



A Comparative Analysis of the Export Technological Complexity of China, Japan, and South Korea from the Perspective of Global Value Chains

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Abstract

Traditional export-complexity measures rely on gross export values and overlook the global division of labor, so they may misjudge the technological content of a country's exports. This paper builds a value-added-based export technology complexity index for China, Japan, and South Korea from a global value chain (GVC) perspective. Using the OECD Trade in Value Added (TiVA) database (2023 edition; 45 industries; 1995-2020), the index weights industries by the domestic value added contained in exports, so that foreign value added embodied in imported intermediate inputs receives no weight, and adjusts industry values with domestic input-output coefficients. The index is computed at three levels: a country-wide index (country-year observations), industry-level indices for three selected industries (country-industry-year observations), and a panel of 135 country-industry units used in a Markov transition analysis. China's country-wide index was the highest of the three in 17 of the 26 years (1995-2007, 2015-2017, and 2020), South Korea's was highest in the other nine (2008-2014 and 2018-2019), and the three converged by 2020; China's compound annual growth (5.1%) was slower than South Korea's (5.7%) and Japan's (6.6%), and log-linear trend tests confirm this difference, also when 2009 and 2020 are excluded. Using terciles of the pooled index and five-year transitions, China's high tier is the most persistent (0.87), whereas its medium tier is less persistent (0.41) and more likely to fall (0.33) than Japan's or South Korea's. The analysis is descriptive: it documents differences in the index and its persistence and does not test whether GVC embeddedness causes higher export technology complexity.

Subject Areas

Development Economics

Keywords

Global Value Chain, Export Technology Complexity, Domestic Value Added, Markov Transition Analysis

1. Introduction

As the pattern of international division of labor has changed, the mode of division of labor has increasingly displayed the characteristics of global value chains. As the world's largest trading nation and second-largest economy, China's exports play a vital role in promoting economic growth. The complexity of export technology reflects the complexity of a country's or region's export structure, and it has become an important criterion for judging whether a country's exports embody advanced technology. Since Hausmann *et al.* [1] proposed the concept of export technology complexity, scholars have used it to assess the technological content of products manufactured by countries such as China, Japan, and South Korea. The concept reflects a country's export commodity structure, trade quality, comparative advantage, and competitiveness from multiple dimensions, and it has gradually gained international currency. Moreover, experts believe that an effective assessment of export technology complexity can even integrate different institutional environments in order to promote a country's productivity and economic development. As the economy continues to develop, the improvement of export technology complexity, combined with the digital economy, may become a new driving force for the high-quality development of domestic export trade and provide new momentum for sustainable development.

From the perspective of global value chains, intermediate-goods trade must be taken into account: the production of a single product may involve multiple countries and regions, each stage of which may generate imports and exports, with different countries and regions playing different roles at different stages of production, thereby forming a structure of vertical division of labor. Having expanded rapidly in volume, China's foreign trade now faces the difficulty of having emphasized quantity over quality. The traditional approach to measuring export technology complexity can neither reflect the characteristics of the industry itself nor account for the effects of the vertical division of labor in global production, which may lead to misjudgments of the technological level of exporting countries or regions. Researchers have, therefore, shifted their focus from quantity to quality in analyzing products, so as to measure the technological level of commodity exports more accurately, which can in turn reflect a product's competitiveness in the international market.

Among the major East Asian economies, Japan and South Korea, like China, are

among the most economically active countries. Japan and South Korea are both high-income economies, while China is still classified as a developing economy. As East Asia's economy has developed rapidly and cooperation has become increasingly close, China and South Korea are gradually strengthening ties and cooperation in export technology, which may help raise China's overall technological level. However, few studies compare the GVC-adjusted export technology complexity of China, Japan, and South Korea at both the aggregate and the industry level. As an indicator, export technology complexity reflects the technological structure of a country's exports in a specific industry—that is, if the export technology complexity of one country's exports exceeds that of another country, its export technology level is taken to be higher; this interpretation rests on the income-based construction of the index (see Section 6.3).

This paper, therefore, constructs a value-added-based export technology complexity index, weighting industry quality levels by real per-capita GDP (Section 3), and uses it to examine the trends and persistence of the export technology of China, Japan, and South Korea over 1995–2020. The contribution is measurement and description: Section 3 defines the index and shows how it differs operationally from the traditional EXPY measure, and states the data and the unit of observation at each level of analysis; Section 4 compares the three countries' country-wide and industry-level indices and tests their trends and convergence; Section 5 analyzes persistence with a Markov transition approach; and Section 6 concludes. The paper documents associations and patterns; it does not estimate the causal effect of GVC embeddedness on export technology complexity.

2. Literature Review

2.1. The Connotation of Global Value Chains

Since the concept of the global value chain was developed [2] [3], it has been widely emphasized in academic circles. There are currently multiple methods for measuring a country's position in the global value chain. Building on the trade specialization index, Hausmann *et al.* [1] proposed an indicator for measuring the overall export technology content of export products, industries, regions, or countries, which can reflect the position of a country, region, or industry in the international division of labor. Koopman *et al.* [4] proposed a framework that decomposes gross exports into value-added components, from which global value chain position indices can be derived to measure the division-of-labor position of a country's industries within the global value chain. Kansheba *et al.* [5] examined the entrepreneurial ecosystem conditions associated with GVC participation, and Coveri *et al.* [6] studied how functional positioning within GVCs relates to within-country inequality. Studies of China document the domestic technological content of its exports and the role of processing trade [7]–[9], and other measures of export sophistication and economic complexity have been proposed [10] [11]. Industrial upgrading, comprising process upgrading, product upgrading, functional upgrading, and value-chain upgrading, is one of the main pathways driving the transformation of China's high-

tech industries, achieved through the optimization of the domestic industrial structure. More researchers have used index-decomposition methods to conduct comparative studies from various angles. However, although many scholars have conducted extensive research, there remain many shortcomings.

2.2. Research on Export Technology Complexity

Wu Xianfu [12] notes that the export complexity index was first proposed by Hausmann *et al.* [1] in 2007. Although it has many aspects that could be improved, its greatest advantage is that it does not require R&D data at the product or sub-industry level. It can directly use the exporting country's export trade data and per-capita GDP level to measure the international technological competitiveness of products (firms), industries (sectors), and countries (regions). The higher the export complexity, the higher the technological level of that industry, which to some extent reflects its position in the international division of labor. Research on export technology complexity has mainly focused on its determinants, such as improvements in infrastructure [13], the strengthening of intellectual property protection [14], and enterprise R&D [15]. With the widespread application of digital technology, new models, new business formats, and new fields in the digital economy and trade continue to emerge, greatly transforming the industrial, product, and technological structure of international trade. Related studies examine the effect of GVC embeddedness on export technology complexity in manufacturing [16]-[20], the role of dependence on foreign intermediate goods [21], participation in domestic and foreign value chains [22], the domestic technological content of Chinese exports [23] [24], and sector-level cases such as wooden furniture [25]. The East Asian production networks in which China, Japan, and South Korea are embedded are analyzed by Athukorala [26], and Orefice and Rocha [27] study the link between deep integration and production networks.

