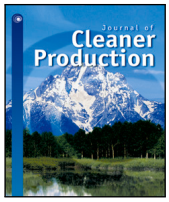
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Trade network dynamics in a globalized environment and on the edge of crises

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ABSTRACT

At the edges of crises, the roles of trade networks and supply chains are evident. Global trade networks aggregate all legal trade activities. Thus, researchers believe that network structure changes reflect phenomena such as crises, globalization, deglobalization, or even technological development, including those related to green technologies. Although trade network analysis has been widely researched, researchers have focused mainly on one or a few products or product groups. While the impact of crises and technological changes in the case of individual products has been demonstrated in some studies, less attention has been given to structural pattern changes in trade on these products. To understand how a shock, crisis, or technological change in one product may affect the trade network of another product, the patterns and relationships of node- and network-level indicators across products need to be identified. In this study, the dynamics and interdependencies of trade networks are analyzed using a combination of network indicators, cluster analysis and causality analysis. Variations and implications of the temporal patterns and causal relationships of trade network indicators are revealed for different products and product groups. Researchers have argued that the deterioration of structural indicators exacerbates crises and amplifies their consequences. A causality analysis shows that disruptions in one product's supply chain quickly affect the trade of other products, altering the structural characteristics of trade networks. The proposed temporal pattern analysis shows that while the 2008 financial crisis did not cause structural changes in the product trade network, indicators improved before, during, and after the crisis. Nevertheless, before the pandemic, there was a noticeable deterioration in almost all structural indicators, signaling more deglobalization. This study contributes to a comprehensive understanding of trade networks, equipping decision-makers with the knowledge to promote the resilience and sustainability of these networks in an evolving global landscape.

1. Introduction

Trade is one of the most fundamental and pervasive human activities shaping the world in which we live (Fernandez-Mora, 2023). Trade networks, which represent the connections and flows of goods and services among economic agents, such as countries, regions, or firms, are essential for understanding the structure and dynamics of the global economy and society. Trade networks can also reveal the effects of globalization (Kim and Shin, 2002), technological changes (Ferrier et al., 2016), and crises (Gutiérrez-Moya et al., 2023) on various aspects of development (Ferrier et al., 2016), such as growth (Teza et al., 2018), poverty (Higgins and Prowse, 2010), inequality (Prell et al., 2015), the environment (Aller et al., 2015), culture (Shutters and Muneepeerakul, 2012), society (Garlaschelli and Loffredo, 2005), and security (Haim, 2016). The study of trade networks is important because it reveals how companies or countries interact to benefit the community as a whole (De Benedictis and Tajoli, 2011). Moreover, by studying trade networks, scholars can gain insight into the opportunities and challenges of trade integration and cooperation and identify best practices and strategies to improve the benefits and mitigate the risks of trade for all stakeholders (Shutters and Muneepeerakul, 2012).

According to permanent crisis theory (Hont, 1994), the economy does not necessarily move toward equilibrium; instead, it moves from one crisis to another. Structural changes in world trade networks can serve as indicators of changes in globalization/deglobalization (Xu et al., 2019), technological development (Shutters and Muneepeerakul, 2012), or the emergence of crises (Gutiérrez-Moya et al., 2023).

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Therefore, it is assumed that the indicators of these phenomena can be identified through temporal patterns of trade networks. Several researchers have argued (Gutiérrez-Moya et al., 2023) that studying trade networks can help predict crises or shocks (Gutiérrez-Moya et al., 2023) or at least help assess their potential impact and propagation (Kali and Reyes, 2010). At the same time, some researchers agree with the findings of Papadopoulos et al. (2023): if structural indicators worsen, the effects of a possible crisis may become more severe. Even if permanent crisis theory is not true, it is still worth observing which indicators may be a sign of a crisis. However, at the same time, if the economy is naturally prone to crises, the effects of crises will intensify when supply chains freeze and the world trade network becomes centralized. Thus, resilience will decrease.

Resilience is usually defined as the capacity to withstand disruptions and recover from them effectively (Kharrazi et al., 2017). Factors such as national culture, geography, and regional variations play a significant role in determining a country's trade resilience during crises such as the coronavirus disease 2019 (COVID-19) pandemic (Karakoc and Konar, 2021). Analyses have emphasized the need to enhance resilience capacity before a disaster strikes through measures such as increasing inventories, developing emergency management procedures, and providing government assistance. Additionally, the concept of dynamic resilience at the micro, meso, and macro levels is crucial for facilitating quick recovery and reconstruction postcrisis (Obashi, 2009). By understanding and incorporating these factors into trade network analysis, countries can better prepare for and navigate through disruptions, ultimately improving their overall resilience in the face of crises.

The topic of global trade is strongly intertwined with the subject of sustainability. Numerous interconnected areas show the importance of striking a balance between them. Researchers are emphasizing the importance of global trade from diverse perspectives, including the impacts of CO2 Emissions (Kander et al., 2015) and the role of trade in advancing the Sustainable Development Goals (SDGs) (Xiao et al., 2024) contribute to reducing global hunger (Janssens et al., 2020) and addressing future food demand due to population growth or considering the effects of price volatility (Brander et al., 2023). Long-term policy suggestions should include sustainability, careful planning, cooperation among counties and consideration of economic, social and environmental aspects.

Researchers usually present an overview of the trades of whole networks, e.g., the trades of countries (De Andrade and Rêgo, 2018; Garlaschelli and Loffredo, 2005). However, they may also focus on one or a few representative products (Kostoska et al., 2020; Ren et al., 2020; Gutiérrez-Moya et al., 2023) or, in rarer cases, their development over time (Shutters and Muneepeerakul, 2012; Gutiérrez-Moya et al., 2023). In other studies, researchers have either examined the trade network of all aggregated products (De Andrade and Rêgo, 2018; Garlaschelli and Loffredo, 2005) or focused on the trade network of a single product group (Kostoska et al., 2020; Ren et al., 2020). However, the network structure and dynamics of different products and product groups may also be interrelated (Shutters and Muneepeerakul, 2012). In this case, the vertices of the network show the countries, and the edges show the import/export volume or value of the given product or product group (Sajedianfard et al., 2021). The indicators that can be used to analyze trade networks can be separated into two subgroups. *Node-level indicators* are crucial for measuring the importance and position of countries in trade networks. By examining node-level indicators in time series, scholars can gain insights into how the role of products and countries changes over time (del Río-Chanona et al., 2017). However, the structures of trade networks are only described by *network-level indicators*. A time series analysis of these properties can reveal how trade networks reflect technological changes, globalization/deglobalization, and crises (Xu et al., 2019). Understanding network structure and behavior is a critical area of research in various fields (Piccardi and Tajoli, 2018). Furthermore, the properties at the network level describe the resilience of the trade networks, reciprocities, and asymmetries of trades (Garlaschelli and Loffredo, 2005).

Despite the importance and complexity of trade networks, there are still many open research questions and challenges in trade network analysis. For example, how can the structural characteristics of various products and product groups be utilized to evaluate and categorize trade networks? Answering this question involves determining the extent to which the structural changes in the trading of individual product groups differ from each other. If the time patterns of these characteristics are similar, then they respond to the crisis and change in a similar way regardless of the product type. If the characteristics can be separated, then an interesting question may be which product groups are included in a cluster. In addition to possible temporal structural similarities, is it possible to reveal the causal relationships between the patterns of product groups? Exploring causality could help identify the spread of shocks and the effects of technological changes.

To understand how a shock, crisis, or technological change in one product's trade network may affect another product's trade network, it is necessary to identify the patterns and relationships of node- and network-level indicators across products. Moreover, to identify which products or product groups share similar structural characteristics or which trade networks' structural features influence those of other trade networks, it is also necessary to analyze the patterns based on the properties of trade networks. To our knowledge, no previous study has investigated the temporal patterns of trade network indicators and their interrelationships. Therefore, the following research question is stated.

RQ What are the variations and implications of the temporal patterns and causal relationships of trade network indicators for different products and product groups, and how can they be used to detect the transmission and impact of shocks, crises, and technological changes?

The aim of this study is to address these research questions and challenges by proposing a novel and comprehensive framework for analyzing the dynamics and interdependencies of trade networks at the product level. This study presents a set of databases to analyze trade network indicators for products and product groups based on a large and detailed dataset of international trade flows. Cluster analysis is used to identify variations and implications of trade network indicators for different products and product groups and to compare their network characteristics with those of technological advancements and trade agreements. Causality tests and centrality measures are employed to examine shocks, crises, and technological changes in trade networks and to identify the key drivers and recipients of structural changes.

The remainder of this paper is organized as follows. Section 2 summarizes the research background and states the contributions to the literature. Section 3 details the employed data and proposes network-based time-series clustering and causality analysis. Section 4 presents the results of the temporal pattern analysis of the trade networks. In Section 5, the results are interpreted. Finally, Section 6 provides conclusions and suggests future research directions.

2. Background

Fig. 1 shows a timeline of shocks and crises that can be related to trade.

