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Rethinking the competition of export trade based on the bipartite network[☆]

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ABSTRACT

As trade competition has regained attention in the current global context, this article seeks to develop a competition measurement grounded in a complex-network framework, thereby overcoming the limitations of conventional indicators that neglect "heterogeneity" and "interconnectedness". We construct a country–commodity bipartite network based on the RCA index and apply the asymmetric reflection algorithm in combination with the Matrix-Estimation Exercise to calculate two indicators: generalized competition intensiveness of country (GCC) and of product (GCP), which quantifies the overall competition status at both the country and commodity levels. Subsequent algorithmic discussions and four case-based analyses support the validity and reliability of the proposed measures, further demonstrating that GCC and GCP are closely interrelated, mutually reinforcing, and determined by export structures rather than trade volumes. Robustness checks across different RCA thresholds, eigenvalue specifications, and trade-data statistical calibers consistently confirm the stability of the results. Cross-sectional comparisons with traditional indicators highlight the superiority of the proposed framework, showing that conventional measures tend to underestimate the competition intensiveness of underdeveloped economies while overestimating that of advanced ones. Finally, sensitivity analyses of intra-country and intra-sector shocks distinguish between two categories of countries, yielding policy insights that suggest divergent developmental pathways.

1. Introduction

The global economic and trade landscape is undergoing profound restructuring. The multilateral trading system, represented by the World Trade Organization (WTO), has fallen into a reform impasse, while trends of regionalization and rule fragmentation are accelerating, rendering the global governance environment increasingly uncertain [1]. At the same time, recurrent geopolitical risks are driving a shift in global production and supply chains from an "efficiency-first" orientation toward a focus on "security and resilience", compelling both multinational enterprises and national governments to adjust their strategies in response to external shocks [2]. In this process, the relative dominance of traditional advanced economies has been eroding, while emerging markets

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and developing economies have risen through intensified "South–South" cooperation and multilateral initiatives, accelerating the transformation of the global economic power structure toward multipolarity [3].

These structural changes have not only reshaped the logic of international competition but also introduced unprecedented complexity into product-level challenges such as market access, regulatory compliance, and supply chain configuration [4]. Competition among nations is no longer confined to tariff and efficiency considerations but increasingly extends to rule-making, institutional influence, and industrial security [5]. Against the backdrop of globalization's shift toward a more "fragmented regionalism", developing a scientific and systematic framework to quantify competition at both the national and product levels has become not only a pressing academic issue but also a practical necessity for improving global governance and informing policy choices.

The first indicator used to measure "competition" was the Revealed Comparative Advantage (RCA) index proposed by Balassa [6]. The RCAs indicate some kind of "competitiveness"[3] by measuring the comparative advantage of exports exhibited by one economy relative to another in a certain product. In fact, since it was proposed, the RCA has been gradually applied to a large number of studies on trade competition, which can be roughly divided into two directions: one is to directly analyze export trade competitiveness based on the RCA [7,8]; the other is to remeasure export trade competition by modifying the RCA index or constructing new indicators based on it [9,10].

Of course, indicators based on RCA have certain inherent advantages. Most notably, they allow for fine-grained analysis at the bilateral level. However, RCA primarily reflects the advantageous position that arises from one country possessing greater capability relative to another, rather than the competitive relationship that emerges from structural overlapping between them. Thus, To avoid the drawbacks of the RCA index in terms of calculation methods and cross-period comparisons [11,12], Glick and Rose [13] proposed an indicator "Trade Linkage" to describe the similarity of productions in the export trade — a typical bilateral indicator for bilateral trade competition reflecting overlapping structure (rather than "competitiveness"), which is improved by Blázquez-Lidoy et al. [14] and then widely used in the study of trade competition [15–17]. In addition, some indicators of intra-industry trade, such as the G-L Index proposed by Grubel and Lloyd [18], the Marginal Intra-Industry Trade Index proposed by Hamilton and Kniest [19], etc., have been similarly used to study international trade competition.

However, these indicators share a common problem: they ignore the economic heterogeneity of commodities themselves while measuring trade competition; at the same time, they treat countries as isolated objects of study and ignore the linkages between countries. Concretely speaking, in the process of constructing and calculating, such indicators regard the impact of different types of commodities on competition as equivalent; and in addition, the calculation of individual countries is based solely on the exports of each category of commodities in that country, which implies that changes in the competition of one country will not affect other countries.

In fact, with the increasing trade between countries, the trade relations of individual countries tend to form an organic whole and thus have the characteristics of a complex system [20,21]. The Linear-Regression Models commonly utilized in traditional economic analysis seem to be difficult to describe and predict complex economic systems, meaning that the complexity of economic systems needs to be emphasized [22]. Therefore, state-to-state relations in the trading system need to be examined from a global perspective by borrowing complex network analysis tools and complexity theory.

Since unweighted undirected networks were introduced into the research of international trade [23], some scholars have conducted research on trade issues or economic issues based on this method, and models such as weighted networks and open flow networks have also been introduced one after another [24,25].

However, worth mentioning, such models just adopted 1-mode networks, which are composed of the vertex set of the same type and the edge set of edges between vertices; this type of network can only map 1-mode data and discard deeper trade information. In reality, however, trade relations between countries are usually reflected by commodities, i.e., countries are indirectly linked to each other through trade information of countries on various commodities, rather than directly. Therefore, when studying international trade issues, the relationship between countries and commodities needs to be included in the analytical framework. Specifically, it is necessary to first consider that different commodities affect the country differently, i.e., the economic heterogeneity of different commodities needs to be considered; it is also necessary to consider that changes in the trade situation of a country will have an impact on the economic properties of the commodities involved, which in turn will affect other countries. Therefore, the construction of international trade networks should consider the use of complex network models that can map 2-mode data.

Borgatti and Everett [26] first proposed the bipartite network based on 2-mode data and proposed an algorithm for the clustering coefficient and the centrality. Later, Hidalgo et al. [27] introduced the bipartite network into international trade research, based on the RCA, and proposed the concept of Product Space. It is a commonplace that the centrality of vertices is widely used in studying economic issues; however, the algorithm of the traditional 1-mode networks for eigenvector centrality is not suitable for the bipartite network, because calculations on the centrality only need to be based on the Adjacency Matrix within 1-mode networks. However, the adjacency matrices of the bipartite network are asymmetric. Hidalgo and Hausmann [28] pioneered the Method of Reflection (MR). They studied the Economic Complexity by constructing a linear iterative calculation based on this method.

[3] In this article, the terms "competition" and "competitiveness" will appear several times. Although they are often used interchangeably in some fields, this article will draw a distinction between them and, on this basis, elaborate on several derivative concepts in the sections that follow. First, competition is a broader concept, i.e., one that describes, in a general sense, relations of rivalry, antagonism, or structural overlap. It can be used as an "issue area", as in this article's discussion of "trade competition", or as a "measurement", referring to a pairwise bilateral competitive relationship between two actors (e.g., countries) or the overall (generalized) competitive configuration among multiple actors (e.g., countries). By contrast, "competitiveness" is a narrower term, i.e., typically referring to a measurement that captures the capacity or advantages demonstrated by actors in competitive settings.

Since then, many scholars have also conducted researches on the topological structure, indicators' constructing and corresponding economic significance based on the bipartite network model and the MR [29–31]; within the bipartite network, some scholars have also targeted some special economic issues, such as competitive advantage of nations, economic growth and economic recovery potential, etc., have been analyzed empirically [32,33].

Therefore, in order to describe the trade relations between countries more objectively, this article aims to explore the competition of countries in export trade from a global perspective based on a bipartite network. First, this article frames an overarching concept, i.e., "competition intensiveness",[4] to describe the overall degree of external competitive pressure a country faces within the global trade network; this notion is analytically distinct from traditional understandings of trade competition and competitiveness, and the subsequent sections seek to develop a quantitative measure for such a concept. Second, this article constructs a country–commodity bipartite network based on the RCA index and then develops two measure: generalized competition intensiveness of country (GCC) and generalized competition intensiveness of product (GCP), through the asymmetric reflection algorithm combined with the Matrix-Estimation Exercise, in order to quantitatively assess both the overall competition status of countries in export trade and that of the sectors in which products (commodities) are embedded. Building on this foundation, this article conducts a series of extended analyses. Specifically, it

- (i) provides algorithmic discussions and four case-based analyses of the results, all of which support the reliability and validity of the proposed approach;
- (ii) performs robustness checks through algorithmic adjustments, confirming the stability of the results;
- (iii) compares the proposed indicators with two conventional trade competitiveness measures grounded in traditional economic frameworks, thereby highlighting the advantages of our approach, i.e., the ability of a complex-network framework to capture "heterogeneity" and "interconnectedness" among actors;
- (iv) conducts sensitivity analyses of trade shocks at both the intra-country and intra-sector levels, offering distinct and insightful policy pathways.

The remainder of this article is organized as follows: Section 2.1 develops the overall framework of the algorithm and describes the computational methods for the two competition intensiveness indicators. Section 3 presents the results for countries (or regions) and products, accompanied by algorithmic discussion. Section 4 compares the computational outcomes with real-world cases to demonstrate reliability and validity. Section 5 recalculates results under three types of algorithmic adjustments to examine robustness. Section 6 contrasts our measurement with conventional indicators, illustrating how the proposed approach avoids their limitations. Section 7 performs sensitivity analyses to show how commodity-level trade shocks affect country-level competition intensiveness, thereby generating policy insights. Finally, Section 8 concludes this article by offering policy recommendations and outlining feasible agenda for future research.

2. Method

2.1. General framework

The bipartite network can be able to encompass the trade information of individual countries on different products and thus explain the deep relationships between countries and products [28,34,35]. In the framework of the bipartite network, the trade relationship between countries and products can be represented by the Adjacency Matrix $\mathbf{M}$, in which the element M_{cp} is the trade indicator of country c on product p.[5]

Based on the bipartite network, complexity theory aims to transform the economic problem into two dimensions — X_c and Y_p, which respectively represent the economic properties of country and product. X_c, which represents the country, is related to $Y_1, Y_2, \dots, Y_p$ and M_{cp}, namely it can be expressed as the function of $Y_1, Y_2, \dots, Y_p$ and M_{cp}; Y_p is just the same. Studying economic problems is just equal to solving the coupled linear equations below:

$$\begin{cases} X_c = f(Y_1, Y_2, \dots, Y_p, M_{cp}) \\ Y_p = g(X_1, X_2, \dots, X_c, M_{cp}) \end{cases} \tag{1}$$

[4] It is worth noting that such a concept differs from traditional usages in two respects. First, although its quantification is based on RCA, the resulting measurement does not capture "competitiveness" — that is, it does not reflect advantage or competitive capability. Instead, it represents solely the competitive relationship that arises from the overlap of trade structures. Second, such a concept also departs from conventional notions of "trade competition": it is a multilateral, general-level indicator of overall competitive conditions rather than a bilateral measure of competition between pairs of countries. In other words, it captures the aggregate competitive pressure exerted on a given country by all external trade partners (excluding itself).

[5] In this article, the terms "product" and "commodity" are used interchangeably. The choice of "product" is primarily driven by notation, specifically the use of the symbol p and the subscript $_p$, which avoids potential confusion with countries denoted by c. The term "commodity", by contrast, is used when the context emphasizes that the objects of analysis are tradable commodities for export, rather than "products" in a broader economic or industrial sense.

To consider $f(\cdot)$ and $g(\cdot)$ as linear functions allow one to recast the determination of X_c and Y_p as the solutions of an eigen-problem of a suitable (approach dependent) transformation matrix W [35]:

$$\begin{cases} X_c = \frac{1}{\sqrt{\lambda}} \sum_p W_{cp} Y_p \\ Y_p = \frac{1}{\sqrt{\lambda}} \sum_c W_{cp} X_c \end{cases} \Longleftrightarrow \begin{cases} X_c = \frac{1}{\lambda} \sum_p \sum_{c'} W_{cp} W_{c'p} X_{c'} = \frac{1}{\lambda} \sum_{c'} N_{cc'} X_{c'} \\ Y_p = \frac{1}{\lambda} \sum_c \sum_{p'} W_{cp} W_{cp'} Y_{p'} = \frac{1}{\lambda} \sum_{p'} G_{pp'} Y_{p'} \end{cases} \tag{2}$$

where W_{cp} can be calculated via M_{cp}; λ is the eigenvalue; $N_{cc'} = (\mathbf{W}\mathbf{W}^T)_{cc'}$ and $G_{pp'} = (\mathbf{W}^T\mathbf{W})_{pp'}$ are both symmetric square matrixes. N/G can be interpreted as the proximity matrixes, describing the similarity of any two countries/technologies in terms of their "participating constructure".

In this way, the key to the study of economic problems is to describe the relationship between the two properties X_c and Y_p, and then solve the eigen-equation based on certain algorithms to obtain the corresponding quantified result $\hat{X}_c$ and $\hat{Y}_p$.[6] This article will also follow this idea to study the competition of countries and products within the framework. In the context of this article's focal concept, "competition intensiveness", X_c refers to the actual degree of aggregate competitive pressure that country c faces from its external trade counterparts. Its quantification counterpart, $\hat{X}_c$, is the algorithm-based quantified estimate computed in this article, corresponding to the indicator of GCC introduced later. Similarly, Y_p denotes the true level of overall competitive pressure experienced by countries within the field of product p, while $\hat{Y}_p$ is its quantified estimate, corresponding to the indicator of GCP later on.

It is worth mentioning that the construction of the bipartite network in previous studies mostly follows the ideas of Hidalgo and Hausmann [28], using the RCA as an indicator to describe the trade information between countries and products [36,37], namely:

$$RCA_{cp} = \frac{V_{cp} / \sum_p V_{cp}}{\sum_c V_{cp} / \sum_c \sum_p V_{cp}} \tag{3}$$

where V_{cp} represents the export trade volume of country c on commodity p. And then, unweighted — undirected bipartite network can be constructed, and whether there will be edges between vertexes of country and product, just depend on if $RCA \geq 1$, namely:

$$M_{cp} = \begin{cases} 1, & RCA_{cp} \geq 1 \\ 0, & RCA_{cp} < 1 \end{cases} \tag{4}$$

The reason for adopting $RCA = 1$ as the criterion for establishing unweighted–undirected bipartite network edges is that, in international trade, $RCA = 1$ is generally regarded as a neutral position, implying neither a relative advantage nor a disadvantage. When $RCA \geq 1$, it indicates that the export share of a given commodity in a country exceeds its share in world exports, meaning that the country has a comparative advantage in that product in the international market. Conversely, when $RCA \leq 1$, it implies the absence of comparative advantage in the international market.

But this article will retain the specific RCA values when describing country–commodity relationships and will construct a weighted bipartite network. At the same time, when measuring competition intensiveness, we will still rely on the unweighted–undirected bipartite network derived from whether RCA exceeds 1. In addition, for robustness checks, we will also consider alternative thresholds for the RCA criterion.

2.2. Asymmetric reflection algorithm

Within the framework mentioned above, this article will construct an asymmetric reflection algorithm, referring to the idea of the MR proposed by Hidalgo and Hausmann [28] and doing some adjustments slightly, namely expressing the one type of economic property as an asymmetric linear iterative function of another type; then the proximity matrixes **N** and **G** can be calculated through algebraic operations.

To construct the iteration, this article first defines two indicators R_c and C_p, which describe the "rivalry" between countries and the "competition"[7] between industries where products located, respectively. Then consider the influence mode between the two indicators: the R_c will depend on three factors: the number of product types, the industry competition C_p of corresponding products, and the participation degree in export of each type of products. The more types of export products, the higher C_p, and the deeper participation in products whose industry are more competitive, the higher the R_c; and just the same as the C_p, However, it is worth noting that the product requires the participation of at least two countries to form competition in the industry, so if only one country participates in the export of a certain type of product, then C_p should be 0.

It can be found that these two types of indicators will affect each other and be accompanied by iterations within calculation, which is the same as the idea of the MR, the differences between them are: in the MR, the mutual influence between the two types of indicators is asymmetrical in this article, and the two types of indicators have anisotropic impacts on complexity. Therefore,

[6] Here, we distinguish between two types of concepts. The symbols X_c and Y_p without hats denote the underlying "properties", i.e., the true, inherent attributes of the objects in this article. In contrast, $\hat{X}_c$ and $\hat{Y}_p$ with hats represent the quantified estimates (or we can say "approximations") of properties, derived from a specific algorithm, for the true values are almost never directly observable.

[7] The term "competition" as it appears here refers solely to the algorithmic parameter C_p, and its usage is restricted to this subsection only.

this article still expresses C_p and R_c as linear functions $f(R_1, R_2, \dots, R_c, M_{cp})$ and $g(C_1, C_2, \dots, C_p, M_{cp})$, constructs a linear iterative process, and standardizes the arithmetic mean of C_p and R_c in each step of iteration:

$$\begin{cases} \tilde{R}_c^{(n)} = k_c \sum_p M_{cp} C_p^{(n-1)} \\ \tilde{C}_p^{(n)} = k_p \sum_c M_{cp} R_c^{(n-1)} \end{cases} \Longleftrightarrow \begin{cases} R_c^{(n)} = \dfrac{\tilde{R}_c^{(n)}}{\left(\sum_c \tilde{R}_c^{(n)}\right)/C} \\ C_p^{(n)} = \dfrac{\tilde{C}_p^{(n)}}{\left(\sum_p \tilde{C}_p^{(n)}\right)/P} \end{cases} \tag{5}$$

where C and P are the number of countries and products respectively; and initial conditions of Eq. (5) are: $\begin{cases} \tilde{R}_c^{(1)} = \sum_p M_{cp} k_c, & \forall p \\ \tilde{C}_p^{(1)} = \sum_c M_{cp} k_p, & \forall c \end{cases}$.

