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# Where is the chokepoint? Mapping supply chain vulnerabilities using firm-to-firm transaction data

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## Abstract

This study proposes a novel approach to quantifying supply chain exposure to global risks with a particular focus on firms' activities. The principal contribution of the study is that the proposed metric is specifically designed to address economic security issues, in which supply chain vulnerability is analyzed with respect to the level of network dependence on critical inputs and/or dominant foreign markets.

**Keywords:** global supply chain, choke point, vulnerability, economic security
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## 1. Introduction

The global economy in the 21st century has given rise to a new form of production arrangement known as global value chains, in which production processes are separated and relocated to countries where tasks can be performed most efficiently. Enabled by rapid advances in transportation systems and information and communication technologies, these production networks span almost every corner of the world.

Concurrently, the pursuit of optimal resource allocation often results in agglomeration and concentration of critical production capacities in specific locations of limited countries. When faced with unpredictable external shocks, these production hubs may become “chokepoints” for the entire economic system. Recent history offers notable examples, such as the Lehman Shock, the Great East Japan Earthquake, and various cyberattacks, in which hyper-economic interdependence renders production and financial systems highly vulnerable to single points of failure. Given today's rising geopolitical tensions, such vulnerabilities may even be deliberately targeted through economic statecraft by political adversaries.

Against this backdrop, this study proposes a novel approach to quantify supply chain exposure to network concentration risk by revealing the extent to which supply chains are susceptible to unexpected incidents in global production networks. The principal contribution of this study is that the proposed metric is specifically designed to analyze economic security issues with a focus on firm activities.

The remainder of this paper is organized as follows: Section 2 provides background narratives of the research, followed by brief overviews of prior methodological developments and relevant literature in Sections 3 and 4, respectively. Section 5 provides a brief description of our approach, and Sections 6 and 7 present empirical analyses based on the new analytical tool. Section 8 discusses the immediate challenges and envisions the path forward.

## 2. Background narratives

Following the Cold War, the global economy evolved through various structural changes, including the establishment of the WTO, the expansion of free trade and FTAs, the globalization of information technology and finance, and the rapid economic growth of emerging economies, all of which have facilitated global supply chain optimization. The business strategies of Walmart and ZARA were considered notable practices in this direction, and it appeared as if the world was becoming “flat” (Friedman 2005).

On the flip side, global supply chain optimization implies that the entire chain may instantly cease functioning if only a few key links are severed. Such supply chain vulnerability has become a serious issue, particularly after a series of natural disasters in East Asia from the 1990s onward. Since the Great Hanshin-Awaji Earthquake of 1995, Japanese companies have experienced recurring supply chain disruptions due to natural disasters. In the case of the 2007 earthquake, physical damage to only one auto parts supplier in Niigata Prefecture led Toyota Motor Corporation to temporarily suspend operations at all its factories. The 2011 Great East Japan Earthquake and Chao Phraya River floods in Thailand further underscore the seriousness of supply chain vulnerabilities across East Asia.

However, these threats were not limited to natural hazards. In 2010, China banned rare-earth exports to Japan, significantly affecting Japanese companies' magnet production capacity and their supply to the U.S. and European markets. This action was driven by China's political calculations regarding the arrest and subsequent release of the captain of a Chinese fishing vessel that had collided with a Japanese coastal guard vessel near the Senkaku Islands. This incident demonstrates how geopolitical rivalry emerged as a major risk factor for supply chains in the 2010s.[1]

The COVID-19 pandemic has clearly demonstrated that supply chain vulnerabilities may pose direct threats to human life. During this crisis, medical supplies such as masks, disinfectants, and ventilators, mostly manufactured in China, were severely compromised, seriously affecting public health and economic activity across multiple nations. Travel restrictions disrupt air and sea transport and stall semiconductor supplies, forcing many factories to halt production. Furthermore, the rise of techno-nationalism vis-à-vis COVID-19 vaccine development has spread to semiconductor manufacturing, accelerating the transition to onshore supply chains for advanced semiconductors.

Geopolitical risks became even more pronounced for global supply chains due to the U.S.–China rivalry and Russia–Ukraine war, as well as disruptions to sea lanes in the Red Sea and Persian Gulf concerning Yemen and Iran. Supply chain management, which has long been dominated by an efficiency-first "just-in-time" mentality, is now subject to major reassessment. The current challenge is identifying supply chain chokepoints under a "just-in-case" mindset and mitigating the risks arising from excessive concentration.

## 3. Methodological development and relevant literature

Until recently, attempts to analyze supply chain vulnerability have primarily focused on input–output tables (IOTs). An IOT is a "map" of an economy in which flows of goods and services are compactly depicted using transaction values between a pair of industries.

In Figure 1, the left panel shows a schematic of the IOT in three industrial sectors: "agriculture," "manufacturing," and "services." Examining the intersection between Agriculture in rows and Manufacturing in columns, the value of "50" indicates that the Manufacturing industry procured agricultural products by 50 units as production inputs. Consider a case in which a soft drink manufacturer uses oranges to produce orange juice. Then, looking at the intersection between Services (row) and Manufacturing (column), the value is "100," which shows that the Manufacturing sector purchased service inputs by 100 units; for example, the soft-drink producer pays for the delivery of oranges to its factories.

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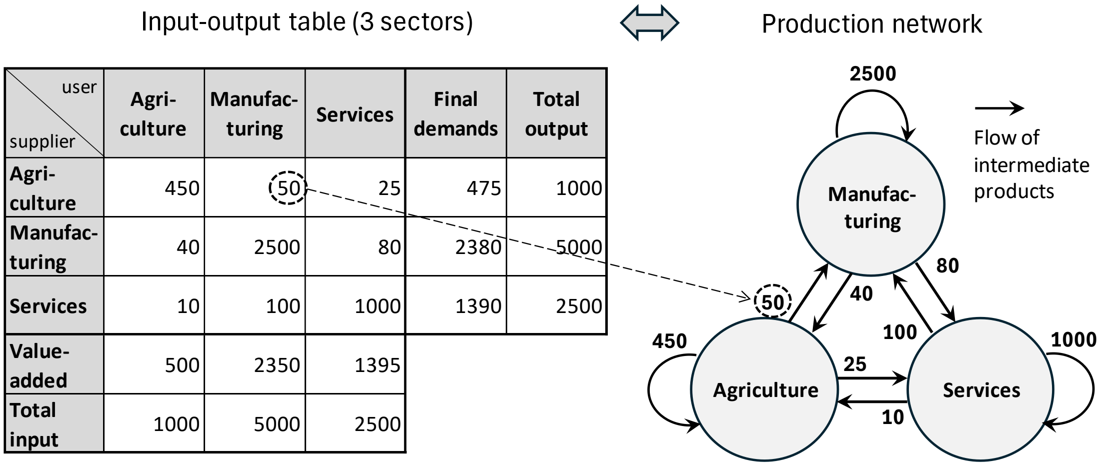
[1] By the late 2010s, China's massive supply capacity began to manifest as a geopolitical risk in the United States, known as the "China Shock" to American jobs (Autor, Dorn, and Hanson 2016). President Trump's 2017 National Security Strategy described China as a "revisionist power" that actively competes against the United States and "steals" U.S. jobs and intellectual property. Since the late 2010s, excessive dependence on China in supply chains has become a major concern for the U.S. and its allies/partners.

From a network theory perspective, the intermediate transactions among industries within an IOT can be regarded as a numerical twin of a "weighted" and "directed" production network (Figure 1, right). Here, nodes correspond to industries, links represent transactions between them, and transaction values serve as link weights. For example, a transaction value of 50 between agriculture as a supplier industry (row) and manufacturing as a user industry (column) in the IOT is mapped onto the production network as a link with a weight of 50, directed from the Agriculture to the Manufacturing node (see the dashed arrow).

Treating an IOT as a transform of a production network enables the identification of "chokepoints" in the production system by examining the network centralities of industries. Within earlier literature, Borin et al. (2021), Baldwin et al. (2022), and Inomata and Hanaka (2024) are prominent studies that use multi-country IOTs to address the issue of global supply chain exposure to concentration risks.

Figure 1. The relationship between an input–output table and a production network



Input-output table (3 sectors)

| user / supplier | Agri-culture | Manufac-turing | Services | Final demands | Total output |
|---|---|---|---|---|---|
| **Agri-culture** | 450 | 50 | 25 | 475 | 1000 |
| **Manufac-turing** | 40 | 2500 | 80 | 2380 | 5000 |
| **Services** | 10 | 100 | 1000 | 1390 | 2500 |
| **Value-added** | 500 | 2350 | 1395 | | |
| **Total input** | 1000 | 5000 | 2500 | | |

Source: Inomata and Hanaka (2024).

However, the input-output approach faces a major limitation regarding economic security. This is because its unit of analysis is either "industry" or "product," while it does not contain information about economic entities, notably, firms.

Consider export control for products that use sensitive technologies. Implementation is examined along two dimensions: "objects" (products, software, and technologies) and "users" (countries, organizations, and individuals). In the case of arms exports, for example, transactions are restricted if the product of concern falls into the "weaponry" category and the export destination is identified as an "arms embargoed country." Exports are restricted to areas in which the two lists overlap (Figure 2).[2]

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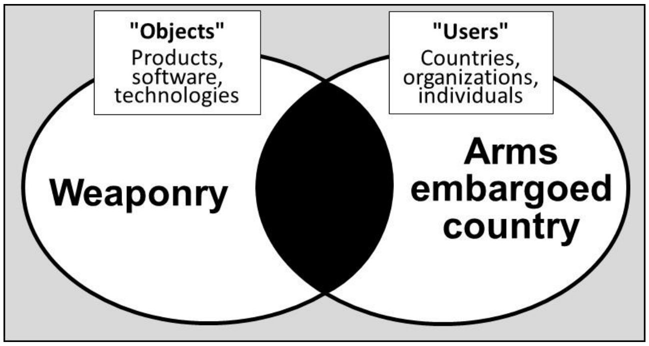
[2] Strictly speaking, there is a third dimension: "end-use."

Figure 2. Image of export controls: "objects" x "users”



Source: Inomata, Satoshi. *Geopolitics of Global Value Chain*s, Nikkei Publishing, 2023

Accordingly, analyzing the geopolitical risks of supply chains requires consideration not only of *what* is being traded (“which products”) but also *with whom* it is traded (“which firms”). IOTs lack information on economic entities and cannot, on their own, serve to analyze, for example, the economic impact of the Entity List issued by the U.S. Department of Commerce, which specifies entities subject to trade restrictions. Although input-output analysis works well for the economic security *of products*, a different approach is required for the analysis *of entities*, namely, firms.

Supply chain analyses using firm-level transaction data have developed rapidly in the aftermath of the Great East Japan Earthquake. Disaster impact analysis requires identifying the firms directly affected by a disaster, and the analytical model is fed their damage estimates as exogenous variables.

However, earlier disaster analyses based on IOTs only identified inter-industry linkages and lacked firm-level information to distinguish affected from unaffected companies. This shortcoming has motivated the development of firm-level network data for disaster analysis.

The corporate database provided by the Japanese credit research company Tokyo Shoko Research is widely used in this field. It is based on data submitted by corporate entities for credit risk management, in which firms obtain credit information on their potential trading partners or disclose their own information for listing purposes.[3]

Saito (2012), Inoue and Todo (2018), and Carvalho et al. (2021) are representative studies, although each employs a different analytical model for different research purposes. When these studies were conducted, the database covered 1.0-1.5 million firms in Japan.

Similarly, a study conducted in the U.S. used the S&P Global Ratings “Compustat” database for disaster analysis. Compustat compiles information from filings such as the SEC Form 10-K. According to the U.S. Securities and Exchange Commission’s accounting standards, listed companies must disclose major trading partners that account for 10% or more of their total

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[3] Among various information covered by this database, transaction data are particularly important for constructing inter-firm networks. For each domestically headquartered firm, the database records up to 24 suppliers and 24 customers, ranked by the importance of the relationship. By linking firm names, IDs, and headquarters’ locational addresses, researchers can approximate the domestic inter-firm network in Japan.

sales. Based on this information, Barrot and Sauvagnat (2016) constructed a domestic inter-firm network of approximately 1,000 U.S.-headquartered firms and analyzed the impact of domestic natural disasters between 1978 and 2013.

