherubini, L., Los, B. (2013) "Regional Employment Patterns in a Globalizing World: A Tale of Four Italies," Paper presented at the Bank of Italy workshop, Global Value Chains: New Evidence and Implications, Rome, June 22.

Dietzenbacher, E., van Burken, B., Kondo, Y. (2019) "Hypothetical Extractions from a Global Perspective," *Economic Systems Research*, 31(4), 505–519.

Dietzenbacher, E., Guilhoto, J., D. Imori. (2013) "The Role of Brazilian Regions in the Global Value Chain," *School of Economics, Business and Accounting Working Paper*, 2013–15, University of São Paulo, São Paulo.

Dietzenbacher, E., Lahr, M. (2013) "Expanding Extractions," *Economic Systems Research*, 25(3), 341–360.

Dietzenbacher, E., Linden, J., Steenge, A. (1993) "The Regional Hypothetical extraction method: EC Input–Output Comparisons," *Economic Systems Research*, 5(2), 185–206.

Dietzenbacher, E., Luna, I.R., Bosma, N.S. (2005) "Using Average Propagation Lengths to Identify Production Chains in the Andalusian Economy," *Estudios de Economia Aplicada,* 23 (2), 405–422.

Dietzenbacher, E., Miller, R.E. (2015) "Reflections on the Inoperability Input-Output Model," *Economic Systems Research*, 27(4), 478–486.

Hanaka, T., Kagawa, S., Ono, H., Kanemoto, K. (2017) "Finding Environmentally Critical Transmission Sectors, Transactions and Paths in Global Supply Chain Networks," *Energy Economics*, 68, 44–52.

Hertwich, E.G. (2021) "Increased carbon footprint of materials production driven by rise in investments," *Nature Geoscience*, 14, 151–155.

Hirschman, A.O. (1958) *The Strategy of Economic Development*, Yale University Press, New Haven.

Inomata, S. (2017) "Analytical frameworks for global value chains: An overview", *Global Value Chain Development Report 2017*, Chapter 1, The World Bank Group, Washington D.C.

Inomata, S. (2019) *Global Value Chains*, Nikkei BP Publishing, Tokyo (Japanese only).

Inomata, S., and B. Meng. (2013) "Transnational Interregional Input-Output Tables: An

Alternative Approach to MRIO?" In *Sustainability Practitioner's Guide to Multi-Regional Input-Output Analysis*, edited by J. Murray and M. Lenzen, 33–42. Champaign, IL: Common Ground Publishing.

Lenzen, M. (2003) "Environmentally Important Paths, Linkages and Key Sectors in the Australian Economy," *Structural Change and Economic Dynamics*, 14, 1–34.

Liang, S., Qu, S., Xu, M. (2016) "Betweenness-based Method to Identify Critical Transmission Sectors for Supply Chain Environmental Pressure Mitigation," *Environmental Science & Technology*, 50, 1330–1337.

Los, B., Timmer, M.P. (2018) "Measuring Bilateral Exports of Value Added: A Unified Framework," *NBER Working paper*, No. 24896.

Los, B., Timmer, M.P., de Vries, G.J. (2016) "Tracing Value-Added and Double Counting in Gross Exports: Comment," *American Economic Review*, 106, 1958–1966.

Meng, B., Wang, Z., Koopman, R. (2013) "How are Global Value Chains Fragmented and Extended in China's Domestic Production Networks?" *IDE Discussion Paper Series* No. 424, Institute of Developing Economies, JETRO, Chiba, Japan.

Miroudot, S., Ye, M. (2021) "Decomposing Value Added in Gross Exports," *Economic Systems Research*, 33(1), 67–87.

Muldrow, M., Robinson, D.P. (2014) "Three Models of Structural Vulnerability: Methods, Issues, and Empirical Comparisons," *Paper Presented at the 2014 Annual Meeting of the Southern Regional Science Association*, San Antonio, TX, USA.

Paelinck, J., de Caevel, J., Degueldre, J. (1965) "Analyse Quantitative de Certaines Phénomènes du Développement Régional Polarisé: Essai de Simulation Statique d'Itinéraires de Propagation," *Bibliothèque de l'Institut de Science économique. No. 7. Problémes de Conversion économique: Analyses Théoriques et études Appliquées*, M.-Th. Génin, Paris, 341–387.