Between 1995 and 2025, the global trade landscape was marked by a series of significant crises and shocks. In the early 1990s, events such as the formation of the European Economic Community and the North American Free Trade Agreement set the stage for increased economic integration. In the mid-1990s, the World Trade Center bombing and the UN Conference on Trade and Development underscored the vulnerability of trade networks to security threats. As the new millennium began, the Doha Declaration and the 9/11 attacks reshaped international trade dynamics, leading to increased focus on security and economic

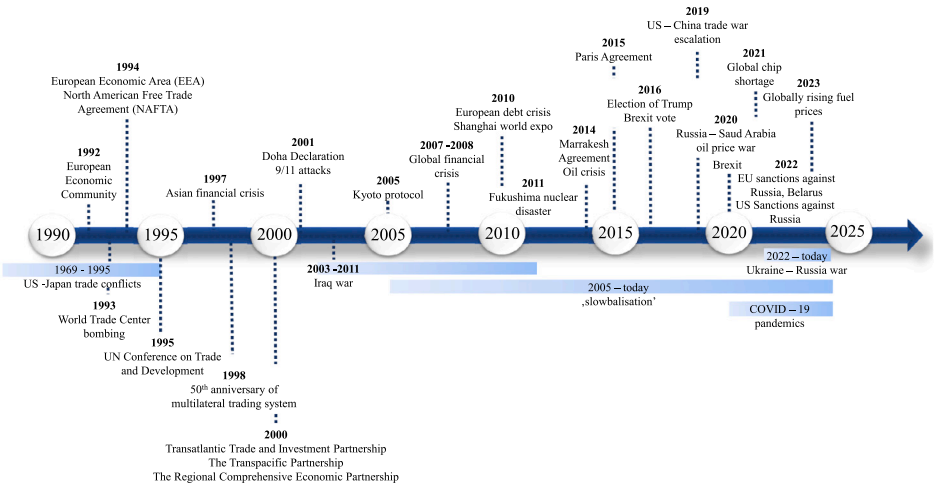


Fig. 1. Shocks and crises that can be related to trade between 1990 and 2025.

cooperation. In the early 2000s, the Kyoto Protocol and the concept of 'slowbalisation' led to a shift toward sustainable practices and slower globalization (Wickes, 2021). The global financial crisis of 2007–2008 had far-reaching implications for trade, prompting a reevaluation of economic policies and trade agreements (Ahmed et al., 2017). Subsequent events such as the European debt crisis, the Fukushima nuclear disaster (Wang et al., 2022), and the Marrakesh Agreement further tested the resilience of global trade networks (Smeets, 2022). In the 2010s, the Paris Agreement (Wu et al., 2022) and the election of Trump brought climate change and protectionist policies to the forefront of trade discussions (Noland, 2018). In 2019, the escalation of the US–China trade war intensified trade tensions, impacting global supply chains and economic stability (Itakura, 2020). The 2020s have been marked by challenges such as the Russia–Saudi Arabia oil price war (Ma et al., 2021), the global chip shortage (Zhang and Zhu, 2023), and the Russo–Ukrainian war. These events, along with the ongoing impacts of the COVID-19 pandemic, continue to shape the future of international trade, emphasizing the need for resilience and adaptability in the face of crises (Steinbach, 2023). Changes in world trade have already been studied using numerous methods, providing answers to different research questions.

To investigate world trade, several freely available databases, such as World Input-Output Database (WIOD), The Atlas of Economic Complexity (ATLAS), Food and Agriculture Organization of the United Nations' Statistical Database (FAOSTAT), and World Integrated Trade Solution (WITS) World Bank (2022), Eurostat (2022), UN Comtrade Database (2022), and BACI-CEPII Database (2022), provide various country-level data on trade and other economic indicators, such as export-import, gross domestic product (GDP), and population trends. However, many studies (see e.g., Hamdi and Hakimi, 2022; Contractor et al., 2020) that use country-specific variables, such as GDP, public debt, private consumption, labor shortage, trade flow or foreign direct investment (FDI), to analyze trade (OECD, 2021) may not capture the complexity and diversity of international trade. As Koopman et al. (2014) and De Benedictis et al. (2014) argued, a country cannot be regarded as a single supplier or buyer of a specific product on the global market; hence, it is more appropriate to deal with export-import data at the product level (De Benedictis et al., 2014; De Andrade and Rêgo, 2018). Various methods have been developed and applied by researchers for this purpose, such as the convergence of iterated correlations (CONCOR) algorithm by Smith and White (1992), the Heckscher–Ohlin model by Baskaran et al. (2011), the SNA by Dong (2022), the gravity model by Herman (2022), and complex network analysis methods (Fagiolo et al., 2010), such as the Exponential Random Graph Model (ERGM) and the network probit model (Herman, 2022). In addition to quantitative methods, qualitative network analysis (QNA) aims to address microperspective instead of macroperspective and qualitative methods instead of quantitative methods and takes an insider instead of an outsider view (Ahrens, 2018). Each of these methods is capable of trade network analysis; however, they can answer different research questions. Nevertheless, the main advantage of the SNA method is that it can provide a holistic and relational perspective on trade, measure various network indicators and visualize network dimensions.

Table 1 shows recent studies on trade networks using SNA. In this table, the main focus of the paper and the main findings are presented along with the analyzed periods or years and product groups. An analysis can contain each product (A) or only pairs of production groups (PGs) or products (Ps). Table 1 also shows whether there is a comparison byproducts. Node-level analysis usually focuses on countries; therefore, the table shows the number of countries compared. In addition, Table 1 also shows whether there was a temporal pattern or causal analysis.

In the studies outlined in Table 1, node-level and network-level variables were examined, focusing on centrality, assortativity, the clustering coefficient, and resilience measures. Typically, the complete network structure was examined, or a small number of product categories were compared. Except Piccardi and Tajoli (2018), scholars have not examined the similarity of the structural parameters of products in trade networks. Researchers analyzing the temporal patterns of complete trade networks have not addressed how these patterns are produced or how many different temporal patterns can be identified. In addition, which product trade structures influence other product trades has not been studied. Researchers have not yet examined the similarities or causal relationships of the temporal patterns of products, as they have either focused on all products and the entire trade network or compared only a few products. Without conducting a product-byproduct examination, it is impossible to determine the number of temporal structural characteristics present. Furthermore, a comprehensive comparison of all trading products is necessary to determine the true extent of differences in their structures. Without a causation test, it is difficult to determine the amount to which a structural change in the trading of one product impacts the trading of another.

In recent studies, various databases that were structurally comparable were analyzed. These databases record trades between certain countries involving specific products. To conduct temporal and structural analyses by country and product, a new database must be created

Table 1
Recent studies on trade networks using SNA.

Author	Focus	Time period	Most findings	Prod. groups	By products	Node- level	Network- level	Temporal analysis	Causality analysis	Employed indicators	Database
Cingolani et al. (2018)	Textiles and electronic products	2007; 2014	High, but recently decreased regionalization.	PG(2)	+	–	+	+	–	Density, clustering, assortativity, centralization	BACI, COMTRADE
Amador et al. (2018)	All industries	1995–2011	Trade agreements have an impact on the network.	A	–	+(5)	+	+	–	Centralities, reciprocity, clustering	WIOD
Piccardi and Tajoli (2018)	High-tech and low-tech industries	2014	High-tech products exhibit high centralization. High centralization of complex products has a strong hierarchy in the trade network.	P(1242)	+	–	+	–	–	Complexities, centralizations, concentrations, vulnerability	BACI, ATLAS
Wang and Dai (2021)	Evolution of global food trade patterns	1992–2018	The complexity of food network is growing.	PG(2)	–	+(7)	+	+	–	Clustering, average path length, connectivity, centralities	FAOSTAT
Zhu et al. (2014)	Evolution of WTN in Asia and Oceania	1996–2019	The rise of China related in trades	A	–	+(2)	+	+	–	Inter- and intra-communities	BACI
Hoang et al. (2023)	Concentrates on the structural changes.	1996–2019	Structural changes: more dense, reciprocal, compact but has not yet reached the full interconnectivity	A	–	+(12)	+	+	–	Centralities, density, assortativity, clustering coefficients	BACI
Nobi et al. (2020)	Structural changes of the trade networks	1995–2013	After the 2008 crisis the products' hierarchy increased. Role of China increased "next Giant hub"	A	–	+(2)	+	+	–	Hierarchical path	COMTRADE
Yazawa (2023)	Trade networks of 5 countries	1992–2020	Existence of imbalances. Detectable crisis, that influence the networks.	A	–	+(5)	+	+	–	Centralities	WITS

Notations: P: product, PG: product group, A: all product. (n): n number of products, product groups or indicators.

to store necessary information. Otherwise, the computations would need to be repeated for each product and country. If a stored network structural database is available, continuously calculating it would allow for tracking changes in structural attributes byproduct and country, aiding future study and decision-making.

To address methodological and research gaps, the following unique contributions to the literature were made.

- **C_1** A database of node- and network-level indicators was constructed for all products and product groups from 1995 to 2021 based on the BACI-CEPII trade network database;
- **C_2** The temporal patterns of trade network indicators were identified for different product groups using a recent nonparametric cluster analysis;
- **C_3** The causal relationships between the structural changes of different product groups were identified using Granger causality tests;
- **C_4** The intermediary roles of product groups and countries in transmitting structural changes were ranked using centrality measures.

The proposed database stores the calculations of node-level and network-level indicators for all countries and product groups (C_1). Analyzing structural changes in trade networks can help identify temporal and spatial patterns without the need to recalculate all variables for every country and product or product group. Based on the proposed database, temporal patterns are classified to identify how many temporal characteristics can be identified and how similar the temporal patterns of the structures of the trade networks are (C_2). In unexpected events and emergencies, similar responses will be observed for product groups with comparable temporal characteristics. Previous studies have demonstrated a connection between network indicators and crises (Yazawa, 2023). It is essential to identify the temporal aspects associated with this process and how they evolve over time. In this article, it is not suggested that crises can be detected through changes in network parameters, in contrast to Yazawa (2023). However, it is believed that the impact of these changes can be heightened in the presence of concentrated or vulnerable network indicators. To determine which changes in a product contribute to structural changes in the trade of another product, defining the typical characteristics and grouping them is not a sufficient approach. However, exploiting the opportunity given by the temporal pattern, it is also necessary to determine the precedential relationship between them with a causality