## 4. Global extension

Subsequently, the number of supply chain risk analyses using firm-level data has increased significantly. However, due to data constraints, such research has been mostly limited to single-country cases, such as the disaster analyses mentioned above, focusing on Japan or the U.S. By contrast, geopolitical risks to supply chains mainly arise from conflicts between nations, which makes relevant global data indispensable for such analyses.

Recently, academic attention has increasingly focused on databases provided by FactSet Research Systems, a private company that offers financial data, analytical tools, and AI solutions. Compared to domestic firm databases used in disaster studies, FactSet's database was designed for global-scale firm analyses, offering a significant advantage in international coverage (Table 1).

Table 1. Number of firms by region

| | | | |
|---|---|---|---|
| The United States | 185,798 | Canada | 21,277 |
| China (PRC) | 77,365 | India | 20,725 |
| United Kingdoms | 26,692 | Italy | 19,048 |
| Germany | 24,112 | Korea, Republic of | 15,426 |
| Japan | 21,813 | Hong Kong, China | 13,423 |

Source: Calculated by the authors from the version released in July 2025.

The FactSet database comprises several data packages prepared for various analytical purposes. Among them, "Revere Supply Chain Relationships" and "Shipping Transaction" are particularly useful for inter-firm network analysis. As of October 2025, these packages in combination covered 617,245 firms and contained more than 2.3 million transactional relationships.

For each firm in the data, relationships with other firms are specified as one of the four types.
(1) Suppliers – providing goods and services to the firm of analytical concerns,
(2) Customers – purchasing products from the firm,
(3) Partners – engaging in joint ventures, collaborative research, etc., with the firm or
(4) Competitors.

Each link is annotated with relevant keywords indicating the nature of the relationship. For example, IBM (Supplier)–Microsoft (Customer), Keyword: Supply of Xbox CPUs.

The supply chain dataset is constructed from publicly disclosed information by listed companies, drawing on a wide variety of sources: SEC filings (e.g., Form 10-K), financial statements, investor relations materials, company websites, and press releases. A full data update is conducted annually, and news on corporate actions is reflected in real time.

The data are cross-referred to fill in missing links ("reverse-matching"). For example, although Walmart disclosed only 11 suppliers, 415 additional suppliers were identified from their separate individual disclosures (as of November 2016). Moreover, relationships can be captured, even for unlisted firms, if they are mentioned in the disclosures of listed firms.

## 5. Risk Exposure Mapping (REM)

Despite its richness, the FactSet database alone is insufficient to measure supply chain vulnerability because it contains little information on transaction volumes. Although it identifies whether a transactional relationship exists between Firms X and Y and the direction of trade (e.g., Firm X = supplier, Firm Y = customer), it does not indicate the *intensity* or *importance* of the relationship.[4]

Our novel risk indicator, risk-exposure mapping (REM), addresses this issue by combining FactSet's firm-level transaction data with information from IOTs. As noted earlier, an IOT is a "map" of an economy showing interconnectedness between industries. Thus, by cross-referencing the business activities of each firm, production relationships can be mapped from IOTs to FactSet's firm networks.[5]

For example, suppose that FactSet shows a supplier–customer link between Firm X and Firm Y, with a primary business activity "a" and "b," respectively. If activities "a" and "b" correspond to input–output industrial sectors "α" and "β," the strength of the X–Y relationship can be approximated using the input coefficient from sector α (row) to sector β (column) in the IOT. This is because input coefficients are the shares of intermediate inputs used to produce a particular product and thus reflect the interconnectedness between the supplier and user industries for that product.

Put differently, FactSet provides the "skeleton" of the networks, and IOTs provide the "weights," which are used to flesh out the "skeleton" to generate firm-level production networks that capture interdependencies based on production relationships.

Firm-to-firm dependency, or Risk Exposure Score (RES), is calculated by multiplying the weights of production pathways. For example, in Figure 3, the exposure of U.S. automaker Firm A on Chinese semiconductor manufacturer Firm J is computed by multiplying the weights along each upstream path (thick arrows: J→G→F→C→A and J→G→C→A), or $(0.5\times0.7\times0.1\times0.4) + (0.5\times0.1\times0.4)$, which makes 0.034 as the exposure score of Firm A to Firm J. Here, the degree of risk exposure is defined as the sum of chained arithmetic products of weights along all transaction paths connecting a particular pair of nodes (i.e., firms).

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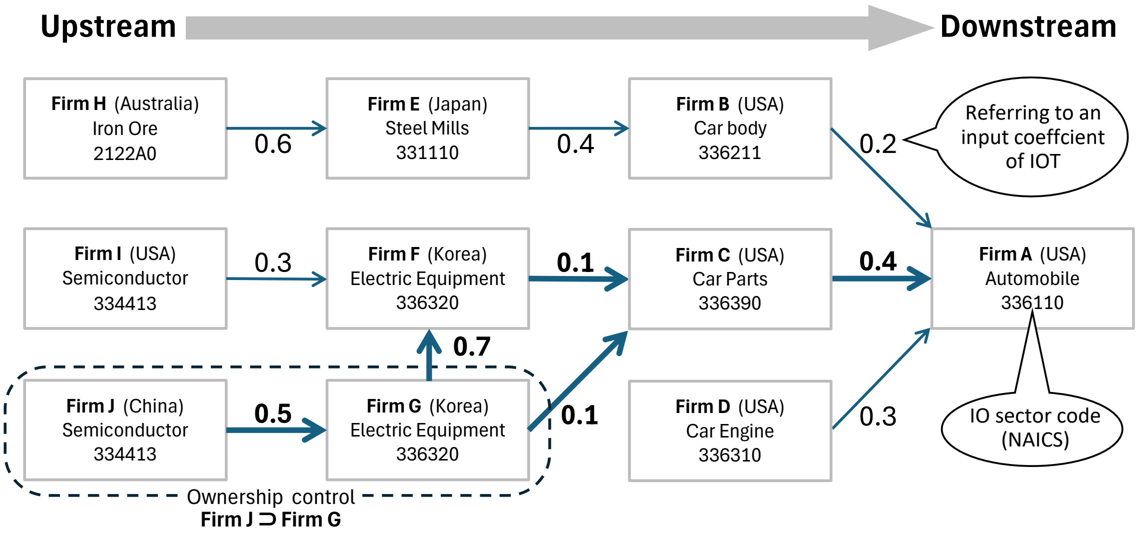
[4] To date, supply chain analyses using FactSet database have relied solely on binary information of whether a transaction exists between firms. For example, Wu (2015), one of the earliest studies to use FactSet data, conducted a network centrality analysis to elucidate the network topology of companies and their effect on the behavior of suppliers' central stock portfolios.

[5] FactSet data assigns each firm one or more sector codes from in-house coding system "RBICS (Revere Business Industry Classification System)." They can be translated into various standard taxonomies such as SIC, NAICS and NACE, which are used for industrial sector classification of IOTs.

FactSet also contains information on ownership-control relationships. If Firm J legally controls Korean electronic products manufacturer Firm G, then Firm A's risk exposure to Firm J increases accordingly: (0.7×0.1×0.4) + (0.1×0.4) = 0.068. This reflects the firm J's more extensive influence on the supply chain. By overlaying ownership information, it becomes possible to delineate the "sphere of influence" of a risk firm within production networks.

Figure 3. Measurement of inter-firm dependency: Risk Exposure Score



Source: Drawn by the authors.

Overall, REM calculates inter-firm dependencies for approximately 2.3 million transactional relationships worldwide to measure each supply chain's risk exposure, with reference to ownership structures and economic security institutions, such as the U.S. Entity Lists.

Although REM lacks general-purpose versatility as demonstrated by alternative databases (see Appendix F), it offers three key competitive advantages.

- <u>Comprehensiveness</u>: Nearly all firms covered by FactSet can be included in the analysis,
- <u>Timeliness</u>: It can be recalculated in line with FactSet's annual updates, and
- <u>Multidimensionality</u>: It can integrate information on ownership control relationships.

Therefore, REM is a practical tool for addressing the unique challenges of economic security.

## 6. Analytical examples: structural path analysis

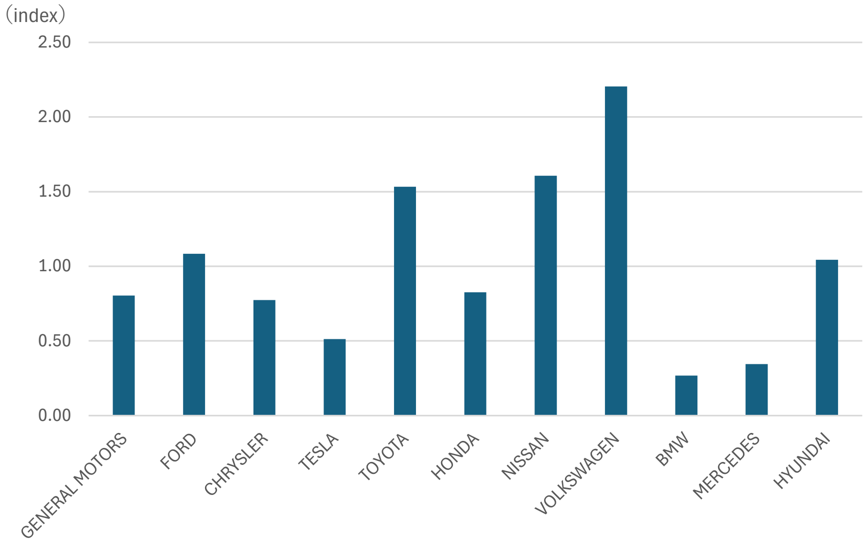
The following analysis concerns a recent supply chain disruption in the automotive industry caused by China's export controls on Nexperia's semiconductors. Nexperia is a Dutch company that specializes in the production of automobile-specific semiconductors. In 2019, the company was acquired by Wingtech Technology, a Chinese electronic product manufacturer, and now operates one of its largest factories in Guangdong Province, China.

Following the decision of the Dutch government in late September 2025 to forcibly seize control of Nexperia, citing "national security concerns," the company suspended the export of semiconductors to its major customers, notably U.S. and European automakers, under strong directives from the Chinese government. This is widely understood as China's retaliation against the Dutch government's measures.[6]

Export restrictions have eased by November 2025. However, they caused significant disruption to the automobile industry's global supply chains, revealing the industry's serious dependence on the company's products.

Against this background, Figure 4 compares the degree of dependence of major automakers on the semiconductor products of Nexperia affiliates in China. Volkswagen, which is well known for its highly modularized product architecture and global outsourcing strategy, shows the highest dependence on this product.

Figure 4. Dependence on Nexperia (China) semiconductors: by enterprises



Source: Drawn by the authors.

Figure 5 shows the dependency structure by region. (Foreign affiliates are counted based on countries of residence rather than nationality.) The U.S. as a region shows an outstanding

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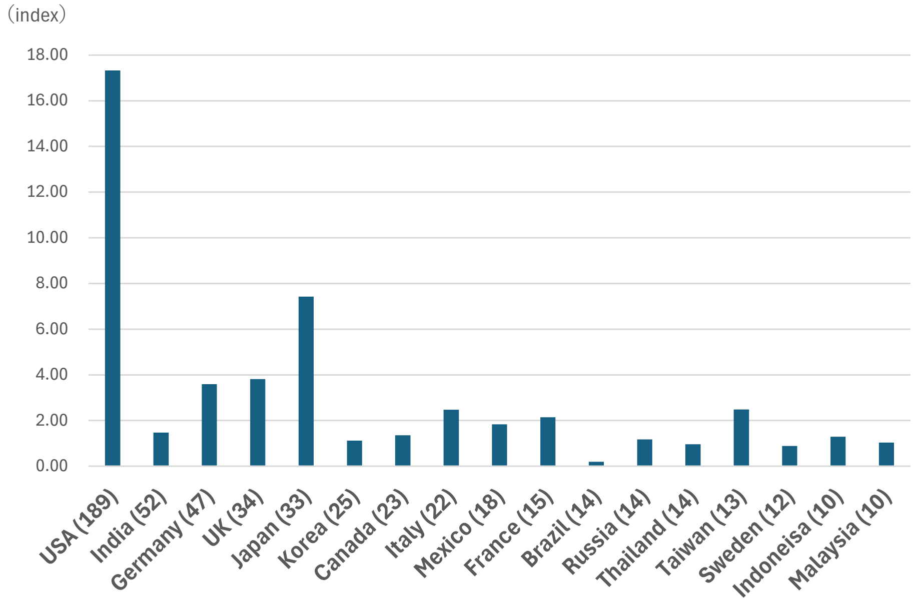
[6] The root of the problem lies in heightening U.S.–China tensions. In late September 2025, the U.S. Department of Commerce expanded the scope of its Entity List, imposing transaction restrictions on companies in which listed entities hold a 50% or greater stake. Consequently, Nexperia, whose parent company Wingtech was on the list, also became subject to U.S. export restrictions.

degree of dependence on Nexperia. Still, a company breakdown in the data reveals that Volkswagen's foreign affiliate in the U.S. drives up the U.S. dependency value.

