Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-024-03450-2 OPEN

Strategies for selecting trading partners based on economic complexity of international trade networks: A comparison between Chinese and the US markets

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Selecting suitable trading partners in the globalized trade landscape remains critical. Traditional selection processes driven by factors like comparative advantage and trade costs are cumbersome and incomplete. Economic complexity offers a more precise measure of a country's economic development and product capacity, facilitating future-oriented choices. Leveraging international trade data from 2001 to 2015, this paper employs economic complexity theories to analyze Chinese and the US' trade networks in the global market. It explores multi-level considerations for exporting countries' partner selection, revealing varying product diversification challenges and market clustering tendencies. China shows increasing overall product proximity relationships, specifically notable in textile-related products, while the US exhibits decreasing product proximities. Additionally, trading positions and product dependencies vary across markets. Some countries, like Japan and Germany, maintain stable positions, while others fluctuate. Notably, countries like Nigeria, Bangladesh, and Cambodia have higher positions in the Chinese market, suggesting promising long-term trade partnerships. Conversely, countries like Yemen, Kazakhstan, Kuwait, and Sudan have higher positions in the US market, indicating significant disparities. Products that are needed in the Chinese market and occupy higher complexity positions are primarily concentrated in the field of non-ferrous metals, while the US market relies more on raw materials. This highlights distinct market dynamics, particularly pronounced in the US market. Hence, there is a greater likelihood of obtaining better economic benefits by trading these products in their respective markets.

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Introduction

International trade is a well-recognized economic activity worldwide, playing a pivotal role in meeting national demand, enhancing production efficiency, reducing costs, optimizing resource utilization, stimulating innovation, and fostering employment. As a crucial form of high-level trade interaction, it contributes to economic convergence (Coscia et al. 2017). The selection of appropriate trading partners is paramount for exporting countries, as it directly impacts economic benefits and indirectly influences the long-term product layout and competitive potential of exporting nations. However, recent years have witnessed escalating tensions between China and the US, contributing to turbulence and uncertainty in the global trade environment. In light of this backdrop, many trading entities are faced with the challenge of reassessing and adjusting their international trade strategies. Comparative advantage, trade policy, trade costs, and business reputation are crucial factors considered by exporting countries when selecting trading partners. However, these indicators are typically estimated based on one or a few dimensions (Purwono et al. 2022; Cardoso-Vargas 2018; Ren et al. 2024), lacking the ability to comprehensively and accurately assess the economic level based on trade outcomes and provide robust capabilities for scientifically planning future development paths, while considering both the present and the future. When individual indicators are judged, the process of allocating weight to different factors may become cumbersome and even miss good trade opportunities. In the specific selection process, traditional approaches such as trade gravity models mainly focus on bilateral trade situations (Xie and Wu 2022; Doumbe and Belinga 2015; Emikönel 2022; Chan and Manova 2015). PESTEL and other decision-making methods lack macro-level data-driven approaches in selecting trading partners (Shatskaya et al. 2016). Based on endogenous growth theory which taking knowledge and technology as key economic drivers, economic complexity is proposed to reversely estimating the production capacity of an economy with exporting products information as carrier, which has more effectiveness of predicting economic growth than classical indicators in traditional political economy (Hidalgo, 2021), and has been successfully used in research on economic development · (Balland et al. 2022; Ma et al. 2022; Britto et al. 2019; Sepehrdoust et al. 2019), green economy (Mealy and Teytelboym 2022; Rafique et al. 2021; Neagu 2019; Pérez-Hernández et al. 2021), social inequality (Hartmann et al. 2017; Chu and Hoang 2020; Lee and Wang 2021; Sepehrdoust et al. 2022), to provide information about the current state of economic development. In the realm of economic complexity, the primary models for assessing the state of economic development include classic measurement methods such as the economic complexity index (ECI) and the product complexity index (PCI) based on Method of Reflections (the following abbreviation "MR"), as well as fitness complexity index (FCI) and product complexity index (FPI) (Hidalgo 2021). The variations in the measurement of countries' economic complexity indexes imply differences in the complexity of their economic structures. Typically speaking, developed countries possess higher economic complexity indexes, enabling them to have an advantage in exporting products with higher product complexity values, thereby acquiring greater economic value-added. Similarly, products with higher complexity embody greater levels of productive knowledge and technology. Based on a country's incumbent production capacities, the continuous development towards products of high-complexity signifies the process of a country's structural transformation. Then, it is important to choose proper export products. As products require specific production conditions such as capital, technology, and policies, the more similar the production conditions are between two products, the greater the possibility of common production. According to the theory of proximity between products, proximity between products makes them closer in product space network. Thus, if a country can offer a certain product based on its production capacity, the higher the proximity value with that product, the higher the likelihood that the country can also produce those products.

Though economic complexity methods have been used widely in investigating trade development issues, extant studies are mainly based on bipartite trade networks, and have not used in selecting trade partners. One stream of studies on economic complexity takes exporters and exporting product as two nodes in the bipartite network (there is no connections within each node), based on international export trade data (Le et al. 2022; Liao and Vidmer 2018), and a small number of import trade data. If the country has advantage in exporting one product, then, a connection between the two nodes can be established; while 'hiding' all different exporters as a unified node. These studies reveal the current status and potential for economic development from a worldwide perspective, so as to serve for a countries trade activity at the world level. For example, the product space network generated from a worldwide perspective allows economies to re-examine the competitiveness of their export products, and to identify proximate products or industries with higher product complexity as the next target for product transformation and upgrading. The second type of studies downgrade the research object in the first stream (Dong et al. 2022), which is to replace the international trade with national or regional trade or other carriers of economic activities, i.e. for example, based on Chinese provincial data (Gao and Zhou 2018) or Japanese prefectural data (Chakraborty et al. 2020). These studies contribute to guide economic development issues inside an economy. The third type of study is to take a single country as the trade object (Du and Ren 2021), and studying the countries and products it trade with. Thus, the economic complexity index ranking of each exporting country can be concluded from a single country's perspective, which represents the economic development level of each country based on a single country's trade market. However, current research only discusses the ranking of export countries or products, but do not provide a relative point of view on comparing the similarities and differences of export products. In addition, in terms of data, the third type of study is based on trade flow data provided by individual country markets, which include a lower number of countries and products than the international economic trade data commonly used in the first type of study. Thus, utilizing results from the third type of study in the selection of trade partners may be subject to errors caused by data inconsistencies, which cannot provide as precise reference for international trade.