Worthing mentioning, in fact, k_c and k_p reflect the source why the algorithm called “asymmetric”. The determination of k_c/k_p stem from the choice of initial conditions in the iterative algorithm. For the initial setup, we assume that different products contribute equally to the competition intensiveness at the country level, and that different countries also contribute equally to the competition intensiveness at the product level. The “heterogeneity” of both dimensions emerges gradually through subsequent iterative calculations. Given this homogeneous influence, the heterogeneity of competition intensiveness captured in the initial conditions originates from the superficial network structure: competition intensiveness at the country level and at the product level can be described in terms of first-order or second-order neighbors.

Specifically, for a given commodity, its competition intensiveness at the commodity level can be represented by the number of “competitive pairs” formed among the countries participating in export trade with regard to that commodity — if n countries participate in trading it, then there are $\binom{n}{2}$ such competitive pairs. From an economic intuition perspective, a “competitive pair” refers to how two countries enter into a competitive relationship, namely, when both export the same product, trade competition arises. Accordingly, k_p represents the scale of all pairwise competitive relationships among countries within product p. Intuitively, this scale grows at a quadratic rate, increasing more rapidly than k_c. When calculating the initial conditions, the average size of competitive pairs that a country c participates in across different products constitutes the country’s initial “rivalry” condition $R_c^{(1)}$.

For a given country, since competition between countries is defined by the export of the same commodity, competition intensiveness at the country level can be represented by the total number of its second-order neighbors. Contrast to k_p, the intuition behind k_c follows a different logic. Here, k_c captures all external trade partners that form a competitive relationship with country c, namely, all countries that compete with c by exporting the same set of products. When computing the initial condition, the average number of competitive partners that countries have within a given product p forms the product’s initial “competition” condition $C_p^{(1)}$.

The computation of k_c/k_p can be implemented by constructing an unweighted – undirected bipartite network (with adjacency matrix **A**), which is derived from the original weighted – undirected bipartite network (**M**) described above. The specific expression of k_c/k_p is given as: $\begin{cases} k_c = \sum_p \sum_{p'} e_{cp} e_{cp'} \\ k_p = \frac{(\sum_c e_{cp})!}{2!(\sum_c e_{cp}-2)!} \end{cases}$, e_{cp} namely the whether there exist an edge between a certain vertex (c) and its adjacent vertexes (p); if so, then $e_{cp} = 1$. The ordinary method for transforming the original weighted – undirected bipartite network to the unweighted – undirected bipartite network is judging if $RCA \geq 1$: $\begin{cases} 1, & RCA_{cp} \geq 1 \\ 0, & RCA_{cp} < 1 \end{cases}$, and e_{cp} can be expressed as: $e_{cp} = \sum_c A_{cp}$. Obviously, different criterions will result on different outcomes, so we will conduct calculations based on the ordinary method, and then discuss different calculation results based on different threshold of the RCA in the later.

Because of standardization in each step of iteration in Eq. (5), $R_c^{(n)}$ and $C_p^{(n)}$ will be asymptotically converged, and Eq. (5) can be expressed as non-iterative form by introducing rescaling factors f_R and f_C:

$$\begin{cases} R_c = f_R \cdot k_c \sum_p M_{cp} C_p \\ C_p = f_C \cdot k_p \sum_c M_{cp} R_c \end{cases} \tag{6}$$

where $c_R = \frac{C}{\sum_p C_p s_p}$, $c_C = \frac{P}{\sum_c R_c s_c}$ and s_c/s_p namely the weigh of country/product vertex: $\begin{cases} s_c = \sum_p M_{cp} \\ s_p = \sum_c M_{cp} \end{cases}$; because rescaling factors c_R and c_C have the same impact on different countries or products, we neglect the rescaling factors in the later part. Let $\begin{cases} X_c = R_c \\ Y_p = C_p \end{cases}$, **W** and the proximity matrixe **N**/**G** can be expressed as:

$$\begin{cases} W_{cp} = k_c k_p M_{cp}, \\ N_{cc'} = (\mathbf{W}\mathbf{W}^T)_{cc'} = k_c k_{c'} (k_p)^2 \sum_p M_{cp} M_{c'p}, \\ G_{pp'} = (\mathbf{W}^T\mathbf{W})_{pp'} = k_p k_{p'} (k_c)^2 \sum_c M_{cp} M_{cp'}. \end{cases} \tag{7}$$

2.3. Matrix-Estimation Exercise

The eigenvector corresponding to the largest eigenvalue within in the proximity matrix **N/G** in Eq. (7) namely the economic property X_c/Y_p, and they can be described as Eigenvector Centrality of the country/product vertex. However, either the MR or other algorithms based on MR, will face the same problem: in the process of calculating the Eigenvector Centrality, it may result on possible risks of circular reasoning, which descends from ad hoc assumptions. For avoiding relevant problems stemming from such a flaw, Sciarra et al. [38] proposed the Matrix-Estimation Exercise based on the Ordinary Least Squares (OLS), providing a new approach on measuring the centrality for vertexes. Therefore, this article will furtherly adopt Sciarra's Matrix-Estimation Exercise with the basis of the algorithm mentioned above, constructing the indicators of GCC (Generalized Competition of Country) and GCP (Generalized Competition of Product):

$$\begin{cases} GCC_c(s) = \left(\sum_{i=1}^{s} \lambda_i^N \left(v_{c,i}^N\right)^2 \right)^2 + 2\sum_{i=1}^{s} \left(\lambda_i^N\right)^2 \left(v_{c,i}^N\right)^2, \quad c = 1, 2, \dots \\ GCP_p(s) = \left(\sum_{i=1}^{s} \lambda_i^G \left(v_{p,i}^G\right)^2 \right)^2 + 2\sum_{i=1}^{s} \left(\lambda_i^G\right)^2 \left(v_{p,i}^G\right)^2, \quad p = 1, 2, \dots \end{cases} \tag{8}$$

In Eq. (8), λ_i^N/λ_i^G namely the ith eigenvalue of matrix **N/G**; $\mathbf{v}_i^N/\mathbf{v}_i^G$ namely the eigenvector corresponding to λ_i^N/λ_i^G. When giving $s = 1$, Eq. (8) will be:

$$\begin{cases} GCC_c(1) = \left(\lambda_1^N (v_{c,1}^N)^2\right)^2 + 2(\lambda_1^N)^2 (v_{c,1}^N)^2, \quad c = 1, 2, \dots \\ GCP_p(1) = \left(\lambda_1^G (v_{p,1}^G)^2\right)^2 + 2(\lambda_1^G)^2 (v_{p,1}^G)^2, \quad p = 1, 2, \dots \end{cases} \tag{9}$$

Worthy mentioning, matrixes **N** and **G** are modified by giving 0 to the elements on the principal diagonal:

$$N_{cc'} = \begin{cases} \frac{1}{\sqrt{k_c}\sqrt{k_{c'}}k_p} \sum_p M_{cp} M_{c'p} & c' \neq c, \\ 0, \quad c' = c. \end{cases}$$

and

$$G_{pp'} = \begin{cases} \frac{1}{\sqrt{k_p}\sqrt{k_{p'}}k_c} \sum_c M_{cp} M_{cp'}, & p' \neq p, \\ 0, \quad p' = p. \end{cases}$$

$GCC_c(1)$ and $GCP_p(1)$ can be described as the "derivative" indicators of Eigenvector Centrality, and the topological meanings of $GCC_c(1)/GCP_p(1)$ are corresponding to the Eigenvector Centrality of the country/product. The larger the GCC is, the higher the competition intensiveness of the country in export trade will be; similarly, the larger the GCP is, the higher the competition intensiveness of the industry in which the product is located will be; in other words, the GCC and GCP can be seen as the weighted similarity of the export trade structure. This article will firstly conduct calculation and analysis the GCC and GCP based on $s = 1$. Actually, while giving $s = 2, 3, \dots, C$, $GCC_c(s)$ and $GCP_p(s)$ may contain more structural information of the bipartite network, and the results may be different from $s = 1$, the later part of text will do more analyses on that.

Regarding the economic implications of the two indicators, GCC and GCP, we can interpret them from two perspectives. First, in terms of the calculation process, both GCC and GCP are derived from the RCA-based bipartite network. Since RCA essentially measures a form of "outperformance", i.e., the degree to which a country demonstrates an "excess" advantage compared to other countries, which is more commonly referred to in trade theory as "comparative advantage". The algorithm developed in this article further excavates the information embedded in this network. Therefore, the results obtained here are not based on "aggregate dimension" but rather on the "density dimension". This implies that the overall level of competition intensiveness measured in this article can be understood as the "competition density", i.e., the trade competition pressure brought by each unit of export trade to a country.

Second, in terms of the underlying algorithmic logic, since the GCC and GCP indicators inherit the concept of eigenvector centrality, a country (or region) with a higher GCC value not only indicates that it is extensively and deeply engaged in the export of commodities characterized by higher levels of competition intensiveness (higher GCP), but also that it is closely connected with other countries that also exhibit high GCC values (corresponding here to similarity in export structures). Similarly, a commodity with a higher GCP value implies that it is extensively and deeply engaged by countries with higher competition intensiveness levels (higher GCC), and also that it is closely connected with other commodities with high GCP values (corresponding here to similarity in the set of participating countries).

3. Result

3.1. Data

The data used in calculating the generalized competition intensiveness indicators refers to the volume of export trade regarding different countries (or regions) on different commodities. The data on export trade comes from UN Comtrade. This article collects the data on export trade from UN Comtrade, which covers 207 countries (or regions) and 97 sectors of commodities classified by 2-digit (AG2) Harmonized System (HS) codes, from 2001 to 2023. Based on unilateral export trade data of a specific country on a specific commodity in a specific year, this article calculates the RCAs of each country on each commodity from 2001 to 2023, so as to construct country–commodity bipartite networks of each year.

It is worth noting that the process by which commodities from different countries participate in competition in the global market may involve considerable time lags and continuity. Such time dynamics mainly derive from two aspects. The first is the time gap between export registration and market competition. In statistical terms, the time point of export registration at customs marks the departure of commodities from the country, and the export data are immediately counted into that year's trade statistics. However, before the commodities actually arrive in the destination market, enter distribution channels, and compete with similar products from other countries, they must undergo transportation, customs clearance, warehousing, and sales, all of which typically involve time lags [39]. Second, the competitive process itself is characterized by continuity and persistence. In particular, for durable and capital commodities, e.g., machinery, electronics, and automobiles, competition with other products continues throughout the entire product life cycle rather than ending in the short term [40]. Even for fast-moving consumer goods, distribution channel development can also result in competitive effects that extend across multiple years. Therefore, the competition process of export trade cannot be equated with the statistical time of export data; instead, it involves intertemporal continuation.

For this reason, while calculating the generalized competition intensiveness among countries (or regions) and commodities, this article introduces a statistical window period as the data benchmark for the algorithm. Specifically, when constructing a bipartite network for a given year, it is necessary to calculate the RCA of each country in different commodities for that year; the RCA is based on the export trade value of each country in various commodities during that year. The introduction of a statistical window period means that, while calculating the RCA for a given year, we will adopt the total export trade values within a certain multi-year window T. That is, while calculating the RCA for a given time point $year$ — which has been expressed in Eq. (3), we summate the export trade values from the preceding T years through that point. The expression is as follows:

$$V_{cp,year} = \sum_{t=year-T}^{year} v_{cp,t} \tag{10}$$

Considering customs registration delays, the persistence of product life cycles, and cross-year fluctuations in international trade, the benchmark statistical window period is set to 5 years, i.e., $T = 5$. Of course, in the subsequent robustness checks of the algorithm, this article will adjust the size of the statistical window, including $T = 4, 3, 2, 1$ in order to further examine the effect of the window length on the calculation results.

3.2. Generalized competition

Tables 1 and 2 show the calculation results for GCPs and GCCs of representative commodities and countries (or regions) in 2023. Full calculation results are provided in the Supplementary Material.

Table 1 lists the top 10 and bottom 10 commodities with regard to GCP rankings. It is not difficult to observe that the top-ranked commodities (i.e., those with the highest overall competition intensiveness status at the commodity level) are largely agricultural and livestock products, industrial and mining raw materials, intermediate inputs for manufactured goods, and primary processed products. Such products are typically produced and exported by countries with lower levels of economic development or scientific and technological capacity. For instance, coffee and tea account for a substantial share of the export structures of Burundi, Rwanda, and Kenya. By contrast, the commodities ranked at the bottom are generally manufactured goods, high-precision machinery and instruments, durable or capital goods, and products with a high share of knowledge and capital inputs. These are typically produced and exported by more advanced economies with higher levels of technological development; for instance, the photolithography industry is almost entirely dominated by the Netherlands, aerospace equipment is largely monopolized by European and American firms, and Japan and the United States account for a significant share of the semi-conductor sector.

Table 2 reports representative results of the GCC calculations. Again, it is apparent that trade competition intensiveness at the country level appears to be associated with the level of economic development and technological capacity. The countries ranked at the top (i.e., those with the highest trade competition intensiveness at the country level) are largely underdeveloped economies lacking innovative capacity, with economic structures dominated by agriculture and livestock, and whose exports are locked in at the low end of the global value chain. As mentioned above, coffee, tea, and sugar account for a substantial share in the export structures of African countries, e.g., Burundi and Kenya, and Latin American countries, e.g., Honduras and Guatemala, along with significant exports of horticultural products, textiles, and mineral products. By contrast, the countries ranked at the bottom are mostly advanced economies with independent R&D capacity, higher shares of secondary and tertiary industries, and the ability to capture significant rents at the high end of the global value chain. For instance, Japan and South Korea dominate the semi-conductor and optical equipment sectors, while motor vehicles and parts, machinery, and optical products constitute a large proportion of exports from Germany, the United Kingdom, and other European countries.

Naturally, the linkages between the export structures of different commodities and countries (or regions) and their trade competition intensiveness will be investigated in greater depth in the case studies presented later.

Fig. 1 illustrates the changes in GCPs of commodities and GCC of countries (or regions) from 2001 to 2023.

First, the evolution of GCP reveals that, for some of the top-ranked and bottom-ranked commodities, trade competition intensiveness remained relatively stable, suggesting that the export conditions of countries engaged in them have not changed significantly over the past two decades. For example, coffee and tea, as well as tobacco products (HS.09 and HS.24), have

Table 1
GCPs of representative commodities in 2023.

HS code	Description	GCP	GCP Ranking
HS.09	Coffee, tea, mate and spices	1.000000	1
HS.11	Products of the milling industry; malt, starches, inulin, wheat gluten	0.832038	2
HS.24	Tobacco and manufactured tobacco substitutes	0.705231	3
HS.25	Salt; sulfur; earths, stone; plastering materials, lime and cement	0.486100	4
HS.08	Fruit and nuts, edible; peel of citrus fruit or melons	0.467206	5
HS.17	Sugars and sugar confectionery	0.447477	6
HS.07	Vegetables and certain roots and tubers; edible	0.378841	7
HS.22	Beverages, spirits and vinegar	0.341480	8
HS.03	Fish and crustaceans, molluscs and other aquatic invertebrates	0.298979	9
HS.15	Animal or vegetable fats and oils and their cleavage products; prepared animal fats; animal or vegetable waxes	0.143621	10
HS.85	Electrical machinery and equipment and parts thereof; sound recorders and reproducers; television image and sound recorders and reproducers, parts and accessories of such articles	0.000024	87
HS.82	Tools, implements, cutlery, spoons and forks, of base metal; parts thereof, of base metal	0.000015	88
HS.50	Silk	0.000014	89
HS.45	Cork and articles of cork	0.000012	90
HS.59	Textile fabrics; impregnated, coated, covered or laminated; textile articles of a kind suitable for industrial use	0.000010	91
HS.29	Organic chemicals	0.000009	92
HS.88	Aircraft, spacecraft and parts thereof	0.000007	93
HS.95	Toys, games and sports requisites; parts and accessories thereof	0.000003	94
HS.97	Works of art; collectors' pieces and antiques	0.000002	95
HS.66	Umbrellas, sun umbrellas, walking-sticks, seat sticks, whips, riding crops; and parts thereof	0.000000	96
HS.37	Photographic or cinematographic goods	0.000000	97

NOTE: GCP values have been Max-Min Standardized.

consistently remained at the top of the rankings, being produced and exported primarily by African and Latin American countries. Conversely, photographic products and aircraft equipment (HS.37 and HS.88) have consistently ranked at the bottom, with their global market shares largely captured by Japan, Korea, and a handful of European and American countries. Of particular note are those commodities in the middle ranks: some, e.g., furskins and ceramics (HS.43 and HS.69), have gradually risen in competition intensiveness, while others, e.g., dyes and paper products (HS.32 and HS.48), have steadily declined. This may reflect two underlying trends. On the one hand, with technology transfer and knowledge spillovers from developed countries, less-developed countries lacking R&D capacity have been able to acquire the production of certain mid- to high-end manufactured products or less complex patents, effectively lowering the technological threshold of such products and enabling them to compete in global markets. On the other hand, the persistent decline in competition intensiveness for some products may suggest that international specialization has already been established — they may rely more heavily on factor endowments and locational advantages, allowing some countries (or regions) to capture greater rents from specialization, while others gradually avoid direct competition.

Second, the evolution of GCC rankings exhibits somewhat similar patterns. Both the countries consistently ranked at the top and those consistently ranked at the bottom have experienced relatively stable competition intensiveness, suggesting limited structural change in their exports over the past two decades. For example, African countries (e.g., Malawi, Burundi, and Rwanda) and Latin American countries (e.g., Guatemala and Honduras) have consistently ranked high, largely due to their reliance on agricultural and primary products. Meanwhile, Germany, the United Kingdom, the United States, as well as Japan and Korea, have consistently ranked low, reflecting their specialization in advanced industries. Nonetheless, we can also observe notable shifts: China and Vietnam have significantly improved their competition intensiveness thanks to rapid economic and technological development, while some advanced economies such as Canada, France, and the Netherlands exhibit the opposite trend. Although these countries accumulated

Table 2
GCCs of each representative countries (or regions) in 2023.