Figure 5. Dependence on Nexperia (China) semiconductors: by country/region



Source: Drawn by the authors.
Note: The number of automaker establishments in each region is given in parentheses. China is not included on the list of countries/regions.

In this line, let us advance to a more detailed anatomy of the supply chains for Volkswagen's U.S. affiliates. Table 2 presents a list of production paths from Nexperia-China to Volkswagen-US in ascending order of importance within the supply chains (down to Path 6 of 104,303 paths in total).

In Figure 6, the top five paths in the table are schematized as production networks. The arrows indicate the direction of the products, and their thickness indicates the importance of the production pathways within the supply chain.

Path 1 (in black), which connects the two establishments via Chinese firm A, a car device supplier, is considered the most important. It alone accounts for 64% of the entire RES (see the column labelled "Share in RES" in Table 2). The second path (in green) is relayed by Chinese Firm A, but through a different product: electric car parts. Therefore, we can reasonably conclude that the Chinese Firm A is a key entity in Volkswagen's risk exposure to Nexperia.

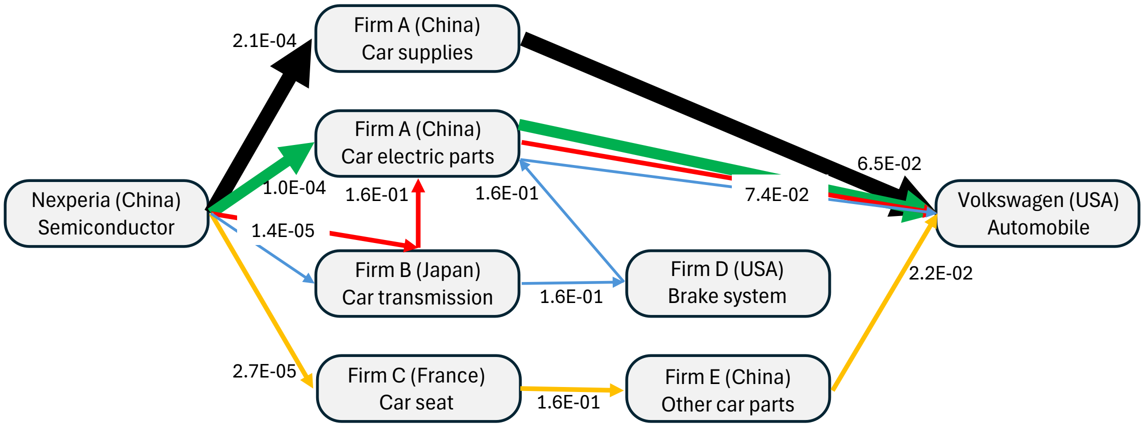
Table 2. Anatomy of supply chains [NX_CH → VW_US]: Production path list

| | supplier | supplier NAICS | customer | customer NAICS | Link weight | Path weight | Share in RES |
|---|---|---|---|---|---|---|---|
| Path 1 | **Nexperia Semi-conductor China** | 334413 | Firm A (China): Car supplies | 423120 | 2.1E-04 | 1.37E-05 | 63.71% |
| | Firm A (China): Car supplies | 423120 | **Volkswagen Group of America** | 336110 | 6.5E-02 | | |
| Path 2 | **Nexperia Semi-conductor China** | 334413 | Firm A (China): Car electric parts | 336320 | 1.0E-04 | 7.41E-06 | 34.40% |
| | Firm A (China): Car electric parts | 336320 | **Volkswagen Group of America** | 336110 | 7.4E-02 | | |
| Path 3 | **Nexperia Semi-conductor China** | 334413 | Firm B (Japan): Car transmission | 336350 | 1.4E-05 | 1.63E-07 | 0.76% |
| | Firm B (Japan): Car transmission | 336350 | Firm A (China): Car electric parts | 336320 | 1.6E-01 | | |
| | Firm A (China): Car electric parts | 336320 | **Volkswagen Group of America** | 336110 | 7.4E-02 | | |
| Path 4 | **Nexperia Semi-conductor China** | 334413 | Firm C (France): Car seat | 336360 | 2.7E-05 | 9.35E-08 | 0.43% |
| | Firm C (France): Car seat | 336360 | Firm E (China): Other car parts | 336390 | 1.6E-01 | | |
| | Firm E (China): Other car parts | 336390 | **Volkswagen Group of America** | 336110 | 2.2E-02 | | |
| Path 5 | **Nexperia Semi-conductor China** | 334413 | Firm B (Japan): Car transmission | 336350 | 1.4E-05 | 2.54E-08 | 0.12% |
| | Firm B (Japan): Car transmission | 336350 | Firm D (USA): Brake system | 336340 | 1.6E-01 | | |
| | Firm D (USA): Brake system | 336340 | Firm A (China): Car electric parts | 336320 | 1.6E-01 | | |
| | Firm A (China): Car electric parts | 336320 | **Volkswagen Group of America** | 336110 | 7.4E-02 | | |
| Path 6 | **Nexperia Semi-conductor China** | 334413 | Firm F (China): Industrial Machinery | 423830 | 7.5E-05 | 1.69E-08 | 0.08% |
| | Firm F (China): Industrial Machinery | 423830 | Firm G (China): Car electric parts | 336320 | 2.0E-02 | | |
| | Firm G (China): Car electric parts | 336320 | Firm A (China): Car electric parts | 336320 | 1.5E-01 | | |
| | Firm A (China): Car electric parts | 336320 | **Volkswagen Group of America** | 336110 | 7.4E-02 | | |
| Path 7 | : | : | : | : | : | : | : |
| : | : | : | : | : | : | : | : |

Source: Calculated by the authors.

Note: In the original data, all company names are known explicitly. However, due to confidentiality concerns, only company attributes, such as the country of residence or main production activities, are presented here except for Nexperia (China) and Volkswagen (US).

Figure 6. Anatomy of supply chains [NX_CH → VW_US]: Schematized production networks

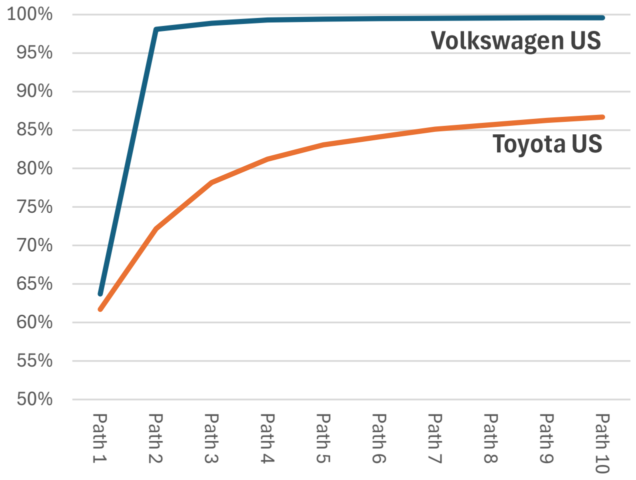


Source: Drawn by the authors.

Note: Arrows indicate the direction of the products, and their thickness indicates the importance of the production path within the supply chain. Note that, within each critical path, the critical *transactions* can be also identified by referring to the corresponding weights allocated to each link.

Table 2 shows that over 98% of the total exposure score is accounted for by only the first two production paths (yellow-highlighted) out of the 104,303 paths, suggesting that the supply chain of Volkswagen-U.S. is characterized by a high degree of path concentration in critical supply dependence. This can be confirmed by comparison with other firms operating in the U.S. For example, Toyota Motors in Kentucky shows more dispersed path dependence on Nexperia. (Figure 7)

Figure 7. Distribution of path concentration for Risk Exposure Score



Source: Drawn by the authors.

## 7. Analytical examples: macro-level overview

In the previous section, we presented a firm-level path analysis for a specific supply chain (upstream: Nexperia, China → downstream: Volkswagen, U.S.). In this section, we extend the scope of REM and propose a framework for a macro-level overview of dependency structures in strategically important industrial domains, using the Taiwan Semiconductor Manufacturing Company (TSMC) and Semiconductor Manufacturing International Corporation (SMIC) as illustrative cases.

The objective is to measure the network exposure of these two focal firms to groups of firms by country of residence to address geopolitical risks at the country level. The degree of exposure is considered in the upstream (procurement) and downstream (sales) directions for designated industries, thereby elucidating chokepoints on both the supply and demand sides.

More specifically, we have the following:

<u>Focal firms:</u>

- TSMC: The world's largest foundry company, headquartered in Taiwan, serving as a core node in the global semiconductor ecosystem.
- SMIC: A representative foundry company of China (PRC), positioned as a key pillar of China's national strategy for building self-sufficient semiconductor supply chains.

<u>Industries to be considered:</u>

<Upstream side>

- "Nonferrous metal smelting and refining," including rare metals
- "Semiconductor manufacturing equipment," including semiconductor machinery

<Downstream side>

- "Motor vehicles"
- "Computers and Computer Equipment"

We first identify all Tiers 1-5 supply chains extending from each focal firm (i.e., TSMC and SMIC) to firms in the industrial domains, as specified above.[7] The RES (see Section 5) for the identified supply chains was then calculated and aggregated based on the firm's country of residence at the endpoints of the production sequences.[8]

Figures 8–11 show the calculation results, presenting the country shares of focal firms' RES for each target industry, as described in Table 3.

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[7] "Tier k" denotes the network layer that includes firms that are k steps away from the focal firm along production paths, which is equivalent to stratification by path length (number of links). Accordingly, "the sum of RES over Tier 1–Tier 5" means the focal firms' total RES to all firms in target industrial domains connected by path lengths of 1, 2, 3, 4, and 5.

Meanwhile, it should be noted that the score contribution of transaction paths which are considered marginal or technically unimportant to the core production sequence are naturally suppressed because the corresponding links are assigned with smaller weights in mapping procedure by means of referring to the information from input-output matrices.

[8] As in Figure 5, the country aggregation is based on the country of residence assigned to corporate entity records in the FactSet database. Therefore, for multinational enterprises, the headquarters and foreign subsidiaries (as separate entities) are counted separately for country aggregation. For example, the U.S. firm's affiliate in China, as a supplier or a customer, is counted in the exposure score to China.

Table 3. Target industrial domains and their NAICS coverage

| Target industry | NAICS coverage |
|---|---|
| [Upstream] Nonferrous metal smelting/refining (excluding copper & aluminum) | 331410 Nonferrous Metal (except Aluminum) Smelting and Refining<br>Notes: Includes refining of rare earths, gallium, germanium, etc. When these are grouped as a set, the NAICS-code noise is limited. |
| [Upstream] Semiconductor manufacturing equipment | 333242 Semiconductor Machinery Manufacturing (corresponds to wafer-processing equipment/front-end processes)<br>334515 Instrument Manufacturing for Measuring and Testing Electricity and Electrical Signal (corresponds to back-end test/inspection equipment, etc.)<br>Notes: Together, these two codes cover the core components of semiconductor manufacturing equipment, and the amount of irrelevant noise is expected to be relatively small. |
| [Downstream] Motor vehicles | 336111 Passenger cars<br>336112 SUVs, minivans, etc.<br>336110 (Umbrella category covering the above)<br>Notes: Covers passenger vehicles excluding trucks; EVs are included. |
| [Downstream] Computers and computer equipment | 334111 Electronic Computer Manufacturing<br>343112 Storage peripheral equipment<br>334110 (covers a broader scope than the two above)<br>Notes: Servers and PCs cannot be separated using NAICS alone. By including 334112, this category covers "computing as a whole" in a somewhat broader sense, including equipment for data centers. |

Source: Prepared by the authors.

