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National Concentration of High-tech Products: The Second Great Divergence?

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Abstract

Based on the product-country level trade data from 2004 to 2017, as well as the High-Tech Products Catalog from the US Census Bureau, this paper examines empirically the current phenomenon of "national concentration" in high-tech exports. The results show that the phenomenon of "national concentration" not only exists but also tends to be self-reinforcing. Compared with other products, the exports of high-tech products tend to be concentrated in certain countries, and this concentration trends were further strengthened after the global financial crisis of 2008–2009. The national concentration of R&D activities may be one of the important causes of the national concentration of high-tech products. This pattern remains robust when we further use the value-added export data and different definitions of high-tech products. We argue that the phenomenon of "national concentration" of high-tech exports may herald the arrival of the "Second Great Divergence" – the divergence between innovative and manufacturing activities – in the global economy.

Keywords: high-tech products, national concentration, R&D, second great divergence
JEL codes: F02, F14, O33

I. Introduction

With the development of technology, innovation and high technology are gradually becoming the core drivers of economic growth. Competition between countries is also more focused on science and technology. On March 23, 2018, the US announced a 25 percent

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tariff on US$50 billion of Chinese goods, starting a trade conflict between China and the US. However, the trade conflict is just the beginning of the friction between China and the US, which has long gone beyond the trade sector and gradually expanded to other areas such as finance and technology. The targeted sanctions of the US against Chinese high-tech companies, such as Huawei, Da Jiang Innovations Science & Technology, and Hikvision, reflect US underlying intention to maintain its leading role in the high-tech sector.

Intangible technology is difficult to measure. Meanwhile, international trade is one of the most important vehicles of globalization, through which technology and products flow globally. In international trade, high-tech products are important carriers of technology. We therefore use the export of high-tech products to measure high-tech exports. We match the product–country level export trade from 2004 to 2017 with the catalog of high-tech products published by the US Census Bureau to identify high-tech products. Data show that in recent years, high-tech product exports have become increasingly concentrated in certain countries. The case study based on a lithography machine, a typical high-tech product, also shows a self-reinforcing trend of concentration, in line with the data pattern. To generally explore the national concentration of high-tech products, this paper further conducts regression analysis. The empirical results show that the export of high-tech products is more concentrated (in certain countries) than that of other products, and this concentration trend is more pronounced after the financial crisis. The pattern of concentration of high-tech products is accompanied by a trend of national concentration of research and development (R&D) activities. Considering that the total export may include other countries' value-added, we also test the above results using value-added exports and obtain a robust conclusion.

This paper points out that the national concentration of high-tech products is an important manifestation of the "Second Great Divergence." The Second Great Divergence is a concept that corresponds to the "First Great Divergence." The first great industrial–agricultural divergence occurred in the 18th century, when the productivity of developed Western countries, which were the first to complete the Industrial Revolution, increased, and the share of global manufacturing became increasingly concentrated in these countries. The First Great Divergence led to the formation of a world where the West was advanced, and the East was lagging. In recent years, the concentration of high-tech product exports has taken on similar characteristics. We argue that this is an important feature of the Second Great Divergence, the great divergence between innovation and manufacturing activities.

Finally, we analyze the possible reasons for the emergence of the Second Great Divergence. We argue that the new form of production in the new era of globalization

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is an important factor contributing to the Second Great Divergence. We divide globalization into four stages: the age of great voyages, the age of global trade, the age of global production, and the age of global innovation. The fourth globalization is fundamentally different from other stages, as it is the era of technological innovation driven by ideas, and physical capital is no longer the most important input factor. Under this production function, fixed costs are high, but marginal costs are very low, leading to a higher level of return to scale. This particular form of production gives the high-tech industry a natural tendency to concentrate, and this tendency will continue to strengthen itself.

This paper follows the literature concerning the Great Divergence. After the First Great Divergence, the West was advanced while the East was lagging. Pomeranz (2021) points out that the world before 1800 was pluralistic, without a single economic center, and the West did not have an obvious unique endogenous advantage. Only after the full development of industrialization in Europe in the 19th century did a dominant Western European center gradually emerge. Baldwin (2018) further points out the concept of "the Great Convergence." In the 1990s, with the development of information technology and the decline in communication costs, there was the separation of production processes and the transfer of industries from developed countries to developing countries, which led to the rapid industrialization of developing countries and brought about the "Great Convergence" of the East and the West. Following this literature, in this paper, we find evidence of the Second Great Divergence, the great divergence between innovative and manufacturing activities. Baldwin (2018) focuses on the reduction of communication costs, while we emphasize that the increasing return to scale leads to the national concentration of high-tech products.

Our paper also contributes to the literature that focuses on the increasing concentration in market structures. Recent literature has pointed out that major countries in the world, including the US, have witnessed an increase in industrial concentration and a decrease in labor share. Autor et al. (2020) point out that a significant decline in labor share has been observed in the US and many other major countries in recent decades, but the reasons for this phenomenon are not clear. The existing empirical studies are mainly based on industrial or macro data, thus ignoring firm heterogeneity. Based on micro data from the US, Autor et al. (2020) note this issue from a new perspective, star firms. Globalization and technological advances lead to a greater concentration of sales from efficient star firms within the industry, and the industry will be dominated by these firms. These firms are usually characterized by higher markups and lower labor share. Thus, the resource redistribution effect within the industry brought by the rise of star firms would lead to an increase in industrial concentration and a decrease in the labor share.

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Akcigit and Ates (2019) find a significant decrease in business dynamism in the US in recent years, as evidenced by an increase in market concentration, an increase in the average markup, an increase in the average profit margin, a decrease in the labor share, a decrease in the frontier and lagging firms' widening productivity gap, declining firm entry rates, and a declining share of young firms in economic activity. The paper further points out that the slower technology diffusion is the cause of the decline in US business dynamism. In the model, the phenomenon mentioned above occurs when the diffusion of high technology to lagging firms becomes slower. Lu et al. (2020) find that the rise in exchange rate volatility would also increase the industrial market concentration in China.

The results in our paper are consistent with the findings in the literature. We find that the export of high-tech products also tends to be more concentrated, i.e., the export shares are concentrated in certain countries, and this trend has become more pronounced in recent years. This paper also differs from related literature. First, this paper studies the national concentration rather than the concentration of firm sales within an industry. Second, it proposes a new framework to explain the phenomenon. Autor et al. (2020) point out that the increase in industrial concentration is due to the fact that more sales are concentrated in star firms, but do not analyze why this trend is occurring. Akcigit and Ates (2019) find that the increase in industrial concentration is also an important manifestation of the decline in business dynamism in the US, and suggest that the slower diffusion of technology is the mechanism behind it. On the other hand, this paper indicates that, due to changes in the production function, the return to scale is enhanced, which can create a tendency for natural monopolies. High technology becomes more concentrated in the hands of certain countries, and high fixed costs prevent other countries from entering the high-tech product market. This phenomenon likewise leads to a decrease in the rate of technology diffusion across countries.

Our research has important policy implications. In the First Great Divergence, Western countries, such as the UK, were in a dominant position. Meanwhile, China's economic position in the world declined sharply and gradually regressed from the top superpowers. Learning from history, the Second Great Divergence, represented by the high-tech wave, is taking place. How to seize this historic opportunity to achieve a technological leap is an important issue that China is currently facing. In the Second Great Divergence, China is bound to face competitive resistance from the leading countries. The targeted sanctions against high-tech companies such as Huawei and Zhongxing Telecom Equipment Corporation by the US reflects its intention to suppress the development of China's high-tech industry. In such circumstances, China should give more support to the targeted high-tech companies so as to catch up with the trend of high-tech competition.

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The remainder of this paper is organized as follows. Section II presents data sources, variable definitions, stylized facts, and empirical specification. Section III shows empirical analysis. Section IV introduces the concept of the Second Great Divergence and attempts to analyze its causes and countermeasures. Section V concludes.

II. Data, variables, and empirical specification

1. Data

To verify the phenomenon of the concentration of high-tech exports, we employed the 2004–2017 global export data at the Harmonized System (HS) 6-digit product level for each country, as well as the catalog of high-tech products (Advanced Technology Products) released by the US Census Bureau. The above two datasets answer two questions: “Are exports of high-tech products more concentrated in certain countries related to general manufacturing products?” and “Has this trend been further strengthened in recent years, especially after the financial crisis?”