ISO	Country	GCC value	GCC ranking	Trade value	Trade ranking
UGA	Uganda	0.303919	5	21.6	115
RWA	Rwanda	0.284733	6	6.1	133
BDI	Burundi	0.243846	7	0.7	156
KEN	Kenya	0.225736	8	33.1	97
HND	Honduras	0.179578	10	19.9	118
GTM	Guatemala	0.156258	11	66.8	80
ARG	Argentina	0.013821	51	353.2	45
IND	India	0.007680	71	1877.6	17
FRA	France	0.006105	78	2888.2	9
NLD	Netherlands	0.005077	80	3327.3	5
VNM	Viet Nam	0.004836	82	1605.8	21
CAN	Canada	0.003917	89	2478	11
DEU	Germany	0.001089	117	7936.1	3
USA	United States	0.000437	129	8908.3	2
GBR	United Kingdom	0.000423	131	2390.9	12
CHN	China	0.000307	135	15 377.7	1
MYS	Malaysia	0.000215	144	1438.3	24
KOR	South Korea	0.000051	152	3014.3	6
JPN	Japan	0.000025	157	3568.6	4
HKG	Hong Kong (PRC)	0.000009	163	2943.3	8

NOTE: GCC values have been Max-Min Standardized; trade values are shown in bn$.

considerable industrial advantages in the twentieth century, these advantages have gradually eroded over time, forcing them into direct competition with developing countries in global markets.

A more detailed vertical comparison of the evolution of competition intensiveness for specific commodities and countries (or regions) will be provided in the case analyses that follow.

3.3. General discussion based on calculation

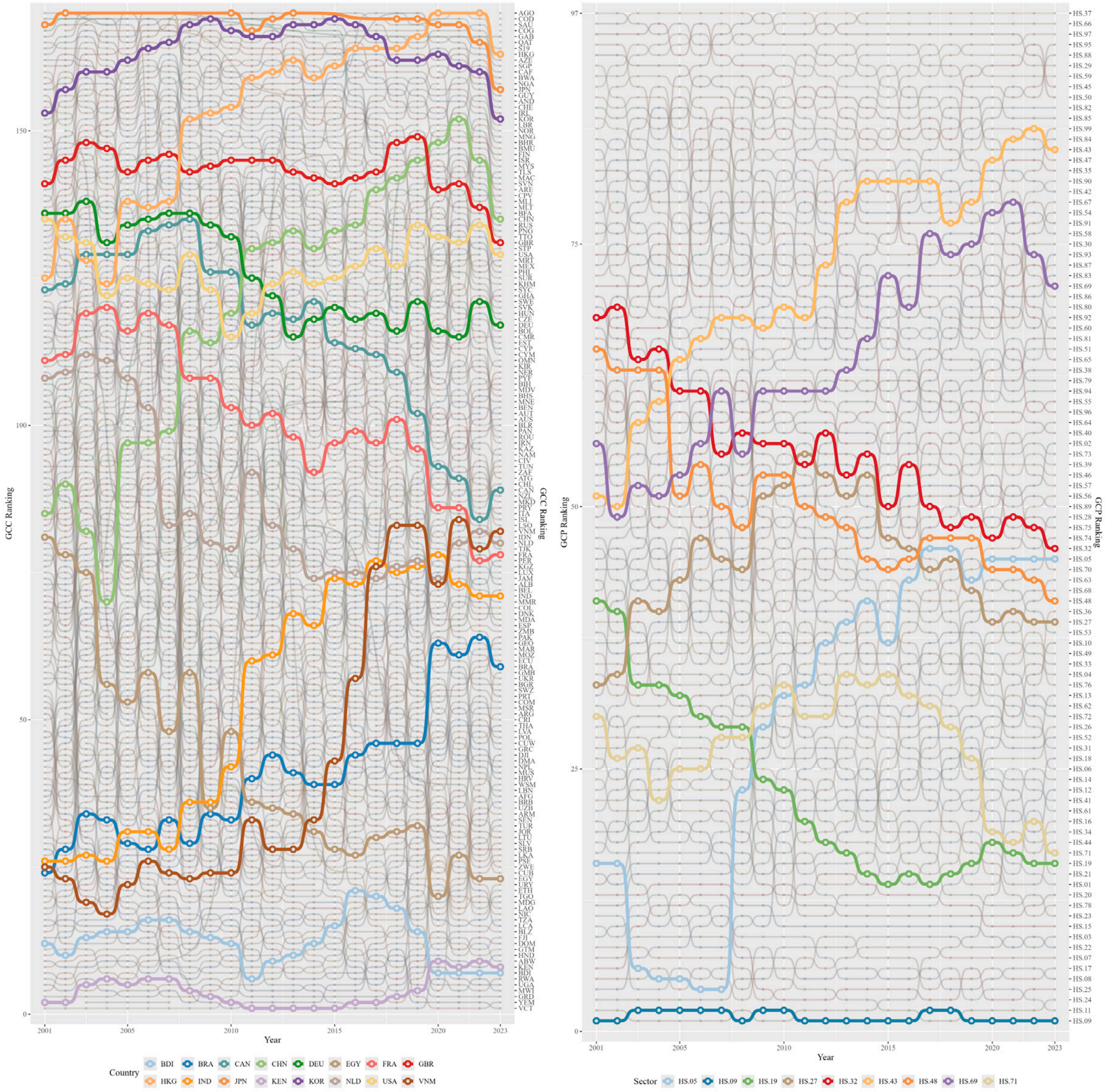
Based on the calculation results, this article further seeks to interpret the algorithmic notions of heterogeneity and interconnectedness, and how these two dimensions ultimately shape the outcomes of competition intensiveness status.

As discussed above, complex network analysis requires us to investigate problems from the perspective of interdependencies among actors. Thus, assessing trade competition intensiveness at the country level must take into account not only the trade structure of the country itself, but also the characteristics of the commodities involved and the export performance of other countries in those same commodities. Similarly, assessing competition intensiveness at the commodity level requires considering the characteristics of participating countries as well as the export conditions of the various commodities in which they are engaged. Fig. 2 present the export profiles of different commodities across countries (or regions) in 2023 along with the corresponding RCA calculations.

The preceding results indicate that commodities with higher levels of trade competition intensiveness tend to be those with relatively low technological intensity, high substitutability, and high homogeneity. Likewise, countries with higher competition intensiveness levels often correspond to lower levels of economic development and a lack of R&D and innovation capacity. The export structures of underdeveloped African and Latin American countries confirm such a pattern. As explained in the construction of the algorithm, for a given commodity, the greater the number of participating countries, the higher their competition intensiveness levels, and the deeper the participation of highly competitive countries, the greater the competition intensiveness pressure that commodity will confront; vice versa. Coffee and tea (HS.09), milling products (HS.11), and tobacco (HS.24) are examples where many underdeveloped, highly competitive countries participate in exports, and where leading countries are deeply engaged. For instance, Uganda and Kenya (ranked 5^{th} and 8^{th}) derive approximately 17% and 23% of their exports from coffee and tea, respectively; Malawi (ranked 4^{th}) derives nearly 47% of its exports from tobacco.

Conversely, products ranked at the bottom tend to be those deeply dominated by advanced countries with lower competition intensiveness levels, such as cinematographic goods (HS.37), watches (HS.91), and transport equipment (HS.87). Countries with lower competition intensiveness are often associated with more substantial capacity of technological innovation and building industrial barriers, as exemplified by Japan, Korea, Germany, and Switzerland. This is further corroborated by advanced economies' specialization in specific technological fields. For example, HS.37 is primarily dominated by Japan and Korea (ranked 157^{th} and 152^{nd}), with RCA values of 9.63 and 2.50, respectively; Switzerland (ranked 154^{th}) has an RCA of 25.32 in HS.91; while Germany (ranked 117^{th}) accounts for 17.4% of global exports in HS.87.

Apart from that, some traditionally developed countries, e.g., France (ranked 78^{th}), Belgium (ranked 72^{nd}), and Denmark (ranked 68^{th}), rank relatively in the middle. Such countries are more of "egalitarianism" in all kinds of commodities. They do not have strong comparative advantages on those commodities with high GCPs, but also do not have obvious disadvantages on those that rank low at the same time. By the same logic, most commodities ranked in the middle positions are widely traded by the majority of countries — regardless of whether developed or less developed (i.e., irrespective of whether their competition intensiveness levels are high or low). In fact, these commodities tend to exhibit a certain degree of substitutability and heterogeneity, along with some production



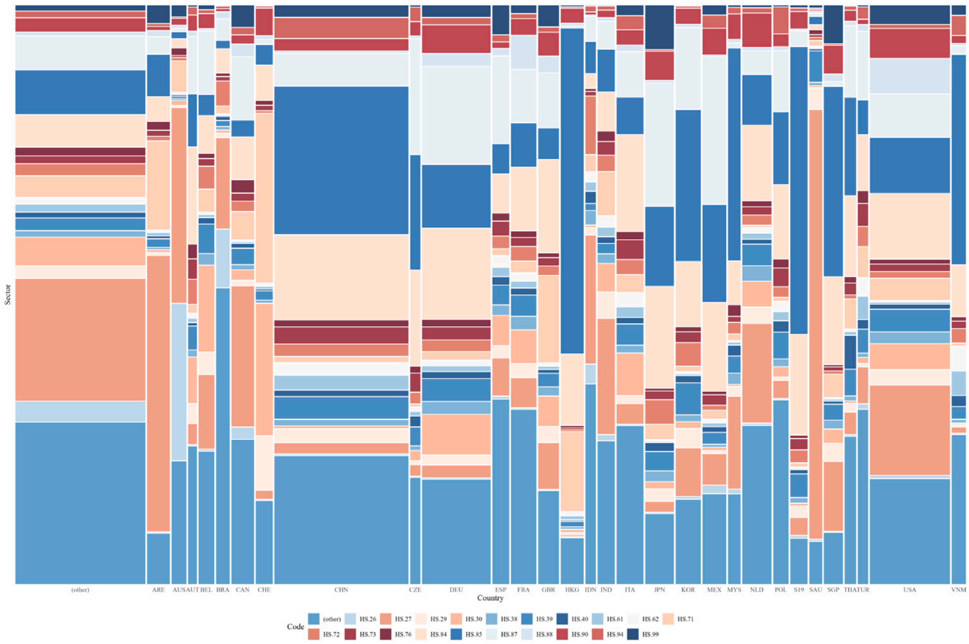
(a) (b)

Fig. 1. Changes of GCP rankings and GCC rankings.
NOTE: Subfigure (a) shows the changes of GCP rankings from 2001 to 2023; Subfigure (b) shows the changes of GCC rankings from 2001 to 2023.

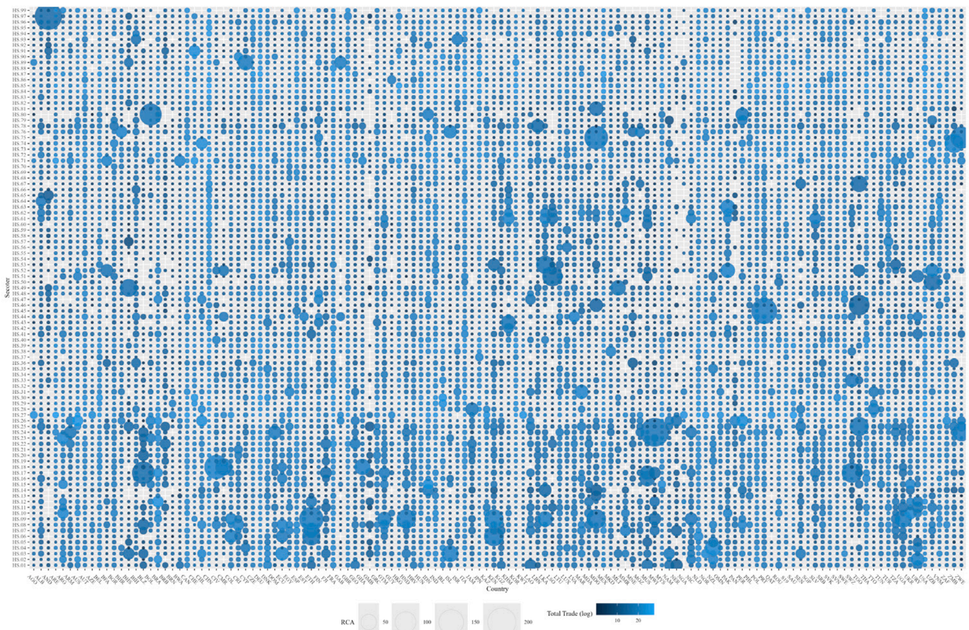
thresholds that are not excessively high. That prevents excessive competition in the market, while also ensuring that market shares are not entirely monopolized by developed countries.

A series of iterative algorithms for bipartite networks, including the one proposed in this article, essentially function by decomposing the bipartite network into two 1-mode networks. A bipartite network represents direct linkages between two different types of nodes — thus, the associations among nodes of the same type are only indirect. By contrast, the two 1-mode networks obtained through decomposition each reveal direct linkages among nodes of the same type, thereby facilitating the analysis of relationships among individual actors.

In fact, the construction of the generalized competition intensiveness indicator in this article is based on two proximity matrices, both of which capture the similarity of export structures. Specifically, the matrix **N** describes the similarity of export structures among different countries with respect to particular commodities, while the matrix **G** describes the similarity of participation structures among different commodities with respect to specific countries. In the final construction of the indicator, the Matrix-Estimation



(a)

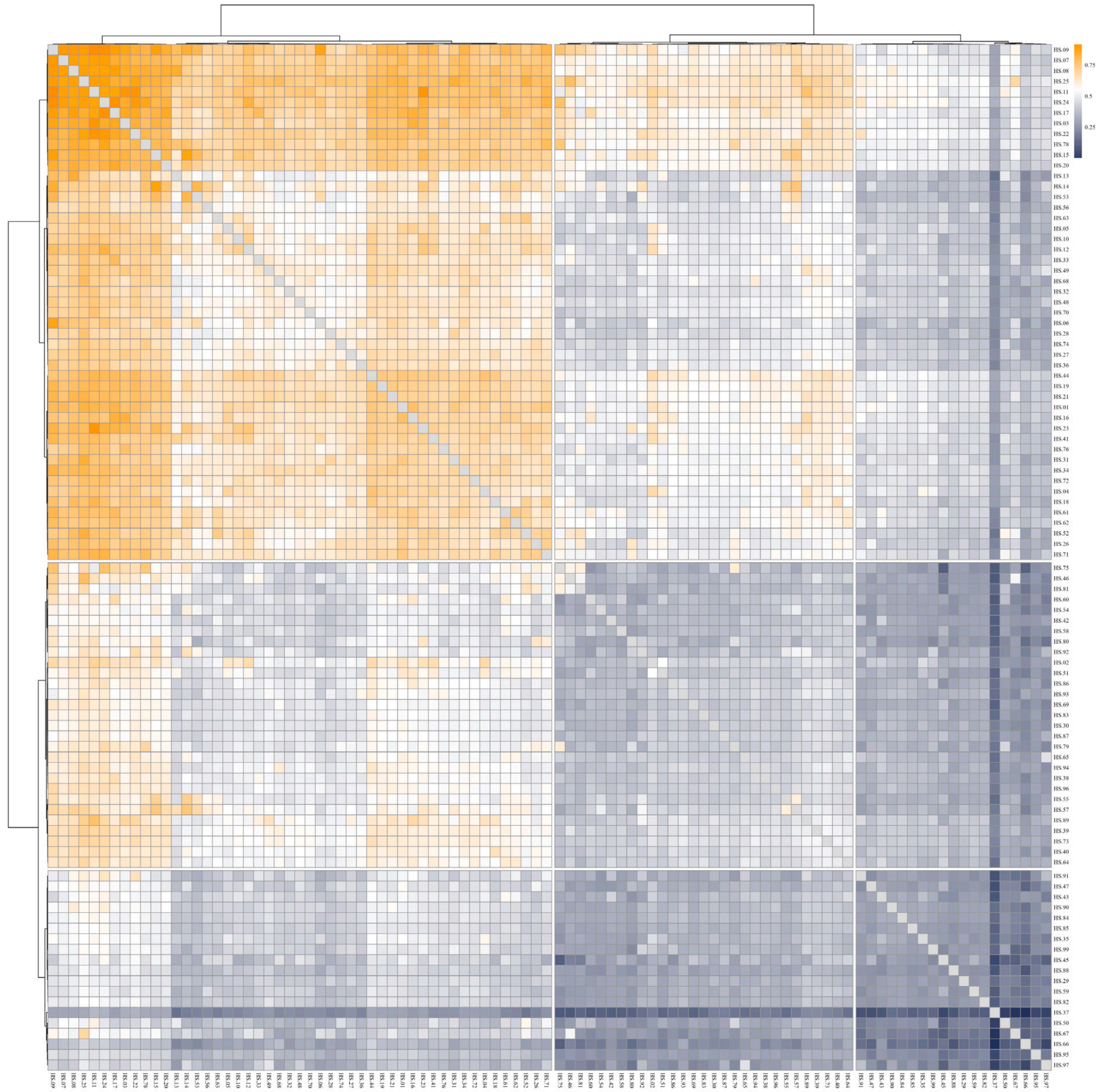


(b)

Fig. 2. Export profiles of different commodities across countries (or regions) in 2023.
NOTE: Subfigure (a) shows export trade situations of 30 countries or regions (with the largest 30 export volumes) on representative commodities; Subfigure (b) shows RCAs of each country (or region) on each commodity.

Exercise employed in this article incorporates the idea of eigenvector centrality: data dimensionality is reduced by extracting eigenvector centralities and eigenvalues from the two proximity matrices.