## [Supply-side analysis: upstream dependence]

On the upstream side, we focus on two industries that can affect the continuity of semiconductor production, "Nonferrous metal refining" and "Semiconductor manufacturing equipment," and compare the focal firms' RES for these industries.

Nonferrous metal smelting and refining (Figure 8): Approximately 90% of rare earth refineries are concentrated in China. Thus, China accounts for more than half of TSMC's RES. However, the diagram also suggests some sourcing diversification toward Japan and the U.S. By contrast, SMIC exhibits an overwhelming share of domestic (i.e., China) sourcing, suggesting a high level of self-sufficiency in this industrial domain.

Semiconductor manufacturing equipment (Figure 9): For the supply of semiconductor manufacturing equipment, the TSMC relies on domestic (i.e., Taiwan) sources for approximately 65% of its exposure. Although foreign dependence (e.g., U.S. and Japanese sources) is considered to reflect the procurement of leading-edge equipment, the current observations suggest that a substantial portion can still be sourced within Taiwan.

By contrast, for SMIC China, the concentration of domestic procurement was even more pronounced than that for TSMC. Although China is generally considered to depend largely on Western countries for semiconductor machinery supply, this is true only for the leading-edge segment. Under current trade restrictions, the results are consistent with the understanding that China can sufficiently supply (technologically mature) volume segments through its own domestic capacity. Here, the findings appear to align with the broader "decoupling" narratives.

## [Demand-side analysis: downstream dependence]

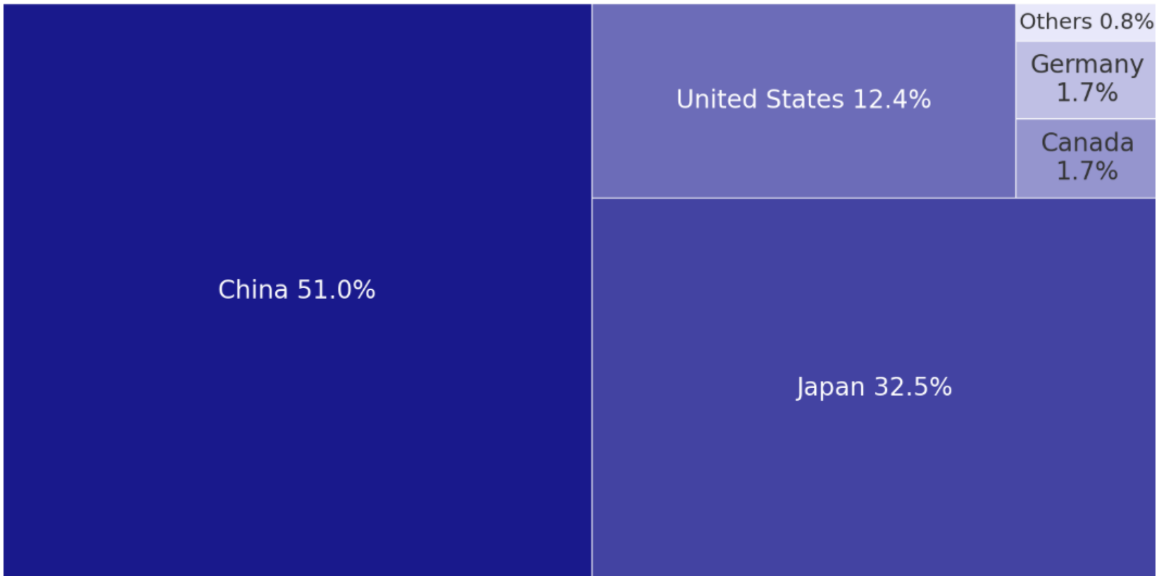
On the downstream side, we examine "Motor vehicles" and "Computers and computer equipment" to provide a macro-level overview of how semiconductors are embedded in final products.

Motor vehicles (Figure 10): For motor vehicles, TSMC shows a very high dependency on China's markets, whereas SMIC has the highest share in the U.S., placing China second. This reveals a "market twist" on the demand side that cannot be fully captured by a naive bloc narrative (West → TSMC, China → SMIC). In contrast to the "bloc-wise" decoupling observed in upstream networks, as stated above, exposure is observed across different economic blocs in downstream networks.

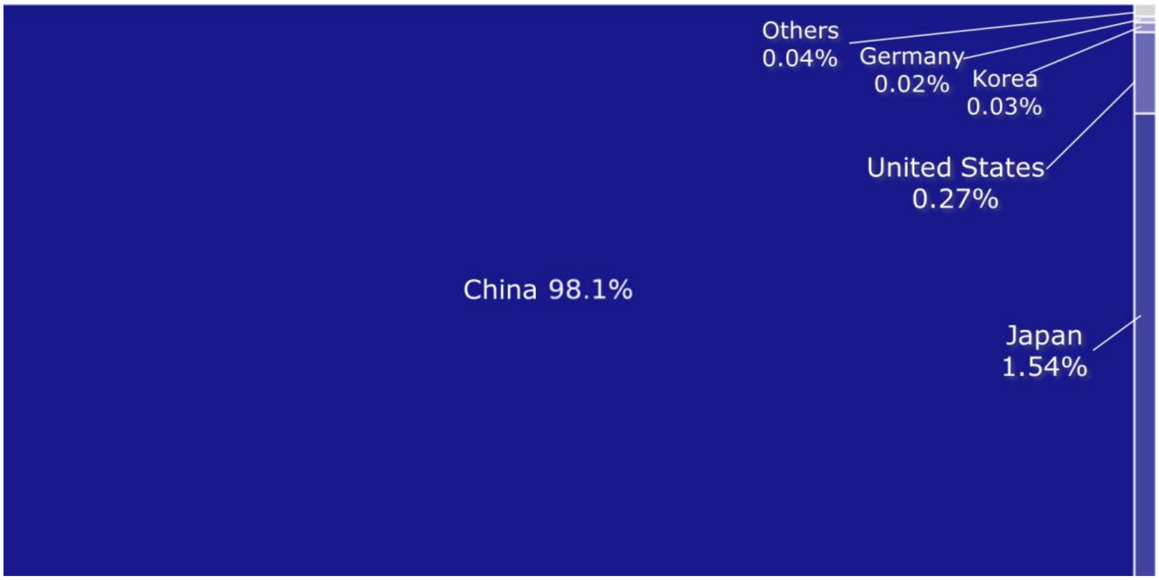
Computers and computer equipment (Figure 11): In the computer manufacturing domain, both firms held the highest share in the U.S., indicating a strong concentration of downstream networks nationwide. Notably, SMIC also has a high share in the U.S. Although SMIC's output is likely to be concentrated in volume-prone rather than high-end segments (such as those associated with TSMC products), the results suggest that U.S. customers' dependency on Chinese legacy chipsets may not be negligible.

Figure 8. Nonferrous Metal Smelting / Refining (except Copper and Aluminum)

[TSMC exposure to source countries]



[SMIC exposure in source countries]

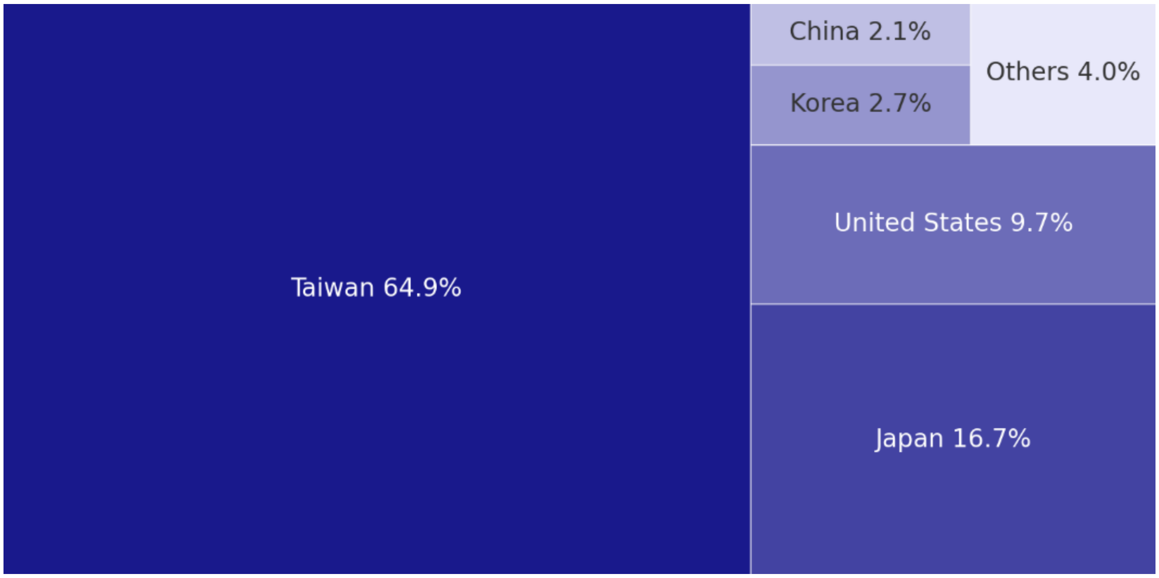


Source: Calculated by the authors.

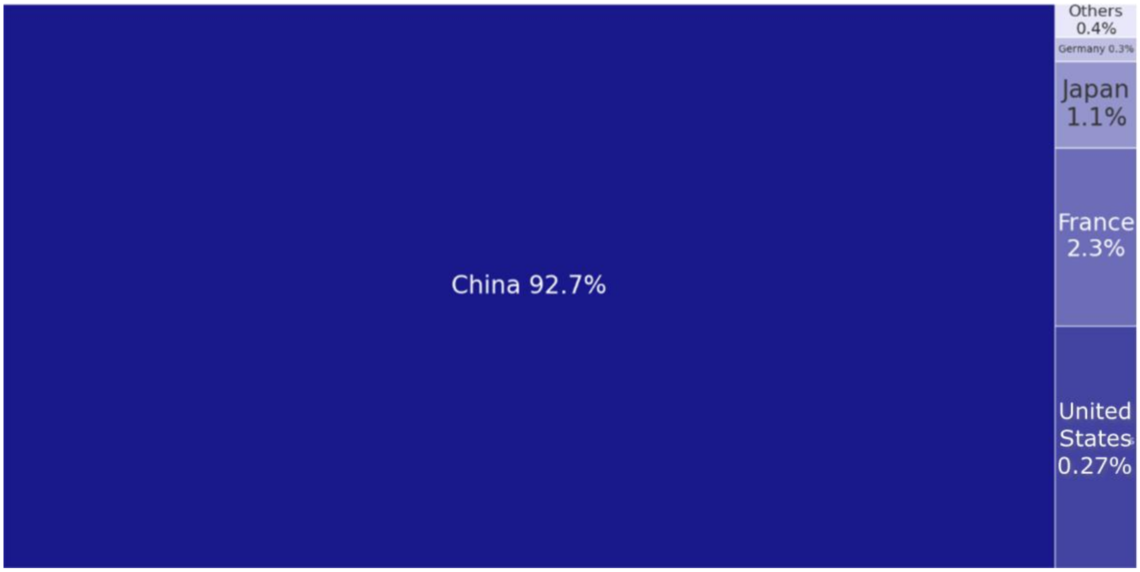
Note: The countries for which their names cannot be presented in the diagram due to limited visibility are consolidated into "Others."