Figure 1 shows a country's share in the average value of exported products in the trade market for the year 2001 to 2015. The different colors in Fig. 1 represent the export information of different countries, from different angles, which are respectively the worldwide, China, and the US. The numbers in the rectangle are product codes indicating different types of export products; the larger the rectangle area, the larger the export share in that market. Observations reveal notable differences in the situations of certain countries under different trade perspectives. For instance, the share of DNK(Denmark) is significantly smaller in the perspectives of China and the United States compared to the world perspective. This indicates that DNK's level of market development in China and the US is notably lower than the world average. Consequently, focusing on the export dependence of products for these two countries might yield better returns. In addition, although the exporting countries have a considerable amount for exporting category 8 products(textile-related

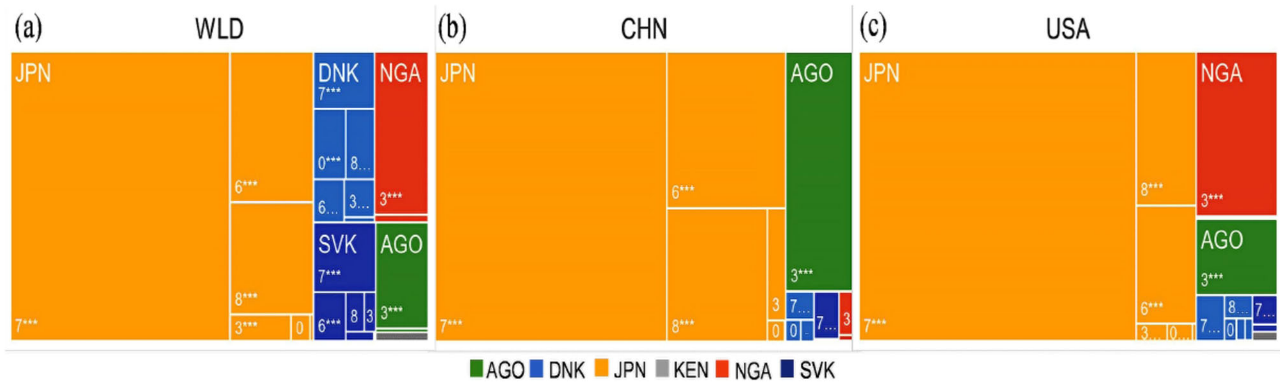

Fig. 1 Trade structure of country's export products in the world, China, and the US perspectives. a World perspective, (**b**) China perspective, and (**c**) the US perspective. The country abbreviations are AGO(Angola), JPN(Japan), KEN(Kenya), NGA(Nigeria), and SVK(Slovakia).

products) in all three markets, it is obvious in Fig. 1a–c that the proportion of such products in different markets is different, specifically, China has the largest share (Fig. 1b), the world has the second largest share (Fig. 1a), and the US has the least (Fig. 1c), We still don't understand if it indicates that exporting such products to China is much easier to benefit from the trade than to other markets of the world.

Figure 1, based on the long-term records of real trade activities, reflects that the trading positions and dependence levels of countries and products in different trade markets may differ. However, this is just a speculation based on export volume. In reality, the qualitative situations in different trade markets require a more in-depth analysis using the economic complexity methods. If a country plans to develop product advantages in more refined target markets such as China, the US, etc., then a criterion of economic complexity results developed from the perspective of target market trade will provide more meaningful reference information, which is important in the trade target selection process. To export more competitive products for better economic gains in the target market, it is essential to strategically approach target products that can capture more economic surplus. This involves assessing the current export product landscape and determining ways to move closer to products that offer higher economic value. Moreover, exporting products with a high degree of import dependence to target trade markets is crucial for ensuring a favorable trading partner position. Therefore, it is imperative to delve into the fluctuations among products exported to the Chinese and the US markets, as well as the complexity of countries and products, based on authentic trade data. Feasible recommendations for trade partner selection are proposed, aiming to provide trading entities with more objective, comprehensive, and reliable decision-making support. This endeavor will not only shed light on cognitive biases resulting from factors such as politics, but also foster the cultivation of amicable and robust trade relationships among nations. Ultimately, it will empower them to adeptly navigate the current complex and dynamic trade landscape, fostering mutual benefits for all parties involved.

With the help of the product proximity algorithm and economic complexity measurement index in the economic complexity framework, we aim to investigate criteria for enhancing the export of more sophisticated products, diversifying export products, and understanding product dependence across various markets for each product-exporting country. This analysis will be conducted using international trade data spanning from 2001 to 2015. Specifically, we will focus on two major trade markets, China, and the US, while also considering the world trade network as a benchmark for comparison. This paper is divided into four parts: Chapter 1 introduces the background of the study; Chapter 2 explains the research data and methodology; Chapter 3 first analyzes the proximity of products from the perspectives of three different markets. It provides references for each country exporting products, offering insights into the overall developmental trajectory of export product diversification and transformation. Subsequently, by calculating the complexity levels of exporting countries and their corresponding export products across various markets, we extract information regarding their trade positions and degrees of dependence in these markets. Then, through various forms of analysis and comparison, valuable observations are furnished for countries engaging in trade activities in Chinese and the US markets. Finally, Chapter 4 summarizes and discusses the research contents of this paper.

Methodology

Data collection

Data. The data used in this study are derived from the international trade dataset from Harvard University Growth Lab according to the trade product codes of the Standard International Trade Classification (SITC) Revision 2, which is introduced in section Data Availability. The lab took raw trade data on products reported to the United Nations Statistics Division (COMTRADE) from all countries and used a specially designed data cleaning method to deal with data inconsistencies, resulting in a more reliable world trade dataset.

Processing. In this research, we extracted exporting countries, importing countries, export product codes, and corresponding product values from the dataset. Three sub-datasets were then filtered for the world, Chinese, and the US markets. For subsequent analysis on the correlation of country economic complexity index values from three different perspectives, we filtered the dataset to ensure stable results. We referred to literature (Hausmann et al. 2014) and included only countries with available product trade and 2008 income data from the United Nations Commodity Trade Statistics Database. Second, only data for countries with a population of more than 1.2 million are used. Third, only countries that exported at least $1 billion per year on average between 2006 and 2008 are considered. Finally, three countries/regions with serious data quality problems, Iraq, Macau and Chad, were removed from the dataset, and a total of 128 eligible countries were used as the target exporting countries included in the data for the seven years before and after 08, i.e., 2001–2015, as shown in the country selection flowchart in Fig. 2 below, for the specific selection process.

In addition, due to the fact that the data itself has no relevant trade records for some countries in some years, when the above

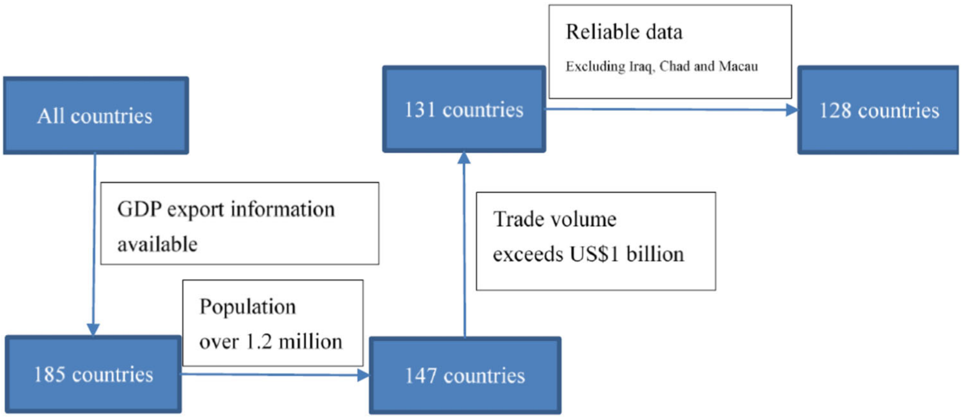

Fig. 2 Country Screening Flow Chart.

data are measured using the ECI, it is found that the real data under the three different perspective systems of the world, China, and the US are missing compared to the screened trade data for 128 countries for a total of 9 countries between 2001 and 2015 (see Supplementary Material Table S1). Therefore, the object of analysis when conducting the correlation analysis of national economic complexity index values in the text is 117 countries, which are indicated in the text as such as WLD (World), CHN (China), USA (the US) and other countries/regions abbreviated (see supplementary material Table S2); similarly, the number of products common to 2001–2015 is 757 in total (see supplementary material Table S3), and the types of products starting with different numbers. A total of 10 kinds, as shown in supplementary material Table S4 below, in which category 0 is omitted in the following because it starts with 0 and ends up showing less than four digits of the product code. In order to enable comparative analysis of the study subjects in terms of time, the data are measured in the following according to three different time periods, 2001–2005, 2006–2010, and 2011–2015, and in consideration of the length of the article, the results of 2006–2010 are generally placed in the main text, and the analysis results of the other two time periods are placed in the supplementary materials.