Rasmussen, P.N. (1957) *Studies in Inter-sectoral Relations*, Amsterdam: North-Holland

River Databook (2021), Ministry of Land, Infrastructure, Transport and Tourism, Japan. https://www.mlit.go.jp/river/toukei_chousa/kasen_db/pdf/2021/2-2-4.pdf

Schultz, S. (1977) "Approaches to identifying key sectors empirically by means of input-output analysis," *The Journal of Development Studies*, 14, 77–196.

Strassert, G. (1968) "Zur Bestimmung strategischer Sektoren mit Hilfe von Input-Output-Modellen," *Jahrbücher für Nationalökonomie und Statistik*, 182, 211–215.

Temurshoev, U. (2009) "Hypothetical extraction and fields of influence approaches: integration and policy implications," *EERC Working Paper Series* 09/06e.

Temurshoev, U. (2010) "Identifying Optimal Sector Groupings with the Hypothetical Extraction Method," *Journal of Regional Science*, 50, 872–890.

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J. (2015) "An illustrated user guide to the world input–output database: the case of global automotive production," *Review of International Economics*, 23, 575–605.

Tokito, S., Kagawa, S., Hanaka, T. (2021) "Hypothetical extraction, betweenness centrality, and supply chain complexity," *Economic Systems Research*, Forthcoming.

Wang, Y., Wang, W., Mao, G., Cai, H., Zuo, J., Wang, L., Zhao, P. (2013) "Industrial CO2 Emissions in China Based on the Hypothetical Extraction Method: Linkage Analysis," *Energy Policy*, 62, 1238–1244.

Xia, Y., Guan, D., Steenge, A.E., Dietzenbacher, E., Meng, J., Mendoza Tinoco, D. (2019) "Assessing the economic impacts of IT service shutdown during the York flood of 2015 in the UK." *Proc. R. Soc. A.* 475, 20180871.

Zhao, Y., Liu, Y., Wang, S., Zhang, Z., Li, J. (2016) "Inter-Regional Linkage Analysis of Industrial CO2 Emissions in China: An Application of a Hypothetical Extraction Method," *Ecological Indicators*, 61, 428–437.

Appendix A: Multiple-counting of the Structural Betweenness Centrality

Consider three-stage paths ($l + m = 3$) for a three-sector input-output system (s_1, s_2, s_3). The total impact of unit production from sector s_3 to sector s_1 is calculated by:

$(\boldsymbol{A}^3)_{13}$

$= a_{11}a_{11}a_{13}$ (Path 1: 3→1→1→1)

$+ a_{12}a_{21}a_{13}$ (Path 2: 3→1→2→1)

$+ a_{13}a_{31}a_{13}$ (Path 3: 3→1→3→1)

$+ a_{11}a_{12}a_{23}$ (Path 4: 3→2→1→1)

$+ a_{12}a_{22}a_{23}$ (Path 5: 3→2→2→1)

$+ a_{13}a_{32}a_{23}$ (Path 6: 3→2→3→1)

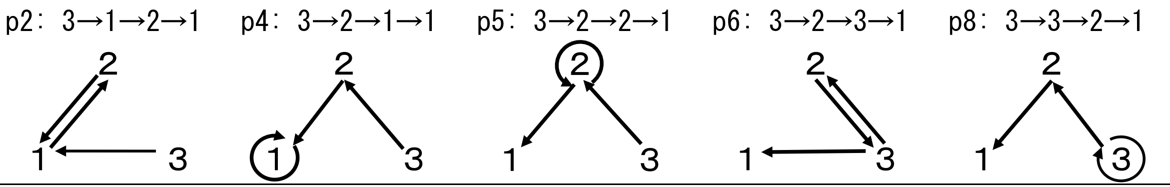
$+ a_{11}a_{13}a_{33}$ (Path 7: 3→3→1→1)

$+ a_{12}a_{23}a_{33}$ (Path 8: 3→3→2→1)

$+ a_{13}a_{33}a_{33}$ (Path 9: 3→3→3→1)

Let us take s_2 as the target sector. Among the nine paths above, we only have to consider those that go through s_2 in order to calculate the Structural Betweenness Centrality, as short-listed in Figure A.[10] The table underneath shows the decomposition of a respective impact propagation into downstream sequence (DS) and upstream sequence (US). Note that Path 5 yields two different DS/US pairs, each corresponding to a different border anchored by s_2.

