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Exploring the forecasting and temporal causality patterns of multilayer trade networks reflecting global economic changes

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ABSTRACT

This study examines the dynamic evolution of global trade networks from 1995 to 2020 using the Organization for Economic Co-operation and Development's (OECD's) intercountry input–output (ICIO) data. This research combines multilayer network theory methods with advanced statistical and econometric procedures, including dynamic multilayer network analysis methods, (bi)clustering, and causal analyses to evaluate the temporal nature of structural, sectorial and country-level indicators. The primary objective of this study is to identify causal patterns in multilayer trade network structures and reveal the roles of specific countries and industries as drivers of changes in global trade dynamics. Using the proposed methods, we define causal graphs between the structural indicators of the multilayer network. The resulting causal graph is organized into groups using modularity analysis, and the relationships are biclustered, thereby determining which structural factors/industries/countries affect other country groups/industries and revealing the dynamics of structural changes. We determine which factors change simultaneously and which factors and actors exhibit a delay between their changes. The analysis reveals significant shifts in structural indicators, highlighting the evolving roles of major players like China and the US. The findings indicate that the structural indicators of trade networks/industries/countries often move in unison, with changes in one country/industry potentially triggering rapid transformations across the entire network. This study also uncovers the cascading effects of economic disruptions on trade patterns, emphasizing the interconnectedness of countries and industries in the face of global economic changes. These insights are crucial for policymakers and business leaders, underscoring the need for adaptive strategies to enhance the level of resilience of countries and industries to persistent global economic fluctuations and crises.

1. Introduction

At the same time as this study was submitted, the US administration announced a large increase in tariffs, with which they intend to bring in a new era in world trade; thus, this study, which aims to explore the actors, industries, and structural relationships of global trade, could perhaps not be timelier. Examining the structural changes in trade networks (Rauch, 2001; He and Deem, 2010; Guo et al., 2023) – especially now, in this rapidly changing economic environment – is essential, as these changes frequently reflect wider economic and social transitions within the economy and society (Stolte and Emerson, 2021; Mahutga, 2006). Shifts in trade patterns may indicate changes in consumer preferences (Janeba, 2007), technical progress (Guerrieri, 1999; Yi and Dan, 2021), the rise of new markets (Antonelli, 2002; Alamsyah et al., 2023), or geopolitical realignments (Barbieri, 2024), thereby impacting local economies and global market dynamics (Bartesaghi et al., 2022; Antonelli, 2002). Furthermore, examining these alterations may reveal power transitions among countries (Li et al., 2024), which can both be a consequence of political and economic decisions (Kosztyán et al., 2024b) and influence further political decisions (Milner, 2017), and highlight the interdependence of economies in a progressively globalized environment (Kosztyán et al., 2024b). Comprehending these structural alterations not only assists in forecasting future economic trends but also enables the recognition of the weaknesses and opportunities within trade systems (Sun et al., 2022), thus enhancing strategic decision-making and promoting sustainable development (Xu et al., 2025).

Recent literature has emphasized the importance of examining trade networks through various lenses (Xu et al., 2025; Li et al., 2024). Focusing on actual policy changes and their consequences (Kosztyán et al., 2024b), rather than hypothetical scenarios, offers a more accurate reflection of trade policy impacts on economic outcomes (Goldberg and

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Pavcnik, 2016; Ortiz et al., 2021). He and Deem (2010) and Guo et al. (2023) highlighted the importance of investigating structural changes in trade networks, while Stolte and Emerson (2021) and Mahutga (2006) explored how these changes reflect wider economic and social transitions and political decisions (Kosztyán et al., 2024b). Janeba (2007) focused on the role of consumer preferences in shaping trade patterns, and Antonelli (2002) examined the impact of technological progress and new market emergence on global market dynamics. More recent studies, such as Li et al. (2024), have delved into power transitions among countries, with Kosztyán et al. (2024b) dealing with the structural changes in trade networks caused by political and economic decisions and crises.