Figure 9. Semiconductor Manufacturing Equipment

[TSMC exposure to source countries]



[SMIC exposure in source countries]

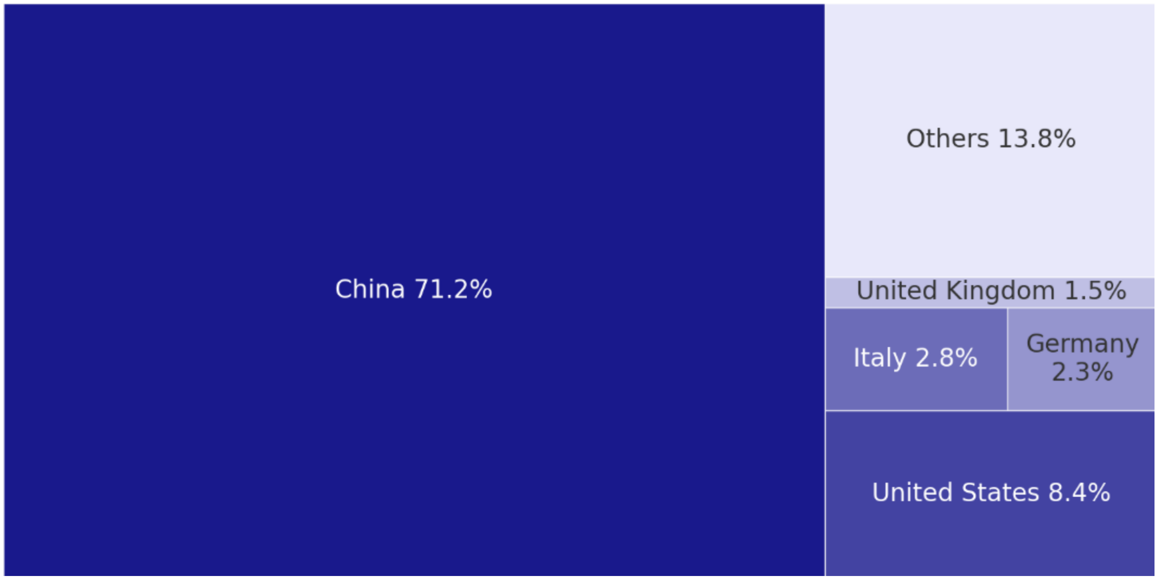


Source: Calculated by the authors.

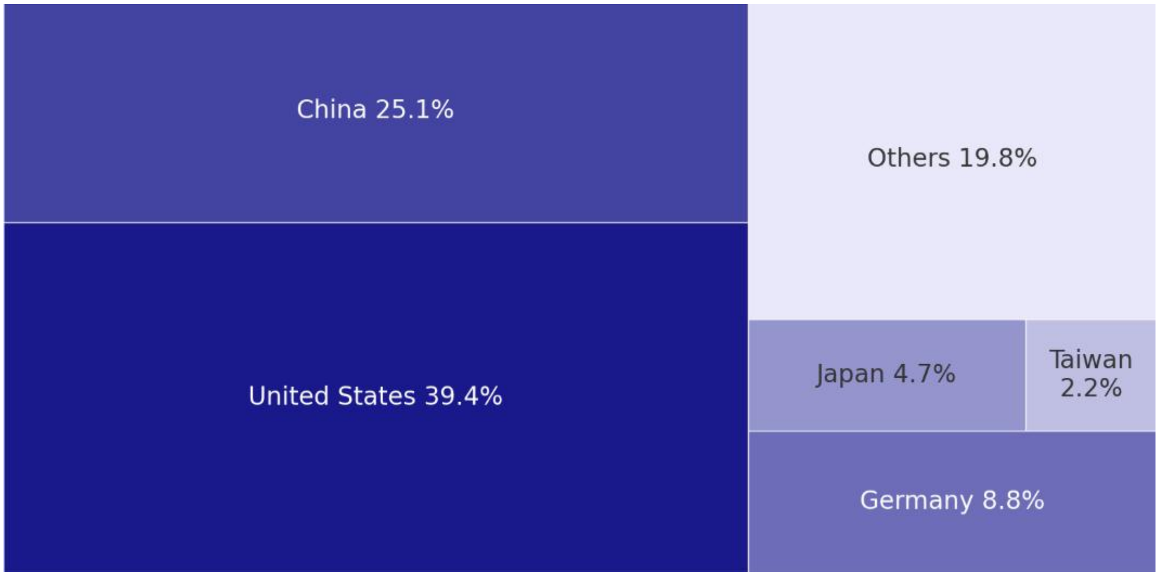
Note: The countries for which their names cannot be presented in the diagram due to limited visibility are consolidated into "Others."

Figure 10. Motor vehicles

[TSMC’s Exposure of TSMCs to final markets]



[SMIC Exposure to Final Markets]

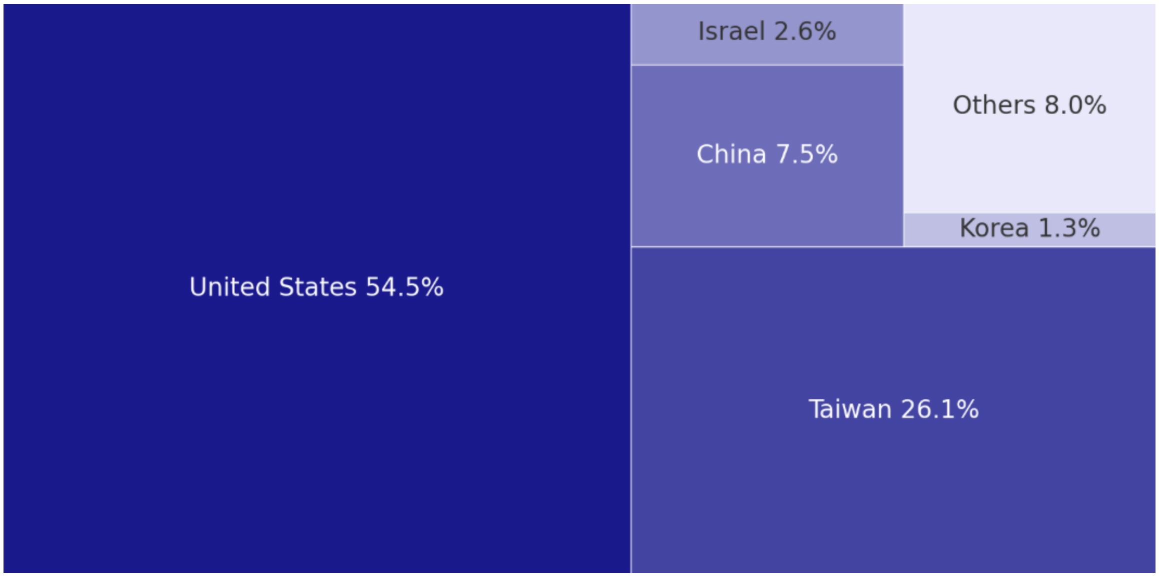


Source: Calculated by the authors.

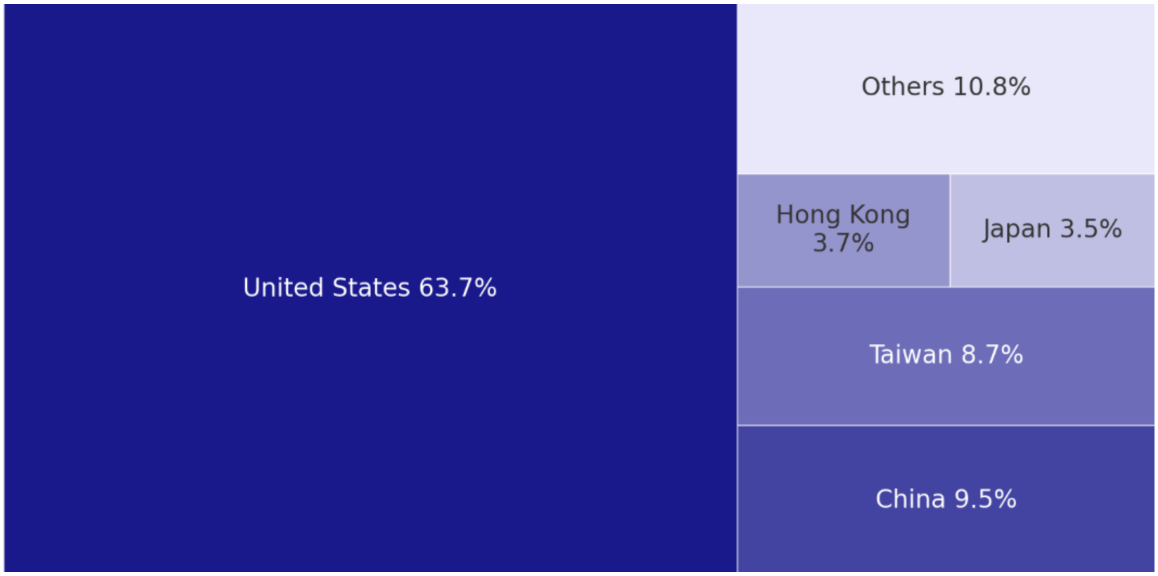
Note: The countries for which their names cannot be presented in the diagram due to limited visibility are consolidated into “Others.”

Figure 11. Computers and computer equipment

[TSMC's Exposure of TSMCs to final markets]



[SMIC Exposure to Final Markets]



Source: Calculated by the authors.

Note: The countries for which their names cannot be presented in the diagram due to limited visibility are consolidated into "Others."

The macro-level visualization presented in this section quantitatively elucidates the structural asymmetry in semiconductor supply chains, in which "bloc-wise" concentration in the upstream (supply-side) networks, and "twisted" dependency in the downstream (demand-side) networks, are simultaneously observed. Furthermore, different logics apply across industries, such that economic decoupling may progress in leading-edge technology segments (e.g., semiconductor machinery) while dependence on China may persist in material-related industries (e.g., rare-metal refining).[9]

## 8. Discussion

This study introduces REM as a novel analytical tool for economic security and demonstrates its use by focusing on supply chain vulnerabilities.

Conventional industrial statistics, most notably IOTs, remain valuable for macro analysis but are less suited for identifying vulnerabilities embedded in firm-level supply chain structures. To address this limitation, REM analysis can be positioned at the center of strategic de-risking in economic security policymaking.

As a methodological advance, REM integrates the quantitative "weights" of IOTs with the topological "skeleton" of inter-firm transaction networks. This hybrid approach enables policymakers to visualize and measure dependence on specific firms or production facilities, thereby identifying concrete chokepoints rather than abstract sector-level risks. By further overlaying capital relationships such as equity stakes, mergers, and acquisitions onto transaction networks, REM enables the delineation of spheres of influence through which risk-prone actors exert control across supply chains.

Policymakers can accelerate targeted de-risking by building REM-based analytical foundations. The transition from efficiency-oriented "just-in-time" systems to risk-aware "just-in-case" architectures requires prioritization. Among the numerous supply chain paths, REM can identify cases in which a small number of highly concentrated paths account for the majority of exposure. These dominant paths are primary targets for diversification and substitution.

While supply chain disruptions often propagate upstream (e.g., in the case of critical minerals and raw materials), dependence also persists downstream in final product markets. REM-based analyses can illuminate these realities and guide pragmatic market strategies. Sharing this analytical approach among like-minded countries enhances collective resilience and coordinated responses in the era of economic security.

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[9] While useful for screening dependency structures, the results of these exercises depend on data coverage, assignment of industrial classifications, and definition of country of residence. Accordingly, they are not particularly suitable for addressing absolute magnitude or causal mechanisms (e.g., policy effects and technological advantage). In addition, the metric is not directly convertible into transaction values.

Furthermore, the results are constrained by FactSet's entity definitions, aggregation across tiers, and the metric being an aggregate of RES. For these technical reasons, this section should be positioned as a screening step to extract "candidate structures." Where needed, it is desirable to conduct (i) tier-wise decomposition, (ii) verification of conducive firms by name, and (iii) sensitivity analyses by changing the weighting formula (e.g., input coefficients, transaction value, or estimated flows).

Despite REM's unique and practical advantages for its use in economic security, promoting its functionality faces several challenges.

First, the statistical accuracy of the link weights must be improved. The current scheme for referring to the OECD inter-country IOT for regional sourcing structures suffers from the table's coarse sector granularity, potentially leading to inappropriate references regarding firms' international transactions. Information from foreign trade statistics (at the HS 6-digit level) can be integrated effectively into the REM weight reference system.

Second, the current "full-matching" approach to connecting multiple NAICS activities across firms (see Appendix C) should be expanded to yield more plausible combinations of linkages based on the nature of the activities involved. Generative AI can be used to assess the plausibility of each link in pruning and streamlining production activity networks.