The export trade data are obtained from the United Nations international trade statistics database (UN COMTRADE). This database is widely used in studies related to international trade. The database discloses detailed product–country level trade information, including destinations, product codes, trade types (imports and exports), transaction amounts, and transaction quantities (weight). The most detailed product in this database is at the HS 6-digit level. In the empirical analysis, we therefore use the annual HS 6-digit product export data for each country for the regression analysis. The final sample includes 198 countries (regions), and the total exports of the sample countries represent 93.8 percent of the total global exports (2017).

To study the concentration trend of high-tech product exports, we need to distinguish the high-tech products from general products. Regarding the definition of high-tech products, each country has different criteria. In addition, the definition of high-tech products may vary with time. For example, a certain product may belong to high-tech products in the 20th century, but in the 21st century, with the development of science and technology, the product may no longer belong to the category of high-tech products.

In this paper, we mainly used the product catalog of Advanced Technology Products disclosed by the US Census Bureau (https://www.commerce.gov/taxonomy/term/4) as the basis for identifying high-tech products. This website provides directly the codes of high-tech products in the US exports between 2004 and 2017. Compared with other definitions of high-tech products, this catalog has the following advantages.

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First, the US is one of the most innovative countries in the world, and its definition of high-tech products has much authority. Second, the high-tech product catalog is highly disaggregated and is defined at the HS 10-digit product level. The highly refined definition of high-tech products helps us to identify more precisely which products are high-tech products. Third, the high-tech product catalog is revised every year to ensure the timeliness and accuracy of the high-tech product definition. For these reasons, we used this high-tech product catalog for identifying high-tech products in the baseline analysis.

Next, we matched the trade data with the high-tech product data. Trade data are defined at the HS 6-digit level, so we needed to further redefine high-tech products at the HS 6-digit code level as well. Each HS 6-digit code may correspond to multiple HS 10-digit products, so some HS 10-digit products may be high-tech products while others may not. We could not therefore determine directly whether a certain HS 6-digit product is a high-tech product or not. To solve this problem we adopted the following method. If a certain HS 6-digit product contains a large share of HS 10-digit high-tech products, then the HS 6-digit product would be identified as a high-tech product. Specifically, we employed the US export data at the HS 10-digit product level from 2004–2017,[1] and calculated the share of each HS 10-digit product export value in the total export value of the corresponding HS 6-digit product. If more than 80 percent of the export value of the HS 6-digit product is contributed by high-tech HS 10-digit products, then the HS 6-digit product would be defined as a high-tech product in that year; otherwise, it would be identified as another common product. This method may suffer from the problem of subjectivity. For example, the 80 percent criterion may not be completely reasonable. In the subsequent robustness tests, we therefore also used the 90 percent and 50 percent criteria to minimize the impact of the subjectivity identification problem on our results.

We also further utilized the Chinese version of the high-tech industry catalog disclosed by the National Bureau of Statistics of China in the robustness checks. This high-tech catalog is cross-referenced with the US high-tech product catalog to mitigate the identification problem of high-tech products further. The export data use HS product codes, while the high-tech industry catalog published by the National Bureau of Statistics uses Chinese Industry Census industry codes. Therefore, referring to Ju and Yu (2015), we compiled a matching table of HS codes and Chinese Industry Census codes to match the high-tech industry with the HS code of export data.

Table 1 shows the distribution of high-tech products in 2017 at the HS 2-digit level; 374 HS 10-digit high-tech products were distributed across nine HS 2-digit industries.

[1]Data source: US International Trade Commission.

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The last two columns of the table show the total export value and the export share of high-tech products. Results show that the industries with the largest number of high-tech products are "Nuclear reactors, boilers, machinery, and mechanical appliances; parts thereof (84)." It can also be seen that the industries with the largest share of high-tech exports are "Aircraft, spacecraft, and parts thereof (88)."

Table 1. Summary statistics of high-tech products (2017)

Industry code	Industry name	Number of high-tech products (HS 10-digit)	High-tech products export value (US$ billion)	High-tech products export share (%)
88	Aircraft, spacecraft, and parts thereof	14	199.5	96.3
85	Electrical machinery and equipment and parts thereof	91	1,338.6	53.9
93	Arms and ammunition; parts and accessories thereof	8	5.1	43.1
90	Optical, photographic, cinematographic, measuring, checking, medical or surgical instruments and apparatus	99	212.6	37.2
84	Nuclear reactors, boilers, machinery, and mechanical appliances; parts thereof	116	643.9	31.8
30	Pharmaceutical products	11	128.5	24.9
38	Chemical products not elsewhere classified	1	12.9	7.0
28	Inorganic chemicals; organic and inorganic compounds of precious metals; of rare earth metals, radioactive elements, and of isotopes	11	4.1	4.0
29	Organic chemicals	23	10.5	3.0

Sources: The high-tech product catalog is from the US Census Bureau. Export data are from the United Nations international trade statistics database.

Note: Industry is defined at the HS 2-digit product level, and high-tech products are defined at the HS 10-digit product level.

Figure 1 shows the evolution of the total exports of high-tech products from 2004 to 2017, including the total exports of high-tech products and the share of high-tech products in total exports. As we discussed above, high-tech products were defined at HS 6-digit level if more than 80 percent of the export value of the HS 6-digit product was contributed by high-tech HS 10-digit products. As seen from the figure, except for individual years, the export value of high-tech products increased rapidly from US$1.21 trillion in 2004 to US$2.56 trillion in 2017. In addition, in terms of the share of high-tech exports, from 2004 to 2017, the share of high-tech exports showed an obvious U-shaped trend. Before 2011, the share of high-tech exports showed a decreasing trend, from 13.4 percent in 2004 to 11.8 percent in 2011. However, since 2011, the share of high-tech exports has shown an upward trend, increasing from 11.8 percent in 2011

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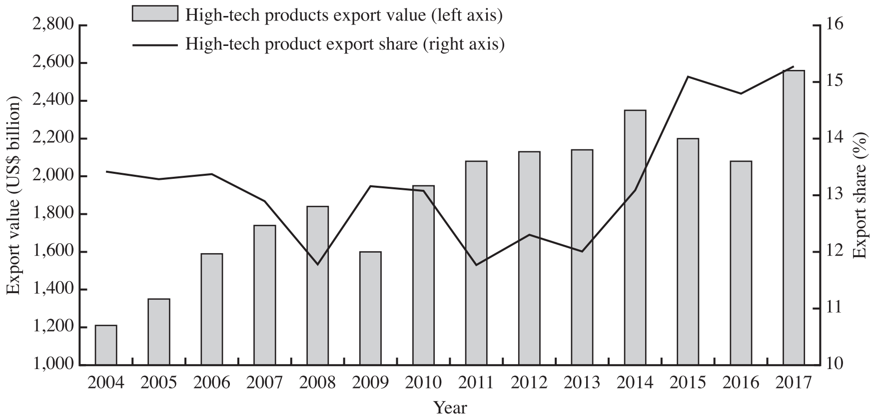
to 15.3 percent in 2017. This indicates that, in recent years, the exports of high-tech products have occupied an increasingly important position.

Figure 1. High-tech products export value and export share



Notes: The high-tech product is defined using the high-tech product catalog from the US Census Bureau. The export share is the share of high-tech product export to total export.

2. Variables

We constructed the variables as follows. (i) The export share of the top five exporting countries (*Share*5) was calculated for each HS 6-digit product each year, and a larger indicator represents a larger degree of export concentration; in the robustness test, we adopted two other definitions, the share of the top three exporting countries (*Share*3), and the sum of squared export shares of all countries (Hirschman–Herfindahl Index, *HHI*), respectively. (ii) A high-tech dummy variable, defined at the HS 6-digit product level, based on the US Census Bureau's high-tech product catalog; in the robustness test. We also employed the high-tech industry catalog provided by China's National Bureau of Statistics. (iii) A control variable – the number of countries that export a certain product each year. (iv) To examine further the time trend of high-tech products concentration over time, we constructed a time dummy variable which takes the value of 1 after the financial crisis (2010 and later) and 0 otherwise. The reason for choosing the financial crisis as the cut-off point is based on the following considerations. First, the financial crisis in 2008 and 2009 strongly affected world trade, and the demographic dividend of main trading countries such as China tended to diminish. After the crisis, global trade required a new driving force, and high-technology becomes an important growth driver for global trade. Second, it can be seen from Figure 1 that, based on the real trade data, the share of high-tech exports showed a high level of growth after the financial crisis.