It is important to note that eigenvector centrality implies that the importance (centrality) of a node depends not only on its own characteristics (e.g., its direct connections to other neighboring nodes), but also on the importance of its neighbors in the

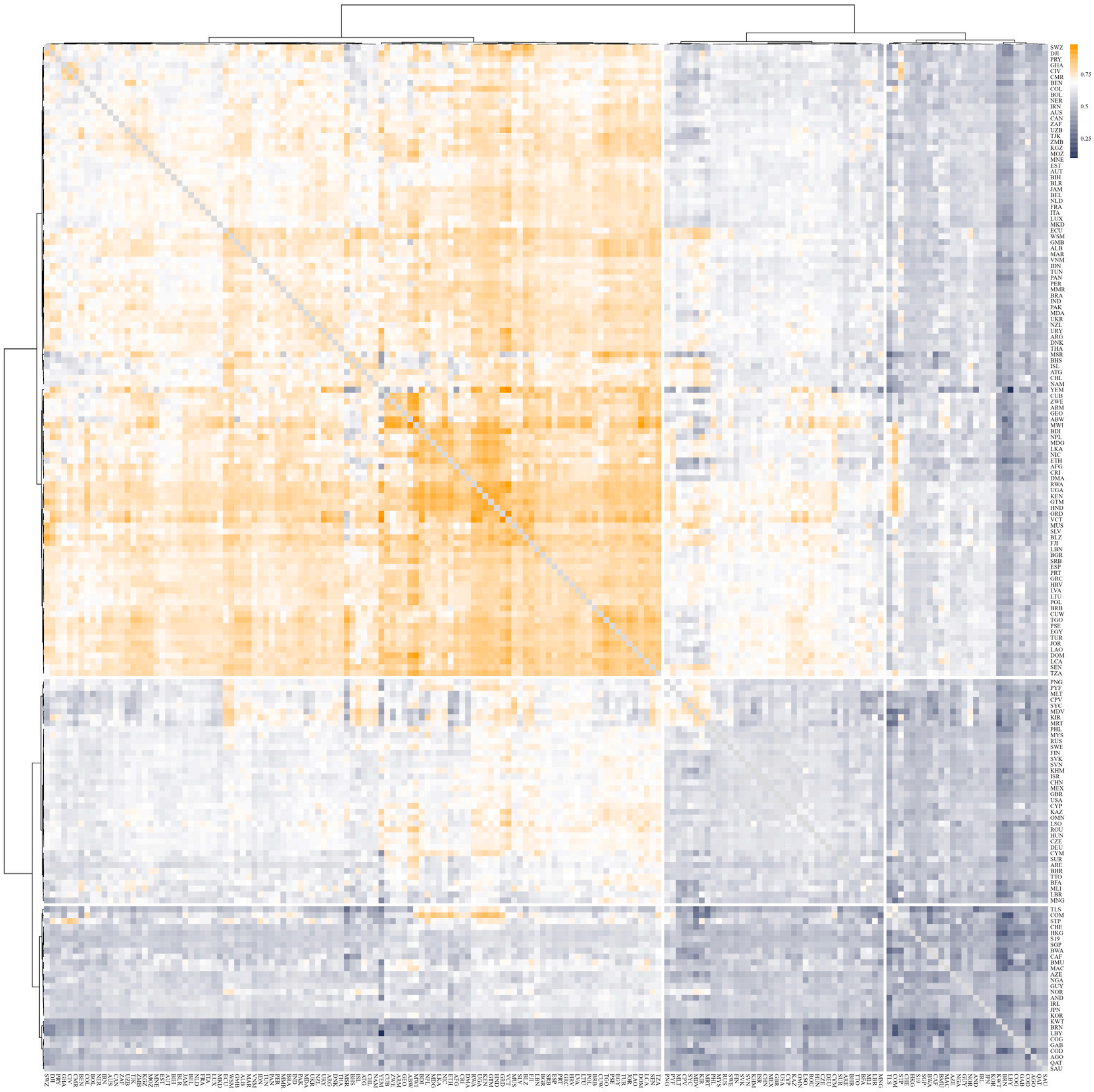


(a)

Fig. 3. Heatmaps of **N** and **G** in 2023.
NOTE: Subfigure (a) shows the heatmap of country proximity matrix **N** of 2023; Subfigure (b) shows the heatmap of commodity proximity matrix **G** of 2023.

network (e.g., their connections to second-order neighbors). In the context of this article, the eigenvector centralities of the two 1-mode networks imply that, a country's trade competition intensiveness is determined not only by its own export structure (its participation across different commodities), but also by the export structures of other countries (particularly those exporting the same commodities). The same logic applies to commodities. Consequently, while a country is confronted with high competition intensiveness, eigenvector centrality suggests that its closely connected neighbors (i.e., countries with similar export structures) are also highly competitive, leading to the formation of clusters within the network. Thus, examining the heterogeneity and interconnectedness in the algorithm can also be investigated through the network structures formed by the two proximity matrices, **N** and **G**. The adjacency matrix heatmaps of these two matrices are shown in Fig. 3.

In terms of the country proximity matrix **N**, the 1-mode network of direct linkages between countries indeed reveals certain clustering patterns. In the corresponding adjacency matrix, a major part of African and Latin American countries exhibit high edge



(b)

Fig. 3. (*continued*).

values between one another (represented by brighter cells in the heatmap), indicating greater similarity in their export structures. By contrast, the edges between these countries and some European and North American countries – as well as among the latter group themselves – tend to be much weaker, implying lower similarity in export structures. This generally reflects that underdeveloped countries, constrained by their industrial structures and domestic production capacity, can only produce and export low-technology, highly homogeneous, and low-value-added agricultural products, raw materials, or primary processed goods. As a result, their export structures are similar, giving rise to clusters in the network. For countries with higher levels of economic and technological development, specialization often plays a larger role. These countries build industry-specific barriers based on their structural and industrial advantages, which differentiate their export structures from those of others and lead to more dispersed patterns in the network.

Turning to the commodities proximity matrix **G**, similar patterns emerge. The adjacency matrix of **G** also exhibits a somewhat clustering pattern, with high structural similarity among agricultural products, livestock products, raw materials, and primary

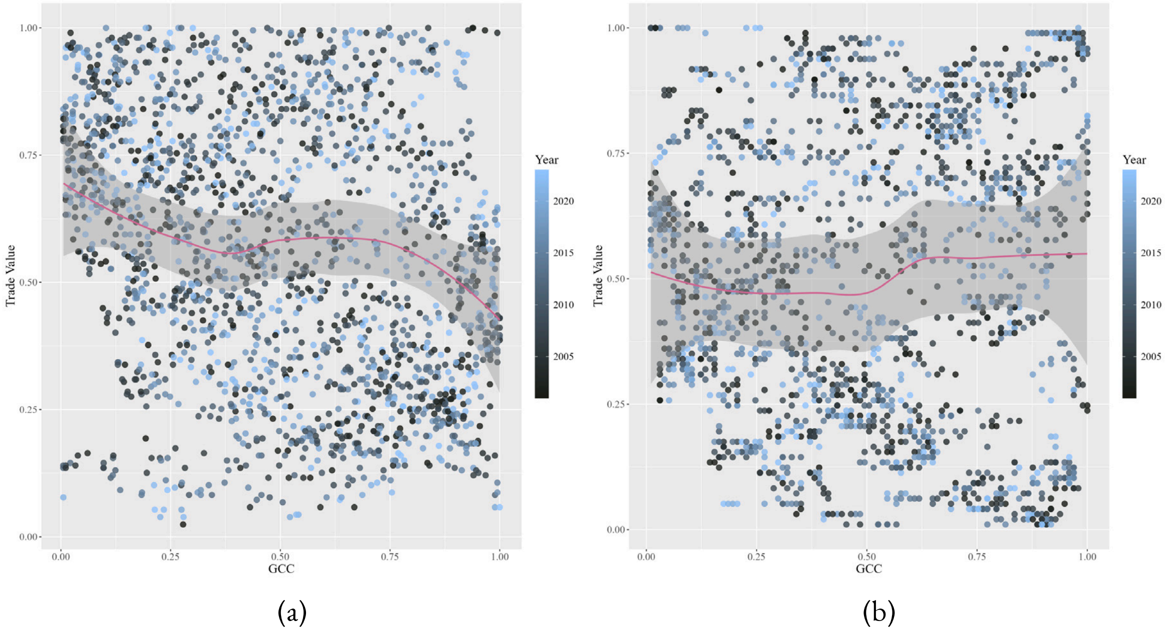


Fig. 4. Scatter plots of GCPs and GCCs and corresponding export trade values.
NOTE: Subfigure (a) shows the scatters of each commodity in the plane of GCP-(export trade)value; Subfigure (b) shows the scatters of each country (or region) in the plane of GCC-(export trade)value. GCC, GCP and export trade value are all Max-Min standardized to corresponding year.

processed goods. As noted above, this clustering arises because such commodities are typically exported by many underdeveloped countries and do not follow specialization patterns. By contrast, industrial manufactures and high-tech equipment exhibit lower structural similarity, as these commodities are often characterized by international specialization — particular commodities are dominated by specific countries, thereby avoiding direct competition.

In addition, as Fig. 4(a) and Fig. 4(b) show, GCP/GCC does not seem to have a direct relationship with export trade value. In fact, in the construction of the country-product bipartite network, the information of “volume” has been omitted, and replaced by “proportion”. Therefore, the GCP/GCC tends to be a measurement of “density” in competition. A higher GCP of a commodities implies that exporting per unit of such product will generate more intense competition in the industry, where the product is located, the same as a country (or region).

Of course, for the purpose of ensuring the stringency, this article further conducts linear fittings of the GCC or GCP of each year on trade volume, in order to examine whether there exists a significant correlation between them (See Figs. 4 and 5). The detailed results of each year can be found in the Supplementary Material.

The test results show that, across all years, there is indeed no significant correlation between the GCP of different commodities and trade volume, with the point estimates of the linear regressions being insignificant even at the 10% level. While the GCC of countries or regions in certain years appears to be partially significant with respect to trade volume, the R^2 values remain extremely small. This indicates that changes in trade volume can hardly account for changes in GCC. We therefore conclude that there is also no sufficiently significant relationship between GCC and trade volume either.

This finding runs counter to conventional wisdom, since it is generally assumed that larger trade volumes imply greater competitive pressure in global markets. However, as we will explain later, larger trade volumes may be associated with the value-added of commodities. Yet the level of added value is, in fact, closely linked to patterns of production and export specialization, which, paradoxically, results in lower levels of trade competition.

4. Analysis by case study

To furnish more direct and concrete evidence from the real economy for the transmission mechanisms underlying our computed results, this article integrates real-world case studies from both the country and product dimensions, and conducts an in-depth analysis of the specific drivers of export competition (both GCP and GCC), through the dual lenses of longitudinal trend dynamics and horizontal disparity analysis. This, in turn, further substantiates the practical economic validity of our algorithm.

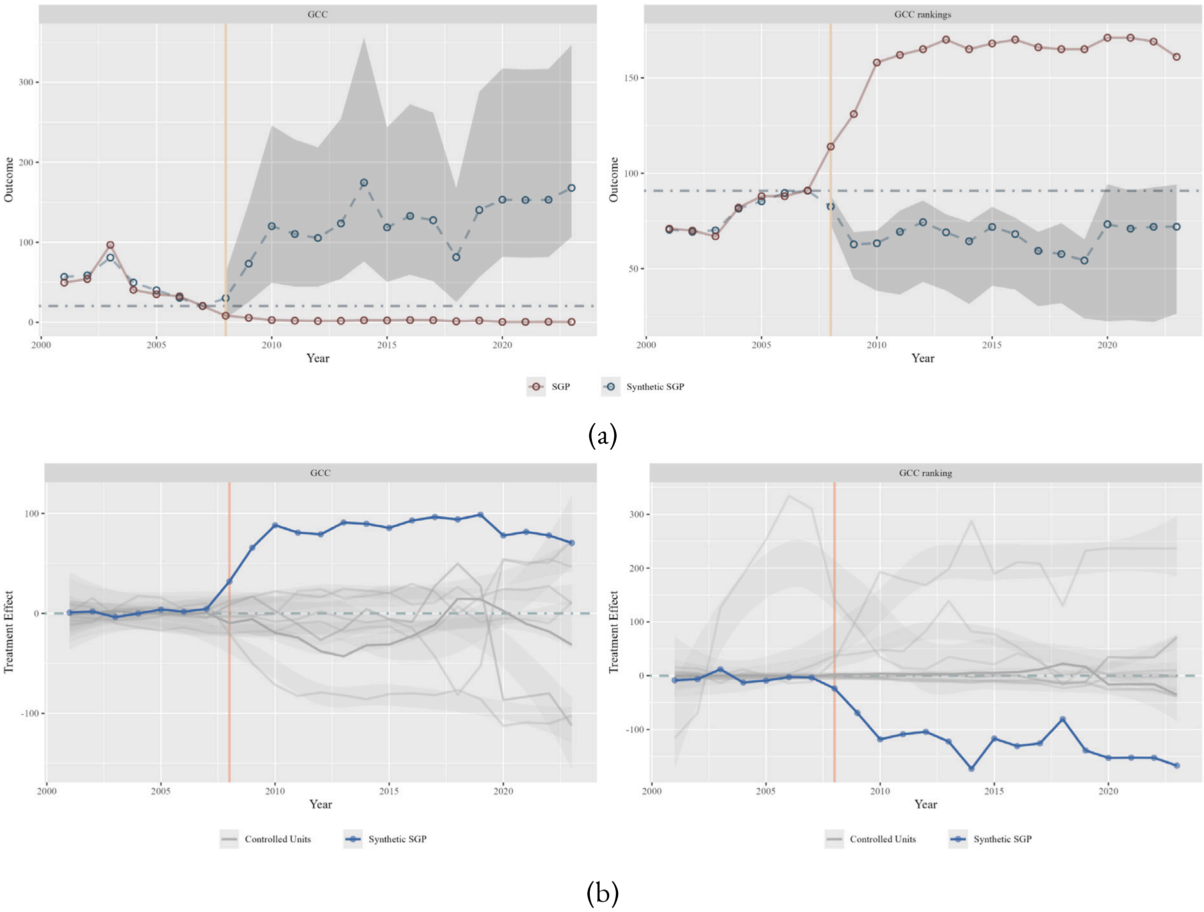


Fig. 5. Causal analysis results based on the Synthetic Control Method.
NOTE: Subfigure (a) shows the predicted results of the synthetic unit based on GCCs and GCC rankings; subfigure (b) shows placebo test results based on GCCs and GCC rankings.

4.1. Longitudinal trend analysis of representative countries

Considering both global economic influence and the time-varying trends of GCCs, this article selects China and Canada as the research subjects. In 2024, the GDPs of the two countries are approximately USD $18.74 trillion and USD $2.24 trillion, ranking 2nd and 9th in the world, respectively. According to data released by the World Trade Organization (WTO), their total exports in 2024 amount to USD $3.577 trillion and USD $567.9 billion, placing them 1st and 12th globally. Throughout the sample period (2001–2023), both countries have consistently maintained high levels of economic output and trade volume, thereby exerting significant influence on the global economy and trade.

It is noteworthy that the changes in GCC faced by the two countries during the sample period diverge sharply. Specifically, based on the algorithm applied in this article, China's export competition ranking was 84th in 2001, but had fallen to 135th by the end of the sample period in 2023, a decline of 51 places. This indicates that China has experienced a significant reduction in competitive pressure within the international export market. Similar patterns can be observed in other countries such as Vietnam (down 56 places), India (down 46 places), and Brazil (down 36 places). While the largest declines are concentrated among developing economies, certain advanced economies – including Norway, New Zealand, and Singapore – have also undergone a substantial reduction in export competition.

In contrast, Canada exhibited the opposite trend: its ranking rose from 121st in 2001 to 89th in 2023, an increase of 32 places. This suggests that Canada has faced a significant intensification of competition in international trade. Comparable upward trends are evident in countries such as Egypt (up 57 places), Ukraine (up 50 places), Iran (up 47 places), Sweden (up 38 places), Italy (up 33 places), and France (up 31 places), demonstrating that both advanced and developing economies have experienced considerable increases in export competition.

Focusing further on the cases of China and Canada, this article investigates the underlying logic of the changes in GCC from the perspective of shifts in their export product structures over the sample period. Specifically, within China's export structure, the share

Table 3
GCC rankings and commodities (with 10% GCP) export shares of China and Canada.

Year	China		Canada	
	Ranking	Top 10%	Ranking	Top 10%
2001	84	0.03336	121	0.02259
2004	72	0.02502	128	0.02332
2007	99	0.01772	134	0.02326
2010	119	0.01556	126	0.02584
2013	133	0.01611	118	0.02768
2016	134	0.01643	113	0.03013
2019	145	0.01722	102	0.03357
2023	135	0.01408	89	0.03348
(Shift)	2.32	−0.00088	−1.45	0.00049

NOTE: The last row measures the average annual change of each indicator.

of products facing relatively low levels of GCPs has been steadily expanding. For example, based on the algorithmic estimation of GCPs at the HS2-digit level, China's share of exports in those industries with the low-level competition (at the bottom 10% of GCP) rose from 17.83% in 2001 to 21.95% in 2023. A representative example is the sector of "Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof (HS84)", where the average competition ranking was around 87. Its share in China's exports increased from 10% to 16%. Correspondingly, China's share of exports in those industries with the high-level competition (at the top 10% of GCP) declined significantly.

In contrast, Canada exhibited the opposite pattern: its share of exports in most competitive industries (at the top 10% of GCP) increased from 2.26% to 3.35%, while its share in least competitive industries (at the bottom 10% of GCP) fell from 12.85% to 10.26%. The optimization of China's export structure began with its accession to the WTO in 2001, accompanied by a series of innovation-driven policy initiatives [41,42], e.g., the Innovation-Driven Development Strategy,[8] supply-side structural reforms,[9] China Government Guidance Funds,[10] and Made in China 2025.[11] As a result, China's export structure has undergone a profound transformation from being predominantly labor-intensive to becoming more capital- and technology-intensive, with a steadily rising position in global value chains. By contrast, during the same period, Canada's advantage in technology-intensive industries has gradually weakened [43]. Taking HS84 as an example, its share of Canada's exports declined from 8.95% to 7.06%. Therefore, we argue that at the national level, export competition is closely and positively related to both the structure of a country's export products and the competition intensiveness of the products themselves.