Figure A: Impact propagation through s_2



	p2	p4	p5	p6	p8
DS	3→1→2	3→2	3→2	3→2	3→3→2
US	2→1	2→1→1	2→2→1	2→3→1	2→1
DS			3→2→2		
US			2→1		

[10] The reason is as follows. By referring back to Equation (10), it is seen that if a path does not go through the target sector t, $c_{(t)}$ is zero (0) by definition, and hence the value for the corresponding path also becomes zero.

Now, Equation (9) can be expanded as follows.

$$(\boldsymbol{L}-\boldsymbol{I})\,\boldsymbol{J}_{(t)}(\boldsymbol{L}-\boldsymbol{I})\,\boldsymbol{y}$$
$$= (\boldsymbol{A}^1+\boldsymbol{A}^2+\boldsymbol{A}^3+\cdots)\,\boldsymbol{J}_{(t)}(\boldsymbol{A}^1+\boldsymbol{A}^2+\boldsymbol{A}^3+\cdots)\boldsymbol{y}$$
$$= (\boldsymbol{A}^1\boldsymbol{J}_{(t)}+\boldsymbol{A}^2\boldsymbol{J}_{(t)}+\boldsymbol{A}^3\boldsymbol{J}_{(t)}+\cdots)(\boldsymbol{A}^1+\boldsymbol{A}^2+\boldsymbol{A}^3+\cdots)\boldsymbol{y}$$
$$= (\boldsymbol{A}^1\boldsymbol{J}_{(t)}\boldsymbol{A}^1+\boldsymbol{A}^2\boldsymbol{J}_{(t)}\boldsymbol{A}^1+\boldsymbol{A}^3\boldsymbol{J}_{(t)}\boldsymbol{A}^1+\cdots$$
$$+\boldsymbol{A}^1\boldsymbol{J}_{(t)}\boldsymbol{A}^2+\boldsymbol{A}^2\boldsymbol{J}_{(t)}\boldsymbol{A}^2+\boldsymbol{A}^3\boldsymbol{J}_{(t)}\boldsymbol{A}^2+\cdots$$
$$+\boldsymbol{A}^1\boldsymbol{J}_{(t)}\boldsymbol{A}^3+\boldsymbol{A}^2\boldsymbol{J}_{(t)}\boldsymbol{A}^3+\boldsymbol{A}^3\boldsymbol{J}_{(t)}\boldsymbol{A}^3+\cdots)\boldsymbol{y}$$

It can be seen that the impact $a_{12}a_{22}a_{23}y_3$ along Path 5, "3→2→2→1", is captured by the term $\boldsymbol{A}^2\boldsymbol{J}_{(t)}\boldsymbol{A}^1\,\boldsymbol{y}$ when taking the first emergence of s_2 as a DS/US border, and it is also counted in $\boldsymbol{A}^1\boldsymbol{J}_{(t)}\boldsymbol{A}^2\,\boldsymbol{y}$ when taking the second s_2 as a border; that is, the equation double-counts the same amount of impacts when the target sector appears twice. Such multiple-counting applies to any combination of downstream/upstream sequences for any higher order propagation.

Appendix B: Pass-through Frequency for a transaction

Multiple-counting of the identical amounts of impacts in accordance with the emergence of (t_1, t_2) transaction is formulated as

$$\left[a_{t_1t_2}\boldsymbol{L}\boldsymbol{J}_{(t_1,t_2)}\boldsymbol{L}\right]_{s_1s_k}$$
$$= c_{(t_1,t_2)}\cdot a_{s_1s_k}+\sum_{k=3}^{\infty}\sum_{s_2,\dots,s_{k-1}}\left(c_{(t_1,t_2)}\cdot a_{s_1s_2}\,a_{s_2s_3}\,a_{s_3s_4}\dots a_{s_{k-1}s_k}\right)$$