Despite the wealth of research in this area, significant gaps in our understand the causal patterns within trade network structures and the identification of key drivers of change among countries and sectors remain. Traditional methods have often focused on static analyses or limited time frames, failing to capture the dynamic nature of trade relationships and their evolution over extended periods. There is a call for more sophisticated methodologies that can explore complex interplay among the economic, political, and social factors driving trade network dynamics. Additionally, many studies have focused only on single-layer networks and have not fully explored the multilayered nature of trade networks, which can provide deeper insights into the complex interactions between different industries and countries.

To address these gaps, this study employs advanced methodologies including the temporal analysis of multilayer networks, clustering, biclustering, and causality analysis. These methods enable the dynamic and causal analysis of structural indicators at the structural, country and industry levels. By utilizing these techniques, we can explore the interplay between industries and countries' trade relations, which is particularly relevant to the eve of the imminent trade war at the time of writing this paper. This approach is particularly important in the context of persistent global economic fluctuations and crises, as we can gain a deeper understanding of how economic disruptions affect trade relations and network structure, which can inform more effective policymaking and business strategies to enhance the degree of resilience to future challenges.

The main research question of our study is as follows:

RQ What causal patterns can be identified in multilayer trade network structures, and how do these patterns reveal the roles of specific countries and industries as drivers of change in global trade dynamics?

The methodological framework employed in this study is grounded in established theoretical principles for causal identification in multidimensional interactive systems, particularly those involving simultaneous country–industry–structural attribute dependencies. Granger causality testing provides a theoretically sound approach for disentangling temporal precedence relationships in complex economic networks where simultaneity bias and reverse causality are prominent concerns (Hamilton, 2020). Recent advances in network econometrics demonstrate that Granger causality, when applied to structural network indicators, effectively captures propagation mechanisms in multilayered systems where traditional instrumental variable approaches fail due to the absence of valid exclusion restrictions (Siggiridou et al., 2019). The integration of Bayesian validation methods (Bayesian Vector Autoregression (BVAR), Markov Chain Monte Carlo (MCMC) analysis, Bayesian Factor Approach (BFA)) addresses the fundamental challenge of parameter uncertainty in finite samples, which is particularly relevant for trade network analysis where structural breaks and nonlinearities can confound classical inference (Koop et al., 1996; Celani et al., 2024). Biclustering methodology complements causality analysis by simultaneously identifying groups of causal relationships and network nodes that exhibit coherent temporal patterns, addressing the curse of dimensionality inherent in multi-country, multi-industry systems (G. Silva et al., 2024). This methodological combination is theoretically justified because trade networks exhibit what Carvalho and Gabaix (2013) term "granular origins of aggregate fluctuations", where microlevel (country–industry) shocks propagate through network structures to generate macrolevel patterns, requiring both temporal precedence identification (Granger causality) and structural pattern recognition (biclustering) to fully characterize the transmission mechanisms; however, to the best of our knowledge these methods are not used together.

2. Background

In the current economic environment, especially at the beginning of another tariff war, it is particularly important to understand the dynamics of trade networks, that is, the interaction of actors and industries. The evolution of network science, boosted by the accessibility of vast datasets and improved processing capabilities, has revolutionized how academics and practitioners study complicated systems such as trade networks (Xu et al., 2025). The volatility of trade arising from political conflicts, economic crises, and health emergencies has underscored the interconnectedness among trade relationships and their effects on economic stability (Wang et al., 2023). While individual countries struggle with the consequences of such disruptions, trying to take countermeasures to reduce these effects, these measures are quite limited due to the interconnectedness of trade networks (Zhao et al., 2024). The increased degree of interdependence of countries in the global trade environment has amplified the possibility of failure propagation across international trade networks (Kang et al., 2024).

Research on the time-series analysis of trade networks has employed predominantly dynamic network theory to examine trade relationships over time (Yazawa, 2023). However, very few studies have addressed the causal investigation of the structural characteristics of trade networks or the exploration of impact mechanisms. Forecasting has been applied using Inter-Country Input-Output (ICIO) (Chen, 2024). These approaches have been instrumental in identifying the key drivers of trade network evolution and predicting future trade patterns (Chen, 2024).