Methods. Economic complexity represents a broad research domain distinct from conventional indicators such as GDP, which measure overall economic output, or traditional metrics that extract specific economic elements. Inspired by the science of complex systems, economic complexity employs modern data analysis techniques, emphasizes quantitative analysis, and is guided by economic trade outcomes. This study employs methods from the field of economic complexity to calculate the product proximity between products and measure the complexity indexes of countries and products. These methods help discern the pathways and levels of difficulty for exporting countries to further expand their export product range in different markets by revealing the correlations between required import products in each market. They also assess the current economic trade positions of exporting countries in various markets and the extent of reliance on their exported products. Based on the real trade capabilities of different markets and exporting countries, these methods provide valuable comprehensive criteria for the process of selecting trading partners.

Product proximity theory. Product proximity theory was originally used to construct the product space network characterizing the correlation relationship between international trade products (Hidalgo et al. 2007), and the magnitude of proximity value depends on the conditional probability that two products are jointly exported by a country with comparative advantage at a certain time. The comparative advantage of country c in exporting product p, means that the share of in exporting all products in country c is greater than the total share of exporting product p all over the world in the total volume of world's exports of all products. The general formula for determining whether a country has Revealed Comparative Advantage (RCA) is $RCA = \frac{X_{cp}/\sum_p X_{cp}}{\sum_c X_{cp}/\sum_c \sum_p X_{cp}}$. The country-product matrix X can be generated from trade data, the rows of the matrix indicate the product exporters c, and the columns of the matrix indicate the trade product p. Using the RCA method, a country is considered to be a comparatively advantageous exporter only when its RCA corresponding to that product is more than 1 (RCA_{cp}>1), otherwise it is not. The following Eq. (1) is the calculation of proximity between products, where i and j denote two different products traded between countries, t is the time of trade involved, and $\varphi_{i,j,t}$ denotes the proximity value between products i and j at time t. The minimum value of the two conditional probabilities derived from the calculation is taken as the final proximity value between the two.

$$\varphi_{i,j,t} = \min\left\{P\left(RCA_{X_{i,t}}, |, RCA_{X_{j,t}}\right), P\left(RCA_{X_{j,t}}, |, RCA_{X_{i,t}}\right)\right\} \tag{1}$$

The higher the value of product proximity, the more similar the factors such as technology, knowledge, policies, and resources required for the production of trade products i and j are for the exporting country. In general, proximity values greater than 0.5 (from 0 to 1) in the proximity matrix are considered indicative of proximity between products. This indicates a stronger correlation between the products, providing the exporting country with a pathway to further export more complex products in the target market based on its existing production capabilities, thereby strengthening and enhancing its trade partnerships in that market. It also signifies the opportunities for the exporting country to enter or exit a particular product type and indicates the level of difficulty in undertaking transformation and upgrading. While product proximity primarily provides information on the expansion of export product types for the exporting country in a specific market, country and product complexity values primarily reveal the current economic and trade position of each exporting country and the level of product dependence in that market.

It should be noted that, in the process of assessing product proximity in the Chinese and the US markets, the RCA method, when applied to the Chinese and the US trade markets, strictly adheres to its original definition. Taking the Chinese market as an example, the trade data of each exporting country to the Chinese market is extracted. Afterward, a matrix X(C) is constructed, where the rows represent exporting countries $\boldsymbol{c}$ in the Chinese market, and the columns represent products $\boldsymbol{p}$ exported to the Chinese market. The data in the matrix is then input into the RCA formula.

Economic complexity index. The Economic Complexity Index is a complexity measurement method based on the Method of Reflections (MR), where the ECI gauges the economic development level of exporting countries in trade markets, and the PCI captures the complexity of exported products in terms of technology, production capacity, and other aspects. The calculation process normalizes the country-product matrix $\boldsymbol{X}$ (noted as X_{cp}) using the RCA algorithm. Similar to the RCA treatment in Section 2.2.1, the result yields a binary matrix containing only 0 and 1. When the RCA result is greater than 1, the corresponding matrix element is set to 1, indicating that the country represented by the matrix row (c) exhibits a significant comparative advantage in exporting product p compared to the average level of exporting that product. Otherwise, it is set to 0. After normalization, the resulting matrix, denoted as $\boldsymbol{M}$, represents countries in rows and products in columns, with matrix elements M_{cp} taking values of only 0 or 1.A matrix $\boldsymbol{M}$ containing only zeros and ones can be obtained, and noted as M_{cp}. $M_{cp}=1$ indicates that the share of country $\boldsymbol{c}$ exporting product $\boldsymbol{p}$ exceeds the average share of product $\boldsymbol{p}$ in worldwide market, which means country $\boldsymbol{c}$ has a comparative advantage in exporting product $\boldsymbol{p}$.

In matrix $\boldsymbol{M}$, the diversity of countries is noted as $K_{c,0}=\sum_p M_{cp}$, and the product universality is noted as $K_{p,0}=\sum_c M_{cp}$. A higher level of product universality $K_{p,0}$ indicates that the production capacity of this product is available in most countries; and the higher the country's diversity $K_{c,0}$, the higher the level of GDP per capita. After several recursive iterations of Eqs. (2) and (3), $K_{c,N}$ and $K_{p,N}$ will reach a relatively stable value, representing the average diversity of countries and the average universality of products, respectively, as follows Eqs. (2) and (3).

$$K_{c,N}=\frac{1}{K_{c,0}}\sum_p M_{cp}K_{p,N-1} \tag{2}$$

$$K_{p,N}=\frac{1}{K_{p,0}}\sum_c M_{cp}K_{c,N-1} \tag{3}$$

As for the economic complexity index, it is obtained by substituting Eq. (3) into Eq. (2),

$$K_{c,N}=\sum_{c'}K_{c',N-2}\sum\frac{M_{cp}M_{c'p}}{K_{c,0}K_{p,0}} \tag{4}$$

Let $\widetilde{M}_{cc'}=\sum_p\frac{M_{cp}M_{c'p}}{K_{c,0}K_{p,0}}$, then $K_{c,N}=\sum_{c'}\widetilde{M}_{cc'}K_{c',N-2}$, where the eigenvector of the second largest eigenvalue of $\widetilde{M}_{cc'}$ is $\vec{K}$. The country's ECI is then shown as Eq. (5), where $<\vec{K}>$ denotes the mean value of $\vec{K}$ and $stdev<\vec{K}>$ denotes the standard deviation of $\vec{K}$.

$$ECI=\frac{\vec{K}-<\vec{K}>}{stdev<\vec{K}>} \tag{5}$$

The PCI of the product is shown as Eq. (6), where $\vec{Q}$ denotes the eigenvalue of the second largest eigenvector corresponding to $\widetilde{M}_{pp'}$.

$$PCI=\frac{\vec{Q}-<\vec{Q}>}{stdev<\vec{Q}>} \tag{6}$$

Results

By employing economic complexity methods, this study examines product proximity, conducts overall correlation analysis, characterizes the dynamics of differential changes, and identifies extreme values across various trade markets. The conditions of different trade objects are first detected from the development layout, followed by a more detailed comparative analysis of complexity values from the intuitive level. Its aim is to uncover the capabilities of different trading partners and provide a basis for countries to select trading partners based on different economic complexity analysis results.