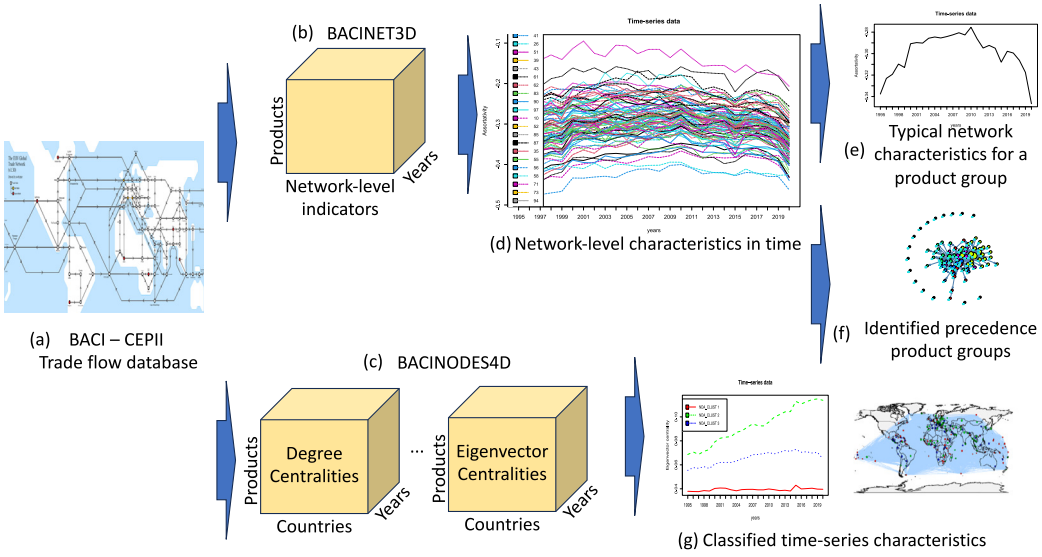


Fig. 2. Process of data preparation and analysis.

analysis (C_3). Performing this task in pairs results in a causality graph. Clustering the graph creates causal groups that indicate the relationships between product changes in the trade networks. The sequence of products within causal groups based on embeddedness determines the leading products that influence changes in other product groups (C_4). The contributions listed are distinct and original. No comparable studies were found during a literature review.

3. Methods

To address RQ, the structural (i.e., network-level) indicators for each product group from 1995–2020 are computed. In addition, role changes, characterized by node-level indicators, for each country over the same period are calculated. Afterward, the temporal patterns of the indicators are classified using a recently introduced nonparametric clustering method. In this way, in part of the RQ: "What are the variations and implications of the temporal patterns of trade network indicators for different products and product groups?" can be addressed. Then, Granger causality tests are applied to analyze and identify the causal relationships between the structural changes of different product groups, allowing scholars to detect the effects of technological changes, shocks, and crises on trade networks. In this way, in the other part of RQ, "What are the causal relationships of trade network indicators for different products and product groups?" can also be addressed. Finally, the specified groups of temporal patterns of indicators are compared to those of major events, shocks and crises, which is the last part of the RQ: "How can the variations in temporal patterns be used to detect the transmission and impact of shocks, crises, and technological changes?" can also be addressed. Fig. 2 shows the data preparation and analysis process.

All data are obtained from the Bilateral Analysis of Correlated Intra-Industry Data (BACI)-Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) database (see Fig. 2(a) and Sections 3.1 and 3.2 for more details). Two databases are constructed for network-level analysis and for node-level analysis: 3D (BACINET3D) (see Fig. 2(b)) and 4D (BACINODE4D) (see Fig. 2(c)) (see Section 3.3). Only network indicators that have economic and commercial interpretations are computed (see Section 3.4). These network-level (see Fig. 2(d)) and node-level (see Fig. 2(g)) indicators are classified using the recently proposed nonparametric NDA method (see Section 3.6). The use of this nonparametric approach means that there is no need to predict the number of clusters. Moreover, this method can provide information on the typical characteristics of the product groups (see Fig. 2(e) and (g)). The generalization of the NDA (GNDA) method is used to classify the precedence graph of the time series of network-level indicators by Granger causality (see Section 3.5) and provide causality groups of trade network structural properties (see Fig. 2(f)). GNDA already handles asymmetries in similarity functions, and in this way, it can group nodes (i.e., indicators) that connect undirected links derived from an asymmetric similarity, such as causality in a causality graph.

The selection of the node- and network-level indicators was based on existing research. However, the criteria for selecting indicators were to depict either the centrality of countries and products in trade networks, the resilience of the network, or the asymmetry and imbalances in trade. Node-level indicators offer valuable insights into the significance and position of nations within trade networks, whereas network-level indicators describe the general structure and characteristics of the trade network. By integrating both categories of variables, a thorough study can be carried out to capture the subtleties of trade interactions at both the individual country level and the entire network level. Analyzing these variables chronologically enables researchers to monitor the progression of the roles of products, countries, and regions within the trade network. An examination of the temporal aspects is crucial in comprehending the manner in which trade networks react to alterations in technology, trends in globalization, crises, and other external disturbances. The chosen indicators aid in discerning fundamental alterations inside trade networks. By examining the temporal distribution of node-level indicators and network-level features, researchers can identify alterations in trading patterns and modifications in network resilience, reciprocities, and imbalances in trade connections. The selected variables allow researchers to perform causality tests to ascertain the presence of causal linkages between various items or nations within the trade network. This study is crucial for comprehending the potential effects that shocks, crises, or technological advancements in one section of the network may have on other associated nodes. These indicators enable comparisons among various items, product groupings, countries, or areas within the trade network. Through the analysis of variances in indicators among different regions of the network, researchers can detect parallels, disparities, and probable groupings based on structural traits.

3.1. Data source

In this study, the BACI-CEPII database, which is an international trade database with a high level of product disaggregation, is employed

as the data source for the analysis. BACI covers more than 200 countries from 1995 to 2020 and reconciles the data reported by the countries to the United Nations Statistics Division using a statistical procedure that ensures consistency and reliability (Gaulier and Zignago, 2010). BACI has several advantages over other similar databases, such as product detail, geographical coverage (Disdier et al., 2010), and unit values (De Benedictis et al., 2014). The product classification is based on the Harmonized System (HS), which consists of 6 digits and includes 5012 products. The HS has been in use since 1989. However, some countries still report using the previous classification, i.e., the Standard International Trade Classification (SITC), which only covers approximately 1241 products at the 4–5-digit level. The BACI database fills in the missing values of bilateral trade flows by using the information reported by at least one partner country (Mayer and Zignago, 2011).

Products can be classified as follows: free main clusters, such as *capital-intensive products*, including chemical substances/products such as organic chemicals and pharmaceuticals as well as electrical machinery, vehicles and nuclear reactors (Rothaermel, 2016); *labor-intensive products*, including small and large commercial goods such as clothing made of wool, cotton, silk and animal skin, and goods made of wood and metals (Hanson, 2021); and resource-intensive products, including agricultural, mining, energy products and basic metals (Vaillant and Gilles, 2017).

3.2. Data collection

The data in the BACI-CEPII database are available free of charge from the official CEPII website. The database contains the annual trade flow, exporter and importer countries and the products with the 6-digit code from the HS system (“product level”, see Table B.5). The structure of a record is as follows: $t|i|j|k|v|q$, where t is the time (1995–2020), i is the exporter (ISO3 country code), j is the importer (ISO3 country code), k is the product (6 digit), v is the value (in USD), and q is the quantity. $2018|AFG|AGO|845420|114.676|26.000$ is an example. The product is the “ingot molds and ladles”, which includes 8454 products (converters, ladles, ingot molds, and casting machines of a kind used in metallurgy or in metal foundries), while the product group is 85 (nuclear reactors, boilers, machinery and mechanical appliances, parts thereof). The exporter is Afghanistan (AFG), and the importer is Angola (AGO). Based on these edge lists, trade networks are calculated for each product group in each year. Based on these networks, the studied network and node-level indicators are calculated.

3.3. Constructed multidimensional graph database from the time series of the trade networks

Two databases were used, one for network-level analysis and one for node-level analysis, i.e., 3D (BACINET3D) and 4D (BACINODE4D). In a trade network database, a node represents a country, and a directed edge represents the quantity or value in USD of the trade flow between two countries. These graphs can be separated byproduct and by year. Let $G_t^g(V, E_t^g, W_t^g)$ denote a trade network in year t of product g, where V is the set of nodes (countries), E_t^g is the set of trade flows between countries, and W_t^g is an n by n positive weight matrix, where $w_{ij} = [W_t^g]_{ij}$ is the weight of the edge from node i to node j. It is assumed that $eij \in E_t^g \Leftrightarrow w_{ij} > 0$, and $e_{ij} \notin E_t^g \Leftrightarrow w_{ij} = 0$.

The BACINET3D database has three dimensions: (1) years (1995–2020), (2) products (classified by 6 digits and 5018 categories), and (3) network-level indicators. The network-level indicators are computed based on the quantities and values of the trade flows. A cell in this database represents the value of a network-level indicator for a given product in a given year. The BACINODE4D database has four dimensions: (1) countries, (2) years (1995–2020), (3) products, and (4) node-level indicators. For convenience, the BACINODE4D database is split into 3D databases for each indicator (see Fig. 2(c)). Similar to the BACINET3D database, the cells of the BACINODE4D database are calculated for 2, 4, and 6 character levels of products and for the quantities and values of trade flows. Due to space limitations, only the results for aggregated products (characterized by 2 digits) are presented. However, for subsequent studies, these databases were constructed for 4 and 6 digits of the production codes (see the contribution C_1). We also investigate whether there is a causal relationship between the time series of network-level and node-level indicators.