This literature points to several channels through which GVC embeddedness may be related to export technology complexity. Chen Huiyi [28] argues that integration into GVCs can strengthen learning, motivation, and technology effects. By joining production systems dominated by multinational corporations from developed countries, firms may obtain organizational, technological, and managerial knowledge and use it to improve their production processes. Qiao Tao [29] argues that participation in international competition requires firms to meet international standards and to keep improving their manufacturing processes in order to seek competitiveness, and that a broader profit-margin market may motivate firms to pursue high-tech products. Li Qiaoling [30] holds that imported high-tech intermediate products, such as spare parts, may generate technology spillovers through learning, digestion, imitation, and innovation, and that exports of intermediate products may affect technology diffusion in the opposite direction. These studies suggest that GVC embeddedness may be associated with export technology complexity through channels such as innovation; whether the association holds for the three economies studied here is not tested in this paper. Measurement should nev-

ertheless take global value chain embeddedness into account by considering how the index changes once intermediate goods and foreign content are accounted for.

2.3. Literature Review Summary

At present, although the export technology complexity of Chinese products continues to rise, numerous studies indicate that there remains room for improvement compared with developed countries. At the same time, China's economy faces the major task of industrial structural adjustment, with service-oriented manufacturing serving as an important direction for restructuring and transforming the manufacturing sector. China's foreign trade has shifted from an emphasis on export quantity to an emphasis on export quality, moving toward the mid-to-high end of the global value chain. It is, therefore, necessary to continuously promote the transformation and upgrading of traditional industries toward servitization, which may promote the development of foreign trade and support domestic economic growth. Overall, research on export complexity that is genuinely constructed from a global value chain perspective remains relatively scarce. In addition, firms embedded in GVCs may face low-end lock-in [31], so GVC participation alone does not guarantee upgrading.

3. Global Value Chains and the Measurement of Export Technology Complexity

3.1. The Traditional Measure (EXPY)

Export technology complexity assumes that the higher a country's per-capita income, the higher its productivity and hence the technological content of the goods it exports. The technological content of each commodity (PRODY) is the weighted average of the per-capita incomes of the countries that export it, where each country's weight is its revealed comparative advantage, that is, the share of the commodity in the country's total exports divided by the sum of these shares across countries. The export technology complexity of a country (EXPY) is then the average of the commodity-level PRODY values, weighted by each commodity's share in the country's total exports [1]:

$$PRODY_k = \sum_j \frac{\frac{x_{jk}}{X_j}}{\sum_j \frac{x_{jk}}{X_j}} Y_j \quad (1)$$

$$EXPY_j = \sum_k \frac{x_{jk}}{X_j} PRODY_k \quad (2)$$

In Equation (1) and Equation (2), x_{jk} is country j 's gross export value of commodity k , X_j is country j 's total gross exports, and Y_j is the per-capita income of country j , measured by per-capita GDP. In this subsection, j indexes countries and k indexes commodities; from Section 3.2 onward, r indexes countries, j and i index industries, and t indexes years. The weights in Equation (1) and Equation (2) are

gross exports, which include the value of imported intermediate inputs embodied in a country's exports.

3.2. Gross-Export Benchmark at the Industry Level

The industry-level analogue of EXPY uses the same two steps as Equation (1) and Equation (2), with industries in place of commodities. With gross exports e_{ijt} of industry j in country r in year t , and $E_{rt} = \sum_j e_{ijt}$, the gross-export version is

$$TSI_{jt}^X = \sum_r \frac{\frac{e_{ijt}}{E_{rt}}}{\sum_r \frac{e_{ijt}}{E_{rt}}} Y_{rt} \quad (3)$$

$$EXPY_{rt} = \sum_j \frac{e_{ijt}}{E_{rt}} TSI_{jt}^X \quad (4)$$

where Y_{rt} is real per-capita GDP. In this paper, Equation (3) and Equation (4) serve only as the traditional benchmark; the empirical results in Sections 4 and 5 use the value-added-based measure described in Sections 3.3 to 3.5, and the benchmark itself is not computed (see Section 6.3).

3.3. Weighting by Domestic Value Added

In the global value chain division of labor, imported intermediate inputs from trading partners contribute to a country's gross exports without reflecting the country's own technology. We, therefore, replace gross exports with the domestic value added contained in exports, following the approach of Qi and Wang [24]. The industry quality level is

$$TSI_{jt} = \sum_r \frac{\frac{v_{ijt}}{v_{rt}}}{\sum_r \frac{v_{ijt}}{v_{rt}}} Y_{rt} \quad (5)$$

where v_{ijt} is the domestic value added contained in the exports of industry j of country r in year t (the TiVA indicator EXGR_DVA, Section 3.7), $v_{rt} = \sum_j v_{ijt}$ is the domestic value added contained in the total exports of country r , and Y_{rt} is real per-capita GDP. Equation (5) differs from Equation (3) only in the weight: domestic value added replaces gross exports. EXGR_DVA counts value added generated by any domestic industry: the direct contribution of the exporting industry (EXGR_DDC), the indirect contribution of upstream domestic industries (EXGR_IDC), and domestic value added that returns home embodied in imports (EXGR_RIM) [32]. Only foreign value added is removed. A weighted-average alternative based on domestic output value is possible but is not used here.

3.4. Input-Output Adjustment

The composite technological content of an industry's product consists of the tech-

nological content of the inputs it uses and the technological content of its own production process. Using the domestic input-output coefficients of country r , the composite technological content of industry j in country r is

$$V_{rjt} = \sum_i a_{ijt}^r TSI_{it} + \left(1 - \sum_i a_{ijt}^r\right) TSI_{jt} \quad (6)$$

where a_{ijt}^r is the direct-consumption coefficient, the value of input i purchased from domestic suppliers in country r that is needed to produce one unit of output of industry j . The first term credits industry j with the technological content of its domestic inputs; the second values the remaining share of output at the industry's own quality level. Because TSI_{jt} is common to all countries, differences in V_{rjt} across countries for the same industry arise from differences in the countries' domestic input coefficients. Because EXGR_DVA already includes upstream domestic value added, crediting domestic inputs in Equation (6) partly counts domestic upstream content twice; Section 6.3 notes a robustness check that uses direct domestic value added (EXGR_DDC) as the weight.

3.5. Aggregation to the Country Level

The country-wide index weights the industry values by each industry's share of the country's domestic value added in exports:

$$V_{rt} = \sum_j \gamma_{rjt} V_{rjt}, \quad \gamma_{rjt} = \frac{v_{rjt}}{v_{rt}} \quad (7)$$

Both the industry-level index V_{rjt} and the country-wide index V_{rt} are, therefore, built from domestic value added, not from gross exports. Index levels are reported as computed; they depend on the normalization and carry no direct dollar interpretation, so the analysis relies on ratios, ranks, and growth rates.