Third, the product substitutability must be considered. Whether a product or its supplier can be swiftly replaced in the case of a contingency is important when assessing supply chain vulnerability. This is particularly true for the supply chains of strategic materials such as advanced semiconductors or critical minerals. Prior studies provide a rich knowledge pool on product substitutability, which should be properly referenced when calibrating the relevant parameters in our analytical model.

Finally, REM data should be applied for simulation exercises of shock propagations, such as supply restrictions of key materials or designation of suppliers in the U.S. Entity Lists, provided that the data elaboration proposed above is achieved. The use of a computable general equilibrium (CGE) model can be an option; however, considering the massive data scale of REM, the computational burden of a full-scale CGE setup is deemed intolerable. More practical and flexible instruments, such as agent-based models, are promising alternatives.

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## Appendix A: How Risk Exposure Mapping works

Risk-exposure mapping (REM) involves two distinct stages: First, using FactSet company data, we drew a global web of firm-to-firm transactions. This forms the "skeleton" of the database and shows the basic structure of the entire production network.

In the second stage, the "skeleton" is fleshed out in an economically meaningful way by assigning appropriate weights to all links in the networks. The weights are derived by drawing information from national and international IOTs that respectively capture two key aspects of a firm's procurement decisions: (1) production input requirements (i.e., *what types* and *quantities* of intermediate products are needed) and (2) the sourcing structure of these inputs (i.e., *where* they are obtained from).

### (a) Weaving firm-to-firm transaction networks

In FactSet database, each company is characterized by multiple attributes: company ID, company name, country of residence, primary SIC code, single/multiple NAICS codes, and a company description. In addition, the types of relationships were identified for certain pairs of companies, such as suppliers, customers, alliances, and OEMs.

In supplier–customer relationships, multiple start and end dates are typically provided, along with varying levels of detail for transactions. The start date indicates when the supplier–customer relationship was established, and the end date indicates when the relationship has ended (if the status is "NULL," the termination of the relationship is unconfirmed). When the relationship is intermittent, multiple pairs may exist.

The transaction networks are then generated from the following set of information:

- Company attributes: FactSet-issued company ID, company name, country of residence, primary SIC code, and single/multiple NAICS codes.
- Supplier-customer relationships for which records of one or more start and end dates are assigned, regardless of whether the end date is NULL.

### (b) From transaction networks to production networks

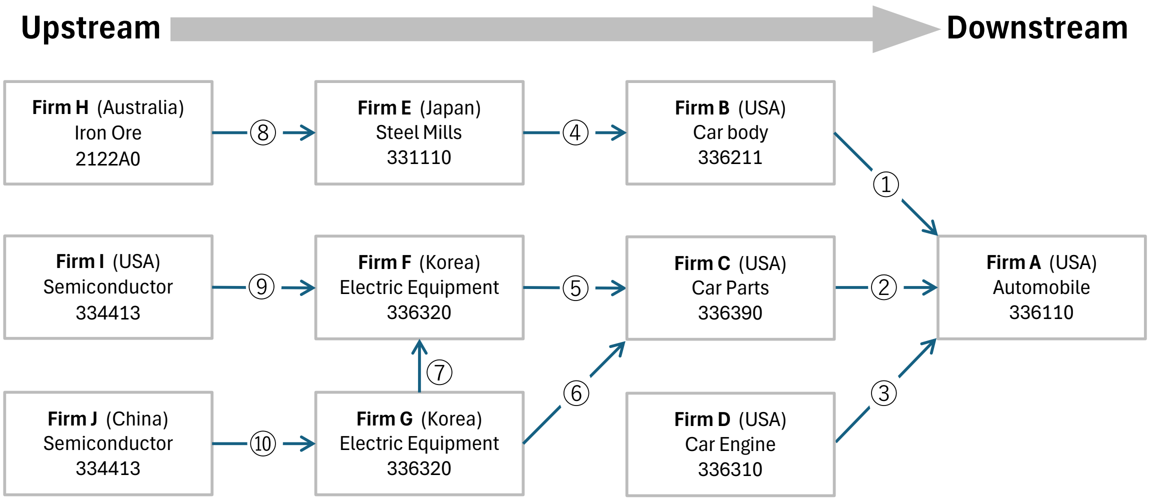
In the second step, appropriate weights are assigned to all links in the network by drawing on IOT data using the NAICS code concordance. Figure A-1 redraws an image of the hypothetical transaction networks presented in Figure 3 after conversion to NAICS linkages for the case of "one company → one NAICS activity." (Companies with multiple NAICS codes are discussed in Appendix C.)

The reference dataset depends on the combination of the resident countries of the parties connected by the transactional link to which a weight is assigned. Table A-1 summarizes the reference sources.

For example, link ① connects "U.S. Car body (336211)" to "U.S. Automobile (336110)"; hence, the corresponding weight will be derived from the dataset specified under Pattern A: namely, the U.S. IOT (domestic). By contrast, link ④ connects "Japan's Steel Mills (331110)" to "U.S. Car body (336211)"; hence, the relevant referential data are specified under Pattern B: namely, the U.S. IOT (import) and the OECD inter-country IOT, etc.

Generally, the weight of a particular link is derived as an arithmetic product of the relevant coefficients/shares/ratios extracted from a specific dataset. Appendix B provides a detailed description of our estimation procedure.

Figure A-1. Reference for link weights



Source: Drawn by the authors.

Table A-1. Summary of referential data for weight calculations

| | Combination of nodes | | Combination of referential data | | | | | Corres-ponding links from Figure 4 |
|---|---|---|---|---|---|---|---|---|
| | supplier's country | customer's country | US Input-Output Table | US Input-Output Table | US Input-Output Table | OECD Inter-country Input-Output Table | OECD Inter-country Input-Output Table | |
| | | | Input coefficients (domestic) | Input coefficients (import) | Input coefficients (merged) | Souce country shares | Souce country shares (import only) | |
| (code) | ISO | ISO | NAICS2022 | NAICS2022 | NAICS2022 | ISIC rev 4 | ISIC rev 4 | |
| Pattern A | USA | USA | ✓ | | | | | ①, ②, ③ |
| Pattern B | Not USA | USA | | ✓ | | | ✓ | ④, ⑤, ⑥ |
| Pattern C | Not USA (but the same as customer's country) | Not USA | | | ✓ | ✓ | | ⑦ |
| Pattern D | USA or the third country | Not USA | | | ✓ | ✓ | | ⑧, ⑨, ⑩ |

Source: Drawn by the authors.

Note: The OECD table covers the input–output relations of industries in 76 economies; therefore, most of the company records included in FactSet can be cross-referenced. Companies that are not part of the 76 economies are classified in the "Rest of the World" category, which is essentially the residual of the designated 76 economies.

## Appendix B: Derivation of link weights

Link weights are derived according to three sequential steps.

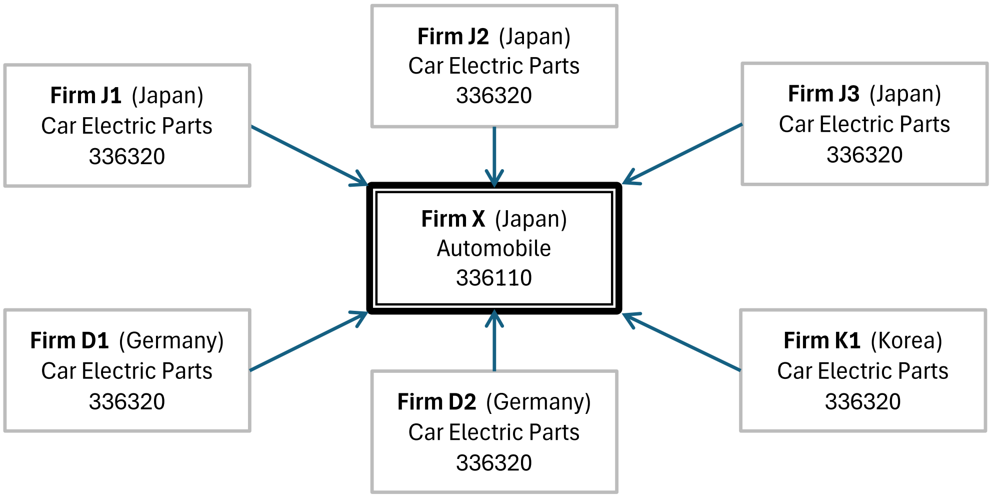
The first step was to identify the corresponding input coefficients for the IOTs. This aims to define the weight from the technical (engineering) aspect of the input–output relationships between production activities. The input coefficients of the U.S. table, which has the most detailed sector classification of the NAICS compared to any other country's IOTs, are used as a representative referential source, assuming that the production techniques and input requirements for a particular industry are largely undifferentiated across countries. (For example, a car, regardless of whether produced in the U.S., Japan, or China, always has one engine and four tires.)

In contrast, individual economies differ in the sourcing structure of intermediate inputs: namely, whether they are procured domestically or purchased abroad, and, if the latter, from which country. This necessitates the second step of weight estimation: the breakdown of an input coefficient by country of procurement origin.

Furthermore, what if a customer has multiple suppliers in the same sector and country? The third breakdown resorts to a simple division of the weight by the number of corresponding suppliers, because no further information on transaction volumes can be extracted.

For example, suppose that, according to FactSet data, a Japanese auto manufacturer "Firm X" has transactions with six different suppliers for the procurement of car electric parts (Figure B-1).

Figure B-1. Firm-to-firm transaction links from FactSet data: an illustrative example



Source: Drawn by the authors.

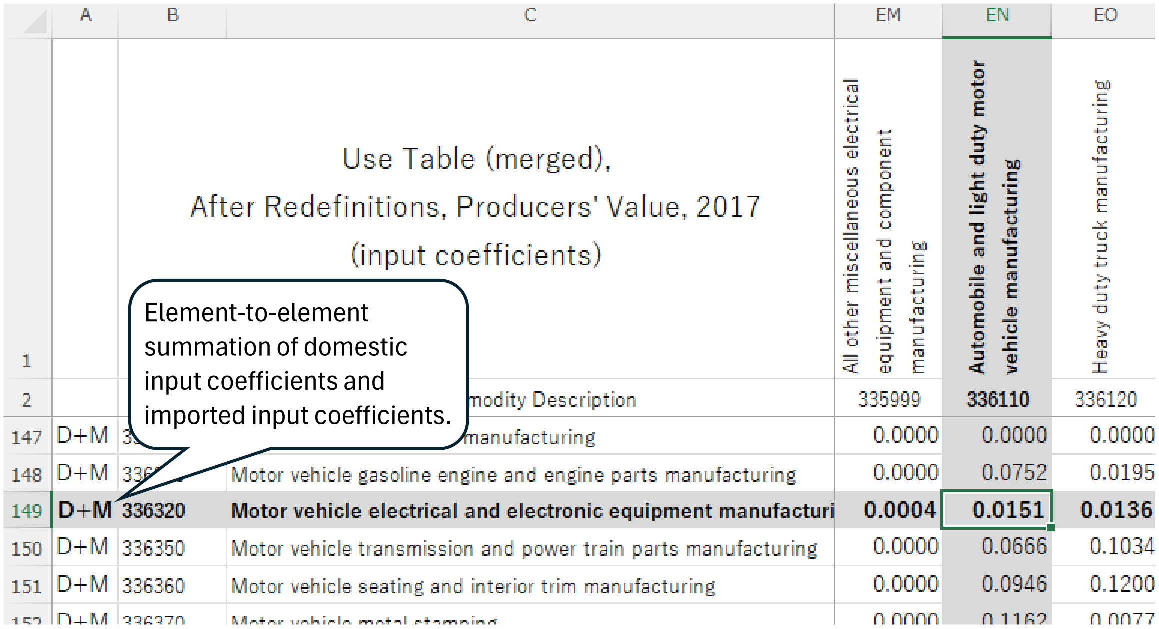
Note: Arrows indicate product flows, and the bottom codes in the nodes are NAICS.

[Step 1: Reference to the input coefficient]

First, a set of U.S. input–output matrices, with one showing domestic transactions and the other showing transactions of imported products, is merged element-by-element into one matrix. This new matrix is explicit about technological requirements (input structure) for producing a product yet neutralized regarding sourcing structure. Hence, it is deemed applicable to any economy based on the stated analytical assumption.