Ways to diversify export products. The product proximity algorithm, applied to international trade data for 128 countries from 2001 to 2015, focuses on product-level proximity without distinguishing between countries in the global, Chinese, and US perspectives. It specifically calculates the proximity between 757 products exported together, following the principles of product proximity theory (Hidalgo et al. 2007). To ensure the stability of the results, the proximity scores of each adjacent five years are averaged. Finally, the product proximity matrix is visualized to obtain a heat map of proximity between the three perspectives. The map has the same horizontal and vertical coordinates, and proximity scores are symmetric about the diagonal. There is a total of 572,292 pieces of proximity information between different products. The same horizontal and vertical coordinates in the figure are all product codes arranged according to SITC.REV2, 4-digit level standard, as shown in the supplemental material product code Table S5.

In the global trade market, the measurement of the average proximity of products represents a general outcome, reflecting the average level of production capacity and economic benefits that products entail in the international trade market. However, this general value is not universally applicable to all countries, and it may be influenced by changes in the global supply chain and fluctuations in market conditions. This is because different countries, due to variations in their natural resources and production structures, have different demands for importing different types of products from the same country to maintain their normal production operations and ensure their economic functioning. For instance, resource-rich countries exhibit lower import dependency in the energy sector but higher dependency in other sectors such as food and agricultural products. Conducting a probability analysis for multi-category simultaneous trade of these products can be advantageous for exporting countries in selecting trade partners. It can be found that the results of proximity measurement under different trade perspectives are different. On the one hand, the distribution of proximity heat map in Fig. 3 is more homogeneous under the world perspective, China and the US show obvious bright partitions, and the bright partitions correspond to product classification areas with homogeneity, what's more the darker areas are products with lower proximity which are mostly distributed in 11–4312 (mostly live animals of food, meat and preparations, dairy products and eggs, fish, crustaceans and mollusks, cereals and cereal products, etc.). It is difficult for countries that can export only this part of the products in a given market to form trade competitiveness in China and the US trade markets. Their path to export highly dependent products requires more accumulation of production capacity. On the other hand, products in bright areas

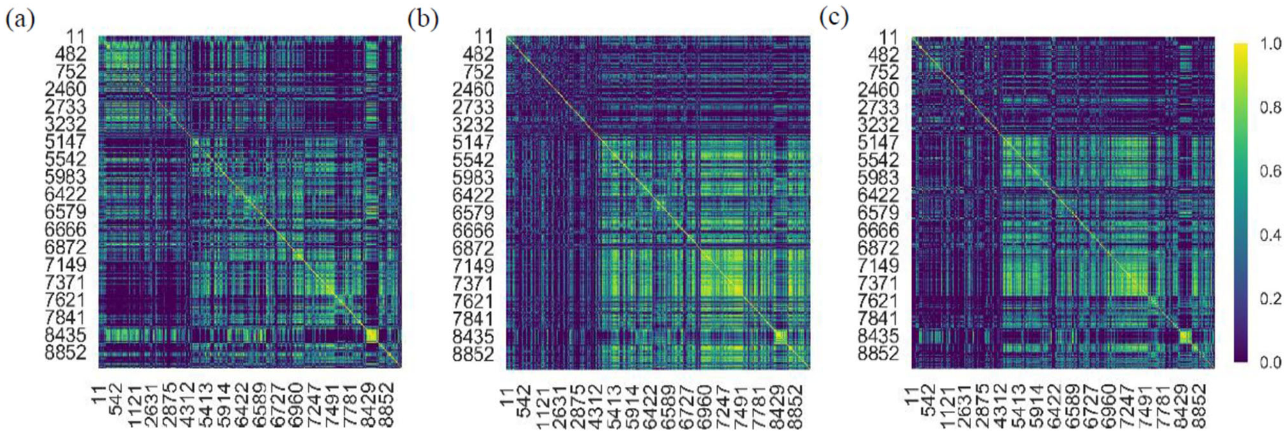

Fig. 3 Heat map of product proximity under 2006–2010. a World, (**b**) China, and (**c**) the US.

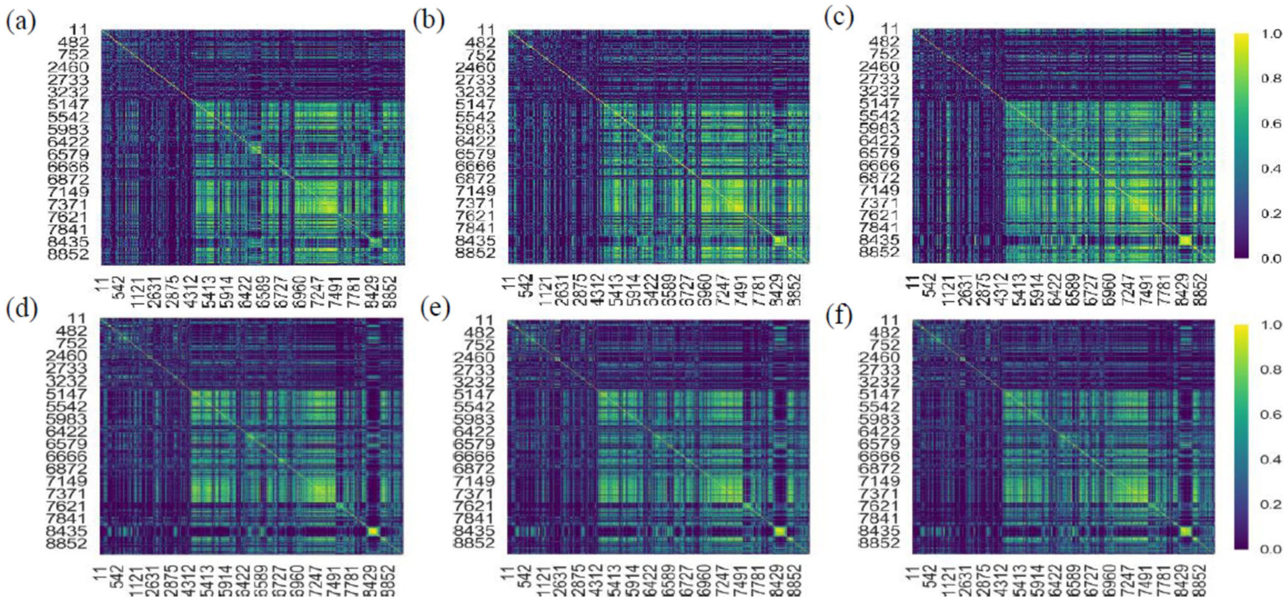

Fig. 4 Heat map of product proximity in China and the US at three time. a–c Heat map of product proximity in China at 2001–2005, 2006–2010, 2011–2015; **d–f** Heat map of product proximity in the US 2001–2005, 2006–2010, 2011–2015.

corresponding to codes 4213–9710 are easier to carry out the transformation of export products.