3.4. Employing node-level and network-level indicators for trade network analysis

Network-level indicators characterize an entire trade network for a specific year and product, while node-level indicators characterize each country in the network. The network-level indicators and the distribution of node-level indicators within trade networks enable different types of analysis that can provide insights into the structure, dynamics, and impacts of trade flows. Additionally, network-level indicators can capture the global properties and features of a trade network, such as its density (Hoang et al., 2023), centrality (Piccardi and Tajoli, 2018), clustering (Grant and Yung, 2021), resilience (the size of the largest component/size of the total network after deleting an edge or vertex) (Sun et al., 2023), assortativity (Dueñas and Fagiolo, 2014), asymmetry (Meshcheryakova, 2020), and reciprocity (Amador et al., 2018). Furthermore, these indicators can reveal how the trade network evolves over time and how it responds to technological changes, shocks, or crises. The network-level indicators in this study have already been examined before in the case of trade network networks. At the same time, the interaction of their product-byproduct temporal characteristics has not yet been investigated. The distribution of node-level indicators on trade networks can reflect the local properties and roles of individual countries or regions in the trade network, such as their centrality (Cingolani et al., 2018), node coreness (Hoang et al., 2023), and inequality (Dueñas and Fagiolo, 2014). The indicators utilized in this study are commonly employed for the examination of trade networks. However, it should be noted that the temporal patterns have not been categorized, and the correlation between them has not yet been studied. Nevertheless, these indicators can demonstrate the disparities between countries or areas, or they can be utilized to assess and contrast their trading patterns and behaviors, as well as the reciprocal influence or interdependence they exert on one another. In addition, by integrating network-level and node-level indicators and conducting timely analysis, a comprehensive understanding of the trade network and its impact on trade policy and development is achieved (refer to contribution C_2).

To answer RQ, the following node- and network-level indicators are employed (see Table 2).

3.5. Causality and forecasting

A time series of trade networks from 1995 to 2020 is applied to examine whether the network-level or node-level indicators of a product or country, such as its centrality or centralization, have a causal effect on the indicators of another product or country. To test for causality, the Granger causality test (Granger, 1969) is applied. This test measures whether the past values of one time series can help predict the current or future values of another time series.

Let X and Y be two time series with observations $X_1, X_2, \ldots, X_t$ and $Y_1, Y_2, \ldots, Y_t$, respectively. The null hypothesis of the Granger causality test is that X does not Granger cause Y, while the alternative hypothesis is that X Granger causes Y. A time series regression model for both Y and X is constructed, the model for Y includes its own past values and the past values of X, and the model for X includes only its own past values. The F statistic is applied to compare the explained variance to the unexplained variance in the regression models, and the null hypothesis is rejected if the F statistic exceeds a critical value based on the degrees of freedom and the significance level. Various lags k are tested via Granger causality tests, where k is always a positive

Table 2
Node-level and network-level indicators of trade networks and their applications.

(a) Node-level indicators			
Group of node-level indicators	Short description	Typical questions to be answered	Analyzed indicators
Asymmetry, inequality	Measures the balance and reciprocity of trade flows between countries or regions.	How fair or reciprocal is the trade between two countries?	Node Asymmetry (NA)
Centrality, coreness	Measures the importance and influence of countries or regions in a trade network based on their connections and positions.	How central or influential is a country in the trade network?	Betwennes Centrality (BC), Harmonic Centrality (HC), Eigenvector Centrality (EC), Node Coreness (NC)
(b) Network-level indicators			
Group of network-level indicators	Short description	Typical questions to be answered	Analyzed indicators
Scale free property, assortativity	Measures the degree distribution and attribute similarity of nodes in a trade network.	How similar are the nodes in terms of their degree or other attributes?	γ, Assortativity Coefficient (AC)
Centralization, coreness	Measures the concentration of power and cohesion of structure in a trade network.	How unequal is the distribution of power or influence in a network? How cohesive is the network structure?	Beetweenness Centralization (BZ), Eigenvector Centralization (EZ), Network Coreness (NR)
Connectivity, clustering, resilience, robustness	Measures the connectivity, clustering, resilience, and robustness of the trade network.	How easy is it to reach one country from another in a network? How strong are the ties between countries in the network? How stable is the network to external shocks or internal failures?	Global Clustering (GC), resilience for random and systematic failures
Asymmetry, reciprocity	Measures the asymmetry and reciprocity of trade flows between pairs of countries or regions.	How asymmetric or reciprocal is trade among countries?	Bilateral Asymmetry (BA), Multilateral Asymmetry (MA), Reciprocity Value (RV)

integer. Because of the relatively short time series of data, to find the best data, lag information criteria (ICs), such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC), are applied to compare different models with different lag orders. For these tests, the lag is generally one year, which is consistent with the similar characteristics of the temporal patterns of the product groups.

$\mathcal{G}k^p(\mathcal{V}, \mathcal{E}_k^p)$ is denoted as DBCG, where $\mathcal{V}$ is a set of nodes (countries or products), and $eij \in \mathcal{E}_k^p$ if and only if node i Granger causes node j with lag k at significance level p. The DBCG shows the direction of causal relationships between the time series indicators and can provide information on how a shock propagates through a trade network (see C_3).

3.6. Network-based time-series clustering and analysis

Kosztyán et al. (2022) proposed an NDA method for nonparametric dimensional reduction. Compared to the Principal Component Analysis (PCA) and Principal Factor Analysis (PFA) datasets, the NDA dataset has several advantages: it does not require predefining the number of groups of variables or the number of Latent variables (LVs), and it can handle High-Dimension Low-Sample-Size (HDLSS) datasets, where the number of variables exceeds the number of observations. Kosztyán et al. (2024) extended the method to GNDA, which allows for arbitrary symmetric or asymmetric similarity functions between variables, such as correlation, partial correlation, or causality functions. In GNDA, a similarity graph of the variables is constructed, and the modules or communities represent groups of variables with dense connections. The number of communities determines the number of latent variables, which are defined as linear combinations of the standardized variables and Eigenvector Centrality (EC). The NDA and GNDA can specify factor loadings and drop variables that do not fit the latent variables or are peripheral in a community.

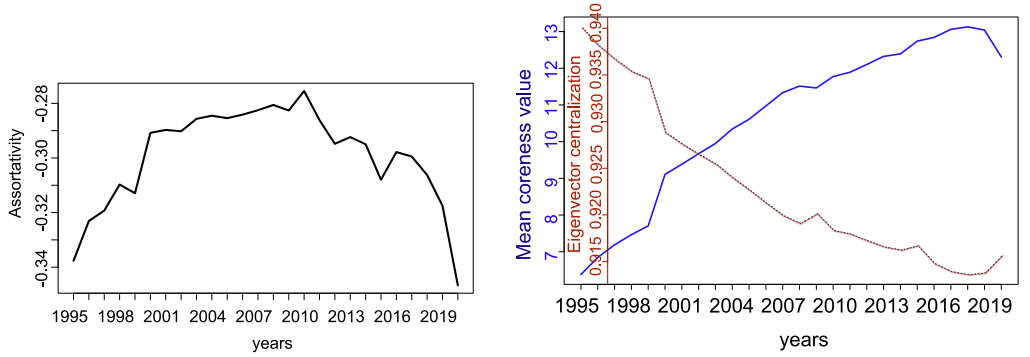
The method can be applied to cluster or reduce dimensions in causal networks or short time series. By applying GNDA to an DBCG network, groups of products and countries with dense causality relations and cluster centers that represent fictive products or countries can be identified. The distance from the cluster center indicates the degree of dependence on other products or countries. By applying GNDA to the time series of indicators, groups of products or countries with similar time-series characteristics and typical patterns over time can be identified. The distance from the typical pattern indicates the degree of deviation from the group; therefore, countries and products can be ranked according to their dependencies (see C_4).

4. Results

To address RQ, two databases are proposed (see C_1) to identify the temporal patterns of structural network-level indicators (see C_2 and Section 4.1). Spearman's correlation is applied as a similarity function between time series to capture different types of product trends. The results of the causality analysis are presented (see C_3) in Section 4.2, and the role-playing countries in a product and their changes over time (see C_4) are presented in Section 4.3.

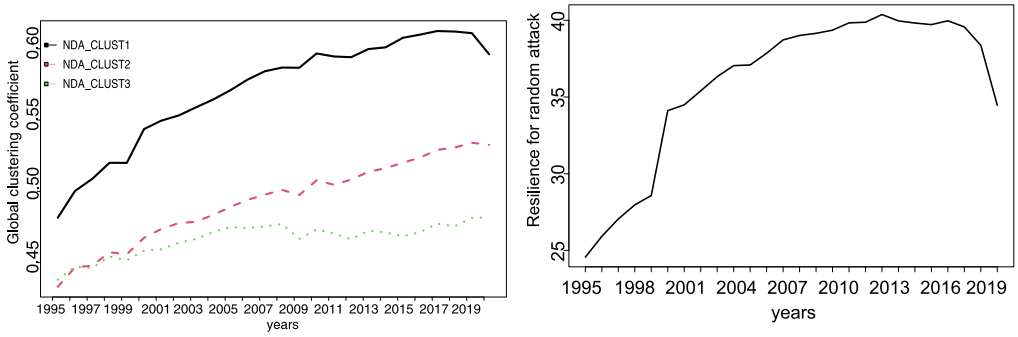
4.1. Temporal patterns of structural network-level indicators

Fig. 3 shows the temporal changes in assortativity (a), eigenvector centralization, and mean coreness (b) in trade networks. Assortativity refers to the quantification of the degree of similarity between trading partners based on their traits or specialties. The phenomenon of assortativity can be understood as a measure of the degree of specialization and trading with comparable partners. An increase in assortativity signifies a greater level of specialization and trade with partners who possess similar characteristics. Conversely, a decrease in assortativity suggests a greater level of diversification and trade with partners with differing characteristics. Eigenvector centralization and mean coreness are two interconnected metrics that assess the level of concentration and cohesion within a network's structure. The phenomenon of growing



(a) Assortativities (b) Eigenvector centralization and mean coreness

Fig. 3. Cluster centers of temporal patterns of assortativity, eigenvector centralization, and mean coreness over time. The dissimilarity (1-similarity) measure is the Euclidean distance of the time series. The number of clusters found is 1.