… (B-1)

where $c_{(t_1,t_2)}$ is the number of times that the transaction (t_1, t_2) appears in a particular backward linkage path. Note that the first term of Equation (B-1) corresponds to a linkage path $s_k \rightarrow s_1$ of length 1, while the second term is for the paths with a length of more than 2. For the first term, if $s_1 = t_1$ and $s_k = t_2$, $c_{(t_1,t_2)}\cdot a_{s_1s_k} = a_{t_1t_2}$; otherwise, $c_{(t_1,t_2)}\cdot a_{s_1s_k} = 0$. Then, the PTF for transaction (t_1, t_2) can be formulated as:

$$f_{(t_1,t_2)_{s_1s_k}} = \frac{\left[a_{t_1t_2}\boldsymbol{L}\,\boldsymbol{J}_{(t_1,t_2)}\boldsymbol{L}\,\right]_{s_1s_k}}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1s_k}}$$
$$= \frac{c_{(t_1,t_2)}\cdot a_{s_1s_k}+\sum_{k=3}^{\infty}\sum_{s_2,\dots,s_{k-1}}\left(c_{(t_1,t_2)}\cdot a_{s_1s_2}\,a_{s_2s_3}\,a_{s_3s_4}\dots\,a_{s_{k-1}s_k}\right)}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1s_k}}$$
$$= c_{(t_1,t_2)}\cdot\frac{a_{s_1s_k}}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1s_k}}+\sum_{k=3}^{\infty}\sum_{s_2,\dots,s_{k-1}}\left(c_{(t_1,t_2)}\cdot\frac{a_{s_1s_2}\,a_{s_2s_3}\,a_{s_3s_4}\dots\,a_{s_{k-1}s_k}}{[\boldsymbol{L}-\boldsymbol{I}]_{s_1s_k}}\right)$$

… (B-2)

By analogy to the sectoral model, the transactional PTF is equivalent to a *weighted average* of $c_{(t_1,t_2)}$, an integer indicating the number of times that the target transaction (t_1, t_2) appears in a particular (s_1, s_k) path, using impact shares as weights.

Further to this, let $\sigma^{(r)}(s_1, t_1, t_2, s_k)$ be the total amount of impact propagations from s_k to s_1 such that transaction (t_1, t_2) appears in (s_1, s_k) path *exactly* r *times*. Then, we have

$$c_{(t_1,t_2)} \cdot a_{s_1 s_k} + \sum_{k=3}^{\infty} \sum_{s_{2,\ldots,} s_{k-1}} \left(c_{(t_1,t_2)} \cdot a_{s_1 s_2}\, a_{s_2 s_3}\, a_{s_3 s_4} \ldots a_{s_{k-1} s_k} \right)$$

$$= \sum_{r=0}^{\infty} r \cdot \sigma^{(r)}(s_1, t_1, t_2, s_k)\,.$$

and

$$[\boldsymbol{L} - \boldsymbol{I}]_{s_1 s_k} = \sum_{r=0}^{\infty} \sigma^{(r)}(s_1, t_1, t_2, s_k)\,.$$

Accordingly, Equation (B-2) can be reformulated as:

$$f_{(t_1,t_2)_{s_1 s_k}} = \frac{\sum_{r=0}^{\infty} r \cdot \sigma^{(r)}(s_1, t_1, t_2, s_k)}{\sum_{r=0}^{\infty} \sigma^{(r)}(s_1, t_1, t_2, s_k)} = \sum_{r=0}^{\infty} r \frac{\sigma^{(r)}(s_1, t_1, t_2, s_k)}{\sum_{r=0}^{\infty} \sigma^{(r)}(s_1, t_1, t_2, s_k)}\,,$$

... (B-3)

which makes it easier to see that the PTF is indeed equivalent to a weighted average of r by impact shares from s_k to s_1 for particular values of r.

Appendix C: Impact decomposition by target transaction emergence: a case study on China's "Computer, electronic and optical equipment" sector (CHN_26 x CHN_26)

Using the transactional PTF model and the preliminary data of the OECD's Inter-Country Input-Output Table (the 2021 release), Figure C and Table C present the result of impact decomposition by the number of times that a target transaction appears on a supply chain. We chose the intra-sectoral transaction of China's "Computer, electronic and optical equipment (26)" sector <CHN_26 x CHN_26> as the target transaction, and considered six supply chains connecting a final product producer of the "Motor vehicles, trailers and semi-trailers (29)" sector in Germany, Japan and the United States, on one hand, and a value-added source in the "Computer, electronic and optical equipment (26)" sector of Korea and Chinese Taipei, on the other.