While network analysis has been extensively used, causality analysis within trade networks has been less common but not entirely absent. Granger causality tests and vector autoregression models have been employed to determine the causal relationships between different countries' economic activities, providing insights into how changes in one country can influence the trade dynamics of other countries (Saimul and Darmawan, 2020). One study has utilized Graph Neural Networks (GNNs) to model causal relationships in trade networks (Monken et al., 2021), particularly in response to major economic events such as trade wars or financial crises. Causal inference techniques have also been explored to understand how external shocks propagate through trade relationships; offering a deeper perspective on economic dependencies (Rigana et al., 2021). However, to our knowledge, no study has explored the causal relationships and mechanisms of effects among countries, industries, and structural properties of the network. Furthermore, biclustering methods have not yet been applied in commercial networks, although combining this method with causality analysis makes it possible to determine close causal groups that simultaneously affect other factors. Biclustering (G. Silva et al., 2024) can allow for the identification of subgroups of countries and industries with similar trade behaviors, revealing hidden trade patterns and dependencies. This approach could improve our understanding of how trade clusters respond to global shocks, aiding policymakers in optimizing trade agreements. Investigating biclustering in trade networks would enhance the analytical depth beyond traditional clustering methods, potentially uncovering new strategic trade insights.

Recent network-based approaches to international trade and Global Value Chains (GVCs) have mapped the architecture of globalization and documented salient topological regularities, but typically in single-layer or sector-specific settings (Liu et al., 2025). Kali and Reyes (2007) that a country's structural position in the global trade network – beyond trade volumes – matters for growth, yet their analysis is single-layer and relies on two cross-sections (1992, 1998), without modeling temporal causality among structural indicators (Kali and Reyes, 2007). Cerina et al. (2015) construct the World Input–Output Network is used to characterize the large-scale topology, providing an important benchmark for system-wide structure but not a multilayer, temporal causal analysis (Cerina et al., 2015). More recently, Piccardi et al. (2024) introduce a network-based measure of GVC "length", revealing heterogeneous, geography-sensitive adjustments in global value networks; however, their focus is on measuring extension and communicability rather than forecasting or identifying temporal precedence among network indicators (Piccardi et al., 2024). Sectoral contributions, such as analysis by Russo et al. (2023) of automotive multilayer clusters, uncover twin dynamics of regionalization and cross-region integration, but remain industry-focused and descriptive with respect to network evolution and inter-indicator causality (Russo et al., 2023). Complementing these strands, the survey by Amador and Cabral (2016) synthesizes drivers and measures of GVCs but does not prescribe a multilayer, time-ordered causal modeling framework (Amador and Cabral, 2016).

Our study advances this literature along four fronts. First, we build a dynamic, multilayer network from Organisation for Economic Cooperation and Development (OECD) ICIO data at the country–industry level over a long horizon (1995–2020), enabling system-wide, cross-sector generality beyond single-sector or short-window analyses (cf. Russo et al., 2023; Piccardi et al., 2024). Second, we move from descriptive topology to mechanisms by applying temporal (classical and Bayesian Granger and instantaneous) causality tests to structural indicators across layers, thereby identifying drivers and propagation pathways among countries, industries, and network properties—an aspect not addressed by the above works. Third, we operationalize structure-based forecasting of network indicators (out-of-sample,2021–2030), which extends prior contributions centered on static maps, length metrics, or cluster detection (Kali and Reyes, 2007; Cerina et al., 2015; Russo et al., 2023). Fourth, by combining dynamic multilayer analysis with modularity-based grouping and biclustering, we detect coherent, co-moving causal groups of indicators and country–industry nodes, providing a decision-oriented decomposition of systemic change that complements survey-based measurement frameworks (Amador and Cabral, 2016). Together, these features position the paper as a bridge between topology, temporal causality, and predictive analytics in multilayer GVC networks.