(a) Global clustering coefficients of product clusters over time (b) Resilience value for random attack

Fig. 4. Temporal patterns of global clustering (a) and resiliences (b). The similarity measure is Spearman's correlation. There are 3 clusters in global clustering and 1 in resilience.

centralization, also known as decreasing coreness, signifies the emergence of a few highly linked nodes or a more integrated community. Conversely, decreasing centralization or increasing coreness suggests a more equitable distribution of centrality or a network that is more fractured. The aforementioned variables may be influenced by a range of factors, including technical advancements, trade policies, comparative advantages, demand trends, geopolitical shifts, market dynamics, competitive forces, political instability, and supply chain disruptions.

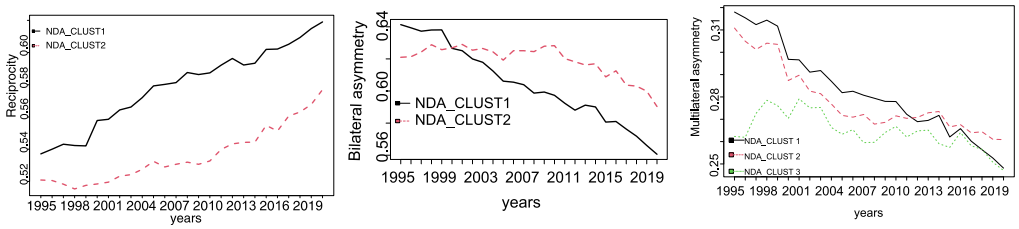
Fig. 3 shows that based on the Euclidean distances, only one type of characteristic can be identified for all product groups. Fig. 3 shows the annual cluster centers (i.e., factor scores) of the product groups as typical assortativity, centralizations, and coreness characteristics. Fig. 3 shows that assortativity increased until 2010, and coreness also increased (centralization decreased) until 2018. Afterward, the trend reverses.

Global clustering (see Fig. 4)(a) and resilience (see Fig. 4)(b) measure the connectivity and robustness of trade networks. Additionally, global clustering measures how well the nodes form clusters or communities based on their trade patterns. Increasing global clustering indicates more specialization and cohesion within the network, while decreasing global clustering indicates more diversification and fragmentation within the network. Resilience (the size of the largest component/size of the total network) refers to the capacity of the network to effectively adapt to and recover from diverse disruptions, including events such as economic shocks, natural disasters, or political instability. Increasing resilience indicates a more robust and adaptable network, while decreasing resilience indicates a more vulnerable or unstable network.

The three identified product patterns exhibit different clustering characteristics, as shown in Fig. 4(a). The first cluster consists of so-called capital-intensive (high-tech) products. For this cluster, trade increased until 2018. However, before the COVID-19 pandemic in 2020, clustering growth halted. The second group contains so-called labor-intensive products. For this group, there is an increase in clustering. However, this group was less affected by the US–China trade war after 2018. The third cluster contains so-called resource-intensive products, and there is insignificant clustering growth. Fig. 4(b) reveals that the network was more resilient before 2012, meaning that it could withstand shocks and disruptions better. However, the network's resilience declined after 2012. During the US–China trade war, but before the pandemic, the decline in resilience accelerated, suggesting a reduced ability to recover from adverse events and maintain efficiency and stability.

The annual changes in reciprocity and bilateral/multilateral asymmetry in a trade network show how balanced and equitable bilateral and multilateral trade relationships are within the network. Reciprocity refers to the idea that trade between two countries or entities is roughly equal in terms of the value and volume of goods or services exchanged. A positive change in reciprocity (negative change in asymmetry) over time suggests that trade relationships within the network are becoming more balanced and mutually beneficial, with each country receiving a fair share of the benefits from trade. On the other hand, a negative change in reciprocity (increasing asymmetry) may indicate that some countries or entities benefit more from trade than others, leading to potential imbalances and inequities within the network.

Fig. 5(a) shows that GNDA identifies two clusters of products when considering reciprocities in time. Cluster 1 consists of capital-intensive



(a) Reciprocity value (b) Bilateral asymmetry (c) Multilateral asymmetry

Fig. 5. Temporal patterns of reciprocity (a) and cluster centers of bilateral (b) and multilateral (c) asymmetry values over time. The similarity measure is Spearman's correlation. There are 2 (reciprocity, bilateral asymmetry) and 3 (multilateral asymmetry) clusters.

products, while cluster 2 consists of labor- and resource-intensive products. Fig. 5(b) shows that in the first, larger cluster, the reciprocity increases, while in the second cluster, the increase in reciprocity is more moderate. The characteristics of the identified temporal patterns of bilateral and multilateral asymmetries are in line with the reciprocity results (see Fig. 5(b)). The multilateral asymmetry follows the clusters identified in the global clustering coefficients (see Fig. 5(c)), while in the case of reciprocity, the two smaller groups are combined.

4.2. Causalities of structural indicators

In the cases of eigenvector centralization, betweenness centralization, global clustering, and multilateral asymmetry, there are very few causalities between products. However, changes in assortativity (Fig. 6(a)), resilience (Fig. 6(b, c)), and reciprocity (Fig. 6(d, e)) are indicated by causality groups of different colors. In part, because the relationship is few years long, the smallest information criterion proved to be a one-year delay. This delay is considered for causality.

Fig. 6 shows that GNDA identifies five causality groups for assortativity (see Fig. 6(a)) and reciprocity (see Fig. 6(d)), six causality groups for resilience (Fig. 6(b, c)), and three groups for bilateral asymmetry of trading products.

Table 3 shows the most embedded products in clustered causality networks. In this case, the factor loading value gives the EC value of the product in a causality network. A higher value indicates greater embeddedness in a causality network. The greater the NDA score of a product in a precedence network is, the more sensitive these product groups are to change.

4.3. Temporal patterns of role-players

This section focuses on product group 81, which consists of base metals; cermets; items that include tungsten and molybdenum; ferrous products obtained by the direct reduction of iron ore; and granules and powders of pig iron, spiegeleisen, iron, or steel. This group is highly influenced by changes in the resilience of other products over time (Table 3(c)). The products in this product group are often used as raw materials for many industrial products and are distributed across low-complexity networks. Therefore, these products are flexible against targeted attacks and do not affect the trade of high-tech products. The trade structure indicators (e.g., assortativity, clustering, γ parameter of fitted power-law distribution) of this group of products are not causally affected by other products (Fig. 6(a)). Moreover, bilateral asymmetry and reciprocity changes in this group over time depend on only a few other product groups (Fig. 6(d), Table 3(d)). Significant disturbances in the trade of this product group were observed, especially before the COVID-19 pandemic.

Fig. 7 shows (in/out) degree centralities over time for all countries. The applied GNDA identifies three classes. There is one cluster of highly increasing products, one of slowly increasing products, and one of stable products.

Table 4 shows the factor loadings of the top four countries.

Table 3
Eigenvector centralities (as factor loadings) of assortativity (a), resilience (b-c), reciprocity (d), and bilateral asymmetry (e) for the top five product groups (PR_i represents the ith cluster of product groups, and NDA_i represents the GNDA loadings of product groups for cluster i). Products in a product group are listed in descending order by their factor loading.

(a) Assortativity

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5
1	33	1.000	15	1.000	22	1.000	38	1.000	25	1.000
2	93	0.583	45	0.720	73	0.625	12	0.785	35	0.762
3	87	0.382	27	0.706	56	0.608	84	0.785	17	0.669
4	94	0.382	86	0.653	34	0.608	67	0.768	88	0.444
5	49	0.371	23	0.588	30	0.476	68	0.682	36	0.380

(b) Resilience for random attack

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5	PR_6	NDA_6
1	76	1.000	39	1.000	10	1.000	46	1.000	30	1.000	14	1.000
2	90	0.935	61	0.905	23	0.798	66	0.869	97	0.790	24	0.764
3	82	0.888	67	0.636	79	0.640	49	0.781	84	0.769	43	0.747
4	25	0.828	38	0.576	72	0.631	26	0.762	96	0.723	53	0.528
5	63	0.798	68	0.514	58	0.442	86	0.723	92	0.620	88	0.504

(c) Resilience for systematic attack

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5	PR_6	NDA_6
1	81	1.000	92	1.000	84	1.000	22	1.000	67	1.000	60	1.000
2	86	0.299	10	0.668	54	0.965	12	1.000	11	0.721	31	0.577
3	20	0.276	47	0.573	88	0.851	15	0.675	85	0.643	90	0.577
4	61	0.276	50	0.516	44	0.844	63	0.675	39	0.643	76	0.577
5	35	0.276	52	0.472	18	0.635	73	0.403	56	0.643		

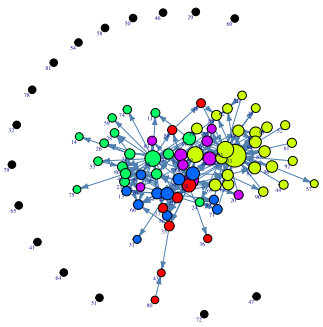
(d) Bilateral asymmetry

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3	PR_4	NDA_4	PR_5	NDA_5
1	50	1.000	55	1.000	32	1.000	88	1.000	69	1.000
2	31	0.611	92	0.953	17	0.860	46	0.834	57	0.852
3	68	0.588	51	0.895	11	0.596	19	0.784	95	0.695
4	76	0.541	15	0.835	34	0.572	66	0.638	64	0.547
5	83	0.502	97	0.826	61	0.572	60	0.581	40	0.547

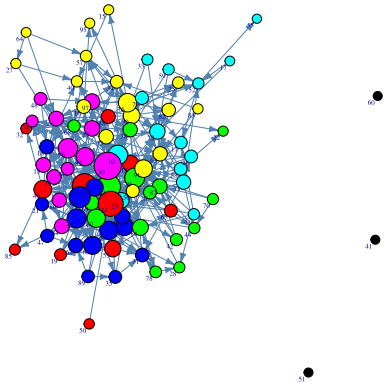
(e) Reciprocity

Ord	PR_1	NDA_1	PR_2	NDA_2	PR_3	NDA_3
1	50	1.000	97	1.000	32	1.000
2	68	0.621	55	0.971	35	0.876
3	69	0.547	45	0.847	33	0.869
4	31	0.539	15	0.801	17	0.811
5	76	0.534	86	0.753	57	0.771