The GCC rankings of China and Canada from 2001 to 2023, as well as the export share of the top 10% most competitive commodities, are shown in Table 3.

4.2. Horizontal comparative analysis among representative countries

Next, this article conducts a cross-country comparison of GCCs. To ensure comparability at the national level, two relatively underdeveloped African countries – Burundi and the Central African Republic – are selected as case studies. Both belong to the ranks of the world's poorest and most fragile economies. Although they differ somewhat in terms of land area and population, their economic scales are similar: in 2024, Burundi's GDP was approximately USD $2.162 billion with a per capita GDP of about USD $253, while the Central African Republic's GDP was around USD $2.752 billion with a per capita GDP of roughly USD $390, ranking 165th and 159th in the world, respectively. According to the United Nations Human Development Report 2024–2025, their Human Development Index (HDI) values in 2023 were 0.439 and 0.414, ranking 187th and 191st globally — both at extremely low levels.

Despite these similarities, the two countries face starkly different levels of export competition. Specifically, the Central African Republic's average ranking in export competition during the sample period was around 150th, showing a gradual decline over time. In contrast, Burundi's average ranking was approximately 12th, and it has moved steadily upward throughout the period.

The algorithmic framework proposed in this article posits that the level of export competition a country faces is closely linked to both its export product structure and the competitive intensity of the products themselves. Accordingly, we conduct a cross-country comparison of the average export structures of the two nations over the sample period, in order to clarify the underlying causes of their differences in export competition.

For the Central African Republic, the top 4 industries by export share between 2001 and 2023 were: "Natural or cultured pearls; precious and semi-precious stones; precious metals, metals clad with precious metals, and articles thereof; imitation jewelry; coin (HS71)" — ranking 27th in GCP, "Wood and articles of wood; wood charcoal (HS44)" — ranking 22nd, "Vehicles other than railway or tramway rolling stock, and parts and accessories thereof (HS87)" — ranking 77th, and "Aircraft, spacecraft, and parts thereof (HS88)" — ranking 90th. Overall, the country's major export commodities do not face particularly high levels of competition. In

[8] See: http://english.scio.gov.cn/featured/chinakeywords/2019-07/11/content_74977614.htm
[9] See: https://en.cdi.org.cn/component/k2/item/287-what-is-supply-side-reform
[10] See: https://english.www.gov.cn/policies/latestreleases/202406/19/content_WS6672c280c6d0868f4e8e8526.html
[11] See: https://merics.org/en/report/made-china-2025

Table 4
GCC rankings and commodity (with the largest share) export shares of Burundi and Central African.

Year	Burundi		Central African	
	Ranking	HS.71	Ranking	HS.09
2001	12	0.84815	108	0.60729
2004	14	0.52289	125	0.64214
2007	16	0.28968	162	0.55973
2010	12	0.34123	153	0.54314
2013	10	0.38679	150	0.59027
2016	21	0.36332	171	0.24924
2019	14	0.40624	168	0.06651
2023	7	0.33996	160	0.49042
(Average)	12.48	0.42494	150	0.43898

NOTE: The last row measures the average of each indicator.

practical terms, the bulk of its exports are unprocessed gold and diamonds (both classified under HS71). Because HS71 also includes other commodities, the overall competition ranking of this sector is 27th; however, if only gold and diamonds are considered, the level of competition would be substantially lower.

In contrast, Burundi's exports are heavily concentrated in the "Coffee, tea, maté and spices industry (HS09)", which accounts for as much as 39.05% of total exports. This category faces an average competition ranking of 1st in GCP, indicating an extremely high level of export competition and a strong likelihood of substitution by other producing countries — particularly those already under substantial competition pressure.

Moreover, both countries suffer from persistent domestic conflicts and political instability, which have stalled economic reforms and industrial upgrading. As a result, their export structures remain relatively rigid, thereby amplifying the observed disparities in export competition. The cases of Burundi and the Central African Republic thus provide further validation of the logic underlying the algorithm: that national-level export competition is significantly shaped by both the structure of a country's exports and the competitive intensity of the products themselves.

The GCC rankings of Burundi and Central African from 2001 to 2023, as well as the export shares of the largest commodities in both countries, are shown in Table 4.

4.3. Longitudinal trend analysis of representative products

Similar to the preceding discussion on representative countries, this article also selects typical cases of products based on the degree of change in export competition during the sample period. Specifically, "Preparations of cereals, flour, starch or milk; pastrycooks' products (HS19)" and "Furskins and artificial fur; manufactures thereof (HS43)" are chosen as representative examples.

For the former, the competition ranking was 41st in 2001 but had risen to 16th by 2023, an increase of 25 places. This indicates that such products have faced a marked intensification of international export competition. Other products with similar upward shifts include "Paper and paperboard; articles of paper pulp, of paper or paperboard (HS48)" — up 25 places, and "Tanning or dyeing extracts; tannins and their derivatives; dyes, pigments and other coloring matter; paints, varnishes; putty, other mastics; inks (HS32)" — up 22 places. By contrast, "Furskins and artificial fur; manufactures thereof (HS43)" experienced the opposite trend. Its competition ranking was 50th in 2001 but had fallen to 84th by 2023, a decline of 34 places. Comparable downward patterns are observed in "Animal originated products; not elsewhere specified or included (HS05)" — down 30 places, and "Ceramic products (HS69)" — down 18 places.

Next, this article focuses on HS19 and HS43 products, analyzing the reasons behind their changes in export competition from the perspectives of shifts in the composition of exporting countries and the competition levels those countries face. Starting with HS19, based on the average national export competition rankings calculated in this article, we find that the share of exports accounted for by those countries with high-level competition (at the top 10% of GCC) has steadily increased — from 0.48% to 0.67%. Representative examples include Guatemala and Senegal, whose average export competition rankings are 9th and 24th, respectively. Turning to HS43, a similar analysis shows the opposite trend. The export share of the top 10% most competitive countries declined from 0.055% to 0.0009%. Zimbabwe and Ethiopia are the most representative cases here, with average competition rankings of 18th and 12th, respectively.

Taken together, these two product cases illustrate from opposite directions that product-level changes in export competition are determined by both the structure of the countries exporting the product and the competition levels those countries themselves face. This finding is consistent with the logic embedded in the algorithm proposed in this article.

The GCP rankings of HS.19 and HS.43 from 2001 to 2023, as well as the export share of the top 10% most competitive countries, are shown in Table 5.

Table 5
GCP rankings and countries (with 10% GCC) export shares of HS.19 and HS.43.

Year	HS.19		HS.43	
	Ranking	Top 10%	Ranking	Top 10%
2001	41	0.00484	50	0.00055
2004	33	0.00538	60	0.00097
2007	29	0.00557	68	0.00066
2010	23	0.0057	69	0.00059
2013	17	0.00627	79	0.00038
2016	15	0.00665	81	0.00021
2019	16	0.00666	79	0.00021
2023	16	0.00672	84	0.00009
(Shift)	−1.14	0.00009	1.55	−0.00002

NOTE: The last row measures the average annual change of each indicator.

Table 6
GCP rankings and representative countries export shares of HS.09.

Year	Ranking	Burundi	Uganda	Ethiopia
2001	1	0.85	0.49	0.58
2004	2	0.52	0.3	0.42
2007	2	0.29	0.26	0.37
2010	2	0.34	0.24	0.29
2013	1	0.39	0.22	0.3
2016	1	0.36	0.2	0.31
2019	1	0.41	0.18	0.32
2023	1	0.34	0.19	0.39
(Average)	1.38	0.42	0.25	0.36

NOTE: The last row measures the average of each indicator.

4.4. Horizontal comparative analysis among representative products

Furthermore, this article conducts a cross-product comparison of export competition to strengthen the real-world economic relevance of the results. By comparing the average levels of export competition faced by HS2-digit industries during the sample period, two representative products are selected: "Coffee, tea, maté and spices (HS09)" and "Aircraft, spacecraft and parts thereof (HS88)". The former ranked 1st on average, while the latter ranked 90th, with the competition ranking of both products remaining relatively stable over time with only minor fluctuations.

In line with the representative country analysis, we investigate the composition of exporting countries to uncover the underlying reasons why HS09 remains in a highly competitive position while HS88 maintains a more advantageous position. Throughout the sample period, the countries with strong revealed comparative advantages in coffee exports were primarily Burundi (ranking 1st), Uganda (ranking 4th), and Ethiopia (ranking 11th). All three rank among the most competitive globally, facing intense international export competition. Coffee exports account for 39.5%, 21.54%, and 34.04% of total exports in these countries, respectively.

The GCP rankings of HS.09 from 2001 to 2023, as well as the export shares of the representative countries in this commodities, are presented in Table 6.

By contrast, countries with strong revealed comparative advantages in HS88 are concentrated in the United States, France, and Germany. Their average competition rankings during the sample period were 127th, 101st, and 125th, respectively, indicating relatively low levels of export competition. In other words, these countries enjoy substantial market advantages in this product category.

The GCP rankings of HS.88 from 2001 to 2023, as well as the global market shares of representative countries in this product, are presented in Table 7.

Through this cross-product comparison of representative cases, this article further validates the underlying logic of the proposed algorithm and provides additional real-world economic intuition in support of its findings.

4.5. Case study based on the synthetic control method: Singapore after 2008

To further enhance the interpretability of the indicators developed in this article with their relevance for policy analyses, we incorporate the Synthetic Control Method (SCM) to investigate how the GCC indicator responds to external shocks, by using Singapore's experience during the 2008 global financial crisis as a case study.[12]

[12] Considering the unique characteristics of Singapore as the treated unit, using the SCM will be helpful in constructing a synthetic Singapore, i.e., a weighted combination of multiple countries whose pre-crisis trends and structural characteristics closely resemble those of Singapore, thereby providing a credible counterfactual against which the post-crisis deviation can be measured [44,45].

Table 7
GCP rankings and representative countries export shares of HS.88.

Year	Ranking	United States	France	Germany
2001	93	0.42	0.14	0.12
2004	85	0.37	0.15	0.14
2007	81	0.39	0.16	0.13
2010	90	0.37	0.18	0.14
2013	93	0.36	0.19	0.14
2016	94	0.38	0.17	0.14
2019	90	0.4	0.16	0.13
2023	93	0.4	0.14	0.12
(Average)	89.88	0.38	0.16	0.13

NOTE: The last row measures the average of each indicator.

The 2008 global financial crisis triggered a sharp decline in global demand, a rapid contraction of trade flows, and widespread shocks to manufacturing-based Asian economies. Setting aside causal attribution here, one direct trade shock that can be clearly linked to the crisis is the substantial collapse in the trade of high-value commodities, especially durable and capital goods; because such industries are particularly sensitive to heightened uncertainty, weakened confidence, and credit-cycle contractions.[13] This implies that the crisis generated not only an average decline in trade volumes but also a structural adjustment, i.e., an asymmetric contraction across different commodities.

Such asymmetric contraction will be helpful in assessing whether our indicators behave in a theoretically consistent manner. Consider an extreme scenario in which the trade shock affects only one specific product, i.e., the trade volume of this specific product collapses while all others remain unchanged. Actually, in this case, countries' RCA values of the affected product would polarize, resulting in a higher degree of "specialization" than before.[14] Consequently, countries highly concentrated in exporting these products would face lower levels of trade competition intensiveness. Durable and capital goods, which in this article largely correspond to products with relatively low levels of trade competition intensiveness, experienced the asymmetric contraction associated with the global financial crisis. It implies that countries heavily concentrated in exporting these goods would, paradoxically, face lower competitive pressure after the crisis — Singapore being a representative case. Therefore, if the algorithm developed in this article is indeed effective in capturing product heterogeneity, we should observe noticeable differences in Singapore's GCC (or GCC ranking) before and after the crisis, particularly in comparison with countries that do not specialize in such products.

The GCC results of Singapore appear to be in line with our expectations. However, an identification problem remains: we do not know whether this pattern simply reflects a regional common shock. Countries that share the same macroeconomic environment as Singapore are similarly exposed to the global financial crisis, but possess very different export structures and may exhibit similar movements. Thus, we employ the SCM to construct a counterfactual trajectory for Singapore under the crisis, allowing us to determine whether Singapore's post-crisis pattern results from its distinctive economic structure, and thereby assess the validity of our indicator.

Because of space limitations, we provide here only a concise description of the SCM procedure; full methodological details are available in the Supplementary Material. We use GCC (with GCC ranking) as the outcome variable. India, Indonesia, Bangladesh, Brunei, Thailand, Myanmar, the Philippines, and Malaysia serve as donor countries, forming a balanced panel with Singapore from 2001 to 2023. The pre-treatment window is 2001–2007. The values of GCC (or GCC ranking) in 2001, 2003, and 2006 serve as special predictors, covering early, middle, and late stages of the pre-treatment period. Three structural dimensions, i.e., economic size, income level, and degree of openness, are included as control variables to characterize the long-run economic features of Singapore and the donor countries. By minimizing the pre-treatment Root Mean Squared Error (RMSE) between actual Singapore and its synthetic counterpart, the model assigns optimal weights to the donor countries and constructs the counterfactual.

Fig. 5(a) shows the differences between actual Singapore and the synthetic control one for GCC and GCC ranking, respectively, over 2001–2023. Before the 2008 crisis, the two trajectories closely tracked each other, indicating that SCM successfully reproduced

[13] See: "Asia and the Global Financial Crisis". Federal Reserve, 19 October, 2009. Available at: https://www.federalreserve.gov/newsevents/speech/bernanke20091019a.htm [https://www.federalreserve.gov/newsevents/speech/bernanke20091019a.htm].

[14] By assigning α as the trade volume of a given country in given commodities, β as the total trade volume of this country, A as total trade volume of this commodities, B as total trade volume of the world, and ϑ as the proportion of trade contraction during the crisis. And assuming that all countries experience a proportional contraction in that product, the RCA of this country before the crisis can be expressed as: $RCA_0 = \frac{\alpha/\beta}{A/B}$, and the RCA after the crisis is: $RCA_1 = \frac{\alpha-\vartheta\alpha/\beta-\vartheta\alpha}{A-\vartheta A/B-\vartheta A}$. Then, the change γ in RCA before and after the crisis can be given by:

$$\gamma(\vartheta) = \frac{RCA_1}{RCA_0} - 1 = \frac{\vartheta(B\alpha - A\beta)}{B(\beta - \vartheta\alpha)} \tag{11}$$

Here, we have: $\begin{cases} \gamma > 0, & \text{while } \alpha/\beta > A/B \\ \gamma < 0, & \text{while } \alpha/\beta < A/B \end{cases}$. And by take the derivative of γ with respect to ϑ, we have:

$$\frac{d\gamma}{d\vartheta} = \frac{B\alpha - A\beta}{B} \frac{\beta}{(\beta - \vartheta\alpha)^2} > 0 \tag{12}$$

which means that, after the crisis, countries' RCAs of the same commodity become "polarized".

Table 8
GCCs of representative countries under different “s” in 2023.

ISO	Country	GCC(1)	GCC(1) Ranking	GCC(2)	GCC(2) Ranking
UGA	Uganda	0.303919	5	0.005878	12
RWA	Rwanda	0.284733	6	0.012951	9
BDI	Burundi	0.243846	7	0.047871	7
KEN	Kenya	0.225736	8	0.002105	24
HND	Honduras	0.179578	10	0.002756	20
GTM	Guatemala	0.156258	11	0.000450	46
ARG	Argentina	0.013821	51	0.000950	32
IND	India	0.007680	71	0.000055	108
FRA	France	0.006105	78	0.000044	113
NLD	Netherlands	0.005077	80	0.000048	110
VNM	Viet Nam	0.004836	82	0.000131	77
CAN	Canada	0.003917	89	0.000143	73
DEU	Germany	0.001089	117	0.000023	139
USA	United States	0.000437	129	0.000017	148
GBR	United Kingdom	0.000423	131	0.000059	106
CHN	China	0.000307	135	0.000009	157
MYS	Malaysia	0.000215	144	0.000025	134
KOR	South Korea	0.000051	152	0.000007	161
JPN	Japan	0.000025	157	0.000009	158
HKG	Hong Kong (PRC)	0.000009	163	0.000003	169

NOTE: GCC values have been Max-Min Standardized. GCC(1) and GCC(2) denote GCC value based on $s = 1$ and $s = 2$.

Singapore’s pre-crisis competitive conditions. After 2008, however, a large and persistent divergence emerges: the GCC of Singapore declines and remains at a substantially lower level (with a corresponding downward trend in its GCC ranking), whereas the synthetic control one instead shows an increasing trend. This result suggests that, in the absence of the structural adjustment induced by the crisis, the competitive pressure of Singapore would have followed a pattern similar to its synthetic counterpart, i.e., rising over time. The observed downward shift thus indicates the presence of the expected structural adjustment, supporting the capability of our indicator to capture product heterogeneity. If such heterogeneity were not embedded in the algorithm,[15] the competitive conditions of Singapore would show an upward trend similar to the synthetic control one.

Fig. 5(b) shows the placebo-in-space tests. During the pre-treatment period, placebo effects for all donor countries fluctuate around zero, indicating a good model fitness. After the 2008 crisis, Singapore’s treatment effect diverges markedly from those of the donor countries, namely, most placebos display only small fluctuations near zero or movement in the opposite direction, which also further strengthens our expectations.