On the other hand, Fig. 4 follows the time nodes 2001–2005, 2005–2010, and 2011–2015. The visual changes corresponding to China are more pronounced, indicating that increasingly brighter products have an increasing probability of co-exporting to the China trade market. In contrast, the changes in the proximity heat map corresponding to the US under different nodes are relatively insignificant (see Fig. S1 for a comparison with the world in Supplementary Material). Numerically, the highest scores for the world product proximity matrix range from 0.1 to 0.2 (from 0.0 to 1.0 in 0.1 units, the same below) and the average scores are 0.1871, 0.1934 and 0.1940 respectively, while the highest scores for the China product proximity matrix range from 0.0 to 0.1 and the average scores are 0.1493, 0.1545 and 0.1551 respectively. The highest proximity matrix scores for US products also range from 0.0 to 0.1, but the mean scores are 0.1403, 0.1382, and 0.1345, respectively. The higher the proximity between products, the greater the likelihood of them being co-exported. From the observed trend in product proximity changes, it is evident that as a trade partner, China's market is increasingly conducive to achieving co-exportation and transformation among products. Conversely, the situation is the opposite for the US. In the US market, the records of products with a proximity value of 0 are the most numerous and are continuously increasing (specifically 41614, 43786, 54308). China follows suit (33766, 35478, 42964), while the global market has the least number of such records (7378, 6830, 7842). From the point of view of temporal evolution, although the US has a similar bright degree of proximity with China partition its change traces are not obvious, compared to China in the 8421-8744 corresponding product range (mainly textiles and other clothing manufactured goods, professional scientific control electronic mechanical instruments, meters, equipment) apparently gradually brightened, more and more countries will be common exports of these products to the China market. This also answers the Fig. 1 whether China is a more preferable trade object of the 8th category of products, in fact, from Fig. 4d–f can be seen 8421–8744 products whose exporters more first in the US market to form a dominant export and continued, and from Fig. 4a–c can be seen in the China market gradually formed, the current capacity of these two markets to accommodate this part of the product equivalent.

In short, the proximity values corresponding to the same product codes in different trade perspectives may be different,

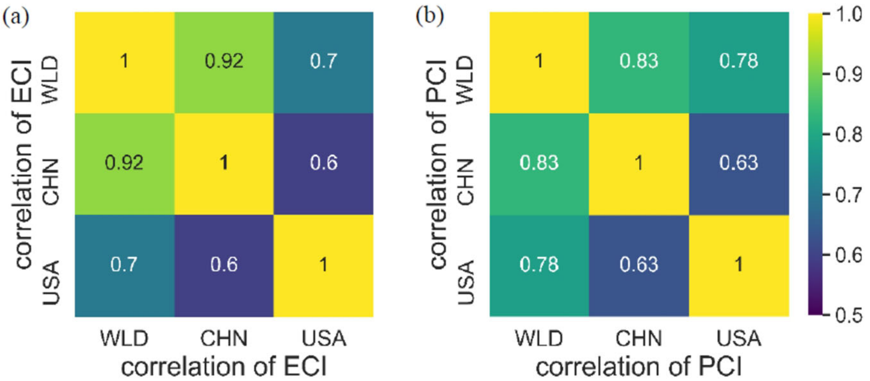

Fig. 5 Correlation coefficients of ECI and PCI. a ECI for 2006–2010, (**b**) PCI for 2006–2010.

and their positions in the corresponding product network space may also be different. The areas with brighter colors have a greater degree of proximity and are distributed in the core gathering areas of the product space, which are easy to transform and upgrade to other nearby locations; while those parts with darker colors have a lower degree of proximity and relatively fewer products are connected to them, and they want to the road is long and full of hardships to have advantageous export capacity in more complex products. For the proximity heat map in Fig. 3 from different perspectives, the proximity between the products with coordinates 8421-8744 is very high and contrasts with the proximity of the rest of the products, indicating that the proximity relationship between these products is almost equivalent under different trade perspectives, and there is a high probability that they can successfully export trade products regardless of which trade object is chosen.

In addition, from the supplementary material table Table S4, it can be found that the top 200 products in the world in terms of proximity in the three time points are mainly apparel and clothing accessories products with codes starting with 84, followed by electronic machinery, instruments and their parts products starting with 77. China in 2001–2005 for wheat, palm oil and other animal and vegetable oils, general industrial machinery and equipment, 2006–2010 transformed into apparel products similar to the world, 2011–2015 although the two products with the highest proximity are palm kernel oil, but similar to the world perspective its apparel products account for a higher proportion, during the period with the passage of time the proximity value of apparel products increasing; the US proximity higher products are gaseous petroleum gas and electricity, hogs, newsprint, potatoes, etc., similar to the world and China, the proximity values between apparel products are also high.

Correlation analysis. The screened trade data of 128 countries from 2001 to 2015 were first organized into corresponding country-product trade matrices, and the country complexity and product complexity indices were calculated separately using the economic complexity index based on MR, and then the ECI values of 117 countries and PCI values of 757 products that co-existed under the three perspectives were extracted for analysis, and the results under each trade market perspective of the world, China, and the US were obtained by averaging the data every five years.

Understanding the condition between different trade markets from an overall perspective is an important foundational analysis. This paper employs the Spearman correlation coefficient formula to ascertain the relationship among the economic complexity measurement results from three distinct trade perspectives. As shown in Fig. 5a, b, the correlation coefficients of ECI and PCI for the three trade systems of the world, China, and the US at the 2006–2010 nodes are shown, and the p-values of the two figures are less than 0.001 after Spearman's significance test.

To begin with, the correlation coefficients of ECI for each trade exporting country's own economic development status are shown in Fig. 5a. It can be observed that the correlation level between China and the world perspective is very high, around 0.9, significantly higher than the correlation level between the US and the world perspective. This emphasizes the higher consistency of China's trade exchanges with other countries in global trade. The lowest correlation, at only 0.6, between China and the US implies significant differences in economic trade patterns between China and the US. For each exporting country, the US market exhibits more distinct characteristics compared to the Chinese market. To further illustrate the situation, Fig. S2 in the Supplementary Material shows that the correlation degree between China and the world increases and then stays the same as the nodes advance in time from 2001–2005, 2006–2010, 2011–2015. The correlation between China and the world increases and then stays the same as the nodes advance, while the correlation between the US and China decreases and then stays basically the same in both the world and China perspectives. The correlation coefficients of product complexity in the trade market are shown in Fig. 5(b), where the degree of correlation between the China perspective and the world perspective has similarities with the case of economic complexity index in Fig. 5(a), i.e., both increase from the 2001–2005 to 2006–2010 nodes first and then remain unchanged until the next 2011–2015 node, and the degree of correlation between the US and the world perspective shows a gradually decreases, and the degree of product complexity correlation between China and the US at each of its nodes remains around 0.65. Although the average correlation between China and the world is also higher than that between the US and the world at this point, the difference is reduced compared to the correlation of economic complexity index. This indicates that the trade position of each product-exporting country in the China market is closer to the average of the world market than in the US market, as is the degree of dependence on the product. Therefore, the impact of each exporting country's choice of China as an object of trade on its own economic development is closer to the average level of trade in the world market, while in the case of the choice of the US as an object of trade there is a greater difference with the average level of trade in the world. In a random situation, it can be said that choosing China as a trade object is a more conservative trade choice, while choosing the US is riskier, and this situation is gradually strengthened over time.