3.6. How the Value-Added Measure Differs from EXPY

Table 1 summarizes the operational differences. The two measures share the income-based logic of Hausmann *et al.* [1]: both value an export at a weighted average of the per-capita incomes of the countries that export the same good. They differ in which export flow supplies the weights, in how imported intermediate inputs are treated, and in the input-output adjustment. The value-added component used is the domestic value added contained in gross exports (EXGR_DVA); the foreign value added component (EXGR_FVA), which is the value of imported intermediates and other foreign content embodied in exports, is never used as a weight. Imported intermediate inputs are excluded in two places: i) through the weights, because foreign value added is not part of v_{rjt} (domestic value added that returns home embodied in imports, EXGR_RIM, stays included because it is domestic in origin); and ii) through the input coefficients, because a_{ijt}^r contains only purchases from domestic suppliers, so imported inputs are not credited with the technological content of their foreign supplier industries.

Table 1. Operational differences between the traditional EXPY and the value-added-based index.

Item	Traditional EXPY [1]	Value-Added-Based Index (This Paper)
Export flow used as weight	Gross exports (x_{jk} , e_{ijt})	Domestic value added in exports (EXGR_DVA, v_{ijt})
Foreign value added/imported intermediates in exports	Included in the weights	Excluded: EXGR_FVA is not used; gross exports = EXGR_DVA + EXGR_FVA
Imported inputs in the input-output step	No input-output adjustment	Only domestic input coefficients a_{ijt}^r ; imported inputs receive no foreign technological content
Input-output adjustment	None	Composite technological content, Equation (6)
Classification level	Commodity (product) level	45 TiVA industries (ISIC Rev. 4)
Income proxy	Per-capita GDP	Real per-capita GDP (constant 2015 US\$); same income-based logic and circularity
Interpretation	Technological content of gross exports	Technological content of domestic value added embodied in exports; comparable across countries and years within an industry, not across industries

3.7. Data, Variables, and Implementation

Database and classification. All value-added data come from the OECD Trade in Value Added (TiVA) database, 2023 edition [32], which is derived from the OECD Inter-Country Input-Output (ICIO) tables. It covers 76 economies (plus a rest-of-the-world aggregate) and 45 industries for 1995-2020 and reports values in millions of current US dollars. Industries follow the ISIC Revision 4 classification used in TiVA; 21 of the 45 industries are services. The OECD cautions that TiVA estimates for the most recent years are extrapolated from the latest available supply-and-use tables and that the effects of COVID-19 in 2020 are not yet well captured [32]; the 2020 values are, therefore, less certain than those of earlier years. The three industries analyzed in Section 4.2 are C13T15 (textiles and apparel), C21 (pharmaceuticals), and C26 (computers and electronics).

Variables extracted. For every exporting economy, industry, and year, we extract gross exports (EXGR), the domestic value added content of gross exports (EXGR_DVA), and the foreign value added content of gross exports (EXGR_FVA) from TiVA. The domestic input coefficients a_{ijt}^r of China, Japan, and South Korea are computed from the corresponding ICIO tables as domestic intermediate purchases of industry j from industry i divided by the gross output of industry j . Real per-capita GDP (constant 2015 US dollars) is taken from the World Bank's World Development Indicators [33]. TiVA indicators are derived from the extended ICIO tables, which split China (and Mexico) into processing exporters and other producers; in 2007 value added was 15.3% of output for China's processing exporters against 23.9% for its non-processing exporters [34]. China's coefficients are computed from the extended tables, aggregating the two China blocks by gross output.

Steps to calculate domestic value added in exports.

1) Extract EXGR_DVA and EXGR_FVA for each economy r , industry j , and year t . In TiVA, gross exports are the sum of the domestic and foreign value added components.

2) Set v_{ijt} equal to EXGR_DVA. Foreign value added (EXGR_FVA) is not used in any weight.

3) Sum v_{ijt} over the 45 individual industries to obtain v_{rt} excluding the aggregate codes of the TiVA hierarchy (such as total manufactures and total services) to avoid double counting.

4) Compute the domestic value-added shares v_{ijt}/v_{rt} and the industry quality levels TSI_{jt} by Equation (5), year by year.

5) Compute V_{ijt} by Equation (6) and the country-wide index V_{rt} by Equation (7).

Missing values. The extracted panel for China, Japan, and South Korea is balanced (45 industries $\times$ 26 years), so no observations were dropped or imputed. In the cross-economy averages in Equation (5), an economy for which the World Bank reports no per-capita GDP in a given year is omitted from both the numerator and the normalizing sum.

Unit of observation. The index is computed at three levels, summarized in **Table 2**. The unit of observation in each annual Markov observation is a country-industry pair (one of 45 industries in one of 3 countries) in one year, that is, the industry-level index V_{ijt} , it is not the country-wide index V_{rt} , and the three country-wide series are not classified into tiers. Country-level results in Section 5 are obtained by pooling the 45 industries of each country.

Table 2. Levels of analysis and units of observation.

Level	Index	Unit of Observation	Number of Observations	Used in
Country-wide	V_{rt} , Equation (7)	Country-year	$3 \times 26 = 78$	Sections 4.1 and 4.3
Industry-level (3 industries)	V_{ijt} , Equation (6)	Country-industry-year	$3 \times 3 \times 26 = 234$	Sections 4.2 and 4.3
Country-industry panel (45 industries)	V_{ijt} , Equation (6)	Country-industry unit, followed over time (135 units)	$3 \times 45 \times 26 = 3,510$ (2,835 five-year transitions)	Section 5

4. Comparative Analysis of the Export Technology Complexity of China, Japan, and South Korea

4.1. Overall Trend Analysis

Among the three most economically active economies in East Asia, Japan and South Korea are high-income economies, and China is a developing economy. This section analyzes the country-wide index V_{rt} (Section 4.1) and the industry-level index

V_{ijt} for three industries (Section 4.2). **Figure 1** shows that the country-wide export technology complexity of China, Japan, and South Korea rose overall from 1995 to 2020. All three indices fell sharply in 2009, which was the trough, rebounded from 2010, and fell again in 2015 and 2020 (China and South Korea also fell in 2016). The 2009 fall coincides with the global financial crisis that followed the U.S. subprime mortgage crisis; because the index is weighted by real per-capita GDP, the fall in per-capita GDP that year may also contribute mechanically, so it should not be read as a change in export structure alone.

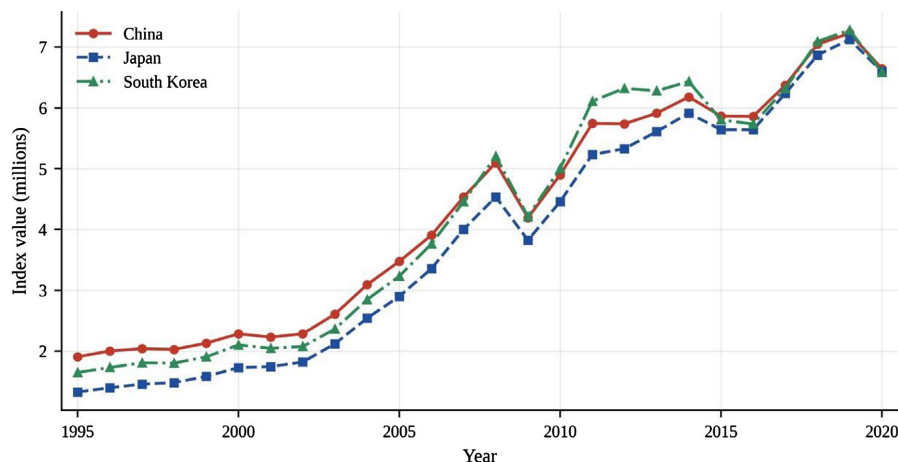


Figure 1. Country-wide export technology complexity index (V_{it}), 1995-2020. Source: authors' calculations based on OECD TiVA data (2023 edition).