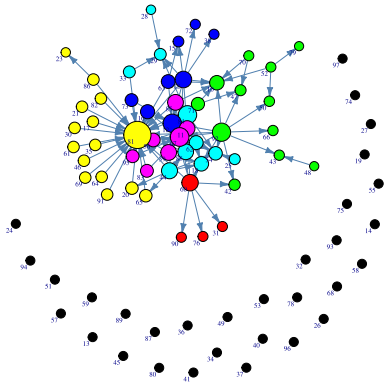
Table 4(a) and Fig. 7 show the diversification of imports characterized by in-degree centrality. First, Cluster 1, consisting of countries such as Lithuania (LVA), Latvia (LTU), Bulgaria (BGR), and Russia (RUS), exhibits high factor loadings that are close to or equal to 1 in terms of in-degree centrality. In addition, Cluster 2 comprises countries such as New Caledonia (NCL), Saint Lucia (LCA), Algeria (DZA), and Tobago (TTO). In the case of these countries, import diversification does not change. The import channels include the same countries. These countries exhibit moderate factor loadings ranging from 0.6 to 0.7 in terms of in-degree centrality. Finally, Cluster 3, comprising countries such as France (FRA), Belarus (BLR), Ukraine (UKR), and El



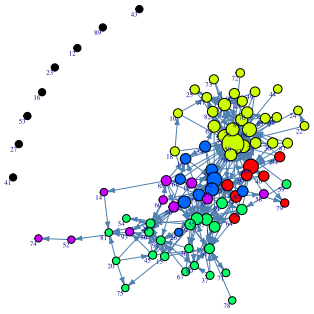
(a) Granger causality network of assortativity indicators



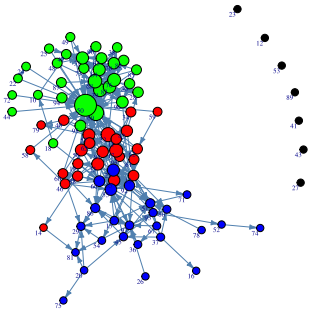
(b) Causalities of resilience for random attack



(c) Causalities of resilience for systematic attack



(d) Causalities of bilateral asymmetries

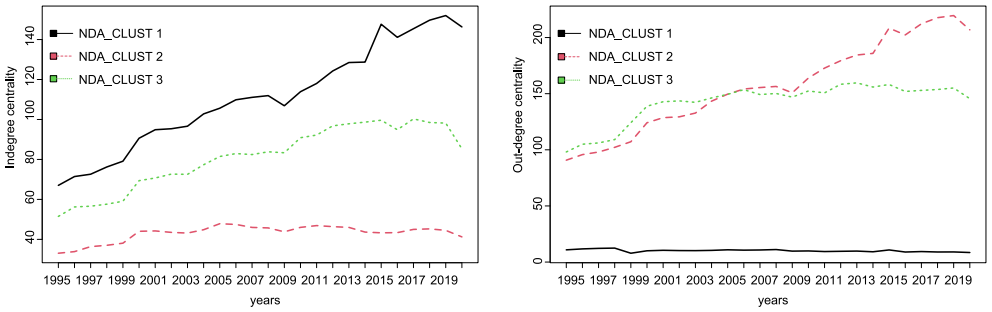


(e) Causalities of reciprocity

Fig. 6. DBCG networks of changing assortativities over time. The significance level is $p = 0.001$.

Salvador (SLV), exhibited high factor loadings above 0.9 in terms of in-degree centrality, indicating strong inbound trade connections similar to those of Cluster 1. The results show that import diversification increases slightly here and then decreases before the pandemic.

Examining the diversification of exports (see Table 4(b) and Fig. 7(b)), the first cluster includes Congo (COD), Moldova (MDA), North Korea (PRK) and the Christmas Islands (CXR). The countries in this cluster either do not have raw materials or participate only to a small extent in the trade of this product group, which is confirmed by the fact that the factor loadings are the smallest here. The countries belonging to the second cluster, namely, India (IND), South Korea (KOR), the Czech Republic (CZE), and Slovenia (SVN), have greatly increased their number of customers. In addition, the factor weights are also the largest here. The third cluster includes Belgium (BEL),



(a) Typical characteristics of indegree centralities (b) Typical characteristics of outdegree centralities

Fig. 7. Typical characteristics of country–group trade network centralities over time.

Table 4
Factor loadings of GNDA for the top four countries (CTY_i represents the ith cluster of countries, and NDA_i represents the GNDA loadings of a country group for cluster i).

(a) Clusters and factor loadings on indegree centralities

Ord	CTY_1	NDA_1	CTY_2	NDA_2	CTY_3	NDA_3
1	LVA	0.980	NCL	0.698	FRA	0.934
2	LTU	0.975	LCA	0.665	BLR	0.926
3	BGR	0.973	DZA	0.649	UKR	0.916
4	RUS	0.973	TTO	0.640	SLV	0.916

(b) Clusters and factor loadings on outdegree centralities

Ord	CTY_1	NDA_1	CTY_2	NDA_2	CTY_3	NDA_3
1	COD	0.598	IND	0.970	BEL	0.847
2	MDA	0.579	KOR	0.967	CHE	0.841
3	PRK	0.553	CZE	0.958	ZAF	0.836
4	CXR	0.440	SVN	0.958	ITA	0.810

Switzerland (CHE), the South African Republic (ZAF) and Italy (ITA), which only slightly increase their number of customers and strengthen their intermediary role. The factor loadings are between those of the first and second clusters.

5. Discussion

Throughout human history, crises are a recurring theme. However, technological change is a new factor that is unique to the modern era. Technological change can affect the structure and performance of supply chains and trade networks in various ways, such as by creating new opportunities, challenges, or risks. However, as many researchers have pointed out (see e.g., Craighead et al., 2020; Notteboom et al., 2021), the recent pandemic crisis had a different impact than did previous crises, such as the 2008 financial crisis. Owing to the emergence of China and the subsequent US–China trade war, specifically before the pandemic crisis, supply chains became more concentrated and more vulnerable. The results showed that several structural indicators (centralization, resilience, asymmetry) of trade networks worsened before the pandemic, indicating a more vulnerable and imbalanced situation. Moreover, these indicators did not exhibit any clear signs of recovery from the 2008 financial crisis. At the same time, partly due to the slowdown of globalization and partly due to the weakening of trade relations, the improvement of structural indicators, such as assortativity, stopped before the financial crisis. After 2010, the network indicators deteriorated one after another. After assortativity, resilience peaked in 2016, and then the decrease in concentration stopped in 2018, clearly reflecting the structural change in trade relations. The predictions indicated an increase in the vulnerability of trade networks, which was also experienced during the COVID-19 pandemic, when serious supply disruptions occurred with China's withdrawal. Therefore, it is important to use methods that can analyze the trade networks of different products simultaneously and reveal their interrelationships. The main finding is that technological change and deglobalization have made supply chains and trade networks more fragile and prone to crises.

5.1. Temporal patterns of structural trade network indicators

The nonparametric clustering method categorized temporal patterns of trade network metrics, emphasizing discernible trends in the interactions between nations and products across time. This discovery implies that specific products demonstrate consistent trading patterns, whereas others display more flexibility in their associations. An analysis of the effects of these temporal patterns on market forecasting, risk assessment, and trade policy adaptation could yield valuable insights for strengthening the resilience of trade networks in response to changing global dynamics.

Fig. 3(a) shows the cluster center of the assortativity of product groups in the world trade network over time, reflecting factors such as technological advancements, globalization, and consumer preferences (see C_1–C_2). After 2010, assortativity growth plateaued, with fluctuations occurring until the election of President Trump in 2016. However, subsequently, the curve experienced a significant decline primarily attributed to the emerging US–Chinese trade war.

The structural changes in centralization and coreness (Fig. 3(b)) followed those of assortativity but with an eight-year lag. Eigenvector Centralization (EZ) decreased between 1995 and 2018, suggesting that the network became more fragmented, with fewer countries dominating the trade flow. This finding could be attributed to regionalization, China's economic rise, and political and economic instability (Shameem and Jayaprasad, 2020; Cai et al., 2023). In addition, the recent increase in centralization since 2018 was partly due to the elimination of alternative transport routes before the COVID-19 crisis. However, this trend reversal preceded the crisis. The network has remained a globalized system, with countries increasingly integrating into the trade flow. New technologies such as blockchain and artificial intelligence could enhance the efficiency and security of global trade, which could increase connectedness in the network (Arias et al., 2021). The coreness measure further confirmed this trend, as there was an increase in coreness until 2018. The trends and trend reversals for all products were due to the interplay of deglobalization before the pandemic-induced disruption (Arias et al., 2021). Moreover, the abovementioned structural indicators indicate only one global pattern. The causal relationship between the products was revealed by later causal investigations (see Fig. 6).

Fig. 4 shows the variations in the cluster centers of product groups before the COVID-19 pandemic. Cluster 1 in Fig. 4(a) represents a cluster of capital-intense products, such as high-tech, long-distance, or luxury products, including nuclear reactors, machinery, apparel, and works of art (product groups 84, 61, and 97; see Appendix B for product codes). These products require advanced production technologies and

specialized shipping methods, or they cater to high-value demands. The countries that were the most severely affected before the pandemic were affected by the emerging trade wars; therefore, their cluster centers decreased sharply in 2018.

In Fig. 4(a), product cluster 3 represents labor-intensive products, such as food products sourced from natural resources, including vegetables, fruits, sauces, and meat (product groups 20, 21, and 16). These products are mainly produced locally and consumed daily. Here, the increase was continuous except in the most recent year. A consistent level of demand was maintained for these products, and minimal or negligible changes were observed in their cluster centers. However, the individual product clusters can be clearly separated.