Generally speaking, these research findings deepen our understanding of the characteristics and differences between China and

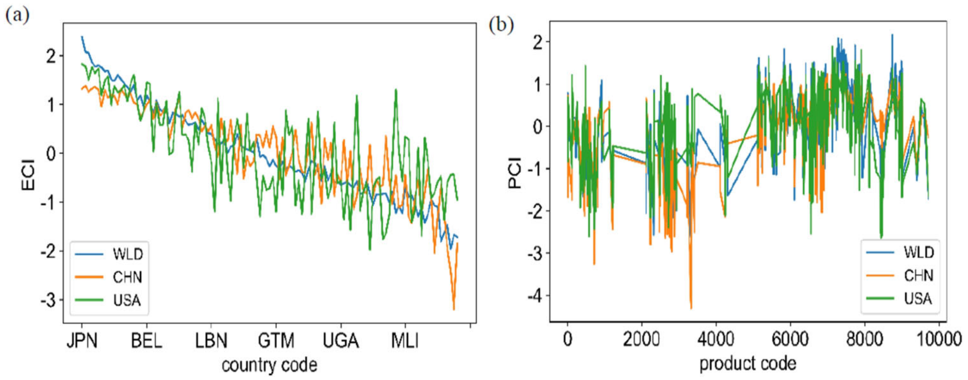

Fig. 6 Trends in the complexity of countries and products in the World, China, and the US Trade Perspective, 2006–2010. a Trends in economic complexity index (ECI), with horizontal coordinates indicating country names in the same order as in Table S2. **b** Trends in product complexity index (PCI), with horizontal coordinates indicating product codes in the same order as in Table S3.

the US in global trade, as well as the strategic variations of product-exporting countries in different market selections.

Comparison of change trends. However, it is not possible to know the comparison of specific countries or products under the three trade perspectives just from the overall correlation coefficient values. To provide a more intuitive representation of the changes over the period, the results of economic complexity measurements were visualized to illustrate the trends in economic complexity under three perspectives, as shown in Fig. 6 below. And the results are similar within different time points (see Supplementary Material Fig. S3). From the measurement results of the complexity of countries and products under different perspectives, the overall trend of changes is generally consistent in the three trade perspectives. The proximity in results across different time nodes indicates a certain degree of consistency in the development of these two indicators in various trade markets.

The visual comparison of the changes in Fig. 6 shows that the overall trends in both the complexity of countries and products measured in the three perspectives are broadly convergent. We can see that the highest complexity value for machinery and transportation equipment in category 7 in the world trade perspective is higher than that in the China-US trade perspective, indicating that both countries are less dependent on this product than the world average, so to some extent these two countries are not the best trade partners for this product. Similarly, China, as a country with the highest coal reserves, has the lowest complexity of raw products such as coal, coke and briquettes in category 3 in the trade perspective, and its dependence on such products in its trade market is lower than that of the US and the world. Overall, the countries in Fig. 6a corresponding to the first 1/6 of the horizontal coordinates are in a relatively high and stable level of ECI in all three trade perspectives, while for the last 1/3 of the data the variability among the three is very significant and fluctuates widely among which the US has two upper peaks of fluctuation while China has a significant lower peak, indicating that compared to the world average, some The variability of the economic position that countries occupy in a given trade market is sometimes very significant, which affects the potential for trade competition of product exporters in a given trade market, as well as the formation of more resilient export partnerships, because a high economic position is largely related to the export of products to that market as products on which they are more dependent. In cases such as the new crown virus, having a good trade base in a disruption-resistant trade market will provide an advantage in achieving a smooth trade flow cycle.

In the correlation coefficient analysis, we only know the overall relationship between the three, but there is no way to determine the relationship between the specific complexity values of countries or products. At this point, Fig. 6 further illustrates the variation among the three. The country codes in Fig. 6a are arranged in descending order according to the average rankings of national ECI from 2001 to 2015, as provided by the Harvard University CID Lab official data. This empirical finding also substantiates the conclusion in terms of the observed trends. For example, the ECI in the world perspective is in the middle in most cases, and the values for China and the US are constantly fluctuating above and below it, especially in Fig. 6b where the horizontal coordinates correspond to categories 2 to 4 (including crude material products other than fuels in category 2, such as seeds of various crops, natural rubber, wood, raw silk, etc., and related materials such as mineral fuels and lubricants in category 3 and animal and vegetable oils, fats, and waxes in category 4, animal and vegetable oils, fats, and waxes, etc.) of these products have low product complexity in the China trade market. The products within these categories exhibit lower ECI in the Chinese trade market, suggesting a lower probability of obtaining favorable economic trade-related returns in these categories from the Chinese market. All are presented in the figure with the results in the top position in the US trade perspective and in the middle position in the world trade perspective. As for the other range of products, the corresponding situation varies, but generally it also shows that the complexity value of the corresponding products in the US or world trade perspective is relatively high, and China is usually in the middle or lower region. In general, China tends to exhibit lower values of PCI for products within these categories, typically positioned in the middle or lower regions. This may imply that in these categories, China has a relatively lower dependence on these products. These conclusions further enhance our understanding of the changes in ECI and PCI under the three perspectives, providing additional details for a more in-depth analysis of the economic positions and product dependencies of countries in specific trade markets.

Extreme values mining. Based on the above analysis, although we can know the overall situation and trends of the three trade perspectives, we cannot know the extreme values of the differences between a particular trade perspective and the world average, but these extreme values are significant when exporting countries make trade target selection, because they often represent the more disparate economic development gains in different markets or deeply affect the strategic layout of exports in the trade market. A significantly lower level of complexity compared