The country-wide index of China was the highest of the three in 17 of the 26 years (1995-2007, 2015-2017, and 2020); South Korea's was the highest in the other nine years (2008-2014 and 2018-2019); China's index exceeded Japan's in every one of the 26 years, and Japan's was never the highest. From 1995 to 2007, China ranked first, South Korea second, and Japan third. South Korea overtook China in 2008 and stayed first through 2014; China regained first place in 2015-2017, and South Korea led again in 2018-2019. By 2020, the three indices had converged (6.65, 6.60, and 6.59 million for China, Japan, and South Korea, respectively), with China first by less than 1%. TiVA estimates for 2020 are extrapolated and should be read with caution [32]; the convergence is not an artifact of 2020, since the dispersion was already small in 2019 (Section 4.3). Japan ranked third in every year until 2019 and second in 2020. Although each index fluctuated in between, all three achieved substantial gains overall compared with 1995.

Analyzed from the global value chain perspective, a country's export technology complexity is related not only to its own technological level but also to the technological complexity of the inputs it uses. China's lead in the first period is consistent with earlier findings that China's exports are more sophisticated than its income level would suggest [7] [8], and such results are sensitive to the treatment of processing trade and imported inputs. This may differ from the conventional understanding of the relative technological levels of these countries, but this

paper does not compute the traditional gross-export index of Equation (3) and Equation (4) on the same scale. Therefore, it is not possible to determine to what extent the rankings in **Figure 1** are attributable to value-added adjustments; the rankings should be read as rankings of the value-added-based index, and a side-by-side comparison with the traditional index is left for future work (Section 6.3). The ranking also differs from external complexity rankings: in the Atlas of Economic Complexity, Japan ranks first in the years shown in the Atlas ranking tool, South Korea third or fourth, and China between 10th and 17th [35]. The two measures need not agree, because the Atlas ranks the diversity and ubiquity of a country's exports, whereas this index is an income-weighted average over the industries in which a country's domestic value added is exported. The disagreement on China's position is a reminder that the index measures income-weighted export structure and not technological capability.

The line chart shows that the export technology complexity of China, Japan, and South Korea trended upward over the past 26 years, but China's growth was the slowest: the compound annual growth rates of the index over 1995-2020 were 5.1% for China, 5.7% for South Korea, and 6.6% for Japan (cumulative growth of 249%, 300%, and 398%). China's initial lead over Japan (about 44% above Japan's level in 1995) had narrowed to less than 1% by 2020, and its lead over South Korea (about 16% in 1995) had narrowed to about 1%. China's index rose from 1995 to 2008 (apart from small dips in 1998 and 2001), fell by about 18% in 2009, and rebounded from 2010; by 2020 the three indices were within about 1% of one another. Part of China's slower growth reflects its higher starting level, so the pattern is partly one of convergence (tested in Section 4.3). Overall, China's export technology complexity has grown more slowly than that of Japan and South Korea, which reflects an area of relative weakness.

4.2. Comparative Analysis by Industry

China's textile and apparel industry is a traditional pillar of the Chinese economy, but since China's accession to the WTO in 2001, the industry has undergone a fundamental shift in supply and demand, with production capacity increasing markedly. Through contracted projects and technological upgrading, the industry is moving toward higher-end, more personalized production models. The textile industry, therefore, plays an important role in both global and Chinese economic development, while facing a constantly changing market environment and competitive pressure that require ongoing technological innovation and industrial upgrading. Meanwhile, the pharmaceutical, electronics, and computer industries, owing to their resource endowments, industrial base, and contribution to economic growth, are recognized by many regions as high-tech industries. The following analysis, therefore, uses these three industries as examples to compare the industry-level index V_{ijt} of China, Japan, and South Korea. The index levels of different industries are not comparable, because the index reflects the incomes of the countries whose exports are weighted and not the engineering content of the

industry. **Figures 2-4**, therefore, show each industry relative to the three-country mean in 1995 (=100), and all comparisons below are made within an industry, across countries and over time; the paper makes no claim about which industry is more technology-intensive.

Figure 2 shows that for C13T15 (textiles and apparel), the export technology complexity of all three countries trended upward during the sample period, with dips in 2001, 2009, 2015, and 2020 (also 2016 for China), indicating that the export technology level of the textile industry in all three countries has grown steadily. China's textile index was the highest of the three in every year from 1995 to 2020. Japan and South Korea were roughly comparable, with alternating rankings until 2013; from 2014, Japan stayed ahead of South Korea. Over 1995-2020 the index grew at compound annual rates of 4.80% for China, 4.91% for Japan, and 4.70% for South Korea (cumulative growth of 223%, 232%, and 215%). China's lead over Japan, therefore, changed little in relative terms (about 7% in 1995 and 4.5% in 2020), whereas its lead over South Korea widened (from about 6.5% to about 9%). Overall, the three curves remain fairly close, indicating a shared sensitivity to the broader economic environment.

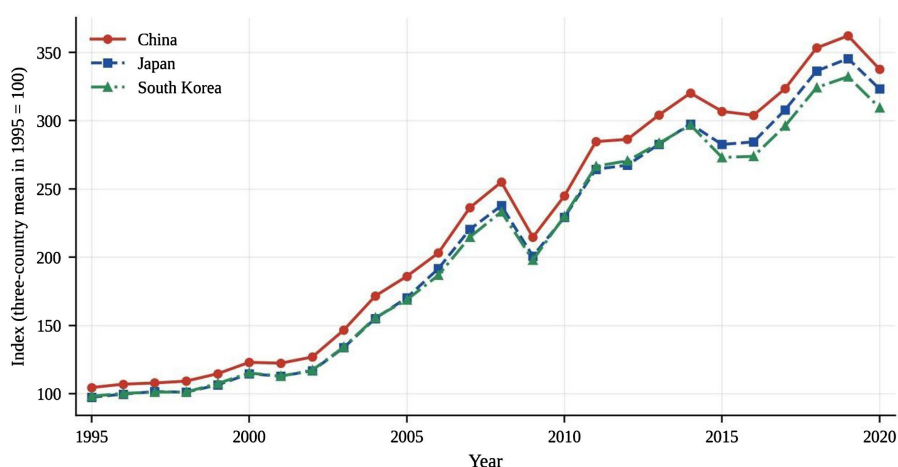


Figure 2. Export technology complexity of the textile industry (C13T15) in China, Japan, and South Korea (three-country mean in 1995 = 100). Source: authors' calculations based on OECD TiVA data (2023 edition).