Building on the literature, the following contributions are made:

- **C_1** Revealing the dynamic evolution of the global trade network structure and its catalysts for change.
- **C_2** Disclosing the cascading impacts of trade interconnectedness and disruptions on international trade connections among nations and sectors.
- **C_3** Identifying intervention points for decision-makers, helping contain potential escalations and mitigating the disruption caused by crises.

We study multilayer trade networks (country × industry × time), which capture cross-industry interdependencies more fully than single-layer representations. (**C_2**). This approach enables researchers to examine how changes in one sector or country can ripple through various layers of the trade network, providing a more realistic representation of the intricate global economic mechanism (**C_1**). The multilayer structure also facilitates the identification of hidden patterns and relationships that may not be apparent when individual layers in isolation are being examined. This enhanced analytical capability is particularly valuable for understanding the cascading effects of economic disruptions and policy changes across sectors and nations, ultimately leading to more informed decision-making in international trade policies and strategies (**C_3**).

3. Data and methods

We examined the OECD ICIO multilayer trade network between 1995 and 2020. We calculated the temporal evolution of structural network-, industry- and country-level node indicators on the multilayer network during this period. We determined changes in the role of sectors and countries over time and then used these to create time series to examine forecasts and determine causal networks based on cause-and-effect studies between indicators. We grouped the effects using clustering and biclustering procedures. Our goal was to determine which structural factors, which sectors and which countries are the driving forces of the structural changes (see **RQ**) and how to map the temporal dynamics of these changes (see **C_1-C_3**).

The research framework of this study is shown in Fig. 1.

3.1. Employed data

The OECD's ICIO tables (see Fig. 1(a)) map production, consumption, investment, and international trade in goods and services. Economic activity and country are split into these tables to show global economic linkages in detail. ICIO tables have the following main segments: intermediate use (Z): goods and services used as inputs in other manufacturing, which shows industry and sector interdependencies within and between countries. In our study, we analyzed this segment in detail. Final Demand (FD) for goods and services in a country, which include household consumption, government spending, investment, and net exports, referencing economic goods and service consumption. The total worth of an industry or sector's goods and services is output (X), which covers intermediate use and FD. This chapter shows the net effect of taxes and subsidies on production and comprises indirect taxes such as value-added taxes (VATs) and government subsidies to various industries. Value added (VA): an industry or sector adding value to its intermediate inputs. The gap between output and intermediate use represents the contribution of labor and capital to production.

3.1.1. Data collection and preparation

In this study, we used mainly the intermediate use (Z) segment to construct a multilayer dynamic network, and examined its structure, industry, and country-level changes. The edge list of the dynamic multilayer data table, which served as the basis for the analysis, was encoded as follows:

Year | From.Sector | From.Country | To.Sector | To.Country | Value

Instead of country and industry codes, we used numbered IDs, and the lists of country and sectorial codes are shown in Tables G.9–G.10. An example of a data row is as follows:

1995 | 1 |1 | 1 | 2 | 8.5029

This means that in 1995, from country 1 (Argentina, ARG), the total amount of trade to country 2 (Australia, AUS; see Table G.9), in sector 1 (agriculture, hunting and forestry, A01_02) was 8.5029 million USD. The employed data structure enabled us to specify a Dynamic Multilayer Network (DMN) (see Fig. 1(b)).

To construct the 77 × 45 (countries ×industries) dynamic panel, we harmonized ICIO flows to the OECD 45-industry (ISIC Rev.4) aggregate using the official concordances and the back-casted, balanced time series that mitigate reclassifications and vintage breaks (Yamano et al., 2023). The residual share of missing entries was negligible; accordingly, no ad-hoc imputation was applied. To improve robustness, we excluded annual bilateral industry flows below USD 1 million, since very small cells in multi-country IO tables are disproportionately affected by confidentiality treatment, balancing residuals, and rounding noise. This conservative sparsification removes negligible aggregate value but materially improves the signal-to-noise ratio for temporal forecasting and causality analysis, while preserving temporal comparability where OECD flags structural breaks.