5. Extended calculation for robustness

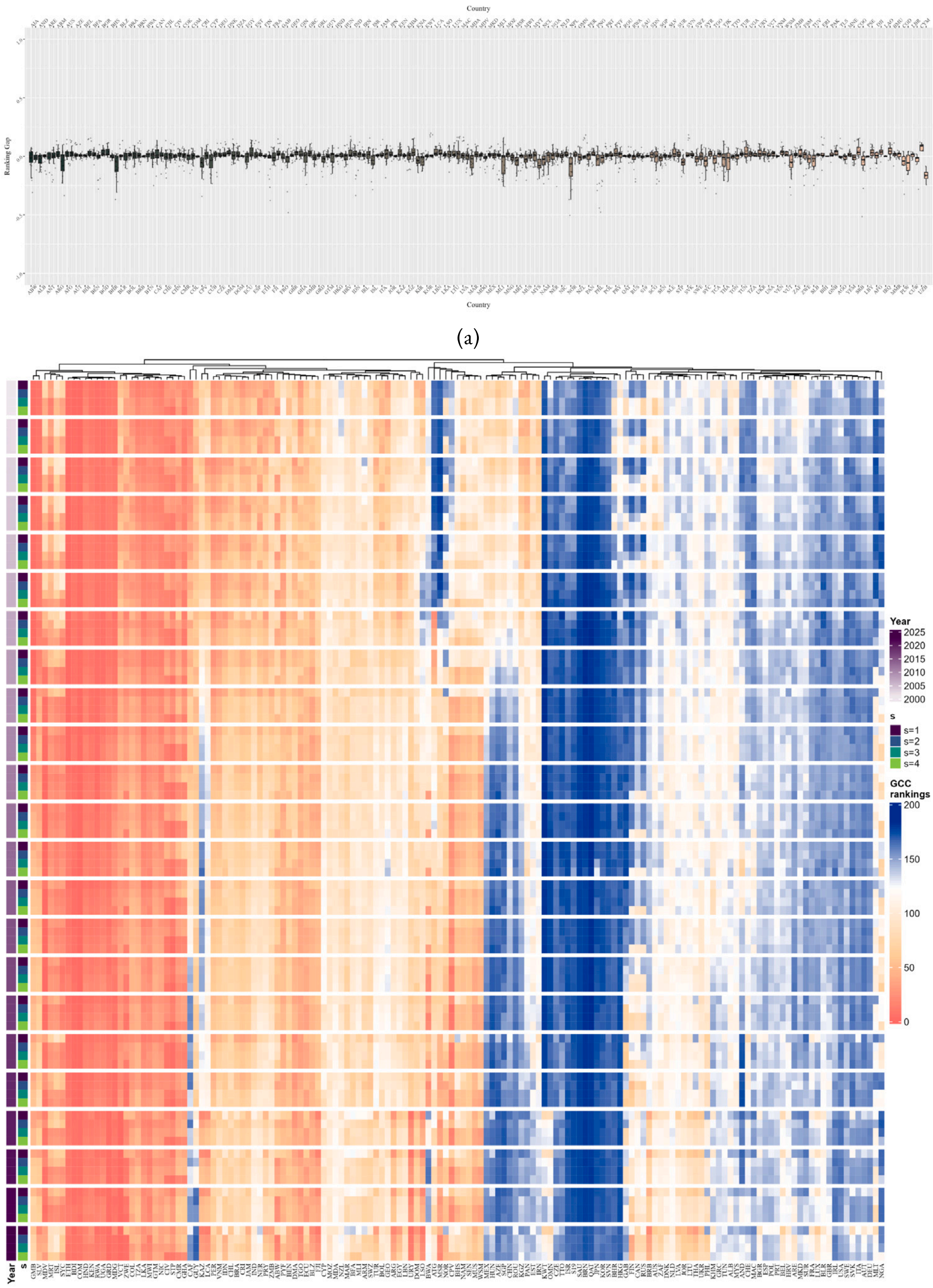
5.1. Additional eigenvectors

The GCC/GCP mentioned above is based on Eq. (9), namely Eq. (8) given $s = 1$. As described above, $v^N_{c,1}/v^G_{p,1}$ is corresponding to X_c/Y_p, which can be seen as some kind of the Eigenvector Centrality; more specifically, $v^N_{c,1}/v^G_{p,1}$ describes the Eigenvector Centrality of country/product vertex within the unweighted network, representing the modified proximity matrix **N/G**. But other eigenvectors of **N/G** may include more information of topological and clustering [35]. Therefore, introducing more eigenvectors in calculation may do favor to mapping more deeper information of complexity, even results on dramatically different conclusions [46]. But as eigenvalues descending, introducing excessive eigenvectors may generate overmuch noise [47].

Therefore, this article considers introducing additional eigenvectors into calculation. As mentioned above, this article has calculated GCCs and GCPs based on the largest eigenvectors derived from **N/G**; thus, here, we will include the 2nd, 3rd, and 4th largest eigenvectors into calculations gradually, namely let $s = 2$, $s = 3$ and $s = 4$. Table 8. and Fig. 6 show the calculation results of GCCs under different value of “s”.

The results of Table 5. show that, GCCs are almost consistence, only little difference exists in some countries among such three situations. Fig. 6. exhibits the results under different “s” more clearly, as to a large part of countries, GCCs of different “s” are just coincide. The process of The Matrix-Estimation Exercise projects $N \cdot N$ (i.e. the number of entries of the Adjacency Matrix) data to $s \cdot N$, which is the number of independent variables used in the estimation [38]. The results above indicate that, while projecting $C \cdot C$ or $P \cdot P$ data to $1 \cdot C$ or $1 \cdot P$ of **N/G** by using the Matrix-Estimation Exercise, there are little topological information of network being omitted; in other words, the eigenvector of the largest eigenvalue of **N/G**, which calculated based on the asymmetric reflection algorithm mentioned above, has contained most of trade information which mapped in original bipartite network. At the same time, the calculation results also indicate that the asymmetric reflection algorithm using in this article has relatively high stability.

[15] E.g., if competition were measured solely through the cosine similarity of export shares, as in most existing trade competition indicators.



(a)

(b)

Fig. 6. Comparison of GCC results under different “s” from 2001–2023.
NOTE: Subfigure (a) shows the overall gaps between results of GCC(1) and GCC(2) from 2001–2023; subfigure (b) shows results of GCC rankings under different “s” from 2001–2023.

The results in Table 8 and Fig. 6 indicate that, when additional eigenvalues and eigenvectors are introduced, the GCC estimates for most countries remain broadly consistent with the benchmark results, with only a limited number of countries displaying differences to some extent. The process of the Matrix-Estimation Exercises maps the total of $N \cdot N$ data entries in the original 1-mode adjacency matrix into $s \cdot N$, thereby achieving dimensionality reduction [38]. The broadly consistent outcomes obtained under different numbers of eigenvectors and eigenvalues suggest that while projecting the total of $C \cdot C$ or $P \cdot P$ data entries of **N** /

Table 9
GCCs of representative countries under different "thresholds" of RCA in 2023.

ISO	Country	GCC_1	GCC_1 Ranking	$GCC_{0.9}$	$GCC_{0.9}$ Ranking
UGA	Uganda	0.303919	5	0.133322	5
RWA	Rwanda	0.284733	6	0.176871	4
BDI	Burundi	0.243846	7	0.117493	6
KEN	Kenya	0.225736	8	0.059497	9
HND	Honduras	0.179578	10	0.057449	10
GTM	Guatemala	0.156258	11	0.046083	12
ARG	Argentina	0.013821	51	0.009470	34
IND	India	0.007680	71	0.002763	67
FRA	France	0.006105	78	0.003700	58
NLD	Netherlands	0.005077	80	0.002521	70
VNM	Viet Nam	0.004836	82	0.002364	74
CAN	Canada	0.003917	89	0.001962	80
DEU	Germany	0.001089	117	0.000631	105
USA	United States	0.000437	129	0.000218	125
GBR	United Kingdom	0.000423	131	0.000235	124
CHN	China	0.000307	135	0.000106	134
MYS	Malaysia	0.000215	144	0.000089	138
KOR	South Korea	0.000051	152	0.000014	154
JPN	Japan	0.000025	157	0.000009	156
HKG	Hong Kong (PRC)	0.000009	163	0.000003	164

NOTE: GCC values have been Max-Min Standardized. GCC_1 and $GCC_{0.9}$ denote GCC value based on $RCA \geq 1$ and $RCA \geq 0.9$.

G into $1 \cdot C$ or $1 \cdot P$ vector, only limited topological information of the network is lost. In other words, the eigenvectors associated with the largest eigenvalues of **N** / **G**, computed through the asymmetric reflection algorithm, already contain most of the trade information mapped from the original bipartite network. Hence, the dimensionality reduction results can be regarded as broadly reliable, and they further demonstrate the high stability of the asymmetric reflection algorithm adopted in this article.

Due to space constraints, we report only the results for $s = 2$ when comparing GCC differences in the main text; the results for other values of "s" are provided in the Supplementary Material. It is worth noting, however, that the inclusion of additional eigenvectors does lead to improvements in the GCC rankings of some countries. This suggests that the benchmark results may underestimate the competition intensiveness of certain countries, which could be related to their specialization in particular commodity categories [31,48].

5.2. Different thresholds

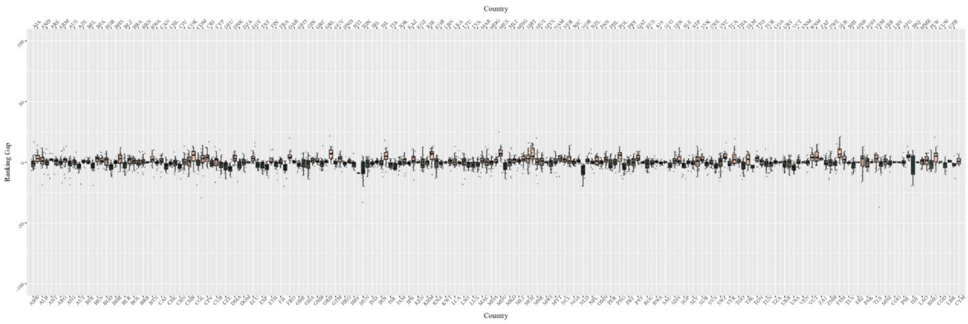
As mentioned above, while calculating the degree of vertex, the algorithm requires transforming the original weighted bipartite network into a unweighted bipartite network (the Adjacency Matrix is **A**). And as the ordinary method does, we can let: $\begin{cases} A_{cp} = 1, & RCA_{cp} \geq 1 \\ A_{cp} = 0, & RCA_{cp} < 1 \end{cases}$, namely if $RCA_{cp} \geq 1$, country c can be seen as having a "prominent" comparative advantage on product p. The calculation results above just based on the ordinary method, but worthy mentioning, judging whether $A_{cp} = 1$ or not depends on judging whether country c has a "prominent" comparative advantage on product p or not; in other words, it depends on judging to what extent country c participates in exporting product p cannot be ignored, that is just to determine the "threshold" of RCA. So, this article conducts calculation for GCCs under different thresholds of RCA, including $RCA \geq 0.9$, $RCA \geq 0.8$, $RCA \geq 0.7$, and $RCA \geq 0.6$. Results are shown in Table 9 and Fig. 7.

Due to space limitations in the main text, Table 9 just reports the GCC results based on $RCA \geq 0.9$ for a set of representative countries, while Fig. 7 shows only the differences in GCC rankings based on $RCA \geq 0.9$ relative to the benchmark ones. Full results of GCCs under different RCA thresholds are available in the Supplementary Material. The results indicate that GCC estimates under different RCA thresholds are broadly consistent with the benchmark results, with the rankings of the vast majority of countries changing by even no more than 5 places.

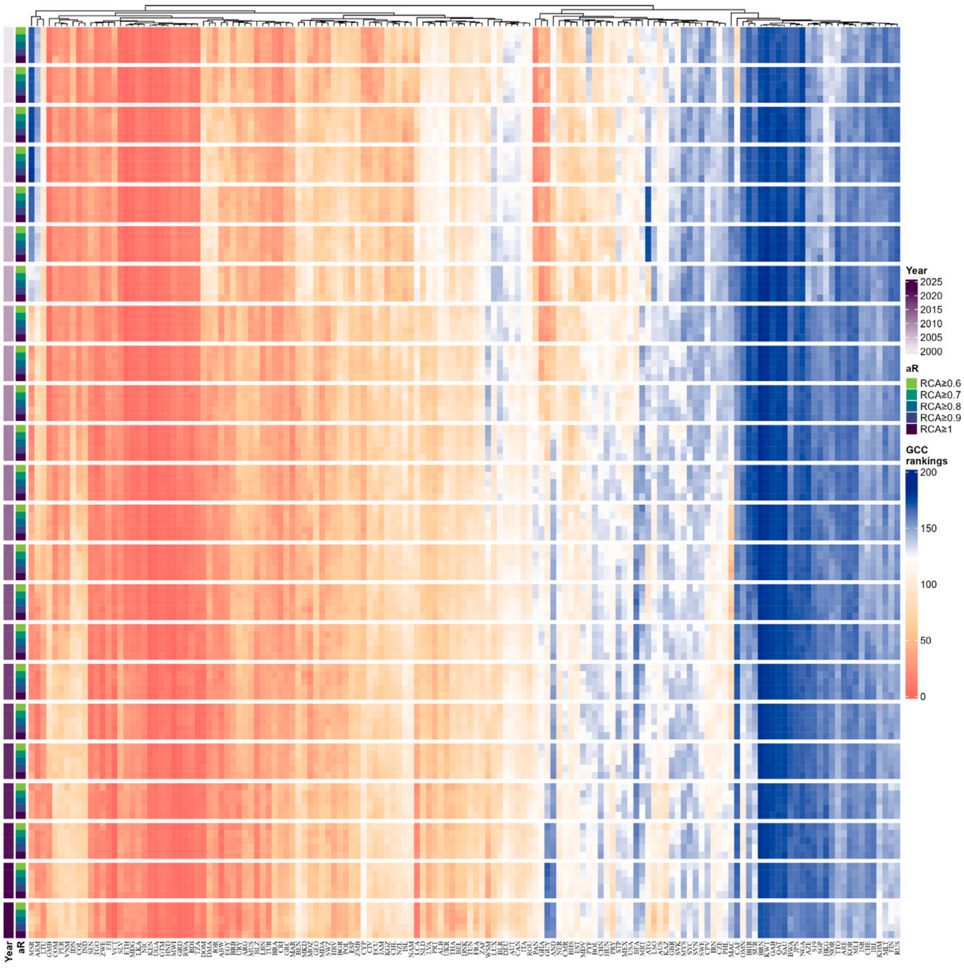
The primary driver of such differences lies in the underlying trade structures of individual countries. For most commodities in most countries, RCA values fall around 1, cases where the RCA values are either far greater than 1 or far below 1 are, in fact, relatively rare. Under different RCA thresholds, this variation yields different **A**s. Excessively high thresholds may result in the loss of relevant information, while overly low thresholds may introduce excessive noise. Hence, the choice of an appropriate RCA threshold is crucial. Nevertheless, the findings suggest that although some differences do emerge under varying RCA thresholds, they do not overturn or materially affect the conclusions presented earlier in this article. In short, the results demonstrate that the algorithm remains broadly robust across different RCA threshold settings.

5.3. Different statistical calibers

To examine the robustness of the results, we adjust the algorithm and recalculate the generalized competition of different countries (or regions) and different commodities. We then focus on comparing the recalculated GCCs of each country (or region)



(a)



(b)

Fig. 7. Comparison of GCC results under different "thresholds" of RCA from 2001–2023.
NOTE: Subfigure (a) shows the overall gaps between results of GCC_1 and $GCC_{0.9}$ from 2001–2023; subfigure (b) shows results of GCC rankings under different "thresholds" of RCA from 2001–2023.

with the benchmark results, in order to identify potentially interesting conclusions. Three adjustments are made to the algorithm: setting different RCA thresholds, incorporating different numbers of eigenvectors, and modifying the statistical window of trade totals.

As noted above, the complete process of export trade usually spans a long time. This means that even if commodities from a given sector are registered at customs in a particular year and recorded in trade statistics of that year, the process by which they actually begin to compete with other products in the global market may not yet have started. Moreover, the competition of similar

Table 10
GCCs of representative countries under different statistical windows in 2023.

ISO	Country	$GCC_{(5)}$	$GCC_{(5)}$ Ranking	$GCC_{(4)}$	$GCC_{(4)}$ Ranking
UGA	Uganda	0.303919	5	0.034325	14
RWA	Rwanda	0.284733	6	0.015065	19
BDI	Burundi	0.243846	7	0.168827	6
KEN	Kenya	0.225736	8	0.049539	10
HND	Honduras	0.179578	10	0.044558	11
GTM	Guatemala	0.156258	11	0.008643	23
ARG	Argentina	0.013821	51	0.000317	106
IND	India	0.007680	71	0.000481	87
FRA	France	0.006105	78	0.000246	116
NLD	Netherlands	0.005077	80	0.000425	93
VNM	Viet Nam	0.004836	82	0.000409	95
CAN	Canada	0.003917	89	0.001231	59
DEU	Germany	0.001089	117	0.000119	144
USA	United States	0.000437	129	0.000146	138
GBR	United Kingdom	0.000423	131	0.000546	85
CHN	China	0.000307	135	0.000089	150
MYS	Malaysia	0.000215	144	0.000271	110
KOR	South Korea	0.000051	152	0.000074	153
JPN	Japan	0.000025	157	0.000101	147
HKG	Hong Kong (PRC)	0.000009	163	0.000035	163

NOTE: GCC values have been Max-Min Standardized. $GCC_{(5)}$ and $GCC_{(4)}$ denote GCC value based on $T = 5$ and $T = 4$.

commodities from different countries in global markets may also involve significant lags and discontinuities. Accordingly, while calculating the RCA values used to construct the bipartite network, we set a statistical window period for trade data — that is, we summate all export trade values within the window.