Figure 3 shows that for C21 (pharmaceuticals), the export technology complexity of all three countries trended upward throughout the observation period, with declines in 2009 and 2020 (China also declined in 2012 and 2016). China maintained the top ranking throughout, followed by Japan and then South Korea. China's lead over Japan ranged between about 2.5% and 10%: it was about 3% in 2002, reached about 8.5% - 9.5% in 2009-2010, and narrowed to about 3% by 2017-2020, when Japan reached a level close to China's, while South Korea remained about 11% below China. Over 1995-2020, the index grew at compound annual rates of 7.02% for China, 7.25% for Japan, and 7.02% for South Korea (cumulative growth of 445%, 476%, and 446%).

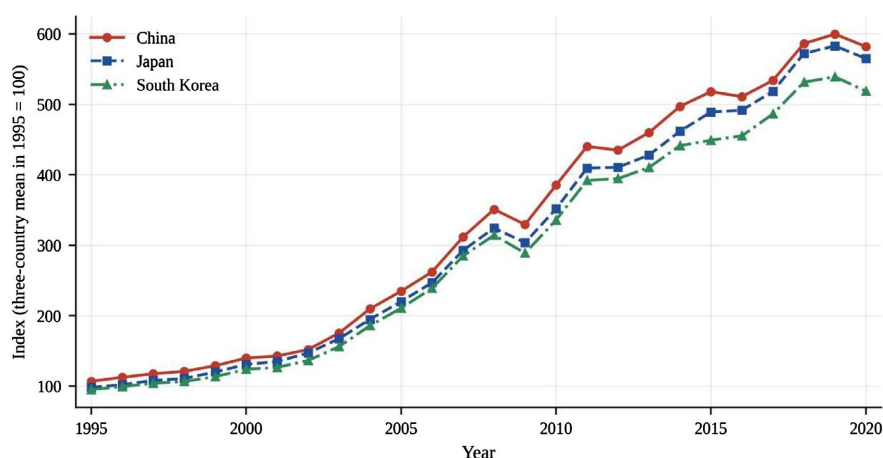


Figure 3. Export technology complexity of the pharmaceutical industry (C21) in China, Japan, and South Korea (three-country mean in 1995 = 100). Source: authors' calculations based on OECD TiVA data (2023 edition).

Figure 4 shows that for C26 (computers and electronics), the export technology complexity of China, Japan, and South Korea likewise trended upward during the observation period, with declines in 2001, 2009, 2015, and 2020. Japan ranked first in every year except 2005. South Korea ranked second from 2007 to 2016, and China ranked second from 2017. Japan's lead over China was about 5% - 7% until 2002, narrowed to about 1% - 3% during 2004-2011 (with China ahead in 2005), and widened again from 2012 (to about 7% by 2020), when Japan was also about 10% above South Korea. Over 1995-2020, the index grew at compound annual rates of 6.43% for China, 6.49% for Japan, and 6.38% for South Korea (cumulative growth of 375%, 381%, and 369%). Because TSI_{it} is common to all countries (Section 3.4), the differences among countries within an industry are small in all three cases.

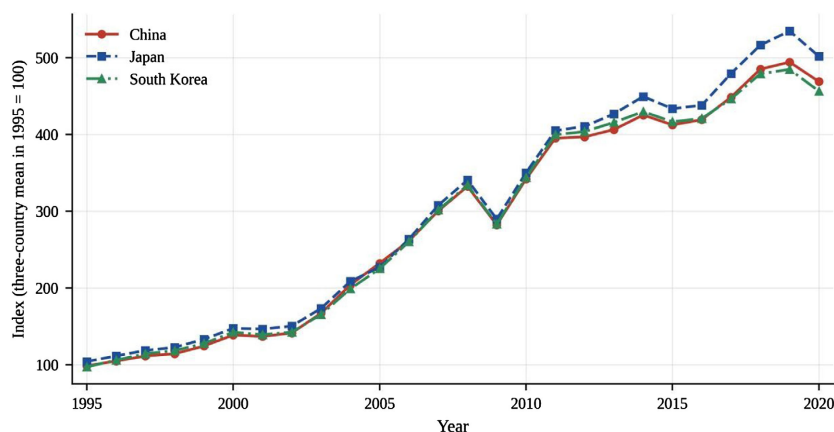


Figure 4. Export technology complexity of the computer and electronics industry (C26) in China, Japan, and South Korea (three-country mean in 1995 = 100). Source: authors' calculations based on OECD TiVA data (2023 edition).

4.3. Trend, Convergence, and Co-Movement Tests

The comparisons above rest on levels and end-point growth rates, which are sen-

sitive to the dips of 2009 and 2020. This section tests them formally. For each series, we regress the log index on a linear time trend and report the slope in log points per year (multiplied by 100) with Newey-West standard errors (three lags); we test differences in growth by regressing the log gap between two countries on the same trend (**Table 3**). With 26 annual observations per series, these tests are indicative rather than exact.

Table 3. Log-linear trends (log points per year $\times$ 100, Newey-West standard errors in parentheses) and trends in the log gap between countries (p-values in parentheses), 1995-2020.

Level	China	Japan	South Korea	Gap Trend: CHN-JPN	Gap Trend: CHN-KOR
Country-Wide	6.06 (0.39)	7.56 (0.46)	6.78 (0.52)	-1.51 (<0.001)	-0.72 (<0.001)
Textiles (C13T15)	5.69 (0.36)	5.78 (0.33)	5.61 (0.36)	-0.09 (0.060)	0.08 (0.014)
Pharmaceuticals (C21)	7.90 (0.44)	8.07 (0.39)	7.94 (0.43)	-0.17 (0.002)	-0.05 (0.058)
Electronics (C26)	7.16 (0.50)	7.16 (0.42)	7.08 (0.51)	0.00 (0.994)	0.08 (0.156)

Country-wide growth. China's trend growth (6.1 log points per year) is significantly lower than Japan's (7.6) and South Korea's (6.8). The log gap between China and Japan narrows by 1.5 points per year, and the gap between China and South Korea by 0.7 points per year (both $p < 0.001$). Excluding 2009 and 2020 leaves the picture unchanged (slopes of 6.3, 7.8, and 7.1; gap trends of -1.54 and -0.78, both $p < 0.001$). Therefore, the slower growth of China's index reported in Section 4.1 is not an artifact of the end points or of the two dips.

Industry growth. Within the three industries, the trends are nearly identical across countries (5.6 - 5.8, 7.9 - 8.1, and 7.1 - 7.2 log points per year). Differences are statistically detectable in only two cases: the pharmaceutical lead of China over Japan narrows (-0.17 per year, $p = 0.002$), and the textile lead of China over South Korea widens (+0.08 per year, $p = 0.014$). The other differences, including all differences in electronics, are not significant at the 5% level, and this classification is the same when 2009 and 2020 are excluded.

Co-movement and convergence. Annual changes in the log index are almost perfectly correlated across the three countries at every level (correlations of 0.98 to 0.99), including the dips of 2009 and 2020. Year-to-year movements are thus common to all three countries, in line with the role of the income weights and the common industry quality level TSI_{it} and they carry little information about differences between countries. **Figure 5** removes this common movement by expressing each country-wide index relative to the three-country mean. China stood 17% above the mean in 1995 and Japan 18% below it; by 2020 all three lay within 0.5% of the mean. The cross-country dispersion of the log index (standard deviation across the three countries) fell from 0.182 in 1995 to 0.005 in 2020, a significant downward trend (-0.007 per year, $p < 0.001$). The dispersion was already 0.011 in 2019, and the trend is unchanged when 2020 is excluded (-0.007 per year, $p < 0.001$).