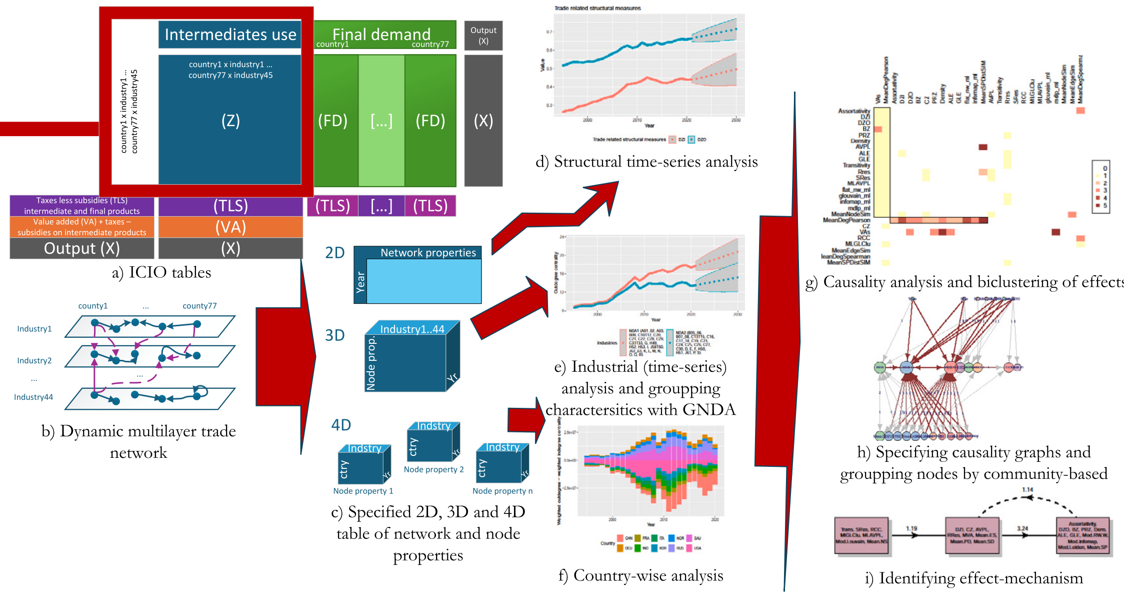


Fig. 1. Research framework.

We extend the dynamic multilayer network with two additional ICIO blocks. (i) The value-added (VA) matrix, available as Year × (Country × Industry), is modeled as an "income" layer in where each country–industry node directs its value added to a synthetic Domestic-Income node of its own country. (ii) The Final-Demand (FD) tensor (Year × (Country × Industry) × Final-User Country) constitutes a "demand" layer whose edges run from producing country–industry nodes to final consumer countries. Together with the intermediate-use (Z) layer, which yields a three-layer Supply–Demand–Income multiplex observed from 1995 to 2020. All network and node indicators are computed for each layer separately, allowing straightforward robustness checks of Z-based results against FD and VA perspectives.

3.1.2. *Specification of multidimensional network- and node-level datasets*

After constructing the DMN, we specified three types of datasets for further examination. We calculated structural network properties for each year. These results were stored in a 2D data table (see Fig. 1(c)), where the columns denote the calculated structural properties of the network and the rows denoted the given years. Utilizing the constructed table, we analyzed the structural changes in the trade network. Similarly, a 3D data table was constructed, where the dimensions were industries (sectors), (aggregated) node indicators and years 1(e). We also created an aggregated data table for countries. The proposed 3D dataset allows us to answer the following question: How much does the change in the role of different industries depends on other industries and on what extently do these characteristics move together? Finally, we created a 4D dataset, where the dimensions are country, industry, and node property under study, and time (see Fig. 1(f)). In this case, we obtained answers to the question of how countries' trade in different sectors changes over time.