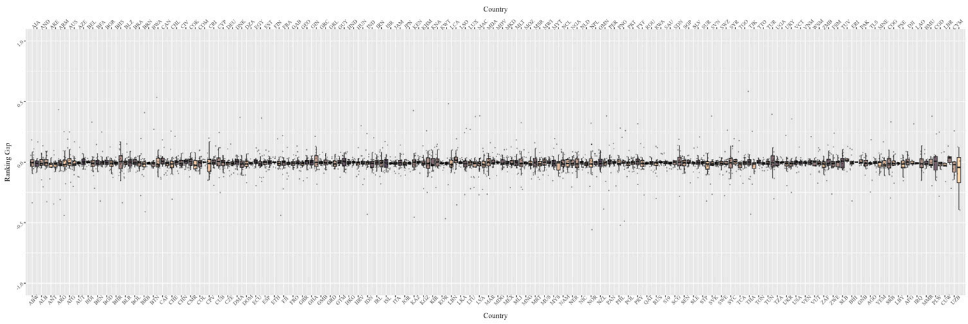
In the earlier calculations, we set the benchmark statistical window period to 5 years. In practice, this implies an underlying assumption that, on average, it takes about five years from the point of customs registration until a country's exported commodities complete their competition process in the global market. Of course, this time span may be too long for certain types of commodities, particularly for fast-moving consumer goods and intermediate products. Therefore, in this section, we set different window periods and recalculate the generalized competition of countries (or regions) and commodities, including $T = 4$, $T = 3$, $T = 2$, and $T = 1$. In fact, the statistical window period helps to smooth out cross-year fluctuations in trade; accordingly, employing different window periods also allows us to investigate how fluctuations in trade affect the results.

Table 10 reports the GCC results based on $T = 4$ for a set of representative countries, while Fig. 8 illustrates only the differences in GCC rankings based on $T = 4$ relative to the benchmark ones. Due to space limitations, the complete set of results will be provided in the Supplementary Material. The findings again demonstrate that the results under different statistical windows remain broadly consistent with the benchmark, with the GCC rankings of most countries shifting by no more than 10 positions.

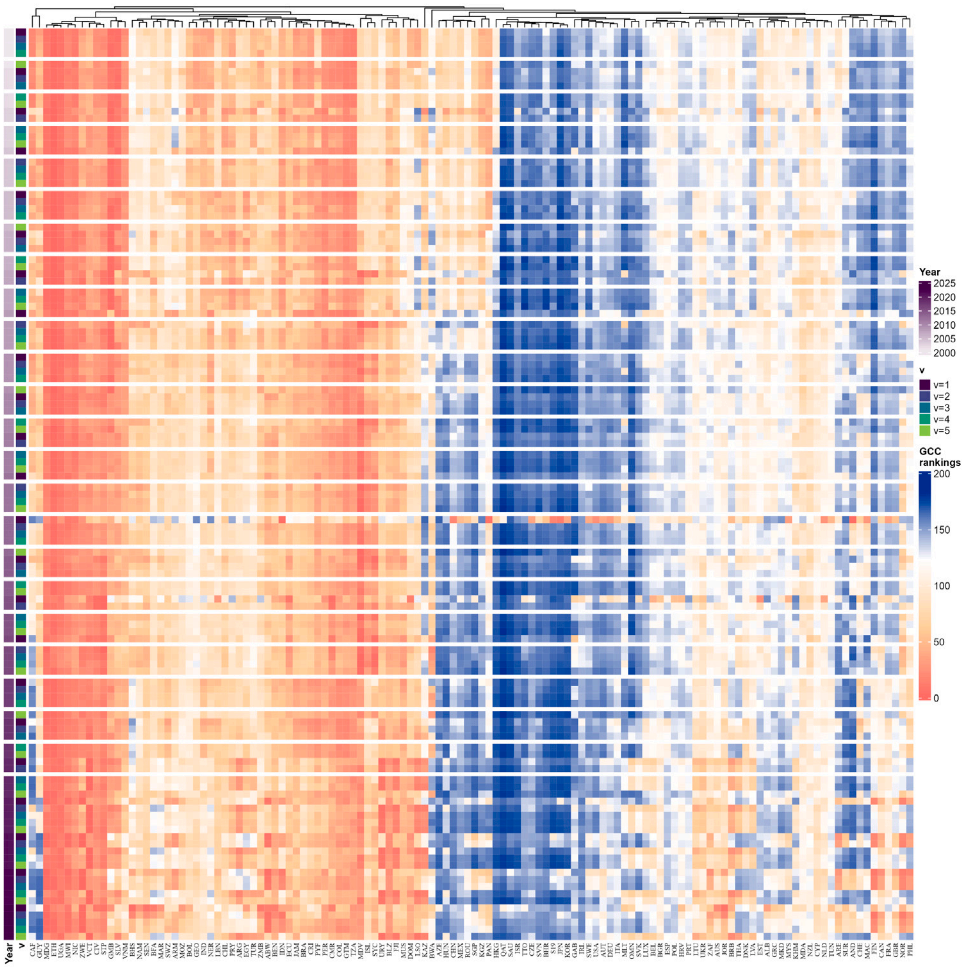
It is worth noting, however, that when the statistical window is adjusted to = 1 (i.e., trade competition intensiveness is assessed solely on the basis of current-year exports without reference to past export performance), the GCC results of some countries diverge from the benchmark. As discussed earlier, several factors may account for these discrepancies. First, different commodities may exhibit varying lags between customs clearance and the point at which they actually participate in global market competition; for countries with comparative advantages in certain products, such lags can generate significant delayed effects. Second, the duration of competitive cycles in global markets varies across products, producing heterogeneous effects for countries with specialized export structures. In addition, fluctuations in exports can also substantially affect competition intensiveness measured under this narrower statistical scope. It is particularly relevant in the current context of increasing global economic uncertainty, frequent trade policy adjustments, and volatile market demand, all of which have introduced considerable fluctuations into the export performance of certain commodities in specific countries. Nevertheless, the conclusions drawn earlier in this article remain broadly robust for the majority of countries (or regions).

6. Comparison with "similarity" indicators

As noted above, the most important innovation of the algorithm proposed in this article lies in its consideration of the "heterogeneity" and "interconnectedness" of different commodities. Heterogeneity means that the contributions of different exported commodities to the competition of countries are not the same. Such heterogeneity can arise from many aspects — e.g., the degree of homogeneity of a product: those with higher homogeneity are more likely to generate competitive effects in global markets; or the input factors required: commodities with higher knowledge or capital intensity entail higher production and trade thresholds, making them less likely to generate competitive effects in global markets. On the other hand, interconnectedness means that the effects of different commodities on the trade competition of countries, as well as the effects of different countries' participation on the competition of particular commodities, are interrelated and closely linked. Consequently, the overall competition of different commodities may change with shifts in the trade structure of different countries or with fluctuations in the export conditions of other commodities; likewise, the overall competition of countries may also change with adjustments in the export structure of commodities



(a)



(b)

Fig. 8. Comparison of GCC results under different statistical windows from 2001–2023.
NOTE: Subfigure (a) shows the overall gaps between results of $GCC_{(5)}$ and $GCC_{(4)}$ from 2001–2023; subfigure (b) shows results of GCC rankings under different statistical windows from 2001–2023.

or shifts in other countries' exports. Any trade shock, through the structure of the trade network, will eventually affect every country and every category of commodities within the global trade system.

6.1. "Similarity" construction

Traditional indicators of trade competition share a broadly similar core idea in measuring overall competition, i.e., comparing the similarity of export structures across countries — usually by calculating some kind of "cosine similarity" [14]. The usual form of similarity in measuring competition can be expressed as:

$$Similarity_{ij} = \frac{\mathbf{x}_i \cdot \mathbf{x}_j}{\|\mathbf{x}_i\|\|\mathbf{x}_j\|} \frac{\sum_{k=1}^{n} \left(x_{i,k} \cdot x_{j,k}\right)}{\sqrt{\sum_{k=1}^{n} \left(x_{i,k}\right)^2 \cdot \sum_{k=1}^{n} \left(x_{j,k}\right)^2}} \tag{13}$$

where $x_{i,k}$ and $x_{j,k}$ can be expressed as: $\begin{cases} x_{i,k} = \frac{V_{i,k}}{V_i} \\ x_{j,k} = \frac{V_{j,k}}{V_j} \end{cases}$, $V_{i,k}$ (or $V_{j,k}$) denote the total export value of commodity k from country i (or j); and V_i (or V_j) denote the total trade value exported by country i (or j). The closer the shares of exports from two exporting countries (i and j) of the same commodity (k), the more similar their export structures are, the higher value the similarity indicator will be, which indicates a higher intensity of export competition.

Then, two main approaches are typically adopted in practice: first, pairwise comparison of bilateral trade structure similarities, followed by some form of weighting, which can be expressed as:

$$Similarity_i = \sum_j w_j \cdot Similarity_{ij} \tag{14}$$

or, alternatively, treating all other countries as a whole and comparing a given country against this aggregate, which means that j denotes the rest of the world, which consists of countries other than i.

However, this approach suffers from fundamental shortcomings, and each of the two operational methods has its own advantages and disadvantages.

First, the calculation of cosine similarity is based on the share of different commodities in total exports; this implicitly assumes that the contributions of different commodities to trade competition are homogeneous — i.e., competition is only affected by changes in the proportions of commodities. Such a framework, which ignores heterogeneity across commodities, typically results in one consequence: the heterogeneous levels of trade competition become averaged out. We often end up overestimating the competition of entities with low competition levels and underestimating those with high competition levels.

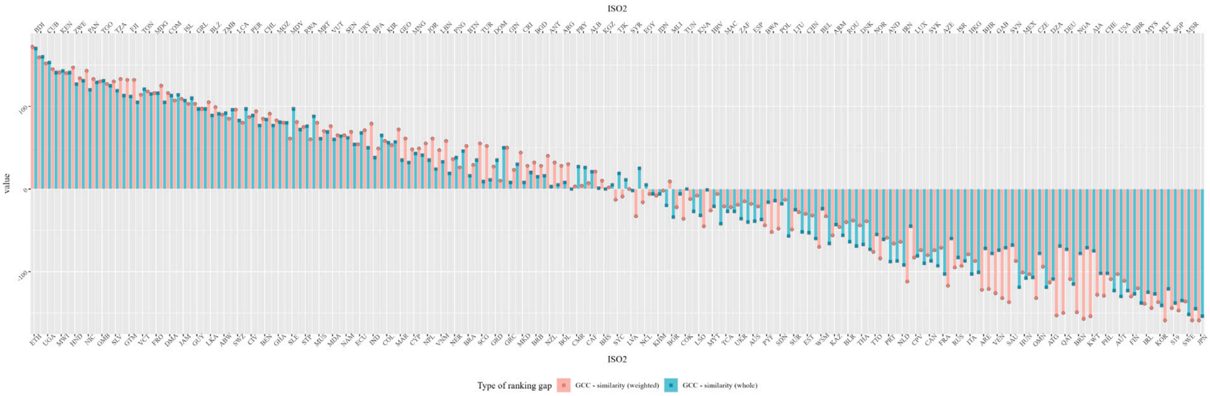
Second, the two operational methods for computing trade competition also involve issues of representativeness and interpretability. On the one hand, treating all countries other than a specific one as a single aggregate has strong interpretability but sacrifices representativeness, since the competition of one country against others is inherently heterogeneous; collapsing all other countries into a single aggregate ignores these differences. On the other hand, comparing export structure similarities pairwise between countries and then applying some form of weighting addresses the representativeness problem, as the competition of each country can be incorporated into the overall measure through weighting. However, the drawback here is a lack of interpretability — the weighting schemes are often "subjective" or "arbitrary" (e.g., based on GDP share or trade volume). It is difficult to determine weights in a manner that is both objective and interpretable.

Therefore, to better demonstrate the reliability and validity of the algorithm proposed in this article, we compute the trade competition of countries (or regions) using traditional indicators and then compare these with the results obtained from our proposed algorithm. This allows us to highlight the innovations of our approach more clearly. The comparison results are presented in Fig. 9.

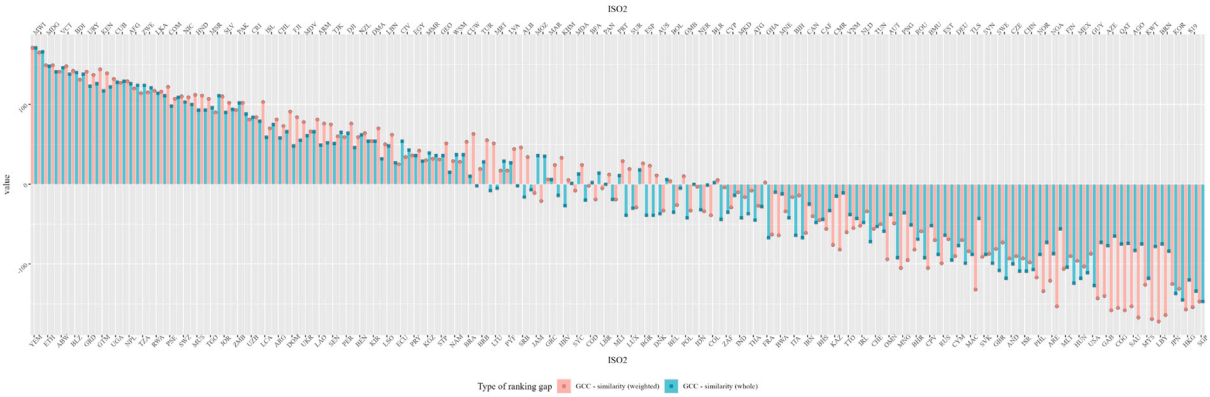
6.2. Comparison result and discussion

As anticipated, the trade competition of most underdeveloped countries with low levels of economic and technological development is underestimated, while the competition of most developed countries with higher levels of economic and technological capacity is simultaneously overestimated. As shown earlier, countries deeply engaged in exports of primary processed goods, raw materials, and agricultural/livestock products — e.g., Burundi, Uganda, and Ethiopia in Africa, as well as Guatemala and Honduras in Latin America — see their competition substantially underestimated. Although such raw materials and primary products have relatively low technological content and low production and trade barriers, which allow most underdeveloped regions to participate in trade, these commodities typically account for only a small share of global trade. In particular, because they are situated at the lower end of the value chain and generate limited added value, their heterogeneity relative to other commodities is "averaged out" by mid- to high-end manufactured commodities in similarity calculations, thus failing to adequately reflect their distinctive competition.

Conversely, the competition of countries such as Japan, South Korea, several European and North American economies, and emerging developing countries with rapidly growing R&D capacities tends to be overestimated. The reasons are similar: these countries often occupy specialized positions in global production and the trade system, which to a large extent shields them from



(a)



(b)

Fig. 9. Comparisons between competition rankings calculated from GCC and "similarity".
NOTE: Subfigure (a) shows the gaps between GCC rankings and similarity rankings in 2001; Subfigure (b) shows the gaps in 2023.

direct competition. However, in similarity calculations, the "averaging" effect of high value-added products – which account for a significant share of their exports – artificially inflates their measured competition levels.

Interestingly, the extent of overestimation and underestimation differs between 2001 and 2023. By 2023, the degree of polarization in over- or under-estimation has weakened compared with 2001, suggesting that heterogeneity across commodities and countries may be gradually diminishing. This trend is likely linked to the recent wave of de-globalization and the growing frequency of geopolitical conflicts, which have fragmented the global trade system under increasingly complex economic conditions and eroded the traditional international division of labor. In turn, this has disrupted established specialization patterns — a dynamic exemplified by the recent Sino-U.S. trade conflict, U.S. sanctions against Russia, and other episodes of geo-economic conflict.

7. Sensitivity analysis

To further evaluate the robustness of the proposed algorithm, we conduct sensitivity analyses by introducing exogenous trade shocks and examining the differences between countries' (or regions') overall trade competition intensiveness in the steady state of the trade network and in the benchmark scenario, which provides additional insight into the two core features embedded in the algorithm — heterogeneity and interconnectedness.

If the trade conditions of other countries remain constant, when the export status of a particular commodity in a specific country (e.g., an unanticipated trade shock) changes, "heterogeneity" implies that shocks of identical magnitude across commodities may yield markedly different changes in competitive pressure for that country; "interconnectedness" indicates that such a shock will ultimately propagate through the trade network and alter the competition intensiveness faced by other countries.

As discussed earlier, heterogeneity is related to product homogeneity, substitutability, and factor input structures. Products characterized by lower homogeneity, lower substitutability, and greater reliance on knowledge and capital inputs typically face higher entry barriers, making them less likely to generate competitive effects in global markets. Consequently, countries participating heavily in such products tend to experience greater competitive pressure. These products are generally distinguished by fewer participating countries, a greater concentration of participating countries that are technologically advanced, and positioning at the high end of value chains with higher value added. Conversely, products with higher homogeneity and substitutability, and greater reliance on labor inputs tend to generate stronger competitive effects, exposing participating countries to greater competitive pressure. These products typically involve a larger number of countries, lower levels of technological and economic development of participating countries, and are often raw materials or primary processed goods.

Accordingly, if the sensitivity analyses conform to our expectations, an increase in the export volume of a commodity with high competition intensiveness in a specific country (accompanied by a relative decline in low-competition commodities) should amplify the overall trade pressure faced by this country. In contrast, an increase in low-competition products (with a relative decline in high-competition products) should reduce the pressure.

Here, two types of trade shocks are implemented, both designed to keep the global aggregate trade volume unchanged. The first alters the distribution of a country's exports across commodities. This setting helps assess how a country's trade policies may reallocate resources to improve competition intensiveness. Specifically, we select one specific commodity within a specific country, increase its exports by 10%, and reduce the remaining commodities proportionally within the same country. Corresponding results are shown in Fig. 10(a). The second alters the distribution of a given commodity's exports across countries. This design helps assess how the global division of labor changes affect national competition intensiveness. In this case, the export volume of a specific commodity from one country is increased by 10%, while the exports of the same commodity from other participating countries are reduced proportionally. Corresponding results are shown in Fig. 10(b).

The color of cells in the heatmap illustrates the following interpretation: how and how much have the GCC percentile ranking results changed (redder shading indicates an increase, while bluer shading indicates a decrease), when the export volume of a specific commodity (horizontal axis) from a given country (vertical axis) increases by 10% (with the export volumes of other commodities of the same country proportionally reduced so as to keep total exports constant). Of course, the choice of "10%" is merely a subjectively selected shock magnitude that we consider reasonable. To ensure robustness, this article also tests responses under alternative shock levels, including 1%, 5%, 20%, 30%, and 50%.[16] Full results are available in the Supplementary Material.