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Table 2 reports the descriptive statistics of key variables. The data are defined at the product–year level. It can be seen that, on average, 2.6 percent of products are high-tech products. In terms of product concentration indicators, Table 2 reports three measures of concentration, including the share of the top five exporters for each product every year (*Share*5), the share of the top three exporters (*Share*3), and the sum of squares of the export share from all countries (*HHI*), with mean values of 0.75, 0.63, and 0.26, respectively. In addition, each product has roughly 70 exporters per year.

Table 2. Summary statistics of variables

Variable	Mean	Standard deviation	Min	Max	Observations
High-tech dummy	0.0261	0.1594	0	1	79,419
*Share*5	0.7493	0.1528	0.2621	1	79,419
*Share*3	0.6324	0.1903	0.1667	1	79,419
HHI	0.2559	0.2351	0.0315	1	79,419
Number of export countries	70	34	1	160	79,419

Notes: The high-tech dummy is constructed based on the high-tech product list from US Census Bureau. *Share*5 and *Share*3 show the export share of the top five and top three exporters for each product. HHI, Hirschman–Herfindahl Index.

3. Stylized facts

Figure 2 shows the share of the top five exporting countries for high-tech products and other products. Specifically, we first calculated the export share of the top five countries per year for each HS 6-digit product in the total exports of the product. After that, we used the export value of each product as the weight to calculate the weighted average of the top five exporter share for the high-tech product group and the other product group, respectively. Figure 2 shows that the top five export country shares for high-tech products are consistently larger than those for other products during the whole period. In terms of trends, the share of the top five exporters of other products remains relatively stable, while the share of the top five exporters of high-tech products maintains an increasing trend. In recent years, the gap between the two has tended to increase. To summarize, the export concentration of high-tech products is larger, and in recent years, this pattern has become more evident.

The more specific question is, which countries are the main exporters of high-tech products? Table 3 lists the top five exporters of high-tech products in 2004 and 2017. The results show that in 2004, the top five exporters of high-tech products were the US, China, Germany, Japan, and Singapore, accounting for 16 percent, 10 percent, 8 percent, 8 percent, and 7 percent, respectively. Among them, the US has an absolute advantage in the export market of high-tech products. In the case of China, its high-tech industry

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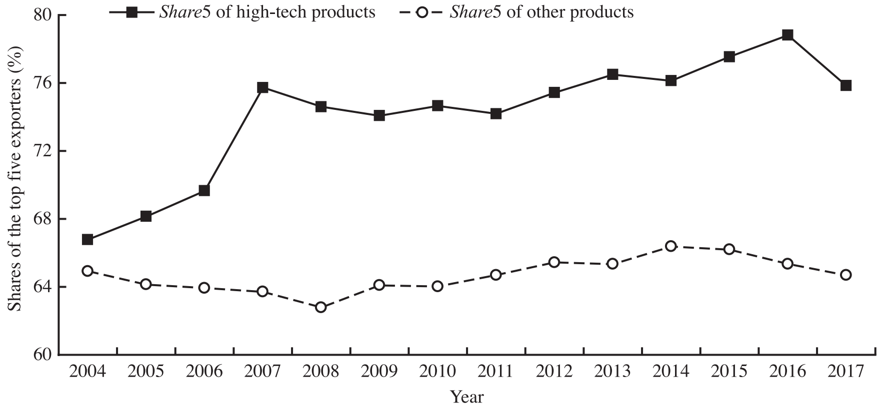
Figure 2. Shares of the top five exporters of high-tech products and other products



Note: This figure shows the shares of the top five exporters (*Share*5) for high-tech and other products.

has shown a rapid growth rate since 2004, and by 2017 it became the world's largest exporter of high-tech products, with its global share reaching 22 percent. In contrast, the second- to fifth-ranked economies (Hong Kong SAR of China, the US, Germany, and South Korea) have shares of only 10 percent, 8 percent, 7 percent, and 6 percent, respectively. Hong Kong SAR of China accounts for a relatively high proportion of high-tech products exports, mainly because its exports contain a large amount of export trade, which carries part of the exports of high-tech products from the Chinese mainland. As China was the world's largest exporter of high-tech products in 2017, the share of high-tech products in Hong Kong's exports is therefore relatively high.

Table 3. Top five exporters of the high-tech products (%)

Year	Largest exporter	Second largest exporter	Third largest exporter	Fourth largest exporter	Fifth largest exporter
2004	US 16	CHN 10	DEU 8	JPN 8	SGP 7
2017	CHN 22	HKG 10	US 8	DEU 7	KOR 6

Notes: This table shows the top five exporters of high-tech products in 2004 and 2017. The number below the economy's name indicates the global share of its high-tech exports. CHN, China; DEU, Germany; HKG, Hong Kong SAR of China; JPN, Japan; KOR, South Korea; SGP, Singapore.

4. Case study

Is the Second Great Divergence real? To explain the Second Great Divergence more intuitively, this section introduces a typical high-tech product for the case study.

Specifically, we select a representative high-tech product from the sample: lithography machine (HS code 848620). Lithography is a very typical high-tech product,

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and its cutting-edge core technology is the core equipment for manufacturing chips and producing large-scale integrated circuits, which is mainly monopolized by a few countries such as the Netherlands and Japan. For now, only a few manufacturers in the world have mastered the core technology, such as Advanced Semiconductor Material Lithography of the Netherlands and Nikon and Canon of Japan. The product is expensive. The unit price of a lithography machine is usually US$30 million to US$500 million, and has been heavily dependent on imports. Lithography technology is one of the key technology bottlenecks that China is currently facing. In 2019, the top three exporters of lithography machines in terms of volume were Japan, the Netherlands, and the US, with export shares of 28.2 percent, 25.7 percent, and 24.2 percent, respectively. At present, the gap between China and leading countries in the core technology of lithography machines is still large.

Second, the product is also important in international trade in terms of volume. In the year 2019, the export volume was as large as US$41.2 billion, with a total of 55 countries and regions exporting the product.

Next, we will analyze the evolution of the export concentration of this product. Table 4 shows the export situation of lithography machines in recent years. From 2011 to 2019, the number of countries (regions) exporting lithography machines showed a trend of rising and then falling, and the export value increased from US$28.7 billion to US$41.2 billion, an increase of 43 percent. From 2017 to 2019, the number of countries (regions) exporting lithography machines gradually decreased, while the export value still increased rapidly, indicating a trend of concentration in the export of this high-tech product.

Table 4. The number of export countries (regions) and the export value of the lithography machines

	Number of export countries (regions)	Export value (US$ billion)
2011	65	28.7
2012	64	22
2013	72	21.6
2014	75	24.7
2015	72	24.8
2016	72	27.3
2017	73	37.4
2018	65	42.4
2019	55	41.2

Source: The United Nations international trade statistics database.

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We then examine the export of this product at the country level. Specifically, we selected the top five exporting countries each year and calculated their export share respectively. The export share is defined as the export value of lithography machines exported from each country as a proportion of the global export value of the product. Table 5 below shows the top five exporters of lithography machines for each year from 2011 to 2019 and their respective export shares. Analyzing Table 5, we draw the following conclusions. First, Japan, the Netherlands, the US, Germany, Singapore, and South Korea are the main countries exporting lithography machines. Second, from 2014, the US replaced Japan as the world's largest exporter of lithography machines, but Japan regained the first place in 2019. Third, the pattern of export of lithography machines is relatively stable, and it seems difficult to be broken at present. Japan, the Netherlands, and the US occupy the first echelon, far ahead of other countries in terms of export share. After 2012, Singapore has been stable in the fourth position, while South Korea and Germany alternate for the fifth.