3.2. *Employed methods*

To answer the research question posed (see **RQ**), it was necessary to employ several methods. First, we calculated the time changes and forecasts in the network and node indicators of the dynamic multilayer trade network (see Fig. 1(d–f) and Section 3.2.3). However, we grouped these factors to determine which countries and sectors have similar structural indicators (see Sections 3.2.2 and 3.2.4). We then analyzed the time series obtained for the network and node indicators using Granger causality tests (see Fig. 1(h) and Section 3.2.5). On the basis of the results of the causality studies, we mapped the causal networks between both structural and industrial and country-level indicators (see Fig. 1(h)). We grouped the relationships by biclustering procedures (see Fig. 1(g–h)), while using module search procedures, we identified those indicator groups with closer relationships (see Fig. 1(h) and Section 3.2.6). Next, we determined the mechanisms of action between the indicators (see Fig. 1(i)).

3.2.1. *The representation of dynamic multilayer trade network*

A dynamic multilayer (trade) network is a triplet, $G(t) = (V(t), E(t), W(t))$, where vertices ($V(t)$) are organized into multiple layers (L) in time $t \in T$ and each node (vertex) corresponds to an actor ($A(t)$), where the same actor at time t can be mapped to nodes in different layers. Formally, $V(t) \subseteq A(t) \times L$. $E(t) \subseteq V(t) \times V(t)$ is set of undirected edges between two vertices at time t. $W(t) : E(t) \rightarrow \mathbb{R}^+$ represents the weights of each edges at time t. A dynamic edge is represented as having the following four members: $e_{ip,jq}(t) = (a_i(t), l_p, a_j(t), l_q)$; the weight of a dynamic edge is $w(e_{ip,jq}(t)) \in \mathbb{R}^+$, where, in this study, $t \in T := \{1995, \ldots, 2020\}$, $a_i, a_j \in A$ are exporters (i), and importers (j) actor (i.e., country), $l_i, l_j \in L$ are the layers of exporters and importers, respectively; $c_{ip} = (a_i, l_p) \in V$ is the node, where $a_i \in A$ is the actor in layer $l_p \in L$. If we fix the year of t, then we obtain a static multilayer trade network.

3.2.2. *Explored node-level properties*

The employed centrality measures can be calculated for each country in all industrial layers and can be aggregated at the industrial or country level. These indicators jointly offer an extensive perspective on the roles and influences of many countries within the multilayered trade network. Utilizing these indicators enables the analysis of countries' interactions in trade, economic robustness, and strategic standing within the global trade framework. The time-series analysis of these indicators can reveal how the role of countries or sectors has evolved over time. Table B.6 in the Appendix shows the mathematical formulation of the employed node-level indicators. Table 1 summarizes the economic insights the employed node-level indicators.

Our selection of node-level metrics is driven by economic relevance rather than methodological exhaustiveness. Degree (in/out; DCI/DCO) captures partner diversification – the export market access and redundancy versus procurement breadth and exposure – while strength (out/in; SCO/SCI) measures realized trade intensity and economic weight, with SCO–SCI informing external balance and current-account sustainability. BC quantifies intermediation power over trade

Table 1
Node-level indicators with economic interpretations.