7.1. Intra-national redistribution

The sensitivity analysis results are largely consistent with our expectations; however, several aspects are worth further interpretation. We first focus on the sensitivity analyses from the perspective of domestic allocation shocks. A clear horizontal-striping pattern emerges, suggesting that cross-country differences are more pronounced than cross-product differences. In other words, as long as a country becomes sufficiently specialized, i.e., concentrates its export shares in a particular product, the resulting effect is largely similar across products. This observation is especially evident for products with low competition intensiveness.

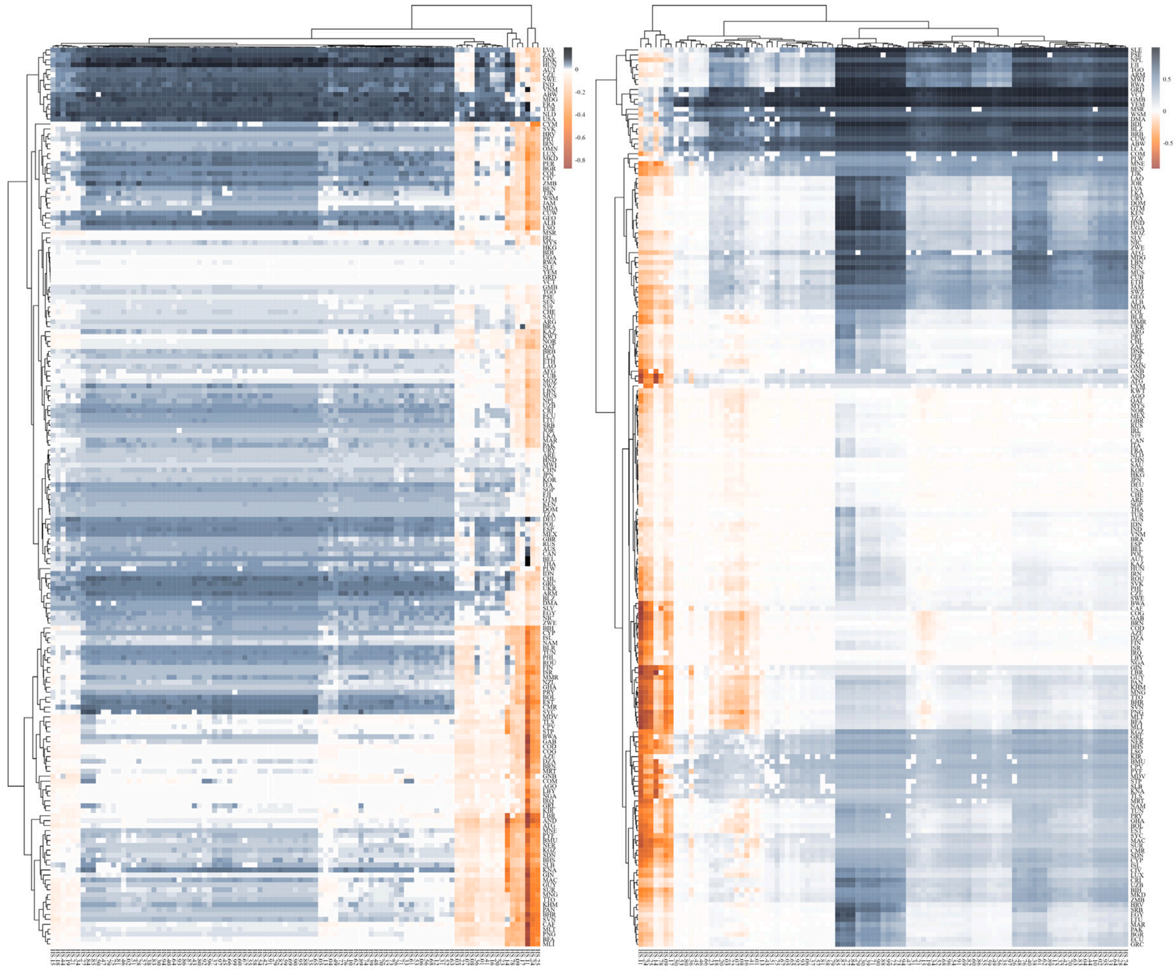
Along the horizontal axis, for raw materials, primary processed goods, and agricultural/livestock products — e.g., "coffee and tea (HS.09)", "milling products (HS.11)", "tobacco (HS.24)", and "salt, sulfur, and other mineral substances (HS.25)" — an increase in trade volume almost invariably raises trade competition intensiveness of countries, regardless of country type. This is because participation in the export trade of these commodities implies competition with the vast majority of countries in the global system. By contrast, for most other product categories, particularly "nuclear reactors machinery (HS.84)" and "electrical machinery (HS.85)", and "aircraft (HS.88)" — which are mid- to high-end manufactures and advanced machinery, increased trade volumes almost always reduce competition intensiveness. These commodities typically follow established specialization patterns, with market shares concentrated in a few countries, thereby avoiding broad-based competition. Moreover, as revealed by vertical comparisons in the heatmap, the direction of the effect of increased trade volumes on competition intensiveness is generally consistent across countries for a given commodity, though the magnitude varies, often reflecting differences in specialization.

Focusing along the vertical axis, we can also distinguish at least two types of countries. For a small subset – typically less-developed countries or regions – competition status does not improve, and may even worsen, regardless of which commodities are expanded. On the one hand, increasing exports of raw materials or primary goods cannot reduce their competitive pressures, even if specialization is achieved, because other countries' trade in such commodities is largely determined by industrial structure and remains stable over time. On the other hand, increasing exports of mid- to high-end products also does little to alleviate competitive pressure, as these commodities constitute only a small share of their total exports. For such countries, relying solely on adjustments in domestic industrial or trade policies is unlikely to meaningfully improve their trade competition status.

For most countries, reallocating export shares across different commodities generates effects, and in many cases, such effects are two-sided. Increasing exports of raw materials or primary products still worsens competition status, but expanding exports of manufactures and high-tech equipment does help reduce competitive pressures, as it lessens direct competition with the majority of underdeveloped countries in global markets. For these countries, the implementation of domestic industrial and trade policies is therefore meaningful, as it can significantly alleviate competition pressure.

Of course, even within this latter group, notable heterogeneity exists. For the majority of these countries, redistributing export shares across commodities indeed produces two-sided effects. However, for the other, the effects are just monotonic, i.e., increasing the export share of highly competitive commodities never generates negative impacts. Thereinto, some are highly ranked countries (e.g., Japan, Korea, Singapore, and Sweden), raising the share of primary products has little effect on competition status, since these countries have already established specialized positions and occupy peripheral locations in the 1-mode network; moreover,

[16] We regard that a 50% reallocation of the total exports within a country, induced by a domestic policy, has been an extremely radical scenario.



(a) (b)

Fig. 10. Sensitivity analysis results based on intra-national and intra-sectoral redistribution
NOTE: Subfigure (a) shows the results based on intra-national redistribution with respect to export trade value in 2023; Subfigure (b) shows the results based on intra-sectoral redistribution in 2023.

primary products constitute a very small portion of their exports, so an increase does not meaningfully alter specialization patterns. And some others are mid-ranked developed economies (e.g., France, Germany, the Netherlands), adjustments in export allocation also produce negligible effects, as their trade structures are typically "egalitarian" — covering the full industrial spectrum without significant comparative advantage in particular sectors. This pattern may be related to the presence of complete industrial chains, such that increased trade volumes in any sector do not substantially alter the overall structure.

7.2. Intra-sectoral redistribution

Subsequently, we examine the redistribution of trade shares induced by cross-country (intra-industry) trade shocks. Above all, it is worth emphasizing that intra-industry redistribution of trade shares in fact signals the gradual formation of specialization patterns. Here, we can observe a more pronounced vertical-striping pattern, indicating that cross-product heterogeneity is stronger than cross-country heterogeneity. Furthermore, we can also observe that intra-sectoral redistribution seems to be more effective than the domestic one, as evidenced by the broader variation in GCC percentile rankings displayed in the figure.

In particular, Along the vertical axis, two sharply contrasting groups of products emerge, such that exporting specialization in these two categories generates entirely opposite competition effects, though the magnitude varies somewhat. Specifically, higher concentration of trade in raw materials and primary products tends to increase trade competition intensiveness of countries (or regions), whereas higher concentration of industrial manufactures tends to reduce competition intensiveness. This divergence is closely tied to the structure of participating countries. On the one hand, for low-value-added products, most countries (particularly less-developed ones) have few choices but to participate in exports and allocate substantial shares within their trade structures. A redistribution equivalent to 10% of a country's sectoral exports does little to alter the structure of participating countries, meaning that higher concentration merely intensifies competition. On the other hand, for industrial manufactures and advanced equipment, greater concentration may push some countries or regions effectively out of the market (in terms of this algorithm, implying $RCA < 1$), thereby reducing competitive pressures with most other countries.

Of course, cross-country responses differ when trade concentration rises for specific products, especially among countries with initially low competition intensiveness. For such countries, with a small amount of raw materials and primary products trade volumes, a redistribution equivalent to 10% of sectoral exports does not generate significant competitive effects. Similarly, there is just a limited number of countries that will be able to produce and export manufactures and mid- to high-end equipment, which are primarily advanced economies with technological capabilities, and those corresponding markets are often dominated by just a few players. Thus, increased concentration in these commodities rarely reduces competition intensiveness either.

From a horizontal perspective, the vertical-striping pattern suggests that intra-industry reallocations generate greater cross-product heterogeneity in competition effects than intra-national redistributions. This implies that when a country is exposed to different industry-specific policies (implemented outside rather than by the country itself) and thereby becomes more specialized, the resulting effects will no longer be uniform. Just contrasty, once cross-national policies are implemented at the intra-sectoral level, the resulting effects tend to be much more uniform, regardless of which specific country is involved. Furthermore, we can observe that intra-sectoral redistribution seems to be more effective than the domestic one, as evidenced by the broader variation in GCC percentile rankings displayed in the figure. The mechanism is similar to the one described above: a redistribution equivalent to 10% of sectoral exports may not be sufficient to alter the set of participating countries, and thus primarily intensifies competition for specific countries. Conversely, concentration may indeed lead some or even many participants to effectively withdraw from competition, thereby alleviating the overall competitive pressure some specific countries are confronted with.

This conclusion is particularly valid for two types of products. For commodities already characterized by very high competition intensiveness, e.g., coffee and tea (HS.09) and milling products (HS.11), increased concentration rarely forces participants out of trade. Because underdeveloped countries are deeply involved in these exports, redistributing trade shares scarcely alters their positions, meaning that greater participation invariably raises competition. Conversely, for commodities characterized by very low competition intensiveness, such as advanced electronic equipment (HS.85) and vehicles (HS.87), where a handful of developed countries dominate the market, higher concentration scarcely alters existing structures, but instead primarily reduces competition intensiveness (since the RCA values of other competing commodities decline).

This conclusion is particularly relevant for less-developed or developing countries (or regions), as it provides policy insights distinct from those arising from intra-national redistribution. These countries correspond precisely to those identified earlier in the intra-national redistribution analysis, i.e., countries of which domestic policies alone cannot significantly mitigate competitive pressures. For such economies, relying solely on domestic industrial or trade policies will be far from beneficial; instead, they require coordination through regional or global multilateral cooperation mechanisms or international organizations to coordinate production and trade effectively. Such coordination can help prevent excessive concentration in low-end sectors, avoid the trap of competing in only a narrow set of products, and enable disadvantaged countries to escape structural lock-in. Moreover, cross-country technology transfer and knowledge spillovers may prove particularly valuable, as they can reshape cross-industry trade structures and foster the emergence of regional advantages.

Existing studies indeed show that cross-border trade coordination mechanisms, e.g., regional trade agreements (RTAs), help refine the international division of labor and promote more specialized participation in Global Value Chains (GVCs). "Deep agreements" that include rules on services, investment, and intellectual property [49], typically reduce the transaction costs of fragmented production and expand trade in parts and components through regulatory harmonization, thereby fostering a finer division of labor and "vertical specialization" [50]. In particular, as export scale grows, developing countries tend to diversify first, whereas high-income economies are more likely to re-specialize [51]. For Asia, which includes a large number of rapidly growing developing countries, empirical evidence likewise shows that agreements, e.g., China-ASEAN Free Trade Area (CAFTA), are associated with increases in export complexity and finer specialization [52].

8. Concluding remark

8.1. Research conclusion

In recent years, the proliferation of de-globalization trends and the frequent eruption of geopolitical and geo-economic conflicts have fragmented the global trading system, thereby reigniting scholarly interest in trade competition. Given the complex-system characteristics of global trade networks, this article adopts a framework that departs fundamentally from conventional economics and develops a new concept, i.e., "competition intensiveness", designed to identify and extract competitive information embedded in the trade network at both the product and country levels. By integrating the asymmetric reflection algorithm with matrix-estimation exercises based on bipartite networks, we quantify the generalized competition intensiveness of both countries and commodities. We then provide detailed discussion and case analyses to demonstrate the reliability and validity of the proposed algorithm, and we reinforce its robustness through a series of algorithmic adjustments. In addition, the proposed measurement is systematically compared against conventional indicators of trade competition intensiveness, and sensitivity analyses at both the intra-country and intra-sector levels are conducted to extract policy implications.

Based on the results and their economic interpretation, several key findings emerge:

- Discussions on algorithm tell us: First, both generalized competition intensiveness of country (GCC) and of product (GCP) capture an intensity of competition, determined jointly by the export structures of countries and the participation structures of products, but not directly by trade volumes. Second, GCC and GCP are closely interrelated and mutually reinforcing. This implies that the competition intensiveness of a country (or region) is shaped not only by the attributes of its own export basket but also indirectly by the economic properties of other countries; the same holds for products. Changes in national or product characteristics, therefore, propagate through the network.
- Robustness checks based on algorithmic adjustments demonstrate that the proposed method is effective and stable in measuring generalized competition intensiveness, retaining most of the topological information embedded in the bipartite network while minimizing noise.
- Across different RCA thresholds, varying numbers of eigenvalues and eigenvectors, and alternative trade-data statistical windows, the calculation results remain robust.
- Comparisons with conventional indicators confirm our prior expectation: traditional measures, by relying on weighted averaging, tend to obscure heterogeneity across countries and commodities — not only underestimating the competition intensiveness of underdeveloped countries, but overestimating that of advanced economies.
- Sensitivity analyses allow us to distinguish between two types of countries: advanced or middle-income economies with an industrial base and technological capacity, and highly underdeveloped economies, each requiring fundamentally different policy approaches.

8.2. Policy implication

From these findings, several policy insights can be drawn:

First, due to some strategic needs, economic entities may try to seek a lower competitive environment. But "competition" will be jointly determined by the export situation of each country (or region) in the world, and investing in any industry much too universally or intensively will change the industry's competition largely. Therefore, from a global perspective, the best way to improve the situation of competition is to realize the international division of labor.

Second, as for many developing countries, limited by their own economic development status, primary products account for the vast majority of their export structure, and it will be unrealistic for them to focus on developing the industry of manufactured products. Such countries can rely on their own endowments of resource elements to further divide labor in the export of primary products. Moreover, for countries with a strong technological foundation, it is meaningful to vigorously develop the industry of manufactured products and realize the international division of labor to optimize their own export trade structure.

Third, as the sensitivity analyses demonstrate, different categories of countries require distinct policy instruments. For advanced or middle-income economies with industrial capacity, domestic industrial and trade policies remain effective. However, for highly underdeveloped economies, domestic efforts alone are insufficient; multilateral coordination mechanisms at the regional or global level will be essential to help escape development traps. In the future, agreements with large market scale and potential to exert substantial influence, e.g., EU–Mercosur, African Continental Free Trade Area (AfCFTA), and ACFTA 3.0, as well as those undergoing membership expansion and likely to reshape regional landscapes, e.g., Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP) and Regional Comprehensive Economic Partnership (RCEP), are important transnational coordination mechanisms worthy of close attention and further study. Even the technology transfer and knowledge spillovers from developed countries may also help these countries overcome low-end lock-in, while RTAs facilitate developing countries' benefits from the flows of factors, capital, and knowledge.

8.3. Directions for future agenda

The quantitative approach employed in this article provides a novel method for measuring the competition intensiveness of countries and products, addressing the limitations of conventional frameworks that neglect heterogeneity. It offers a more objective and nuanced reflection of inter-country linkages in export trade. Nevertheless, several avenues remain for improvement:

- There is still room for algorithmic refinement. This article constructs bipartite networks based on 2-digit HS codes; disaggregating to finer categories of commodities may yield different results due to heightened sensitivity to detailed information. Moreover, the linear nature of the algorithm implies that fine-grained network structures may be under-identified, since linear methods often sacrifice some heterogeneity.
- Second, this article provides only a limited assessment of the algorithm's validity. On the one hand, the interpretation relies heavily on the internal logic of the algorithm itself; on the other hand, the empirical grounding depends primarily on case studies, especially those that trace temporal changes in domestic competition conditions following the implementation of specific policies. Future research would benefit from employing rigorous econometric identification strategies to examine the causal effects of policies on competition intensiveness.
- Third, the economic interpretations of the results are necessarily limited. In particular, results under different RCA thresholds, different numbers of eigenvectors and eigenvalues, and alternative trade-data statistical calibers warrant deeper investigation. Further exploration of comparisons with conventional indicators and sensitivity analyses also promises to yield richer insights.
- Finally, the present analyses focus mainly on the relationship between the algorithmic outcomes and the structural properties of the global trade network. It does not yet offer a systematic examination of the economic consequences that arise from temporal changes in trade competition. Future work that integrates complex-network approaches with causal inference in international economics may yield more insightful policy guidance.

CRediT authorship contribution statement

Sin-Som (Sergio) Tsiong: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Shuaihang Li:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Formal analysis, Data curation. **Mingqian Zhang:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Conceptualization.

Declaration of competing interest

All authors disclosed no relevant relationships.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.chaos.2025.117677.

Data availability

Data will be made available on request.

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