Table 5. The analysis of the main export countries of the lithography machine (%)

Year	Largest exporter	Second largest exporter	Third largest exporter	Fourth largest exporter	Fifth largest exporter
2011	JPN 30.1	NLD 25.1	US 20.8	DEU 8.0	SGP 3.4
2012	JPN 34.0	US 25.2	NLD 21.6	SGP 6.7	DEU 2.8
2013	JPN 28.2	US 28.1	NLD 25.3	SGP 4.3	KOR 4.0
2014	US 30.2	JPN 25.7	NLD 24.8	SGP 5.4	KOR 4.5
2015	US 33.2	JPN 24.1	NLD 20.3	SGP 7.6	KOR 5.0
2016	US 32.4	JPN 29.6	NLD 15.7	SGP 9.2	DEU 3.2
2017	US 33.4	JPN 27.6	NLD 16.5	SGP 10.9	DEU 2.7
2018	US 29.0	JPN 27.4	NLD 22.9	SGP 8.8	KOR 2.6
2019	JPN 28.2	NLD 25.7	US 24.2	SGP 10.0	KOR 4.9

Source: The United Nations international trade statistics database.

Notes: DEU, Germany; JPN, Japan; KOR, South Korea; NLD, the Netherlands; SGP, Singapore.

We also calculate the top five exporting countries' share indicator (*Share*5) of the product for each year. Figure 3 further shows the change in the concentration of lithography machine exports from 2011 to 2019, where the export concentration is

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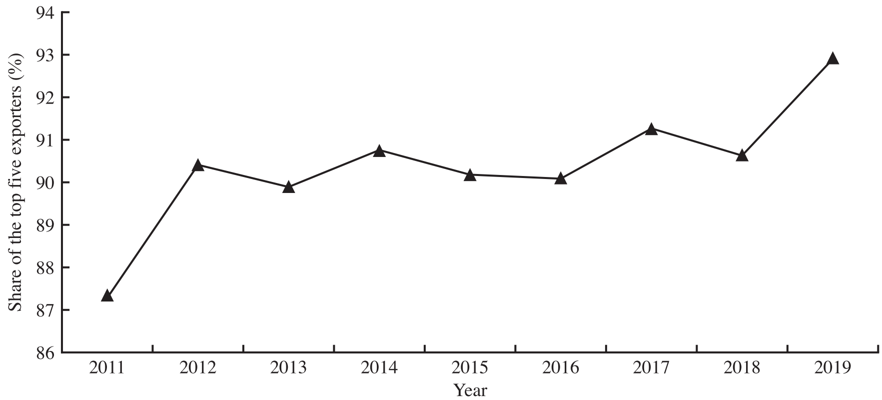
measured by the total share of the top five exporting countries. From 2011 to 2019, the share of the top five exporting countries of lithography machines increased from 87.3 percent to 92.9 percent. The export concentration shows an upward trend.

Figure 3. The share of the top five exporters of the lithography machines



Source: The share is calculated based on the lithography machine export data from the United Nations international trade statistics database.

The case study demonstrates the national concentration pattern of a typical high-tech product. The results show that not only is the concentration level of the product high, but also that the trend has been more evident in recent years.

5. Specification

From the stylized facts and case study above, it can be seen that the export concentration of high-tech products is indeed high, and this trend has become more pronounced in recent years. Next, to verify the concentration phenomenon among high-tech products in general, we conducted a more rigorous empirical regression analysis.

To investigate the relationship between export concentration and high-tech products, we construct the following empirical specification:

$$Concentration_{pt} = \alpha + \beta \times HighTech_{pt} + \ln N_{pt} + \theta_t + \varepsilon_{pt}, \tag{1}$$

where p refers to the HS 6-digit product and t refers to the year. The $Concentration_{pt}$ is the index of the export concentration of each product, including *Share*5, *Share*3, and *HHI*. The $HighTech_{pt}$ is the high-tech product dummy variable, N_{pt} is the number of countries or regions exporting product p each year, and θ_t refers to the year dummy variable. The robust standard error is clustered at the HS 6-digit product level.

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To explore further the differences between the concentration of high-tech products and other products before and after the financial crisis, we added the interaction term of high-tech products and financial crisis dummy variable into Equation (1):

$$Concentration_{pt} = \alpha + \beta_1 \times HighTech_{pt} + \beta_2 \times HighTech_{pt} \times AfterCrisis_t + \ln N_{pt} + \theta_t + \varepsilon_{pt}, \tag{2}$$

where $AfterCrisis_t$ denotes a time dummy variable that takes the value of 1 after the financial crisis and 0 in other years. Other variables are the same as those in Equation (1).

III. Empirical results

1. Baseline results

The baseline results are reported in Table 6. In column (1), the dependent variable is *Share*5, which is the share of exports from the top five countries for each product. The larger the indicator, the more concentrated is the export of the product. The coefficient of the high-tech product variable is significantly positive, indicating that the exports of high-tech products are more concentrated among certain countries compared with other products. In columns (2) and (3), we use other indicators to measure the degree of product concentration, namely, the *HHI* indicator and *Share*3. The *HHI* indicator represents the sum of squares of export shares of all countries for each product, while *Share*3 represents the export shares of the top three exporting countries for the product. We find that the coefficients for high-tech products remain significantly positive. After replacing the concentration indicators, the baseline result still holds and remains robust.

Table 6. Baseline result

	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)
High-tech products	0.1075*** (5.80)	0.0512** (2.29)	0.1032*** (4.25)
Number of export countries	–0.1575*** (–11.70)	–0.1429*** (–16.94)	–0.1693*** (–12.80)
Constant	1.3587*** (22.61)	0.7873*** (19.84)	1.2764*** (21.65)
Year FE	Yes	Yes	Yes
Observation	79,419	79,419	79,419
R^2	0.277	0.276	0.251

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at HS 6-digit product level. *Share*5 is the proportion of exports from the top five exporters for each product every year, *Share*3 is the proportion of exports from the top three exporters, and *HHI* is the squared sum of the export shares of all exporters of the product. These indicators all measure the degree of concentration of a product's exports, and a larger value indicates a higher degree of product concentration. FE, fixed effects; HHI, Hirschman–Herfindahl Index.

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We next examined whether the pattern of a larger concentration of high-tech products export differed across time. In column (1) of Table 7, we include the interaction term of the high-tech product and time dummy variable into the equation. The time dummy variable takes a value of 1 after the financial crisis (2010 and later) and 0 otherwise. The results show that the coefficients of high-tech products remain significantly positive, while the coefficients of the interaction term of the high-tech products and time dummy variable are also significantly positive. This indicates that the stronger concentration of the high-tech product, in comparison with other products, is more pronounced after the financial crisis. In columns (2) and (3), we used the *HHI* and *Share*3 to measure product concentration and found that the coefficients of the high-tech product were still significantly positive, while the coefficients of the interaction terms were also significantly positive. The results in Table 7 indicate that the concentration characteristics of high-tech products strengthened after the financial crisis. The trend of export concentration of high-tech products has strengthened in recent years.

Table 7. High-tech products and product concentration: After the financial crisis

	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)
High-tech products	0.0806*** (3.74)	0.0327* (1.96)	0.0740*** (2.86)
High-tech products × after crisis	0.0412** (2.27)	0.0284* (1.79)	0.0448* (1.94)
Number of export countries	–0.1581*** (–11.77)	–0.1433*** (–17.17)	–0.1699*** (–12.89)
Constant	1.3651*** (22.80)	0.7917*** (20.36)	1.2833*** (21.91)
Year FE	Yes	Yes	Yes
Observations	79,419	79,419	79,419
R^2	0.279	0.277	0.253

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at HS 6-digit product level. *Share*5 is the proportion of exports from the top five exporters for each product every year, *Share*3 is the proportion of exports from the top three exporters, and *HHI* is the squared sum of the export shares of all exporters of the product. These indicators all measure the degree of concentration of a product's exports, and a larger value indicates a higher degree of product concentration. FE, fixed effects; HHI, Hirschman–Herfindahl Index.