Economic dimension	Indicators	Economic meaning and interpretation
Market Access and Trade Diversification	Indegree Centrality (DCI) Outdegree Centrality (DCO) Degree Centrality (DC)	Measures a country's trade relationship diversification and market access breadth. High DCI indicates strong import demand and supplier dependency, signaling domestic market attractiveness but potential vulnerability to supply disruptions. High DCO reflects robust export capacity and market penetration across multiple destinations, indicating competitive advantage and reduced dependency on single markets. Together, they reveal a country's integration into global supply chains and resilience through diversification.
Economic Scale and Trade Volume	Instrength Centrality (SCI) Outstrength Centrality (SCO)	Captures a country's actual economic weight and trade intensity in global markets. High SCI represents substantial import dependency and domestic consumption capacity, indicating economic size but potential external vulnerability during supply chain disruptions. High SCO demonstrates export-oriented economic strength and international competitiveness, contributing to GDP growth and foreign exchange earnings. The difference (SCO-SCI) reveals trade balance dynamics, crucial for understanding current account sustainability and economic stability.
Strategic Trade Position and Market Control	Betweenness Centrality (BC) Closeness Centrality (CC)	Measures a country's strategic importance in global trade routes and market accessibility. High BC indicates critical intermediary role, enabling control over trade flows and potential for rent extraction through gateway positions. Countries with high BC can influence global supply chains and may benefit from trade disruptions affecting competitors. High CC ensures efficient access to diverse trading partners, reducing transaction costs and enhancing trade opportunities, particularly valuable during market volatility and crisis periods.
Economic Influence and Network Power	Eigenvector Centrality (EC) PagRank Centrality (PRC)	Evaluates a country's influence by considering not just connection quantity but partner quality and importance. High values indicate trade relationships with economically powerful nations, enhancing technological spillovers, knowledge transfer, and economic stability through association with stable partners. This is particularly crucial for developing countries seeking technology transfer and for developed nations maintaining leadership in innovation networks. Such positions provide resilience during economic downturns through diversified high-quality partnerships.
Hub Economy Functions	Authority Centrality (AUT) Hubness Centrality (HUB)	Measures a country's role as a trusted trade node in global commerce. High AUT signifies reputation as a reliable export destination, often associated with high-quality goods, advanced manufacturing, or specialized services, creating premium positioning and pricing power. High HUB indicates major exporter status to influential importers, suggesting critical supply chain importance and potential for economic leverage. Together, they identify countries that serve as essential connectors in global trade networks, with significant bargaining power and economic influence.
Industrial Specialization and Risk Concentration	Homophily (HOM)	Measures the percentage of a country's trade relationships within the same industry, revealing specialization patterns and associated risks. High homophily indicates strong industrial specialization and competitive advantage in specific sectors, potentially leading to higher productivity and export revenues. However, it also signals vulnerability to industry-specific shocks, technological disruptions, or demand shifts. Low homophily reflects diversified trade portfolios and risk management strategies, providing stability during sector-specific crises but potentially sacrificing specialization benefits and economies of scale.

routes (gatekeeping, rerouting options, rent extraction), and closeness (CC) reflects the average market access costs and speed of adjustment, key for resilience and price pass-through. Eigenvector and PageRank (EC/PRC) measure embeddedness in "high-quality" neighborhoods – the importance of partners' partners – linked to demand stability, technology spillovers, and sanctions contagion. Hub/authority (HUB/AUT) disentangles upstream vs downstream roles in GVCs (major suppliers to influential buyers vs trusted destinations), informing upgrading, reshoring, and supplier diversification strategies. Finally, homophily (HOM) gauges specialization versus diversification in a country–industry trade portfolio, balancing productivity gains against sector-specific shock vulnerability. Table 1 synthesizes these economic interpretations.

3.2.3. Explored network-level properties

In addition to the aggregation of node-level indicators for industries and the network, it is also possible to calculate network-level indicators.

We calculate network centralization by first determining the centrality values of each node. Afterward, we calculate the difference between the highest centrality value and the centrality values of all the other nodes. Finally, we sum these differences and divide them by the sum of the maximum possible differences to obtain the centrality value of the network. A formal description of network-level indicators are provided in Table C.7 in Appendix. The Table 2 shows a brief summary of the economic insight into the employed network-level indicators.

3.2.4. Similarity measures of layers

For each similarity indicator, the industry-by-industry matrices of a given similarity is specified for each year, the average values are also determined annually. Table 3 summarizes the economic insight of the employed layer similarity measures.

If these similarity metrics increase over time, then it suggests a trend toward greater interconnectedness and uniformity across industries, indicating that countries are aligning their trading strategies and reinforcing established partnerships. Conversely, a decreasing trend may imply a growing segmentation of the trading landscape, where industries become more isolated from each other, possibly driven by shifts in economic policy, competitive dynamics, or global market changes, leading to potential inefficiencies and disruptions in economic integration. The formal descriptions of the similarity indicators are in Table F.8 in Appendix.

Table 2
Network-level indicators with economic interpretations.