Within industries, there is no such trend: the dispersion is 0.039 in 1995 and 0.044 in 2020 in textiles ($p = 0.39$), 0.060 in both years in pharmaceuticals ($p = 0.054$), and 0.037 and 0.049 in electronics ($p = 0.76$).

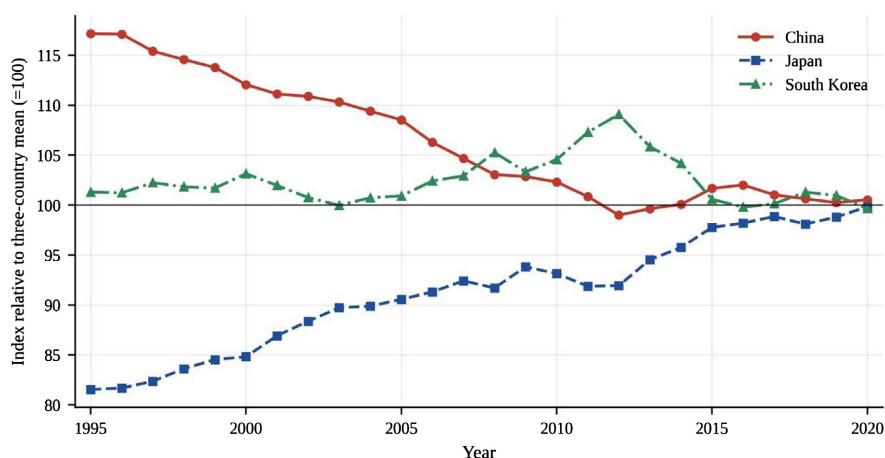


Figure 5. Country-wide index relative to the three-country mean (mean = 100), 1995-2020. Source: authors' calculations based on OECD TiVA data (2023 edition).

Because within-industry gaps are at most about 10% in the three industries examined, whereas the country-wide gap between China and Japan was 44% in 1995, the country-wide convergence most likely reflects changes in the industry composition of domestic value added in exports (the weights γ_{ijt} in Equation (7)) and not convergence within industries. This is an inference from the structure of the index; a formal decomposition into a composition and a within-industry component requires the full 45-industry panel.

5. Transition Probability and Persistence Analysis

5.1. Analytical Principles

With the evolution of the global value chain division of labor, using intermediate products to manufacture high-tech end products has gradually become a standard course of action for firms entering the international market. Because production processes differ at each stage, when a country's level of technological development changes, the various components of different products undergo corresponding transformations. This paper uses a Markov chain approach to study the persistence of export technology complexity in China, Japan, and South Korea, that is, the probability that a unit stays in, or moves between, complexity tiers. The state-transition probability is

$$P_{uv} = \frac{N_{uv}}{N_u} \quad (8)$$

where u and v denote the complexity tier (low, medium, or high) of a unit in year t and in year $t + 5$, respectively; N_{uv} is the number of five-year transitions from tier u to tier v , and $N_u = \sum_v N_{uv}$ is the number of all transitions that start in tier u , both

counted over all units and all starting years $t = 1995, \dots, 2015$. The five-year horizon smooths short-run fluctuations such as the dips of 2009 and 2020, and with data for 1995–2020 each unit contributes 21 overlapping five-year transitions.

Unit of observation. The annual observation is the industry-level index V_{ijt} of one country-industry pair ($45 \text{ industries} \times 3 \text{ countries} = 135 \text{ units}$; 3,510 unit-years and 2,835 five-year transitions; **Table 2**). Each country, therefore, contributes $45 \times 21 = 945$ transitions to its row of **Table 4**. The country-wide index of Section 4.1 is not used in the Markov analysis.

5.2. Persistence of Export Technology Complexity

Based on the 33rd and 66th percentile values of the industry-level index V_{ijt} , complexity is divided into three tiers (low, medium, and high), denoted by (1), (2), and (3) in **Table 4**. The percentile cut-offs are computed pooled over all three countries, all industries, and all years to ensure a consistent, comparable benchmark for cross-country mobility. Terciles give tiers of similar size within the set of observations used to set the cut-offs, so persistence and mobility are measured relative to the sample distribution; the tiers are not classifications of industries by technology intensity. The transition probabilities among the three tiers were then calculated for each country, as shown in **Table 4**.

Table 4. State transition probabilities of export technology complexity for China, Japan, and South Korea, 1995–2020 (five-year horizon; 945 transitions per country).

Country	P(1→1)	P(1→2)	P(1→3)	P(2→1)	P(2→2)	P(2→3)	P(3→1)	P(3→2)	P(3→3)
CHN	0.4409	0.4791	0.0800	0.3308	0.4128	0.2563	0.0178	0.1084	0.8736
JPN	0.4702	0.4569	0.0729	0.2144	0.5106	0.2749	0.0474	0.2798	0.6727
KOR	0.3907	0.5219	0.0874	0.2279	0.4449	0.3271	0.0357	0.2394	0.7247

Table 4 presents the state-transition probabilities of export technology complexity for China, Japan, and South Korea. From an individual-country perspective, the probability that China remains in the same tier (high, medium, or low) after five years is 0.87, 0.41, and 0.44, respectively, indicating that China's high tier is the most persistent, the low tier is less persistent, and the medium tier is the least persistent and has the greatest volatility.

Specifically, the probability of climbing from the low tier to the medium tier is 0.48, from the medium tier to the high tier is 0.26, and from the low tier directly to the high tier is 0.08. These figures indicate that China can advance both step by step and by skipping tiers, with step-by-step advancement being more probable, though upward mobility overall remains difficult. Meanwhile, the probabilities of falling from the medium tier to the low tier and from the high tier to the medium tier after five years are 0.33 and 0.11, respectively, and the probability of falling from the high tier directly to the low tier is 0.02, indicating that persistence is high

in the high tier, with some risk of decline. The probability of upward movement from the medium tier (0.26) is clearly lower than that of downward movement (0.33), whereas the probability of climbing from the low tier to the high tier (0.08) exceeds that of falling from the high tier to the low tier (0.02). Overall, China's high tier is highly persistent, but its medium tier is the weak point: a medium-tier unit is more likely to fall than to rise.

From a cross-country perspective, the probability that Japan remains in the same high, medium, or low tier after five years is 0.67, 0.51, and 0.47, respectively, while for South Korea the corresponding probabilities are 0.72, 0.44, and 0.39. Therefore, China is more persistent than Japan and South Korea only in the high tier (0.87 versus 0.72 for South Korea and 0.67 for Japan). In the medium tier, China is the least persistent of the three (0.41 versus 0.51 for Japan and 0.44 for South Korea), and in the low tier it is less persistent than Japan (0.44 versus 0.47) but more persistent than South Korea (0.39). China's probability of climbing from the medium tier to the high tier (0.26) is close to Japan's (0.27) and lower than South Korea's (0.33), while its risk of falling from the medium tier to the low tier (0.33) is clearly higher than Japan's (0.21) and South Korea's (0.23). The differences in upward mobility are small and, because no standard errors are reported, should not be over-interpreted; the difference in downward risk is larger. Persistence in the high tier is also partly mechanical, because the index trends upward while the cut-offs are fixed over time (Section 6.3).