2. Robustness checks

In the baseline regression, we define an HS 6-digit product as a high-tech product if the share of HS 10-digit high-tech product exports (to the total export value of the HS 6-digit product) exceeds 80 percent. The 80 percent criterion choice is somewhat subjective. To mitigate the possible impact of subjective judgment on the results,

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we adopt other criteria to redefine high-tech products. Table 8 reports the regression results when we define high-tech products using other identification criteria. In columns (1) and (2) of Table 8, we specify that an HS 6-digit product is identified as a high-tech product only when the share of high-tech exports of that product exceeds 90 percent. We obtain very similar results to the baseline result. The coefficients of the high-tech product dummy variable remain significantly positive, and the coefficients of the interaction term of the high-tech product and time dummy variable also remain significantly positive. In columns (3) and (4), we use the 50 percent criterion and still obtain similar results. Our baseline result remains robust after replacing the high-tech product identification criterion.

Table 8. Robustness checks: Changing the high-tech product identification standard

	*Share*5			
	90% standard		50% standard	
	(1)	(2)	(3)	(4)
High-tech products	0.1075*** (5.62)	0.0785*** (3.47)	0.1058*** (5.90)	0.0806*** (3.93)
High-tech products × after crisis		0.0439** (2.35)		0.0387** (2.25)
Number of export countries	–0.1574*** (–11.66)	–0.1581*** (–11.74)	–0.1575*** (–11.70)	–0.1580*** (–11.77)
Constant	1.3599*** (22.54)	1.3667*** (22.72)	1.3575*** (22.59)	1.3637*** (22.79)
Year FE	Yes	Yes	Yes	Yes
Observations	79,419	79,419	79,419	79,419
R^2	0.273	0.275	0.278	0.280

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the HS 6-digit product level. *Share*5 is the proportion of exports from the top five exporters for each product annually. FE, fixed effects.

In Table 9, we conduct a series of additional checks to verify the robustness of our benchmark results. In columns (1) and (2), we use the high-tech industry catalog of the National Bureau of Statistics of China. We find that the coefficients of the high-tech product and the interaction term of the high-tech product and time dummy remain significantly positive. In column (3), we set a stricter clustering from the HS 6-digit product level to the HS 2-digit product level, thus relaxing the assumption of regression standard error clustering. In column (4), we control for HS 2-digit product fixed effects so as to compare the concentration of high-tech and non-high-tech products within the same industry. The results maintain a high degree of robustness across a range of tests.

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Table 9. Other robustness checks

	*Share*5			
	Chinese high-tech products list		HS-2 cluster	HS-2 FE
	(1)	(2)	(3)	(4)
High-tech products	0.0560*** (3.15)	0.0466*** (10.98)	0.0806*** (3.25)	0.0690*** (3.37)
High-tech products × after crisis		0.0145** (2.73)	0.0412* (1.95)	0.0444** (2.50)
Number of export countries	–0.1493*** (–12.08)	–0.1498*** (–27.19)	–0.1581*** (–9.15)	–0.1612*** (–11.37)
Constant	1.3201*** (22.44)	1.3248*** (53.22)	1.3651*** (17.75)	1.3781*** (20.97)
Year FE	Yes	Yes	Yes	Yes
HS-2 FE	No	No	No	Yes
Cluster	HS 6	HS 6	HS 2	HS 6
Observations	59,896	59,896	79,419	79,419
R^2	0.332	0.333	0.279	0.465

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the HS 2-digit product level in column (3) and at the HS 6-digit product level in other columns. *Share*5 is the proportion of exports from the top five exporters for each product annually. FE, fixed effects; HS-2, Harmonized System 2-digit.

After the financial crisis, the concentration of high-tech product exports has tended to strengthen. To verify this hypothesis, in Table 10, we show the changes in product concentration of some typical high-tech products from 2010 to 2017. Taking the product "Engines; reaction engines, other than turbo-jets" with product code 841210 as an example, its export share of the top five exporting countries in 2010 was 0.741, and 0.932 in 2017, with an increase of 0.191. The concentration strengthened during the period after the financial crisis. Other products also show similar patterns.

Table 10. Changes in product concentration of typical high-tech products

Product code	Product name	*Share*5 in 2017	*Share*5 in 2010	*Share*5	Export value in 2017 (US$ billion)
841210	Engines; reaction engines, other than turbo-jets	0.932	0.741	0.191	4.11
854232	Electronic integrated circuits; memories	0.882	0.725	0.157	1,660
854233	Electronic integrated circuits; amplifiers	0.866	0.737	0.129	123
851712	Telephones for cellular networks or for other wireless networks	0.825	0.697	0.128	2,500
847330	Machinery; parts and accessories	0.746	0.640	0.106	1,130

Notes: *Share*5 is the proportion of exports from the top five exporters for each product annually. A larger value suggests a more concentrated product.

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In Table 11, we include an interaction term between the indicator variable for high-tech products and the time trend to test whether the national concentration of high-tech exports becomes more pronounced over time. The time trend variable is defined as the sample year *t* minus 2004. The results show that both the coefficients of the high-tech dummy and the interaction term (high-tech products × time trend) are significantly positive, which implies that the national concentration of high-tech exports is indeed strengthening over time. This could also partly explain why we observe a more pronounced concentration of high-tech exports after the global financial crisis.

Table 11. Time trend in the national concentration of high-tech exports

	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)
High-tech products	0.0632** (2.46)	0.0279*** (2.63)	0.0554* (1.79)
High-tech products × time trend	0.0061** (2.43)	0.0032** (2.16)	0.0066** (2.07)
Number of export countries	–0.1582*** (–11.80)	–0.1433*** (–37.28)	–0.1700*** (–12.92)
Constant	1.3677*** (22.91)	0.7921*** (43.26)	1.2862*** (22.00)
Year FE	Yes	Yes	Yes
Observations	79,419	79,419	79,419
R^2	0.280	0.277	0.254

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the 6-digit HS level. The time trend is defined as the sample year *t* minus 2004. *Share*5 is the proportion of exports from the top five exporters for each product every year, *Share*3 is the proportion of exports from the top three exporters, and the *HHI* is the squared sum of the export shares of all exporters of the product. These indicators all measure the degree of concentration of a product's exports, and a larger value indicates a higher degree of product concentration. FE, fixed effects; HHI, Hirschman–Herfindahl Index.

3. Mechanism Analysis

What are the possible driving factors behind the concentration of high-tech exports? We propose that one possible explanation is the national concentration of R&D activities. R&D expenditure is an important input for innovation and is also the infrastructure of high-tech products (Aw et al., 2011). A country's large investment in R&D may play an important role in promoting the development of its high-tech industry. We believe that the national concentration of R&D expenditure in recent years could be a possible reason behind the concentration of high-tech products mentioned in our paper.

Global R&D activities have indeed tended to concentrate in recent years. As shown in Figure 4, the concentration of R&D activities, as measured by the R&D

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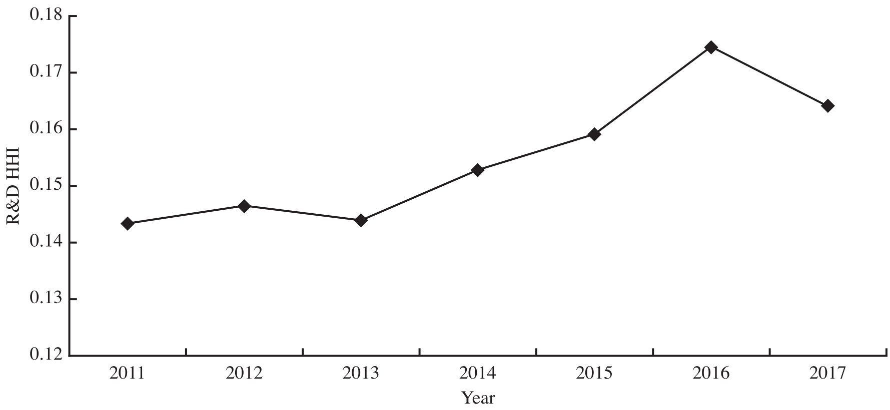
HHI, is indeed increasing after the financial crisis. The R&D HHI is defined as the sum of squares of each country's share in global R&D spending. A larger R&D HHI means that global R&D is more concentrated in a small number of countries. The country-level R&D data come from the World Bank World Development Indicators (WDI) database. We also calculated the global share of the top five and top three R&D spending countries. The conclusion is consistent: after the financial crisis, global R&D is increasingly concentrated in major countries such as the US and China.