Product cluster 2 in Fig. 4(a) represents the labor-intensive products with the least pronounced decrease. These products include organic chemicals, explosives, steel product footwear, fabrics, and precious metals (product groups 51, 36, 72, 80, 46, 60, 52, and 14). These products are essential for transportation, recreation, and health. The only difference between these products is their rate of growth. The largest increase in clustering was observed for high-tech products. However, a decline was observed before 2018, which was due to the unfolding US–China trade war and the rise of China.

Fig. 4(b) shows the global pattern of resilience in the trade network. Resilience measures the ability of a network to withstand shocks and disruptions. The network was more resilient before 2012 but declined after 2012. In this scenario, the same pattern changes as those for assortativity were observed, but with a two-year lag. This finding suggests a reduced capacity to recover from adverse events and maintain efficiency and stability. Additionally, this decline preceded the pandemic and the Russo-Ukrainian war by more than six years. Moreover, the decline in the growth of resilience can be traced back even earlier to 2006, which can also be attributed to the slowdown in globalization (slobalization) and the slowdown in the growth of new trade relations. Furthermore, the pandemic accelerated this decline, increasing the vulnerability of trade networks to supply problems. The same trend reversals can be observed in the patterns that reacted uniformly to all products. The impact of crises first appears in assortativity since this indicator indicates what types of nodes are in contact with each other. Structural changes affecting resilience can be observed after two years, while centralities appear only later. Thus, for example, the 2008 financing crisis did not affect the reduction in centralization, even if the other structural indicators of the trade network changed.

Reciprocity increased (bilateral and multilateral asymmetry decreased) over time (see Fig. 5) for most products, especially for high-tech technology and luxury products, while this increase (decrease) was moderate for raw materials and other products. This growth is clearly due to globalization, which, unlike other indicators, was not affected by the pandemic. The persistent imbalance in the availability of raw resources can be rationalized by geographical factors, specifically the infrequent discovery of new deposits. Consequently, the trading network for these commodities remained relatively consistent over time. The time pattern of the indicators with uniform structural changes indicated delays of two and six years, and by comparing such temporal patterns, which provide different temporal characteristics, similar product clusters were identified.

The results revealed the structural similarity of the trade networks of different product groups. These product groups exhibited one or a few global temporal patterns, indicating their synchronized response to global changes and crises. However, a similar temporal pattern does not imply the absence of causal relationships between the trading of different products. To detect such relationships, causality tests (see Section 5.2 and an assessment of their contributions C_3) are needed.

5.2. Causality groups of products

The causality analysis identified substantial causal links among various product groupings in the trade network, demonstrating the interconnectedness of trade flows. This discovery implies that alterations in the trading behaviors of a certain group of products can result in a series of consequences for interconnected sectors. Naturally, geopolitical factors, trade policies, and market dynamics could also contribute to the observed causal links between product groups. Additional analysis could examine the consequences of these cause-and-effect connections for the management of supply chains, methods for diversifying markets, and the discovery of crucial factors that influence the dynamics of trade networks.

The dependencies between the structural characteristics of product groups are analyzed using Granger causality and GNDA (Fig. 6) (see C_4). The product groups are ranked by their importance scores within a cluster (Table 3 and contribution C_4).

The assortativity of a product over time depends on the assortativity of many other products in the network. This means that a product's trading patterns are influenced by other products' attributes and connections. These products have central roles in the causality graph and are sensitive to shocks and crises.

Five product groups (groups 33, 15, 38, 22, and 25) were significant, serving as focal points in the network. Table 3(a) shows their key attributes and roles. The assortativity values of these product groups indicate connections with many other products, showing their interdependence and impact on trade behaviors. Sixteen product groups (groups 60, 29, 46, 50, 58, 54, and 81) exhibited unique characteristics and trading behaviors that are not influenced by other products, showing their distinct market presence. This diversity is due to market differentiation, specialization, comparative advantages, global supply chains, consumer demand and preferences, and technological changes. While it is not possible to study all causality arcs, the product group shown in yellow is chosen as an example in Table 3(a). The yellow module encompasses product groups with mutual interactions. The materials in this category consist of wood and wood products (44), paper (48), tableware (82), ships and boats (89), musical instruments (92), and furniture (94). The underlying rationale is that the primary constituent of these materials is wood, which is subsequently utilized to manufacture a diverse range of wooden commodities, such as paper, furniture, and musical instruments. The precedence between systematic and random attacks on the resilience of the product groups are also compared (Fig. 6(b–c) and Table 3(b–c)). The trade networks were more sensitive to random attacks, meaning that a resilience anomaly in one product group affects other trades. GNDA identifies the most connected precedence of product groups. The first set of product groups in Table 3(b) (groups 76, 39, 10, 46, 30, and 14) was sensitive to random attacks when other trades' resilience changed. These products are essential for sectors such as telecommunications, plastics, cereals, tobacco, pharmaceuticals, and precious metals. Moreover, there is broad market demand, extensive applications, and diversity within the subsectors of these products. Therefore, these factors provide stability and resilience against random disruptions.

The second set of product groups in Table 3(c) (groups 81, 92, 84, 22, 67, and 60) was found to be sensitive to systemic attacks when other trades' resilience changed. These products exhibited strong interdependencies, cooperative relationships, or strategic collaborations within their industries, adapting and responding collectively to external shocks and thus leveraging their interconnectedness and collaborative efforts. There are various examples pertaining to the route of causality. The presence of SiO_2 in product 69 impacted the aluminum and aluminum-based products due to the insulating, semiconducting, and conductive properties of the ceramics. Additionally, optical, photographic, and medical/surgical devices were affected, as this product serves as a raw material in glass production and measuring instruments.

These products also have robust supply chains, efficient distribution networks, and coordinated industry practices. These factors contribute to recovery and functionality during systemic disruptions. Table 3(b–c) and Table 3(d–e) show that products sensitive to other trades' resilience changes were also sensitive to other trades' bilateral asymmetry

changes. One such central product group is group 81, which includes electronic equipment and raw material for military equipment.

The results indicate that the temporal patterns of the structural indicators for network trades were similar, but their formation can still be characterized by causal networks in the case of most indicators. By applying GNDA to the causal network, causal communities were detected, and the causal relationships were denser within communities than between communities. The product groups are also ranked within a causal community based on their embeddedness, revealing that a few product groups act as drivers of structural indicator changes.

5.3. Temporal patterns of role-players

The investigation indicated that countries did not accumulate specific high-tech equipment or anti-tank guns in product group 81 as a precautionary measure for war. This discovery prompted inquiries regarding the nations implicated in this product category and their strategic deliberations. Possible areas for further analysis include investigating the underlying factors contributing to the absence of stockpiling, examining the consequences for regional security dynamics, and assessing the influence of diplomatic ties on trade patterns within this specific product category.

While trading patterns are used to identify clusters of product groups, country groups can be identified by structurally examining the trading of a given product. Product group 81 was the most sensitive to targeted attacks (see Fig. 6(c)) on supply chains. At the same time, this product group is interesting because tungsten is an important raw material not only for electronic devices but also for anti-tank structures. In light of these findings, it is particularly interesting to note which countries had significantly increased imports, which are identified by specific clusters based on the change in the in-degree centrality (see Fig. 7(a)). The employed GNDA identifies three clusters.

Cluster 1 countries are central to the network and receive more trade inflows. The in-degree centrality increased from 1995 to 2020, except for a decrease in 2020. Their trade relationships were influenced by various trade agreements and arrangements, such as EU enlargement, association agreements, ASEAN Free Tread Area (AFTA), and the EU Customs Union. The in-degree centrality of cluster 2 countries also increased from 1995 to 2020, with a decrease in 2017. Their trade relationships were shaped by several trade agreements, such as the Economic Partnership Agreements (EPAs), Southern African Development Community (SADC) Trade Protocol, and African Continental Free Tread Area (AfCFTA). Cluster 3 countries had a stable in-degree centrality of approximately 40, indicating consistent trade inflows. Their trade relationships were affected by several factors, such as the EU Single Market, Eurasion Economic Union (EAEU), bilateral and regional Free Trade Areas (FTAs), and Generalized System of Preferences (GSP). Generally, the growth of incoming and outgoing centralities was due to the involvement of African countries in trade (1995–1999) and other developing countries (2000–2008). A slow break could appear during the financial crisis (2008–2010); however, growth was observed after the crisis but before the emergence of the US–China trade war. Before the pandemic, decreases were observed for all cluster centers.

In the upcoming period, a conflict between two opposing forces can be observed. The advancement of technology and the process of digitization should contribute to the increased decentralization of the network. The level of assortativeness should increase along with the level of resilience. The COVID-19 pandemic significantly boosted the growth of digital commerce. At the same time, the Russo-Ukrainian war, followed by the Red Sea conflict, has caused trading partners to seek alternative routes. Simultaneously, there is a process of centralization characterized by the ascension of China and the development of trade wars and sanction policies. These procedures are contrary to the aforementioned effects. Furthermore, the expansion of trade routes is also a matter of environmental concern.

In this study, it was not found that some countries stockpiled products in group 81 that can be used for high-tech equipment and anti-tank guns in anticipation of war. However, it is intriguing which countries belong to the same group. One alternative explanation for the lack of stockpiling of high-tech equipment and anti-tank guns in product group 81 could be that diplomatic efforts to promote disarmament and peace initiatives have influenced countries to limit their military equipment reserves, leading to the observed trading patterns. An explanation for the disparities in node-level indicators across countries within the trade network could stem from historical trade relationships, cultural ties, and geographical proximity influencing trading patterns. The economic development levels, resource endowments, and political stability of countries may also contribute to the observed differences in degree centrality. Additionally, the presence of trade barriers, tariffs, or trade agreements could shape the node-level disparities in trade relationships.