These results are descriptive. They show how the three countries' country-industry units move between tiers; they do not show that participation in global value chains raised or lowered persistence. The literature reviewed in Section 2.2 suggests channels through which GVC participation may matter, but testing them requires a measure of GVC participation for each unit and an identification strategy (Section 6.3).

6. Main Conclusions and Policy Recommendations

6.1. Main Conclusions

Taking the construction of an export technology complexity indicator from the global value chain perspective as its point of departure, this paper has characterized the trends in each country's export technology complexity and analyzed its persistence. The main conclusions are as follows.

- 1) On the value-added-based index, China's country-wide export technology complexity is the highest of the three in 17 of 26 years (1995-2007, 2015-2017, and 2020); South Korea's is the highest in the other nine (2008-2014 and 2018-2019), and the three converged by 2020. China's index has grown more slowly (5.1% per year) than South Korea's (5.7%) and Japan's (6.6%), partly because it started from a higher level; log-linear trend tests confirm that its trend growth is significantly lower than that of Japan and South Korea, even when 2009 and 2020 are excluded, whereas growth differences within the three industries are small. Because the traditional gross-export index is not computed here, the paper cannot attribute these

rankings to the value-added adjustment.

2) Year-to-year movements of the index, including the dips of 2009 and 2020, are almost perfectly common to the three countries (correlations of annual changes of 0.98 to 0.99). The convergence of the country-wide indices by 2020 is not matched by convergence within the three industries, and so most likely reflects changes in industry composition.

3) The export technology complexity of China, Japan, and South Korea all display a gradually increasing trend, indicating that the export technology levels of all three countries are rising. In terms of persistence, China's high tier is more persistent than that of Japan and South Korea; China's medium tier, however, is less persistent than those of Japan and South Korea, with a lower probability of climbing than South Korea's and a considerably greater risk of falling to the low tier than Japan's and South Korea's. China is not more stable than both neighbors across all tiers.

4) These findings are associations and descriptive patterns. Whether GVC embeddedness itself raises export technology complexity is not tested in this paper and is left for future work.

6.2. Policy Recommendations

Because the evidence in this paper is descriptive, the following suggestions rest on the literature and on the patterns found here, not on an estimated effect of GVC embeddedness.

First, GVC participation may be a channel through which industries obtain advanced intermediate inputs, knowledge, and management practices [28]–[30], although it does not guarantee upgrading and can lead to low-end lock-in [31]. Industries or regions with lagging production technology should, therefore, integrate into global production processes while building their own capacity to absorb and innovate. Industries or regions that already possess the most advanced production technology must rely on their own scientific research and technological capacity for R&D and innovation, and progressively seek to raise their technological level further.

Second, although China's product exports are becoming increasingly complex, there remains room for improvement. China's economy faces the task of industrial restructuring, and should start from the actual conditions of different industries in different regions, formulating industrial and regional development policies—especially policies for global value chain integration—based on the differing production levels and technologies across regions.

Third, China's medium-tier industries are the least persistent: the probability of falling to the low tier (0.33) exceeds that of rising to the high tier (0.26). Governments and relevant departments should, therefore, combine independent R&D and innovation with continued integration into global value chains for these medium-tier industries, in order to raise their technological level and prevent technological decline.

Fourth, as major East Asian economies linked through regional production networks [26], China, Japan, and South Korea can strengthen cooperation, for exam-

ple through the mutual supply of intermediate goods, forming a production network for joint development. This recommendation rests on the regional-network literature rather than on the analysis in this paper, which does not examine bilateral intermediate-goods flows.

6.3. Limitations and Future Research

Three limitations remain. First, the index is income-based and, therefore, partly circular, and its levels are not comparable across industries as a ranking of technology intensity (the unnormalized textile index exceeds the electronics index; Section 4.2); we compare countries within an industry and over time. The trend results are robust to excluding 2009 and 2020, and year-to-year movements are common to the three countries (Section 4.3), but the traditional gross-export index of Equation (3) and Equation (4) is not computed. Computing it on the same scale, separating processing from ordinary trade [4] [9], and valuing the residual share in Equation (6) by the value-added share alone would show how much the value-added adjustment changes the rankings. Two further robustness checks are weighting by direct rather than total domestic value added (EXGR_DDC), which avoids the partial double counting noted in Section 3.4, and using PPP-adjusted income, as Hausmann *et al.* [1] do.

Second, the transition probabilities in Table 4 are point estimates from overlapping five-year windows, with tiers defined on the pooled sample distribution. Because the index trends upward, the high tier is partly absorbing by construction. Bootstrap confidence intervals, year-specific or detrended tiers, and tests of the first-order and time-homogeneity assumptions require the unit-level panel of 135 units, and so does the composition decomposition suggested in Section 4.3.

Third, and most important for interpretation, the paper does not test the effect of GVC embeddedness on export technology complexity, and its findings are associations. A causal claim would require a panel regression of the index on a unit-level measure of GVC participation (for example, the foreign value-added share of exports or the participation rates available in TiVA), with country-industry and year fixed effects, controls, and an identification strategy such as China's WTO accession in 2001 or instruments based on foreign demand or tariff changes.