Figure 4. Changes in R&D Hirschman–Herfindahl Index (HHI) after the global financial crisis



Notes: The R&D HHI is defined as the sum of squares of the proportion of R&D of each country in global R&D. The country-level R&D data comes from the WDI database of the World Bank. HHI, Hirschman–Herfindahl Index.

We used regression analysis to test whether the concentration of R&D activities is a driving mechanism for the concentration of high-tech exports. Specifically, on the basis of regression Equation (1), we added the interaction term between the high-tech product dummy and each year's R&D HHI. If our hypothesis holds that the concentration of R&D expenditures leads to the concentration of high-tech exports, then it should be seen that when global R&D activities are more concentrated, the concentration of high-tech exports will also be more significant. The regression results in Table 12 show that the coefficients of the interaction term of R&D HHI and high-tech products are all significantly positive, which confirms our hypothesis: the trend of concentration of high-tech exports mainly occurs in years when global R&D activities also concentrated. In other words, the concentration of global R&D activities may be a possible explanation for the concentration of high-tech exports.

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Table 12. Mechanism: The national concentration of R&D activities

	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)
High-tech products	–0.0274 (–0.98)	–0.0813** (–2.40)	–0.0574* (–1.67)
High-tech products × R&D HHI	0.4353*** (2.74)	0.5496*** (2.79)	0.5714*** (2.89)
Number of export countries	–0.0936*** (–113.98)	–0.1793*** (–222.47)	–0.1233*** (–143.49)
Constant	1.1111*** (363.70)	0.9459*** (270.39)	1.1070*** (339.83)
Year FE	Yes	Yes	Yes
Observations	79,419	79,419	79,419
R^2	0.442	0.690	0.495

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the HS 6-digit product level. The R&D HHI is defined as the sum of squares of the proportion of R&D of each country in global R&D. A larger R&D HHI indicates that R&D is more concentrated in certain countries. FE, fixed effects; HHI, Hirschman–Herfindahl Index.

One possible concern is that the high-tech product catalog is revised every year. In such cases, it is possible that varieties that fall into the high-tech product catalog are increasing. If this is indeed the case, and the added varieties happen to be exported by fewer countries, we can still observe the phenomenon of the concentration of exporting high-tech products even if such a concentration is not driven by the concentration of R&D activities. In order to rule out this possibility, we have conducted the following tests.

First, we directly checked if the high-tech product catalog has been increasing by the year. Table 13 shows the variety of high-tech products (HS 6-digit), as well as the share of high-tech products to the total variety of products from 2004 to 2017. Results show that both the number of varieties and the variety share of high-tech products have been relatively stable over the years. In such case, the concern that the increasing varieties of high-tech products catalog drives our results may not be severe.

Second, we have adopted two different definitions of high-tech products to control for the impact of changes in the high-tech products catalog.

In the first definition, we use the catalog of high-tech products from the first year of the sample (2004). Specifically, we replace the "high-tech products" dummy in our baseline regression with "initial high-tech products." The dummy "initial high-tech products" is defined as 1 if one product is in the high-tech catalog in 2004. Regression results are reported in Table 14. In columns (1)–(3), we directly test the relationship between initial high-tech products and product concentration. The results show that the coefficients of the initial high-tech products dummy are all significantly positive. In columns (4)–(6),

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we rerun the regressions in Table 12 and find consistent results. The concentration trend of high-tech exports mainly occurs in years when global R&D activities are also concentrated. We still find that the national concentration of R&D activities could be a possible channel after controlling the added high-tech products catalog.

Table 13. Varieties of high-tech products

Year	Varieties of high-tech products	Variety share of high-tech products (%)
2004	147	2.6
2005	145	2.6
2006	144	2.6
2007	146	2.5
2008	149	2.6
2009	147	2.6
2010	145	2.7
2011	146	2.7
2012	150	2.6
2013	146	2.6
2014	149	2.5
2015	149	2.5
2016	150	2.5
2017	158	2.8

Notes: The table shows the varieties of high-tech products (HS 6-digit) and their share of the total varieties of products in our sample.

Table 14. Initial high-tech products catalog

	*Share*5	*HHI*	*Share*3	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)	(4)	(5)	(6)
Initial high-tech products	0.0981*** (3.78)	0.0633* (1.85)	0.1036*** (3.18)	–0.0271 (–1.01)	–0.0578 (–1.53)	–0.0262 (–0.78)
Initial high-tech products × R&D HHI				0.4333*** (2.80)	0.4808** (2.21)	0.4164** (2.12)
Number of export countries	–0.1573*** (–11.07)	–0.1428*** (–15.43)	–0.1695*** (–12.18)	–0.0936*** (–111.31)	–0.1796*** (–215.83)	–0.1235*** (–140.73)
Constant	1.3590*** (21.18)	0.7852*** (17.55)	1.2776*** (20.32)	1.1112*** (352.27)	0.9468*** (261.13)	1.1076*** (330.27)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,230	74,230	74,230	74,230	74,230	74,230
R^2	0.262	0.284	0.249	0.441	0.695	0.497

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the HS 6-digit product level. Initial high-tech products is a dummy variable, which is defined to be 1 if a product is in the high-tech catalog in 2004. FE, fixed effect; HHI, Hirschman–Herfindahl Index.

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We then adopted an alternative definition of high-tech products by excluding products that entered or exited the high-tech product catalog during the 2004–2017 period and by keeping only products that were always in the high-tech catalog or that never entered the catalog. Specifically, in our baseline sample, approximately 96.6 percent of the products are consistently non-high-tech during the sample period (stable non-high-tech products), and 1.7 percent are constantly high-tech (stable high-tech products). The remaining 1.7 percent have entered or exited the high-tech catalog midway through the period, which is excluded from the following robustness tests.

Table 15 reports the results when this alternative definition of high-tech products is applied. In columns (1)–(3), we compare the export concentration level of stable non-high-tech products with that of stable high-tech products. The coefficients of the stable high-tech product dummy are all significantly positive, which is consistent with our baseline results. The export concentration of stable high-tech products is significantly larger than that of stable non-high-tech products.

In columns (4)–(6), we further explore the role of national concentration of R&D (R&D HHI) behind the phenomenon of the concentration of high-tech products. The results demonstrate that the coefficients of the interaction term between the stable high-tech products dummy and the R&D HHI are also significantly positive, indicating that the national concentration trend of the stable high-tech products appears mainly in years when R&D activities are also more concentrated in certain countries.

Table 15. Using the stable high-tech products definition

	*Share*5	*HHI*	*Share*3	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)	(4)	(5)	(6)
Stable high-tech products	0.1085*** (3.64)	0.0721* (1.73)	0.1141*** (2.97)	–0.0338 (–1.21)	–0.0799** (–2.30)	–0.0566 (–1.59)
Stable high-tech products × R&D HHI				0.4605*** (2.99)	0.5569*** (2.85)	0.5484*** (2.71)
Number of export countries	–0.1603*** (–11.01)	–0.1401*** (–15.99)	–0.1711*** (–12.07)	–0.0936*** (–112.17)	–0.1790*** (–221.96)	–0.1232*** (–141.45)
Constant	1.3774*** (21.24)	0.7763*** (18.60)	1.2901*** (20.47)	1.1110*** (357.13)	0.9449*** (269.10)	1.1064*** (334.48)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,094	78,094	78,094	78,094	78,094	78,094
R^2	0.255	0.265	0.238	0.439	0.688	0.492

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the HS 6-digit product level. Stable high-tech products is a dummy variable that is defined to be 1 if a product is always in the high-tech catalog during the sample period 2004–2017. FE, fixed effect; HHI, Hirschman–Herfindahl Index.

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The results in Tables 14 and 15 show that our results are still robust after we control the effects of the time-varying high-tech catalog.

4. Extensions: An analysis based on value-added exports

In the baseline regression, we calculate the concentration measure for each product based on standard trade volume measures. However, because country A's exports can contain other countries' value added, it may overcount the production capacity of country A by not excluding value added from other countries. This problem is particularly pronounced in the case of processing trade exports.