Here, we derive link weight information from a particular element in the input coefficient matrix of the merged table according to the link's corresponding pair of NAICS codes; in this case, 336320 (row) and 336110 (column) (Figure B-2).

Figure B-2. The U.S. input–output table (merged)



| | A | B | C | EM | EN | EO |
|---|---|---|---|---|---|---|
| 1 | | | Use Table (merged),<br>After Redefinitions, Producers' Value, 2017<br>(input coefficients) | All other miscellaneous electrical equipment and component manufacturing | **Automobile and light duty motor vehicle manufacturing** | Heavy duty truck manufacturing |
| 2 | | | modity Description | 335999 | **336110** | 336120 |
| 147 | D+M | 3 | manufacturing | 0.0000 | 0.0000 | 0.0000 |
| 148 | D+M | 336 | Motor vehicle gasoline engine and engine parts manufacturing | 0.0000 | 0.0752 | 0.0195 |
| **149** | **D+M** | **336320** | **Motor vehicle electrical and electronic equipment manufacturi** | **0.0004** | **0.0151** | **0.0136** |
| 150 | D+M | 336350 | Motor vehicle transmission and power train parts manufacturing | 0.0000 | 0.0666 | 0.1034 |
| 151 | D+M | 336360 | Motor vehicle seating and interior trim manufacturing | 0.0000 | 0.0946 | 0.1200 |
| 152 | D+M | 336370 | Motor vehicle metal stamping | 0.0000 | 0.1162 | 0.0077 |

Element-to-element summation of domestic input coefficients and imported input coefficients.

Source: Drawn by the authors based on the U.S. input–output table, 2017.

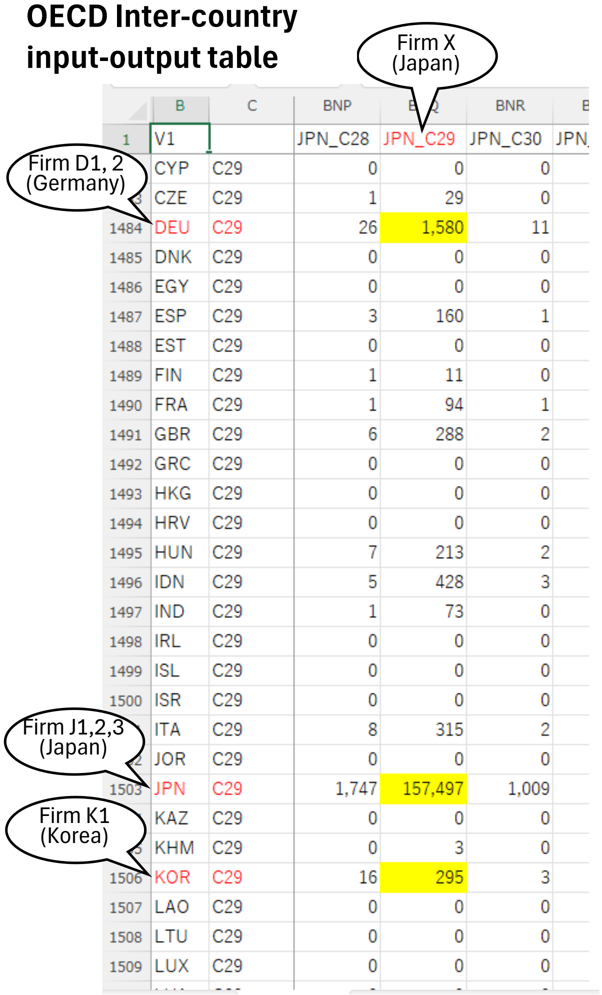
Note: At the time of writing this article, the 2017 table is the latest version of the U.S. IOT.

[Step 2: Breakdown by country of procurement source]

The U.S. IOT does not have information regarding the source country of the imported products and hence requires further reference for country breakdown. Here, the OECD's inter-country IOT was utilized. The table presents cross-border transactions in a matrix format across multiple countries, from which we can derive import shares by country of origin for each activity. Figure B-3 indicates the reference points for the six transaction links in our example, which were identified by code concordance between NAICS (2022 version) and the OECD industrial sector classification (45 sectors).

Figure B-3. Country breakdown of procurement sources

**OECD Inter-country input-output table**



| | B | C | BNP | B Q | BNR | B |
|---|---|---|---|---|---|---|
| 1 | V1 | | JPN_C28 | JPN_C29 | JPN_C30 | JPN_ |
| | CYP | C29 | 0 | 0 | 0 | |
| 3 | CZE | C29 | 1 | 29 | 0 | |
| 1484 | DEU | C29 | 26 | 1,580 | 11 | |
| 1485 | DNK | C29 | 0 | 0 | 0 | |
| 1486 | EGY | C29 | 0 | 0 | 0 | |
| 1487 | ESP | C29 | 3 | 160 | 1 | |
| 1488 | EST | C29 | 0 | 0 | 0 | |
| 1489 | FIN | C29 | 1 | 11 | 0 | |
| 1490 | FRA | C29 | 1 | 94 | 1 | |
| 1491 | GBR | C29 | 6 | 288 | 2 | |
| 1492 | GRC | C29 | 0 | 0 | 0 | |
| 1493 | HKG | C29 | 0 | 0 | 0 | |
| 1494 | HRV | C29 | 0 | 0 | 0 | |
| 1495 | HUN | C29 | 7 | 213 | 2 | |
| 1496 | IDN | C29 | 5 | 428 | 3 | |
| 1497 | IND | C29 | 1 | 73 | 0 | |
| 1498 | IRL | C29 | 0 | 0 | 0 | |
| 1499 | ISL | C29 | 0 | 0 | 0 | |
| 1500 | ISR | C29 | 0 | 0 | 0 | |
| | ITA | C29 | 8 | 315 | 2 | |
| 2 | JOR | C29 | 0 | 0 | 0 | |
| 1503 | JPN | C29 | 1,747 | 157,497 | 1,009 | |
| | KAZ | C29 | 0 | 0 | 0 | |
| 5 | KHM | C29 | 0 | 3 | 0 | |
| 1506 | KOR | C29 | 16 | 295 | 3 | |
| 1507 | LAO | C29 | 0 | 0 | 0 | |
| 1508 | LTU | C29 | 0 | 0 | 0 | |
| 1509 | LUX | C29 | 0 | 0 | 0 | |

**[NAICS - OECD ICIO sector concordance]**

NAICS: **336110** Automobile and Light Duty Motor Vehicle Manufacturing

→ OECD ICIO: **C29** Motor vehicles, trailers and semi-trailers

NAICS: **336320** Motor Vehicle Electrical and Electronic Equipment Manufacturing

→ OECD ICIO: **C29** Motor vehicles, trailers and semi-trailers

**[Calculaiton of source country shares]**

Firm J1-3 (Japan)

157,497 ÷ (1,580+157,497+295)

= 0.988235

Firm D1-2 (Germany)

1,580 ÷ (1,580+157,497+295)

= 0.009914

Firm K1 (Korea)

295 ÷ (1,580+157,497+295)

= 0.001851

Source: Drawn by the authors based on the OECD Inter-Country Input–Output Table, 2020.

Note: At the time of writing this article, the 2020 table was the latest version of the OECD IOT.

[Step 3: Breakdown by number of suppliers]

If more than one supplier is identified in the FactSet data for the procurement of the same NAICS product in the same country, the weight is split and equally shared among the corresponding suppliers. In our example, the weights for the Japanese and German suppliers are split into 3 and 2, respectively.

Table B-1 presents the estimation process. Weights are calculated as an arithmetic product of (1) the corresponding input coefficient from the U.S. IOT, (2) source country shares from the OECD table, and (3) split ratios.

Table B-1. Calculation of link weights

**Customer X: Automobile (336110), Japan**

Input coefficient (336320 x 336110): **0.0151** ...from Fig. B-2

| **Suppliers: Car electric parts (336320)** | ① Country share ...from Fig. B-3 | ② Split ratio by number of suppliers | ③ Procurement share = ① x ② | Link weight = ③ x input coefficient (= 0.0151) |
|---|---|---|---|---|
| J1 (Japan) | 0.988235 | 0.333333 | 0.329412 | **0.004974** |
| J2 (Japan) | | | 0.329412 | **0.004974** |
| J3 (Japan) | | | 0.329412 | **0.004974** |
| D1 (Germany) | 0.009914 | 0.500000 | 0.004957 | **0.000075** |
| D2 (Germany) | | | 0.004957 | **0.000075** |
| K1 (Korea) | 0.001851 | 1.000000 | 0.001851 | **0.000028** |

**Share total 1.000000**

Source: Calculated by the authors.

Note: If no foreign link is identified in the FactSet data, the country's share of domestic sources will be 100%, despite the OECD table possibly presenting import values for the sector. Similarly, in the case of no domestic links, the foreign country's share is 100%.

This example corresponds to the treatment of the case in Pattern D presented in Table A-1 in Appendix A: the combination of non-US customers (= Japan) and third-country suppliers (= Japan, Germany, and Korea). This method can also be applied to cases involving other patterns.

However, note that for Patterns A and B, the original domestic or import table of the U.S. IOT (before merging) should be used to refer to the input coefficients.

## Appendix C: Firms with Multiple Activities

Appendix A considers a simple case in which each firm corresponds to a single NAICS code. However, FactSet data often assigns multiple NAICS codes to a single company. For example, the U.S. firm PepsiCo is associated with three codes:

311919 (Other Snack Food Manufacturing)

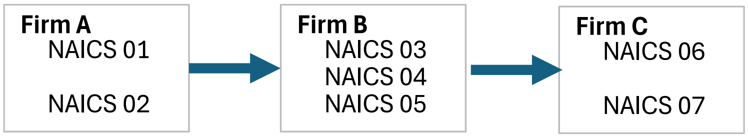
312111 (Soft Drink Manufacturing)

312112 (Bottled Water Manufacturing)

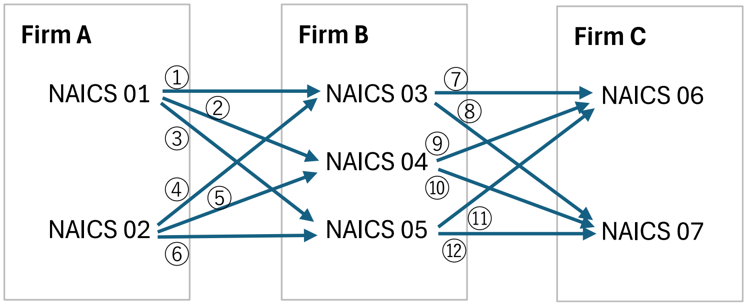
FactSet data does not provide internal linkage information among these activities. Therefore, our methodology assumes all possible combinations of input–output relationships among the firms' NAICS codes. In the example illustrated in Figure C-1, Firm A is tagged with two NAICS activities, Firm B with three, and Firm C with two, resulting in 12 potential input-output relations across all firms.

Figure C-1. Firms with multiple activities (an illustrative example)

Explicit Firm-to-Firm Transaction Networks (as observed in FactSet Data)



Implicit input–output relations



Source: Drawn by the authors.

## Appendix D: Treatment of the commerce sector

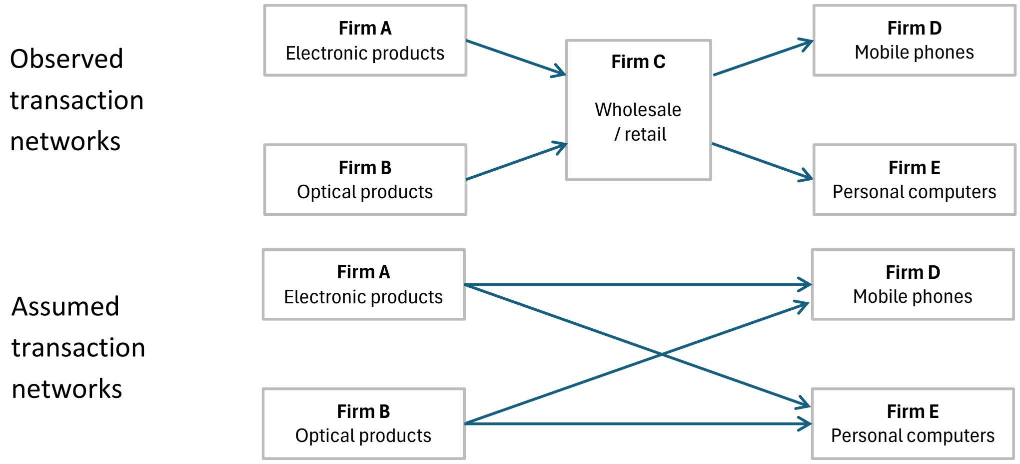
The commerce sector encompasses a wide range of establishments, from global trading corporations to small-scale street retailers. Its primary function in the supply chain is to serve as an intermediary between producers and consumers, both spatially (facilitating logistics between locations) and temporally (managing inventories for future supply). Firms pay for the commerce sector's expertise in sales and procurement, which draws on their in-house knowledge of prices, quality, availability, substitutability, and risk of transactions involving key commodities.