Figure C. Decomposition of delivered impacts with respect to the number of times that the target transaction appears along the selected supply chains: 2018

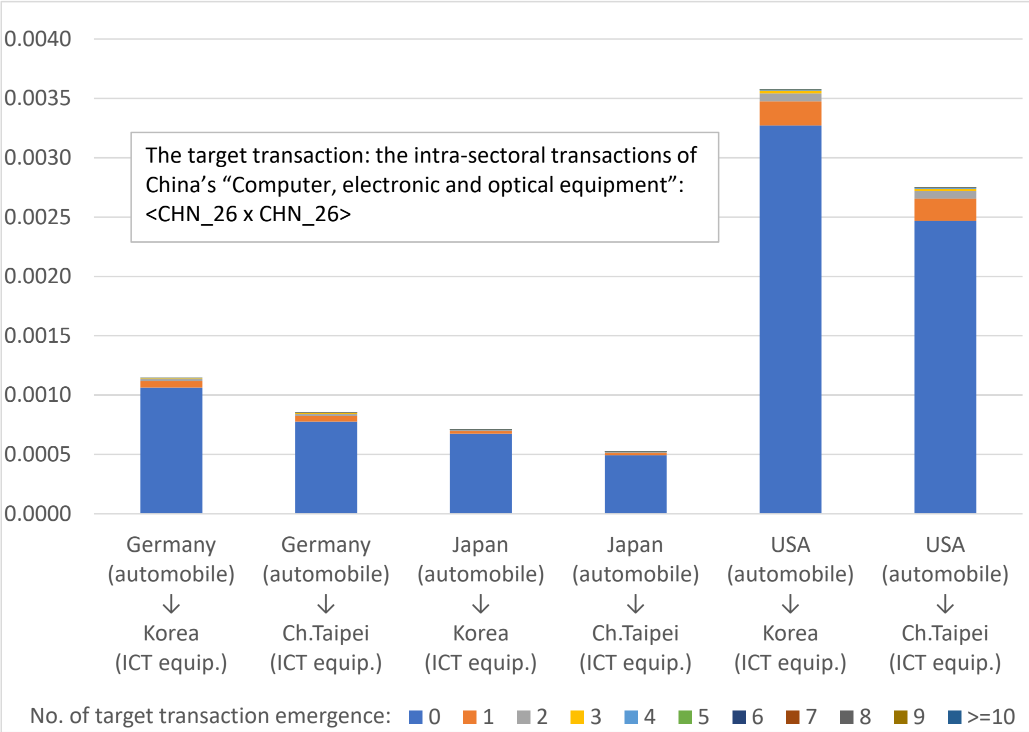


Table C. The share of delivered impacts with respect to the number of times that the target transaction appears along the selected supply chains: 2018

No. of target transaction emergence	Germany (automobile) ↓ Korea (ICT equip.)	Germany (automobile) ↓ Ch.Taipei (ICT equip.)	Japan (automobile) ↓ Korea (ICT equip.)	Japan (automobile) ↓ Ch.Taipei (ICT equip.)	USA (automobile) ↓ Korea (ICT equip.)	USA (automobile) ↓ Ch.Taipei (ICT equip.)
0	92.95%	91.27%	95.25%	94.09%	91.54%	89.87%
1	4.74%	5.86%	3.19%	3.97%	5.69%	6.80%
2	1.56%	1.92%	1.05%	1.30%	1.87%	2.23%
3	0.51%	0.63%	0.34%	0.43%	0.61%	0.73%
4	0.17%	0.21%	0.11%	0.14%	0.20%	0.24%
5	0.05%	0.07%	0.04%	0.05%	0.07%	0.08%
6	0.02%	0.02%	0.01%	0.02%	0.02%	0.03%
7	0.01%	0.01%	0.00%	0.00%	0.01%	0.01%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
>=10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