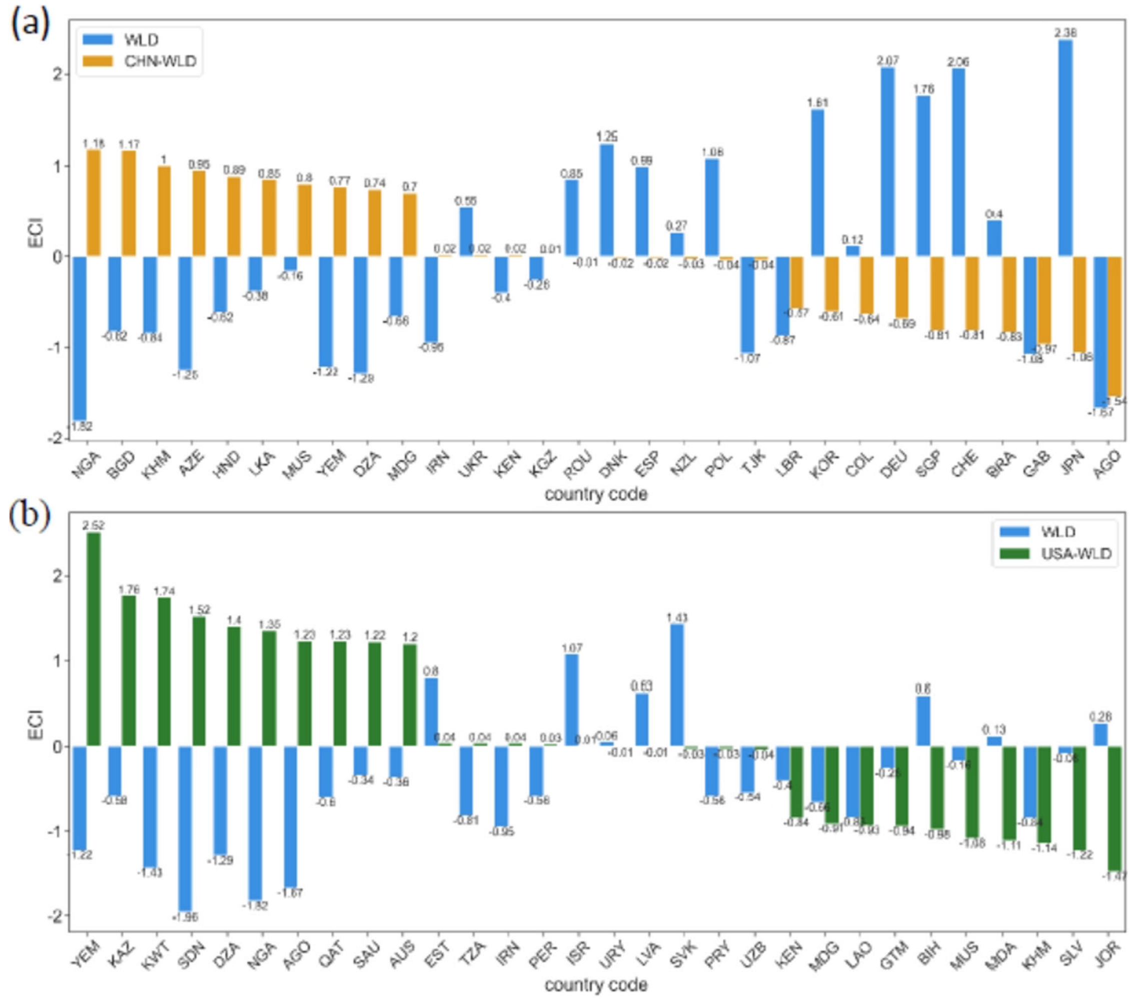

Fig. 7 Analysis of the complexity of countries gap extremes for 2006–2010. a Extreme values of the complexity of countries gap between China and the world; (**b**) extreme values of the complexity of countries gap between the US and the world.

to the world average means that the trade market is less dependent on this product than the world average and needs to try to find a more appropriate trade target, which is similar to the interpretation of the complexity of countries. In the specific calculation process, the complexity value of a product in the China or US trade perspective is subtracted from the complexity value of the corresponding product in the world trade perspective, and the results with more significant differences, here the top ten products with positive differences and the bottom ten products with negative differences, and the results with the least differences, here the ten products with the least differences from the complexity value in the world trade perspective, are plotted together with the original values in the world perspective. are plotted together in Fig. 8. At the same time, the calculation process for the extreme values of the countries' complexity is similar, and the results are shown in Fig. 7.

The results of the overall calculation of correlation coefficients in Fig. 5 above do not exactly correspond to the extreme values obtained in this section. Although the correlation analysis shows a higher correlation coefficient between the complexity results of products in the US and the world market, indicating a stronger overall correlation, in this context, the extreme values analysis in Figs. 7 and 8 reveals a larger disparity in product complexity, surpassing the difference observed between the complexity of countries in the two markets. Meanwhile, in the correlation analysis, the complexity of countries in the Chinese and world markets appears more similar. However, upon examining the differences in minimum values, it becomes evident that the complexity of products in the Chinese and world markets is closer to each other than to corresponding countries' complexity. In addition, it should be noted that in Fig. 7, the positive differences between China, the US, and the world (CHN/US-WLD) indicate that the original country complexity values in the world market are negative. This implies that in the analysis results where significant positive differences exist, the economic trading position of these countries in the world trade market is much lower than in the Chinese and US markets. The situation is similar for product complexity in Fig. 8, where the extreme values of positive differences between China and the US compared to the world correspond to negative values of the original product complexity of the world, i.e., the average degree of dependence in the world trade market is lower, and at this time the China and US markets can have a better competitive advantage and thus gain more economic benefits.

When the difference between China, the US, and the world (CHN/US-WLD) is significantly negative, the diversity of differences becomes more pronounced. Regarding country complexity, in the Chinese trade market, the complexity of these countries tends to be positive in their corresponding world trade markets, while in the US trade market, the complexity of these countries tends to be negative in their corresponding world trade