To mitigate this problem, in this section, we further use the value-added export data to analyze the national concentration of high-tech export. We apply the methodology proposed by Wang et al. (2022) to construct the country–industry level value-added export. According to the methodology proposed by Wang et al. (2022), global economic activities can be classified into three categories, which are value-added in Pure Domestic Production Activities, Final Goods Trade, and Global Value Chains, respectively. The last two categories – value added in Final Goods Trade and Global Value Chains trade – reflect exports of value added.

We use data from a newly updated Asian Development Bank Multi-Regional Input–Output database, which covers 63 economies and 35 industries from the years 2000 and 2007 to 2019 to calculate the country–industry level value-added export. On this basis, we further construct the value-added-based concentration measures, the *Share*5, *HHI*, and *Share*3, for each industry each year. For high-tech industry identification, using the OECD classification criteria for industry R&D intensity, we define the following five industries as high-tech industries: chemicals and chemical products, basic metals and fabricated metal, machinery, electrical, and optical equipment, and transport equipment.

Regression results using the value-added-based concentration measures are reported in Table 16, and the coefficients of the high-tech industry dummy are all significantly positive, supporting the hypothesis that high-tech industry exports are more concentrated in certain countries. Our main results still hold after using the value-added exports instead of the total exports.

The reason why we use the total export data instead of the value-added data in the baseline regression is that we could only analyze the topic at the coarse industry level (35 industries in the sample) using value-added export data. Meanwhile, using the standard export volume data, we could explore the concentration difference between high-tech products and other products at the more disaggregated HS 6-digit level (6509 HS 6-digit products in our sample).

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Table 16. Analysis using the value-added export data

	*Share*5	*HHI*	*Share*3
	(1)	(2)	(3)
High-tech industry	0.0637** (2.20)	0.0109*** (5.01)	0.0491** (2.25)
Constant	0.5066*** (29.84)	0.0766*** (20.49)	0.3806*** (31.49)
Year FE	Yes	Yes	Yes
Observations	490	490	490
R^2	0.202	0.085	0.182

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. The *t*-values are in parentheses. Robust standard errors are clustered at the industry level. *Share*5 is the proportion of value-added exports from the top five exporters for each industry every year, *Share*3 is the proportion of value-added exports from the top three exporters, and *HHI* is the squared sum of the value-added export shares of all exporters of the industry. FE, fixed effect; HHI, Hirschman–Herfindahl Index.

IV. The Second Great Divergence?

In the empirical part, we find that high-tech product is characterized by natural and self-reinforcing national concentration. In our view, the pattern is the signal of the Second Great Divergence, the great divergence between innovative and manufacturing activities. As a result, the global economic and trade pattern may face reshaping. In this section, we first review the economic consequences of the First Great Divergence. With the First Great Divergence as the background, we propose the concept of the Second Great Divergence. Finally, we provide an analysis of the causes and countermeasures of the Second Great Divergence.

1. Historical review: The First Great Divergence

The First Great Divergence occurred during the Industrial Revolution. It refers to the divergence between industry and agriculture, and geographically, between the West and the East. Western European countries, represented by the UK, were the first to witness the Industrial Revolution. The Industrial Revolution enabled capitalist production to complete the stage of transition from workshop craftsmanship to machine-based mass industry, which liberated labor and greatly increased productivity. Since then, the Western capitalist countries, which were the first to complete the Industrial Revolution, gradually established their domination over the world, and the world became a situation where the West was advanced, and the East was backward. The First Great Divergence in the world thus emerged. Table 17 shows the share of manufacturing output of the world's major economies from 1750 to 1913. The table indicates that from 1800 to

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1900, the countries that first completed the Industrial Revolution, such as the UK, Germany, and the US, saw a significant increase in their share of manufacturing. Meanwhile, China's share of manufacturing production shrank significantly, from 33.3 percent in 1800 to 6.2 percent in 1900.

After the First Great Divergence, the production share of global manufacturing was increasingly more concentrated. Furthermore, the share was mainly concentrated in the Western European countries, which were the first to complete the Industrial Revolution, and in the US. Taking the sum of the shares of the UK, Germany, and the US, the share was only 5 percent in 1750, while by 1900, the share of manufacturing production of the three countries had grown rapidly to about 55 percent.

Table 17. Relative shares of different countries in the total world manufacturing output (%)

	1750	1800	1830	1860	1880	1900	1913
Developed countries	27.0	32.3	39.5	63.4	79.1	89.0	92.5
Austria-Hungary	2.9	3.2	3.2	4.2	4.4	4.7	4.4
Belgium	0.3	0.5	0.7	1.4	1.8	1.7	1.8
France	4.0	4.2	5.2	7.9	7.8	6.8	6.1
Germany	2.9	3.5	3.5	4.9	8.5	13.2	14.8
Italy	2.4	2.5	2.3	2.5	2.5	2.5	2.4
Russia	5.0	5.6	5.6	7.0	7.6	8.8	8.2
Spain	1.2	1.5	1.5	1.8	1.8	1.6	1.2
Sweden	0.3	0.3	0.4	0.6	0.8	0.9	1.0
Switzerland	0.1	0.3	0.4	0.7	0.8	1.0	0.9
UK	1.9	4.3	9.5	19.9	22.9	18.5	13.6
Canada	—	—	0.1	0.3	0.4	0.6	0.9
US	0.1	0.8	2.4	7.2	14.7	23.6	32.0
Japan	3.8	3.5	2.8	2.6	2.4	2.4	2.7
Developing countries	73.0	67.7	60.5	36.6	20.9	11.0	7.5
China	32.8	33.3	29.8	19.7	12.5	6.2	3.6
India-Pakistan	24.5	19.7	17.6	8.6	2.8	1.7	1.4
Brazil	—	—	—	0.4	0.3	0.4	0.5

Source: Bairoch (1982).

Table 18 further demonstrates the changes in the economic development of the major economies over the same period. We use GDP per capita to measure the level of economic development. The results show that the developed countries, which were the first to complete the Industrial Revolution, experienced rapid economic growth, whereas the developing countries experienced little growth in GDP per capita over the same period.

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In summary, the First Great Divergence was driven by the first and second Industrial Revolutions, which led to a major divergence between global manufacturing and agriculture. The economies of the countries that completed the Industrial Revolution first achieved higher growth rates and gradually opened the gap between the economic growth rates of the countries that were still predominantly agricultural.

Table 18. GDP per capita of different countries

	1700	1820	1830	1850	1860	1880	1900	1913
Developed countries								
Austria	993	1,218	1,399	1,650	1,778	2,079	2,882	3,465
Belgium	1,144	1,319	1,354	1,847	2,293	3,065	3,731	4,220
France	910	1,135	1,191	1,597	1,892	2,120	2,876	3,485
Germany	910	1,077	1,328	1,428	1,639	1,991	2,985	3,648
Italy	1,100	1,117	—	1,350	—	1,581	1,785	2,564
Spain	853	1,008	—	1,079	1,236	1,646	1,786	2,056
Sweden	750	819	870	1,019	1,195	1,520	2,209	3,073
Switzerland	890	1,090	—	1,488	1,745	2,450	3,833	4,266
UK	1,250	1,706	1,749	2,330	2,830	3,477	4,492	4,921
Canada	430	904	1,000	1,330	1,451	1,816	2,911	4,447
US	527	1,257	1,376	1,806	2,178	3,184	4,091	5,301
Japan	570	669	—	679	—	863	1,180	1,387
Developing countries								
China	600	600	—	600	—	—	545	552
India	550	533	—	533	—	—	599	673
Brazil	459	646	—	686	—	752	678	811

Notes: The GDP per capita data comes from the 2010 Maddison database, all in the 1990 international dollar.

2. The Second Great Divergence

As a lesson from history, China did not catch the tide of the Industrial Revolution and was therefore at a disadvantage in the First Great Divergence. But with the changing economic situation and the continuous development of technology, a new revolution is emerging. Nowadays, in the new era of globalization, high-tech competition has become the core competition among countries.