Author Contributions

Conceptualization: M.A., M.Y., and T.Z.; Methodology: M.A. and M.Y.; Software: M.A.; Validation: M.A., M.Y., and T.Z.; Formal analysis: M.A.; Investigation: M.A. and M.Y.; Resources: M.Y. and T.Z.; Data curation: M.A.; Writing—original draft preparation: M.A.; Writing—review and editing: M.Y. and T.Z.; Visualization: M.A.; Supervision: M.Y. and T.Z.; Project administration: M.Y. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Hausmann, R., Hwang, J. and Rodrik, D. (2007) What You Export Matters. *Journal of Economic Growth*, **12**, 1-25. <https://doi.org/10.1007/s10887-006-9009-4>
- [2] Gereffi, G. (1999) International Trade and Industrial Upgrading in the Apparel Commodity Chain. *Journal of International Economics*, **48**, 37-70. [https://doi.org/10.1016/s0022-1996\(98\)00075-0](https://doi.org/10.1016/s0022-1996(98)00075-0)
- [3] Hummels, D., Ishii, J. and Yi, K. (2001) The Nature and Growth of Vertical Specialization in World Trade. *Journal of International Economics*, **54**, 75-96. [https://doi.org/10.1016/s0022-1996\(00\)00093-3](https://doi.org/10.1016/s0022-1996(00)00093-3)
- [4] Koopman, R., Wang, Z. and Wei, S. (2014) Tracing Value-Added and Double Counting in Gross Exports. *American Economic Review*, **104**, 459-494. <https://doi.org/10.1257/aer.104.2.459>
- [5] Kansheba, J.M., Fubah, C.N. and Marobhe, M.I. (2024) Unravelling the Entrepreneurial Ecosystem Conditions Spurring the Global Value Chains: A Configurational Approach. *International Journal of Entrepreneurial Behavior & Research*, **30**, 1400-1424. <https://doi.org/10.1108/ijebr-07-2023-0738>
- [6] Coveri, A., Paglialonga, E. and Zanfei, A. (2024) Global Value Chains and Within-Country Inequality: The Role of Functional Positioning. *Structural Change and Economic Dynamics*, **70**, 382-397. <https://doi.org/10.1016/j.strueco.2024.05.001>
- [7] Rodrik, D. (2006) What's So Special about China's Exports? *China World Economy*, **14**, 1-19. <https://doi.org/10.1111/j.1749-124x.2006.00038.x>
- [8] Schott, P.K. (2008) The Relative Sophistication of Chinese Exports. *Economic Policy*, **23**, 6-49.
- [9] Upward, R., Wang, Z. and Zheng, J. (2013) Weighing China's Export Basket: The Domestic Content and Technology Intensity of Chinese Exports. *Journal of Comparative Economics*, **41**, 527-543. <https://doi.org/10.1016/j.jce.2012.07.004>
- [10] Lall, S., Weiss, J. and Zhang, J. (2006) The "Sophistication" of Exports: A New Trade Measure. *World Development*, **34**, 222-237. <https://doi.org/10.1016/j.worlddev.2005.09.002>
- [11] Hidalgo, C.A. and Hausmann, R. (2009) The Building Blocks of Economic Complexity. *Proceedings of the National Academy of Sciences*, **106**, 10570-10575. <https://doi.org/10.1073/pnas.0900943106>
- [12] Wu, X.F. (2019) A Review of Research on the Global Value Chain Export Technology Complexity Index. *Technoeconomics*, **38**, 16-21, 90. (In Chinese)
- [13] Wang, Y.J., Sheng, D. and Shi, B.Z. (2010) How Does Infrastructure Raise Export Technology Complexity? *Economic Research Journal*, **45**, 103-115. (In Chinese)
- [14] Dai, Z.Q., Liang, J.W. and Sun, Q. (2015) Intellectual Property Protection, Economic Development, and the Export Technology Complexity of Service Trade. *Finance & Trade Economics*, No. 7, 109-122. (In Chinese)
- [15] Mao, Q.L. and Fang, S.H. (2018) Innovation-Driven Growth and the Export Technology Complexity of Chinese Manufacturing Enterprises. *World Economy and Politics Forum*, No. 2, 1-24. (In Chinese)
- [16] Ren, Y.H., Lei, F.L. and Tan, D.D. (2019) The Effect of Global Value Chain Embeddedness on Export Technology Complexity. *Journal of Hunan University (Social Sciences)*, **33**, 83-89. (In Chinese)
- [17] Yu, N. (2020) The Effect of Global Value Chain Embeddedness on the Domestic Technology Complexity of China's Manufacturing Exports. Master's Thesis, Shandong University of Finance and Economics. (In Chinese)

- [18] Zheng, D.Q. (2021) Global Value Chain Embeddedness, Independent Innovation, and Enterprise Export Technology Complexity. *World Economy and Politics Forum*, No. 6, 55-84. (In Chinese)
- [19] Ma, X.D. (2022) Global Value Chain Embeddedness, Local Technological Development, and Enterprise Export Technology Complexity. *Journal of Xinjiang University (Philosophy and Social Sciences)*, **50**, 1-8. (In Chinese)
- [20] Zhao, Y.J. and Meng, Q.W. (2023) The Matching of “Financial Structure and Technology Level” and Global Value Chain Embeddedness. *Statistics and Decision*, **39**, 134-139. (In Chinese)
- [21] Chen, X.H., Du, W. and Yang, G.J. (2023) How Does Foreign Intermediate-Goods Dependence in Export Technology Complexity Affect Global Value Chain Division-of-Labor Position? *Journal of Nanjing University of Finance and Economics*, No. 5, 89-99. (In Chinese)
- [22] Yang, X.M., Zhang, S.L. and Li, B. (2023) Two-Way Participation in Domestic and Foreign Value Chains and China’s Export Technology Upgrading: A Sector-Level Analysis of China’s Manufacturing Industry. *World Economy Studies*, No. 12, 13-27. (In Chinese)
- [23] Yao, Y. and Zhang, Y. (2008) A Dynamic Study of the Upgrading of the Domestic Technological Content of China’s Export Goods—Evidence from the Nation and from Jiangsu and Guangdong Provinces. *Social Sciences in China*, No. 2, 67-82. (In Chinese)
- [24] Qi, J.Y. and Wang, L. (2015) Trade Transformation, Technology Upgrading, and the Evolution of the Full Domestic Technological Content of China’s Export Goods. *World Economy*, **38**, 29-56. (In Chinese)
- [25] Liu, Y.F. and Shen, J. (2021) Measuring and Improving the Export Technology Complexity of China’s Wooden Furniture under the Global Value Chain. *Journal of Jiangxi Science and Technology Normal University*, No. 5, 52-66. (In Chinese)
- [26] Athukorala, P. (2011) Production Networks and Trade Patterns in East Asia: Regionalization or Globalization? *Asian Economic Papers*, **10**, 65-95.
https://doi.org/10.1162/asep_a_00045
- [27] Orefice, G. and Rocha, N. (2013) Deep Integration and Production Networks: An Empirical Analysis. *The World Economy*, **37**, 106-136.
<https://doi.org/10.1111/twec.12076>
- [28] Chen, H.Y. (2020) A Study of the Effect of Global Value Chain Embeddedness on the Export Technology Complexity of the Manufacturing Industry. Master’s Thesis, Capital University of Economics and Business. (In Chinese)
- [29] Qiao, T. (2021) A Study of the Effect of Manufacturing Integration into Global Value Chains on Export Technology Complexity. Master’s Thesis, Anhui University. (In Chinese)
- [30] Li, Q.L. (2021) Research on the Determinants of Export Technology Complexity in China’s Manufacturing Industry. Master’s Thesis, Shandong University. (In Chinese)
- [31] Lu, F.C. and Hu, P.B. (2008) A Game-Theoretic Analysis of the Low-End Lock-In of Chinese Enterprises under the Global Value Network. *China Industrial Economics*, No. 10, 23-32. (In Chinese)
- [32] OECD (2023) Guide to OECD’s Trade in Value Added (TiVA) Indicators. 2023 Edition. OECD Publishing.
<https://www.oecd.org/content/dam/oecd/en/topics/policy-sub-issues/trade-in-value-added/tiva-indicators-guide-2023.pdf>
- [33] World Bank (n.d.) World Development Indicators. World Bank.

<https://databank.worldbank.org/source/world-development-indicators>

- [34] Yamano, N., Alsamawi, A., Webb, C., Cimper, A., Zürcher, C. and Chiapin Pechansky, R. (2023) Development of the OECD Inter-Country Input-Output Database 2023. OECD Publishing.
- [35] Harvard Growth Lab (n.d.) Atlas of Economic Complexity. Harvard University.
<https://atlas.hks.harvard.edu>