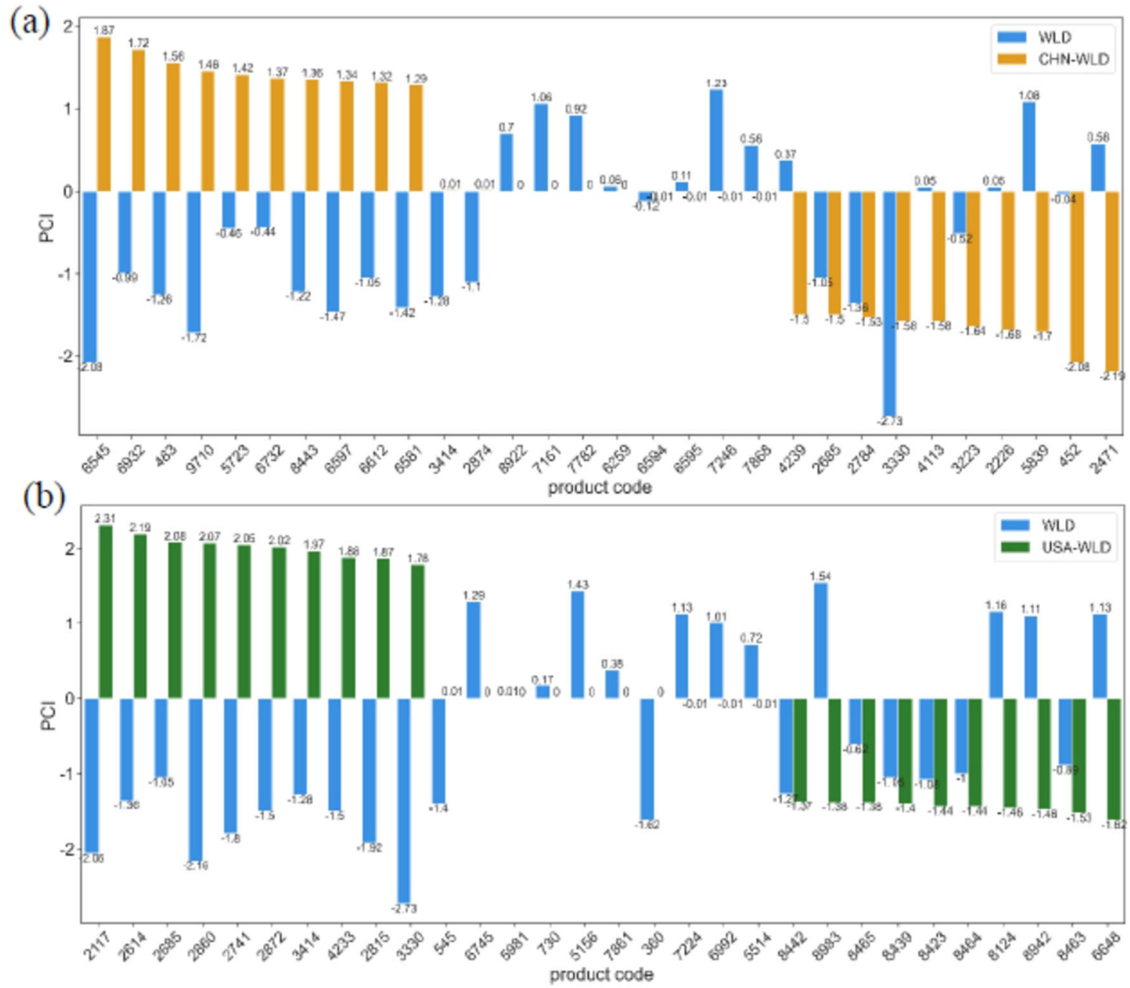

Fig. 8 Analysis of product complexity gap extremes for 2006–2010. a Extreme values of the product complexity gap between China and the world; (**b**) extreme values of the product complexity gap between the US and the world.

markets. This indicates that in the Chinese market, where the trading position is lower than the world trading position, the countries are mostly recognized as developed countries worldwide, while the US is generally considered a developing country. Compared to the world trade market, the economic status of developed countries such as JPN(Japan) and CHE(Switzerland) in the China market is downgraded, while only developing countries such as GTM(Guatemala) in the US market are further downgraded in their trade status.

On the other hand, in terms of temporal development (see Supplementary Materials Figs. S5, S7, and S9), when the product complexity of Chinese market compared to the world market shows a significantly negative difference, the corresponding product categories from 2001 to 2005 mostly consist of Class 2, crude materials other than fuel, or Class 3, mineral fuels, except for edible items. From 2006 to 2010, Class 7, machinery and transport equipment, or Class 8, manufactured goods, dominate. Finally, from 2011 to 2015, the range of product categories involved becomes relatively richer, and during this period, the gap in product complexity with the world market shows a decrease followed by an increase. In contrast, the difference between the US and the world market in terms of product complexity among the top 10 products with the largest differences is significantly smaller than that of Chinese. Furthermore, from 2011 to 2015, the products involved in the world market are all Class 7 or Class 8 products, and these products themselves have a higher level of product complexity in the world market.

We can find that although the trend of changes in the complexity of the counties or products of China, the US and the world trade perspective is similar, there are still many countries or products with different situations that cannot be ignored. The economic development status of countries in different trade markets is very different as the status of trading partners in different markets is also different, and the complexity value of the same product may appear more different, which in turn has a greater impact on the economic development efficiency in the trade target market and the bargaining power of the product itself, and the relevant countries or products need to be more careful when choosing trade targets. Simultaneously, the importance of the resilience of trade markets to disturbances is noteworthy. In the context of global trade environment turbulence, a trade market with strong resilience is crucial for maintaining smooth trade and preserving economic standing. When selecting trade partners, countries need to take into account the resilience to disturbances in the target market, aiming to establish a more robust foundation for trade.

Conclusions and discussions

This paper utilizes the economic complexity approach to analyze the diversification paths, trade positions, and product dependence of various exporting countries in the Chinese and US markets based on international trade data. It provides a new measurement framework for selecting trade partners in light of the evolving trade landscape. The study begins by constructing heatmaps of product proximity in different trade markets, revealing that the world trade market exhibits a relatively even distribution of product proximity among different product categories. Over time, the Chinese market shows an increasing proximity between textile-related products in the eighth category, indicating a strengthening overall product proximity relationship. In contrast, the overall product proximity in the US market demonstrates a declining trend, particularly evident in the weakened relationship between animal oils and fats (category 431*), nitrogen compounds (category 514*), and metalworking machinery (category 73**). Consequently, expanding the export product variety in the US market for these specific products becomes more challenging. Overall, China presents a trade market that offers relatively easier opportunities for diversifying export products compared to the US. In the analysis of the complexity of countries and products, it is observed from a macro perspective that the economic trade positions of countries exporting from China and the world market, as well as the degree of product dependence, exhibit a closer resemblance between the two. This suggests that China, overall, represents a relatively conservative choice of trading partner, whereas the volatility between the US and the world is stronger, indicating a comparatively riskier option for trade partners. Moreover, this trend intensifies over time. At a micro level, significant differences in complexity exist for specific export products in particular trade markets. For instance, China, as the world's largest coal reserve holder, exhibits low complexity values for category 3 products such as coal and coke raw materials, implying a limited import dependence for these products. Hence, China may not be an ideal trade partner for countries specializing in the export of such products.

Through this study, our objective is to furnish trading entities with profound insights and dependable recommendations derived from the genuine trading capacities discerned from exporting countries and various trade markets. This is achieved by employing methodologies that prioritize the quality of economic development and data-driven economic complexity. Such an approach aids in making informed decisions amid the current tumultuous trade environment, refining international trade strategies, and fostering long-term, sustainable development in global trade. Exploring the economic complexity theory across diverse trade markets is crucial for further expanding the application scope of economic trade research (Ren et al. 2020; Mariani et al. 2019). Using economic complexity as a comprehensive measure of productive knowledge inherent in export products, this study primarily focuses on the classical economic complexity index tool based on MR and examines the complexity measurement outcomes across three markets. However, there remains a dearth of application of alternative measures of economic complexity to a broader range of trade markets. Consequently, the attention transitions towards generating pertinent global trade network results and conducting comparative analyses with identification methodologies employed in prior network research (Fan et al. 2014; Bartesaghi et al. 2022).

Since the emergence of globalization, almost all countries have participated in international trade. The 2030 Agenda for Sustainable Development explicitly emphasizes the significant role of international trade in achieving sustainable development goals. However, faced with uncertainties such as pandemics and wars, the international trade network requires the development of more effective methods to promote favorable international trade cycles (FAO 2022). This paper applies the economic complexity approach to address the issue of trade partner selection in the international trade network. By leveraging the information on product proximity among different markets, it reveals the potential of trade countries to diversify their export product types in the future. Additionally, by capturing the current trade position of each exporting country in different markets and the level of product dependence, it provides a comprehensive basis for trade countries by considering both future development prospects and current economic conditions. Furthermore, this method also serves as a new reference strategy for exporting countries to formulate their future trade layout and planning based on their current productive knowledge.

Data availability

The open datasets used to support the findings of this study are available from the Growth Lab at Harvard, University. International Trade Data (Sitc, Rev. 2). V7Harvard Dataverse, 2019. https://doi.org/10.7910/DVN/H8SFD2.

Received: 9 August 2023; Accepted: 5 July 2024;
Published online: 16 July 2024

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Acknowledgements

The work is partially supported by National Natural Science Foundation of China (Grant Nos. 61803137 and 11805128), and Major Humanities and Social Sciences Research Projects in Zhejiang Higher Education Institutions (Grant Number: 2021QN006).

Author contributions

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Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval was not required as the study did not involve human participants.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-024-03450-2.

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