Despite its important functions in supply chains, the commerce sector has been excluded from REM. This is because we focus on engineering linkages within production activities to account for risk exposure to a particular product from a particular supplier, such as the value of Firm X's chipsets embodied in Firm Y's mobile phones. Transactions between Firm X and Trading Company Z, or between Z and Firm Y, do not reflect these technical linkages and are therefore excluded from our analytical scope.

This said, however, eliminating commercial intermediaries from a network poses challenges. As shown in Figure D-1, suppose Firms A (Electronics) and B (Optical Equipment) are connected to Firms D (Mobile Phones) and E (Personal Computers) through transactions with Firm C (a trading company). Removing Firm C from the network leaves us unable to determine which products Firms D and E procured.

Our current solution assumes that Firms D and E purchase products from both Firms A and B, as depicted in the bottom half of the figure. Although this may introduce links for which no direct transaction actually exists, it is considered permissible because the expected weights for such hypothetical links should be small if their existenece is not technically plausible, given the characteristics of the input–output data (i.e., the corresponding input coefficients should be negligible).

Figure D-1 Removal of commercial sectors



Source: Drawn by the authors.

## Appendix E: Issues of zero-weight links

The main feature of the REM procedure is that a set of weights derived from the IOTs is assigned to the FactSet transaction networks. Naturally, various types of data conflict exist in this exercise because the data sources and construction methods are entirely different for the two datasets.

The most prominent mismatch is observed in the zero-entry problem. Specifically, an element in IOT has a zero value when addressing a particular link in a FactSet transaction network. This means that, despite FactSet data indicating a transaction between a pair of firms, the IOT shows no input–output relationships corresponding to these firms' activities.

In view of the analysis of supply chain vulnerability, this causes an underestimation of risk exposure because the chained multiplication of weights along supply chains is interrupted by zero values, and risk-tracking paths are truncated.

Several possible reasons can be considered for this data conflict.

(1) Time lags between FactSet data retrieval and the IOT reference year. FactSet data are updated annually; however, the latest U.S. IOT available is for 2017. This implies that transactions after 2017 were not reflected in IOT.
(2) Treatment of capital goods. FactSet records firms' transactions on sales/purchases of capital goods, such as industrial machinery, whereas in IOTs they are recorded in final demand and do not appear as intermediate transactions; therefore, no corresponding input coefficients exist. (However, machine repair and maintenance services are treated as intermediate inputs that can be used as proxies for the volume of product purchase.)
(3) Presence of "rolled-up" companies. Big companies often integrate small firms (e.g., start-ups) into adjacent industries through mergers and acquisitions. If these firm transactions are recorded in the FactSet data as parent company's activities, inappropriate NAICS codes may be assigned. A similar problem occurs in the relationship between headquarters and foreign affiliates, because IOT is based on the residency principle.
(4) Differences between NAICS2017 and NAICS2022. FactSet data were tagged with NAICS2022, whereas U.S. IOT is classified under NAICS2017. The two versions have some observable differences, particularly regarding their treatment of the service sector.
(5) Concordance between NAICS and RBICS (in-house FactSet classification system). If they are inappropriately specified, this leads to a mismatch between supplier–customer pairs and input–output relationships.

The remedies for these problems are rather limited. For the time-lag issue, a mathematical method exists to update an IOT using information from a benchmark table, such as that employed in the extrapolation of OECD intercountry IOTs. However, this does not provide a fundamental solution to the current problem, as the underlying input structure of intermediate transactions remains largely intact through mathematical transformations. Therefore, we must wait for the release of the new U.S. IOT 2022, which is expected to be in 2027.

The issue of capital goods transactions is related to the statistical characteristics of IOTs; therefore, other data sources must be sought to address this problem. Some countries, such as the U.S. and Japan, publish the “fixed capital formation matrix,” which is the capital goods version of the input–output matrix. However, its sectoral classification is not sufficiently granular for current purposes. Furthermore, there is the issue of aligning the weights derived from different sources into a single indicator.

The issue of rolled-up firms and foreign affiliates is fundamentally rooted in the misclassification of their activities as biased toward the parent companies’ business segments. Therefore, we consider that these subsidiary activities should be sorted into the “unclassified” category of respective (nested) industrial group, such as “Other Communications Equipment” or “Miscellaneous nonmetallic mineral products.” Relabeling reduces the number of zero-weight links by 5%.

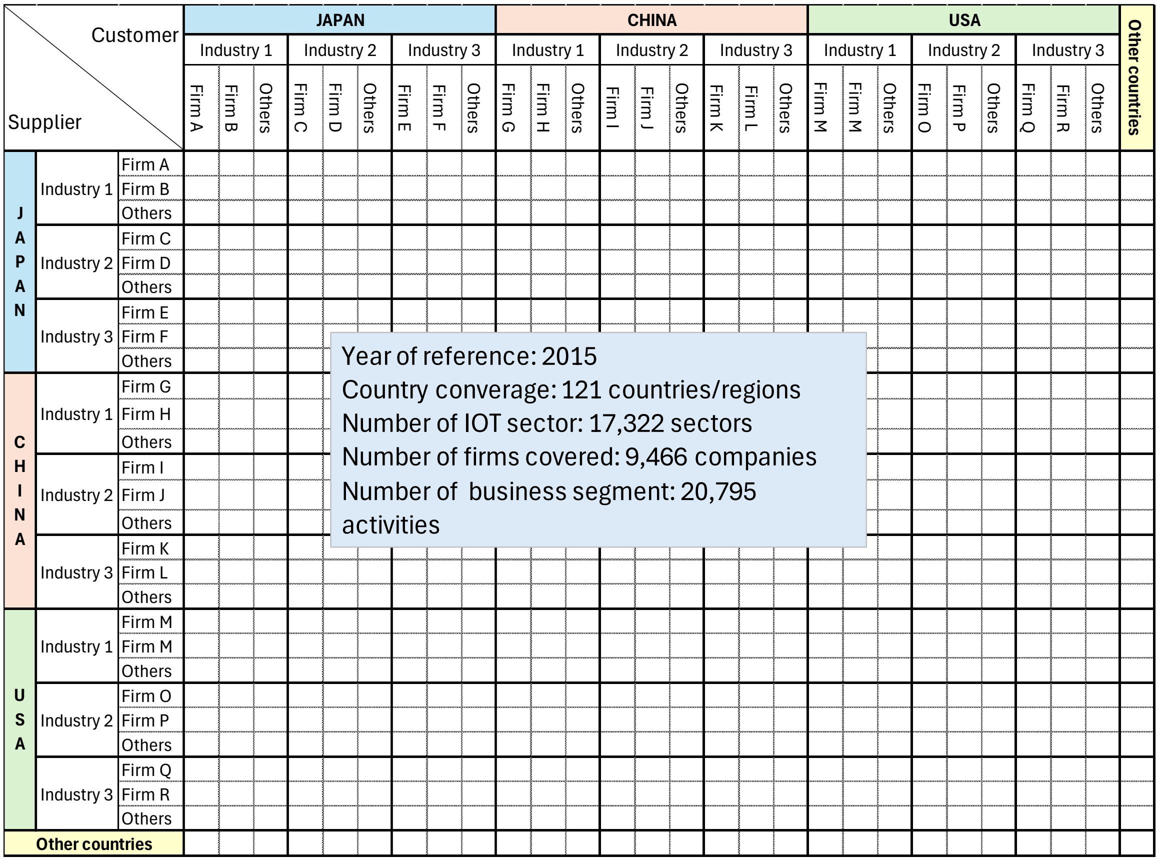
The remaining issues of sectoral taxonomy and concordance are considered minor and thus left untreated.

## Appendix F: The Enterprise-level Multi-Regional Input–Output Table (EMRIO)

An alternative approach to the REM method is enabled by the Enterprise-level Multi-Regional Input–Output Table (EMRIO), which aims to introduce firm-level granularity to traditional inter-country IOTs (Kanemoto et al., 2023).

The EMRIO is based on the Eora database developed by the University of Sydney. While the OECD's inter-country IOT (the 2022 version) links 76 country/regional tables using a common 45-sector classification, the Eora database connects the IOTs of 121 countries and regions, retaining the original sectoral classifications (e.g., 810 sectors for the U.S. and 395 for Japan). This resulted in 17,322 sectors. Each sector is then subdivided into [firms → business segments → subsegments], ultimately producing a massive 86,305 × 86,305 matrix (Figure F-1).

Figure F-1. Illustrative image of EMRIO



| Customer<br>Supplier | | | JAPAN | | | | | | | | | CHINA | | | | | | | | | USA | | | | | | | | | Other countries |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Industry 1 | | | Industry 2 | | | Industry 3 | | | Industry 1 | | | Industry 2 | | | Industry 3 | | | Industry 1 | | | Industry 2 | | | Industry 3 | | | |
| | | | Firm A | Firm B | Others | Firm C | Firm D | Others | Firm E | Firm F | Others | Firm G | Firm H | Others | Firm I | Firm J | Others | Firm K | Firm L | Others | Firm M | Firm M | Others | Firm O | Firm P | Others | Firm Q | Firm R | Others | |
| JAPAN | Industry 1 | Firm A | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm B | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | Industry 2 | Firm C | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm D | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | Industry 3 | Firm E | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm F | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| CHINA | Industry 1 | Firm G | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm H | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | Industry 2 | Firm I | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm J | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | Industry 3 | Firm K | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm L | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| USA | Industry 1 | Firm M | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm M | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | Industry 2 | Firm O | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm P | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | Industry 3 | Firm Q | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Firm R | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | Others | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Other countries | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Year of reference: 2015
Country converage: 121 countries/regions
Number of IOT sector: 17,322 sectors
Number of firms covered: 9,466 companies
Number of business segment: 20,795 activities

Source: Drawn by the authors.

To achieve this level of detail, FactSet data were used for disaggregation, including information on supplier–customer relationships, business segment sales shares, and bills of lading. Additional data sources, such as NEEDS (Nikkei, Inc.), OSIRIS (Bureau van Dijk), and

Bloomberg, are used to separate domestic activities from overseas operations, as input–output statistics are based on the residency principle.

Both REM and EMRIO combine FactSet's firm transaction data and IOT's linkage information; however, they differ in the dataset that serves as the primary framework. REM generates firm-to-firm transaction networks that capitalize on IOT information, whereas EMRIO is essentially a firm-level IOT.

The EMRIO effectively transforms a coarse IOT into a highly disaggregated table while maintaining an accounting balance between supply and demand. This enables data application in conventional input–output analyses, such as Scope 3 Carbon Footprint estimation, at the firm level. As corporate social responsibility for climate change garners increasing public attention, it should mark a significant advancement in empirical research in environmental analysis.

Although the EMRIO is the product of unprecedented statistical efforts, it has several key constraints.

Coverage limitation: Only firms meeting the following criteria are isolated and explicitly presented in the table (such as "Firms A" and "Firm B" in Figure F-1):

- Their home country must have an IOT,
- Sales data must be available by business segment, and
- SEC filings or equivalent disclosures must be accessible.

Any firms that do not satisfy these criteria are aggregated under "Other Firms." Consequently, only 9,466 firms appear explicitly in the EMRIO, reflecting a sharp reduction in the 617,245 firms covered by FactSet.

Timeliness limitation: Although the FactSet database is updated annually, the EMRIO cannot immediately respond to and reflect these updates because it requires extensive adjustments to maintain input–output balances. Currently, the EMRIO is only available for 2015, with no planned updates.