We hold the view that the Second Great Divergence is now gradually emerging. If the First Great Divergence is the divergence between global manufacturing and agriculture due to the first and second Industrial Revolutions, then the Second Great Divergence refers to the divergence between advanced technology and general

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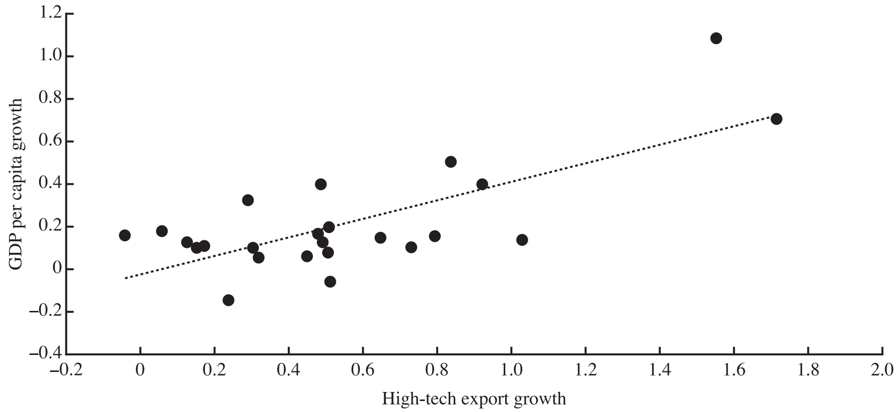
manufacturing. In recent years, the export of high-tech products has become increasingly concentrated in certain countries, which means that countries on the periphery of technology are gradually losing the possibility of catching up, and the gap between technology owners and countries on the periphery of technology will become increasingly wide. This is the key trigger for the possible occurrence of the Second Great Divergence.

To visualize the existence of the Second Great Divergence, we calculate the growth rate of high-tech exports and GDP per capita of the major economies from 2004 to 2017 and explore the relationship between the two. The results are shown in Figure 5. We define the growth rate of high-tech exports as the difference between each country's high-tech product exports in 2004 and 2017. The growth rate of GDP per capita is defined in a similar way. The identification of high-tech products is consistent with the benchmark regression, and the export data are from the UN COMTRADE database. The GDP per capita data (in 2015 constant USD) are from the World Bank WDI database. Figure 5 shows that there is a significant positive correlation between the growth rate of high-tech exports and GDP per capita. Differences in the development of high-technology industries have become one of the key explanatory factors for differences in economic growth rates between countries, which to some extent supports our argument that high technology is driving the Second Great Divergence.

Figure 5. The relationship between high-tech export growth and GDP per capita growth



Notes: The high-tech export growth is defined as the logarithm of high-tech export in 2017 minus the logarithm of high-tech export in 2004. The GDP per capita growth is defined as the logarithm of GDP per capita in 2017 minus the logarithm of GDP per capita in 2004. The sample countries include Austria, Australia, Bahrain, Belgium, Brazil, Canada, China, France, Germany, India, Italy, Japan, the Netherlands, New Zealand, Norway, the Philippines, Russia, Singapore, Spain, South Korea, Sweden, Switzerland, the UK, and the US.

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3. Analysis of the Second Great Divergence

The previous analysis shows that high-tech exports have become increasingly concentrated in certain countries in recent years. Corresponding to the First Great Divergence caused by the Industrial Revolution, we call this phenomenon the Second Great Divergence. It is worth exploring further why this phenomenon is occurring at this stage. We hold the view that, in the new era of globalization, the change in production function and factors is an important factor in the emergence of more concentrated high-tech products and the Second Great Divergence.

We try to interpret this issue by cutting through the evolutionary process of globalization. Globalization is the process of market expansion worldwide. Related literature has studied the evolution of globalization and divided stages for globalization from different perspectives (Bordo et al., 1999; Taylor, 2002; Findlay and O'Rourke, 2003; Friedman, 2005).[2] In our opinion, globalization can be divided into four stages. Globalization 1.0 is the era of individual adventure, where the dominating countries were Spain and Portugal, and the products traded were final goods; globalization 2.0 is the era of multinational corporations and trade globalization, where the dominating country was the UK and the products traded were final goods as well as capital; globalization 3.0 is the era of production globalization, where the dominating country was the US and the products traded were intermediate goods and final goods. Globalization 4.0 is the era of innovation, the era of technological globalization, and is driven by multiple countries.

In the current era of globalization 4.0, the leap in technology has made innovation a key determinant of economic growth, and innovation activities inherently require scale. Unlike the previous globalization stages, the fourth globalization is an era of technological innovation driven by ideas, where the material is no longer the most important input factor. This type of production activity tends to have a difficult start, but its expansion is gradually accelerated after scaling up. In other words, this type of production activity corresponds to a production function with high fixed costs and low marginal costs, which results in extremely high returns to scale. Specifically, in the last three globalizations, the production of material goods dominated and drove economic growth, and the process of globalization was mainly the optimal global allocation of

[2]Friedman (2005) divides the history of globalization into three phases according to the most important globalization participants: Globalization 1.0 (1492–1800), Globalization 2.0 (1800–2000), and Globalization 3.0 (2000–present). Bordo et al. (1999) compared the degree of globalization at the end of the 20th century with that at the end of the 19th century and concluded that globalization at the end of the 20th century was deeper than before and was mainly reflected in the extensive trade in services and the rise of multinational corporations, which was facilitated by the continuous reduction of transportation costs, trade barriers, and information barriers.

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material resources (e.g., labor and capital). Since the marginal productivity of material factors decreases, there is an optimal scale of production. In contrast, in the fourth globalization, innovation dominates and drives economic growth, and the process of globalization is mainly the optimal allocation of ideas. While the production of material goods has diminishing returns to scale, innovation has increasing returns to scale. The more people have access to ideas, the more efficient innovation is. In such cases, the larger the scale of production and the more concentrated the production resources, the more ideas and the accompanying innovations, which further facilitate the expansion of high-tech production and create a strong technological barrier that prevents later entrants from entering the field. Thus, we observe that the export of high-tech products is increasingly concentrated in certain countries and markets. The extremely high return to scale is thus an important reason for the emergence of the Second Great Divergence.

Someone may argue that innovation driven by ideas tends to spread more easily, which may lead to convergence rather than divergence. The following argument might mitigate the concern. First, although knowledge flows easily, it is also very easy to control. Secondly, the application of knowledge and technology requires early-stage accumulation. If the early accumulation of technology is not enough, even if we have access to the cutting-edge knowledge, we cannot make good use of it. Finally, under the new form of production, economies of scale are very strong.

However, the over-concentration of innovation activities in high-tech products, i.e., the singular pursuit of “size,” may not be conducive to further innovation. Aghion et al. (2005) showed an inverted U-shaped relationship between competition and innovation. Subsequently, some papers have further discussed based on Aghion et al. (2005). Hashmi (2013) re-examined the relationship between competition and innovation using the US data and found a negative relationship between competition and innovation. Aghion et al. (2018) used an experimental approach to make causal inferences and found that increased competition would significantly promote the R&D level of frontier firms but significantly reduce the R&D level of lagging firms. Aghion et al. (2015) used data on industrial firms in China and further found that industrial policies that promote competition contributed to the progress of industry productivity.

To summarize, on the one hand, we need a certain market size and production concentration to make innovation more profitable and thus incentivize innovation. Under perfect competition, the incentive to innovate is eliminated because of zero profits. But on the other hand, under a high degree of concentration, a dominant market structure can similarly inhibit innovation. A monopolist enjoying excess profits would have no incentive to innovate further and would suppress other innovative rivals. We therefore need a moderate market structure to promote innovation.

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V. Conclusion

Based on the product–country level export trade as well as the high-tech product data, this paper found an increasing concentration of high-tech exports. Corresponding to the First Great Divergence caused by the Industrial Revolution, we defined this phenomenon as the Second Great Divergence. The empirical results show that in the fourth globalization, especially in recent years, there is a larger concentration of the export of high-tech industries. Increasing returns to scale of innovation are important reasons behind the concentration of high-tech export. In the new era of globalization, new forms of production make the concentration of high-tech products tend to be self-reinforcing. In the Second Great Divergence of high-tech competition, China should further increase its support for R&D and innovation in high-tech industries.

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