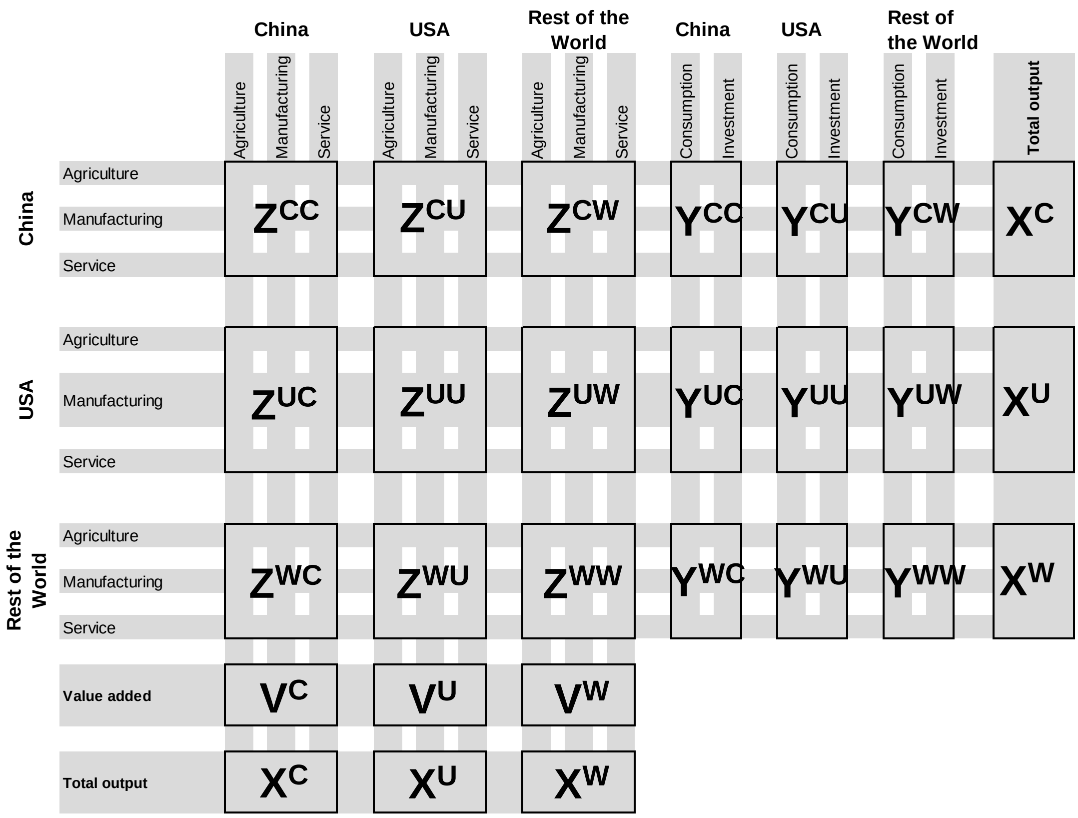
Source: Calculated and drawn by the authors.

Appendix D: Multi-country input-output tables

A multi-country input-output table brings together national tables of different countries into a single framework, and thus have the same basic structure of a national input-output table. The rows of the table show supply sectors of products, and the columns represent demand sectors for products, and an intersection of a row and a column indicates the value of transaction exchanged between these two sectors. The distinctive feature of multi-country tables, however, is that they explicitly present international transactions in the form of import/export matrices by trading partners, which allows for a comprehensive mapping of global production networks.

Figure D gives a schematic presentation of the table for a simplified example of three sectors (Agriculture, Manufacturing, Service) and three countries (China, The United States, Rest of the World).

Figure D: Multi-country input-output table (3 sectors / 3 countries)



Source: drawn by the authors.

In the column-wise direction, entries in the table indicate input compositions of industrial sectors of a respective country. Entries in $\mathbf{Z}^{CC}$, for example, shows the input composition of China's industries for domestically produced goods and services, i.e., domestic transactions of China. Those in $\mathbf{Z}^{UC}$ by contrast show the input composition of China's industries for imported products from the United States. The entries in $\mathbf{Z}^{WC}$ allow the same interpretation vis-à-vis China's imports from the Rest of the World; i.e., all other countries in the world except China and the United States.

Turning to the 10th and 11th columns from the left, they present China's final demands for goods and services. For example, $\mathbf{Y}^{CC}$, $\mathbf{Y}^{UC}$ and $\mathbf{Y}^{WC}$ map China's final demands for domestic products, for imports from the United States, and for imports from the Rest of the World, respectively. Other columns are read in the same manner.

$\mathbf{V}$s and $\mathbf{X}$s are value added and total output, as seen in the conventional national input-output table.

The multi-country input-output system shown in Figure D can be presented in a matrix form as follows:

$$\boldsymbol{x}=\begin{pmatrix} x_1^C\\ x_2^C\\ x_3^C\\ x_1^U\\ x_2^U\\ x_3^U\\ x_1^W\\ x_2^W\\ x_3^W \end{pmatrix}=\begin{pmatrix} a_{11}^{CC} & a_{12}^{CC} & a_{13}^{CC} & a_{11}^{CU} & a_{12}^{CU} & a_{13}^{CU} & a_{11}^{CW} & a_{12}^{CW} & a_{13}^{CW}\\ a_{21}^{CC} & a_{22}^{CC} & a_{23}^{CC} & a_{21}^{CU} & a_{22}^{CU} & a_{23}^{CU} & a_{21}^{CW} & a_{22}^{CW} & a_{23}^{CW}\\ a_{31}^{CC} & a_{32}^{CC} & a_{33}^{CC} & a_{31}^{CU} & a_{32}^{CU} & a_{33}^{CU} & a_{31}^{CW} & a_{32}^{CW} & a_{33}^{CW}\\ a_{11}^{UC} & a_{12}^{UC} & a_{13}^{UC} & a_{11}^{UU} & a_{12}^{UU} & a_{13}^{UU} & a_{11}^{UW} & a_{12}^{UW} & a_{13}^{UW}\\ a_{21}^{UC} & a_{22}^{UC} & a_{23}^{UC} & a_{21}^{UU} & a_{22}^{UU} & a_{23}^{UU} & a_{21}^{UW} & a_{22}^{UW} & a_{23}^{UW}\\ a_{31}^{UC} & a_{32}^{UC} & a_{33}^{UC} & a_{31}^{UU} & a_{32}^{UU} & a_{33}^{UU} & a_{31}^{UW} & a_{32}^{UW} & a_{33}^{UW}\\ a_{11}^{WC} & a_{12}^{WC} & a_{13}^{WC} & a_{11}^{WU} & a_{12}^{WU} & a_{13}^{WU} & a_{11}^{WW} & a_{12}^{WW} & a_{13}^{WW}\\ a_{21}^{WC} & a_{22}^{WC} & a_{23}^{WC} & a_{21}^{WU} & a_{22}^{WU} & a_{23}^{WU} & a_{21}^{WW} & a_{22}^{WW} & a_{23}^{WW}\\ a_{31}^{WC} & a_{32}^{WC} & a_{33}^{WC} & a_{31}^{WU} & a_{32}^{WU} & a_{33}^{WU} & a_{31}^{WW} & a_{32}^{WW} & a_{33}^{WW} \end{pmatrix}\begin{pmatrix} x_1^C\\ x_2^C\\ x_3^C\\ x_1^U\\ x_2^U\\ x_3^U\\ x_1^W\\ x_2^W\\ x_3^W \end{pmatrix}+\begin{pmatrix} y_1^{C*}\\ y_2^{C*}\\ y_3^{C*}\\ y_1^{U*}\\ y_2^{U*}\\ y_3^{U*}\\ y_1^{W*}\\ y_2^{W*}\\ y_3^{W*} \end{pmatrix}$$

$$=\boldsymbol{Ax}+\boldsymbol{y}$$

where superscripts refer to countries such that C: China, U: the United States, W: Rest of the World, and subscripts indicate industrial sectors such that 1: Agriculture, 2: Manufacturing, 3: Services.

<The OECD Inter-Country Input-Output Table, the 2021 release>

[Industrial sector classification]

Code	Description
01T03	Agriculture, forestry and fishing
05T06	Mining and extraction of energy producing products
07T08	Mining and quarrying of non-energy producing products
09	Mining support service activities
10T12	Food products, beverages and tobacco
13T15	Textiles, wearing apparel, leather and related products
16	Wood and products of wood and cork
17T18	Paper products and printing
19	Coke and refined petroleum products
20T21	Chemicals and pharmaceutical products
22	Rubber and plastic products
23	Other non-metallic mineral products
24	Basic metals
25	Fabricated metal products
26	Computer, electronic and optical products
27	Electrical equipment
28	Machinery and equipment, nec
29	Motor vehicles, trailers and semi-trailers
30	Other transport equipment
31T33	Other manufacturing; repair and installation of machinery and equipment
35T39	Electricity, gas, water supply, sewerage, waste and remediation services
41T43	Construction
45T47	Wholesale and retail trade; repair of motor vehicles
49T53	Transportation and storage
55T56	Accommodation and food services
58T60	Publishing, audiovisual and broadcasting activities
61	Telecommunications
62T63	IT and other information services
64T66	Financial and insurance activities
68	Real estate activities
69T82	Other business sector services
84	Public admin. and defence; compulsory social security
85	Education
86T88	Human health and social work
90T96	Arts, entertainment, recreation and other service activities
97T98	Private households with employed persons

Source: The OECD Inter-Country Input-Output Database, the 2021 release.

[Countries of reference]

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

Source: The OECD Inter-Country Input-Output Database, the 2021 release.