5.4. Impact of major events on trade networks

The analysis yielded valuable insights into the impacts of trade agreements, slowbalization, financial crises, the US–China trade war, and the recent pandemic on trade networks. This discovery implies that key events have a substantial influence on the organization and movement of worldwide commerce. Simultaneously, the analyses revealed that specific network indicators exhibit a decline even prior to crises, hence magnifying their influence. During the writing of this paper, the ramifications of many crises can be observed, including the Russian-Ukrainian conflict and the resurgent trade dispute between the United States and China. The European Union elections are occurring concurrently with the publishing of this article. Upcoming elections in the United States will have an impact on commerce. Prior to these events, there was already a decline in the indicators of trade networks; thus, it is anticipated that the impact of the crisis will be more pronounced. Naturally, the role of speculative trading, market sentiment, or external shocks in driving fluctuations in trade flows cannot be neglected, which can further increase the variability of trades.

6. Summary and conclusion

This study delves into the intricate interplay between trade networks, technological advancements, and trade agreements. Through the use of causality tests and centrality measures, the shocks, crises, and structural changes within trade networks are examined, shedding light on the key drivers and recipients of these changes. Network-based time-series clustering and causality analysis are used to analyze the temporal patterns of trade networks, offering valuable insights into the evolving landscape of global trade. By comparing network characteristics with those of technological advancements and trade agreements, this study provides a comprehensive overview of the factors influencing trade dynamics in a globalized environment.

The impact of major events on trade networks underscores the need for adaptive strategies, risk mitigation measures, and scenario planning to address the uncertainties of the global trade landscape. By recognizing the vulnerabilities exposed by events such as trade agreements, economic crises, geopolitical tensions, and pandemics, decision-makers can proactively strengthen supply chains, diversify market exposure, and enhance resilience to external shocks. Leveraging insights from past events to inform future trade policies, investment decisions, and crisis response mechanisms can empower stakeholders to build agile and sustainable trade networks in an ever-evolving global environment.

This study provides several novel contributions compared to those of existing studies in the field. One key novelty lies in the comprehensive analysis of trade networks across multiple products and product groups rather than focusing solely on individual products. By examining the interdependencies and patterns of node- and network-level indicators across various products, this study offers a holistic

understanding of how shocks, crises, or technological changes in one product can impact the trade networks of other products. Additionally, the importance of structural indicators in predicting and mitigating crises is emphasized, highlighting how disruptions in one product's supply chain can swiftly reverberate throughout the entire trade network, altering its structural characteristics. Furthermore, the analysis of temporal patterns has revealed insights into the effects of major events, such as the impact of trade agreements, slowbalization, the 2008 financial crisis, the election of Donald Trump, the emerging US–China trade war, and the recent pandemic on trade networks, providing valuable information for decision-makers to enhance the resilience and sustainability of trade networks in an ever-evolving global landscape.

The observed lack of stockpiling of high-tech equipment and anti-tank guns in product group 81 suggests a shift toward more strategic and efficient inventory management practices among countries. This finding underscores the importance of considering geopolitical factors, disarmament initiatives, and evolving security paradigms in analyzing trade patterns within sensitive product groups. Decision makers and policymakers could leverage this insight to promote transparency in the arms trade, enhance diplomatic efforts for conflict resolution, and strengthen international cooperation to mitigate the risks associated with arms proliferation.

This study has two main implications. First, it is recommended that scientists analyze not only trade networks but also the (temporal) patterns of networks (C_1). Second, it is demonstrated that structural characteristics vary byproduct and network (C_2). In addition, the dependence of one product's trades on other products' trades is highlighted (C_3). Moreover, this study demonstrates how crises and technological changes affect all trading networks (C_4).

This study does not claim that the decline of structural features, such as resilience, or the halt of the movement toward improvement, such as centralization and asymmetry, directly leads to crises. Nevertheless, scholars contend that as the decline of these structural indicators worsens, crises have magnified repercussions. If the idea of a permanent crisis is accurate, it is probable that the decline of the structural indicators will promptly be succeeded by a crisis. However, in this scenario, these signs do not forecast the crisis but rather enhance the impact of the constantly existing potential disaster. However, in this particular situation, the decline of the indicators is inevitably followed by a crisis. This theory can be evaluated by the implementation of the recommended methodologies. If the hypothesis is not valid, a decline in indicators does not necessarily lead to crises. However, it can still be argued that the onset of a crisis has a greater impact when the indicators deteriorate.

The correlation and causality of the structural characteristics indicate that a disruption in one product's supply chain quickly affects the trade of other products, altering the structural characteristics of the trade networks. Additionally, the 2008 financial crisis did not cause any structural changes in product trade networks. Moreover, the indicators improved before, during, and after the crisis. However, before the pandemic, there was a deterioration in almost all structural indicators, with different time lags, which reflects slowbalization. This slowbalization and subsequent signs of deglobalization made supply chains more vulnerable to shocks and disruptions.

The *implication of this study for decision makers* is that it provides valuable insights into the function and resilience of trade networks, as well as the opportunities and challenges for trade policy and market strategy. For governments, there is a need to prioritize policies that promote diversification and resilience in trade networks, considering the potential risks associated with overcentralization and vulnerability to disruptions. Governments can also leverage digitalization to enhance trade facilitation, streamline customs procedures, and promote cross-border collaboration. Businesses can capitalize on technological advancements to optimize supply chain management, enhance transparency, and explore new market opportunities through digital platforms. International organizations play a crucial role in fostering global cooperation, setting standards for digital trade, and facilitating knowledge sharing to address common challenges and promote sustainable trade practices. By embracing digitalization and adopting proactive policies that enhance the resilience and efficiency of trade networks, stakeholders can navigate the complexities of the global trade environment and unlock new opportunities for growth and innovation.

The emphasis on sustainable research is crucial in the long term to promote a more sustainable society through purchasing patterns and decisions. According to Guyomard et al. (2023), the decisions made by consumers have the potential to influence international trade. This is particularly relevant in the context of the transportation of goods and food waste in developed nations, which are significant areas of concern due to the strategic emphasis placed on these issues by the European Union SDGs. In light of SDGs, the pursuit of sustainable development emerges as a significant undertaking for the future, encompassing crucial responsibilities for policymakers and trade networks (Xiao et al., 2024). Furthermore, it is widely acknowledged by various scholars that a sustainable future necessitates the proficient administration of a wide range of resources (Xu et al., 2020). The efficient allocation and utilization of resources are crucial for promoting economic development and societal well-being.

By understanding the structural characteristics and causal relationships of different product groups, policy makers can design and implement policies that enhance the efficiency, stability, and sustainability of trade networks. Policy makers can also use this study to monitor and anticipate the effects of global events and technological changes on trade networks as well as to mitigate potential risks and vulnerabilities. Furthermore, this study can help policy makers identify the most influential and sensitive product groups and countries in the trade network, which can enhance their decisions regarding trade agreements, resource management, and economic cooperation.

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CRediT authorship contribution statement

Zsolt Tibor Kosztyán: Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation. **Dénes Kiss:** Visualization, Investigation. **Beáta Fehérvölgyi:** Writing – review & editing, Validation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request. All calculations were computed in R using the following packages. To calculate the node- and network-level indicators, the **igraph** (Csárdi et al., 2024) and **brainGraph** (Watson, 2020) packages were used. Nonparametric clustering was performed with the **nda** (Kosztyán et al., 2024) package, while Granger causality was computed with the **lmtest** (Zeileis and Hothorn, 2002) package.

Table B.5
BACI-CEPII database product classes up to 2 digits.

HS code	Product class
01–24	Live animals; animal products
25–27	Vegetable products
28–38	Foodstuffs, beverages, and tobacco
39–40	Mineral products
41–43	Raw hides, leather, furs, skins, and articles thereof
44–49	Wood and articles of wood; wood charcoal; cork and articles of cork; articles of straw, of esparto or of other plaiting materials; basketware and wickerwork
50–63	Textiles and textile articles
64–67	Footwear, headgear, and parts thereof
68–71	Stone, plaster, cement, and articles thereof; ceramic products; glass and glassware
72–83	Metals and articles thereof
84–85	Machinery and mechanical appliances; electrical equipment; parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles
86–89	Vehicles, aircraft, vessels, and associated transport equipment
90–92	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; clocks and watches; musical instruments; parts and accessories thereof
93–96	Arms and ammunition; parts and accessories thereof
97–99	Miscellaneous goods, including works of art, collectors' items, and antiques

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Appendix A

Glossary

AC Assortativity Coefficient.

AfCFTA African Continental Free Tread Area.

AFTA ASEAN Free Tread Area.

ATLAS The Atlas of Economic Complexity.

BA Bilateral Asymmetry.

BACI Bilateral Analysis of Correlated Intra-Industry Data.

BC Betwennes Centrality.

BZ Beetweenness Centralization.

CC Closeness Centrality.

CEPII Centre d'Etudes Prospectives et d'Informations Internationales.

DBCG Directed Binary Causality Graph.

EAEU Eurasion Economic Union.

EC Eigenvector Centrality.

EPA Economic Partnership Agreement.

ERGM Exponential Random Graph Model.

EZ Eigenvector Centralization.

FAOSTAT Food and Agriculture Organization of the United Nations' Statistical Database.

FTA Free Trade Area.

GC Global Clustering.

GNDA Generalized Network-based Dimensionality Analysis.

GSP Generalized System of Preferences.

HC Harmonic Centrality.

HDLSS High-Dimension Low-Sample-Size.

HS Harmonized System.

LC Local Clustering.

LV Latent variable.

MA Multilateral Asymmetry.

NA Node Asymmetry.

NC Node Coreness.

NDA Network-based Dimensionality Reduction Analysis.

NR Network Coreness.

NZ Network Centralization.

PCA Principal Component Analysis.

PFA Principal Factor Analysis.

RV Reciprocity Value.

SADC Southern African Development Community.

SDG Sustainable Development Goal.

SITC Standard International Trade Classification.

SNA Social Network Analysis.

SP Shortest Path.

WIOD World Input-Output Database.

WITS World Integrated Trade Solution.

Appendix B. Product codes

See Table B.5.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.142699.

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