Economic dimension	Indicators	Economic meaning and interpretation
Market Integration and Connectivity	Density (Dens) Average Path Length (AVPL) Multilayer Average Path Length (MLAVPL)	Measures the degree of global economic integration and trade efficiency. High density indicates tightly interconnected markets with extensive trade relationships, fostering collaboration and knowledge spillovers but potentially increasing systemic risk. Low AVPL suggests efficient trade routes and reduced transaction costs, enabling rapid price arbitrage and market equilibration. MLAVPL captures cross-industry connectivity, revealing how efficiently goods and services flow between sectors, crucial for understanding supply chain optimization and industrial interdependencies during economic shocks.
Network Resilience and Stability	Transitivity (Trans) Random Resiliency (RRes) Systematic Resiliency (SRes)	Evaluates the robustness of global trade networks against disruptions. High transitivity indicates clustering among trading partners, providing alternative trade routes and reducing vulnerability to single-point failures. This creates redundancy that protects against supply chain disruptions. Random resilience measures network stability against unexpected failures (natural disasters, political instability), while systematic resilience evaluates vulnerability to targeted attacks or coordinated disruptions (trade wars, sanctions). Together, they assess the global economy's capacity to maintain trade flows during various crisis scenarios.
Trade Concentration and Market Power	Indegree Centralization (DZI) Outdegree Centralization (DZO) Betweenness Centralization (BZ) PagRank Centralization (PRZ)	Measures the concentration of trade power and potential market dominance. High DZI indicates few countries dominate as major importers, creating dependency relationships and potential bottlenecks. High DZO suggests export market concentration, where few countries control global supply, increasing market power but creating vulnerability points. High BZ reveals concentrated control over trade routes by specific nations, enabling strategic leverage and potential for market manipulation. High PRZ indicates overall economic influence concentration, suggesting unequal global trade relationships and potential for economic coercion or beneficial spillovers from dominant economies.
Economic Efficiency and Performance	Average Local Efficiency (ALE) Global Efficiency (GLE) Reach Club Coefficient (RCC)	Assesses the economic efficiency of trade networks and elite country interactions. High ALE indicates efficient regional trade distribution, suggesting well-developed local supply chains and reduced logistics costs. High GLE demonstrates that goods and services flow efficiently across the entire network through few intermediaries, minimizing transaction costs and enabling rapid market responses. High RCC shows that economically powerful countries trade intensively among themselves, creating an exclusive “rich club” that may drive global economic trends but potentially excludes smaller economies from premium trade opportunities and technology transfer.
Market Structure and Competition	Assortativity (Assort) Modularity (Mod) Multilayer Global Clustering Coefficient (MlGlClu)	Reveals the competitive structure and fragmentation of global markets. Positive assortativity indicates that countries with similar trade capacities preferentially trade together, suggesting stable market tiers but potential for reduced competition and innovation. High modularity reveals distinct trading blocs or communities with dense internal trade but sparse inter-community connections, indicating regional integration but global fragmentation that may impede efficiency and increase trade barriers. High MlGlClu shows strong cross-industry clustering, facilitating industrial cooperation and technology spillovers but potentially creating sector-specific vulnerabilities during industry-wide disruptions.
Trade Balance and Asymmetries	Mean of Vertex Asymmetries (MVA) Closeness Centralization (CZ)	Captures trade imbalances and accessibility inequalities in the global economy. High MVA indicates widespread trade imbalances across countries, suggesting structural economic asymmetries that may lead to current account sustainability issues, currency pressures, and potential for trade disputes. This reflects underlying competitiveness differences and economic development gaps. High CZ shows unequal access to global markets, where few countries enjoy superior connectivity while others face higher trade costs and limited market access, potentially perpetuating economic inequalities and limiting development opportunities for peripheral economies.

3.2.5. Employed forecasting methods and causality measures

Between 2021 and 2030, various network indicators were predicted via the Autoregressive Integrated Moving Average (ARIMA) model. The forecast obviously cannot account for the aftermath of COVID-19, the consequences of the Russia–Ukraine conflict, or the effects of the trade wars of the Trump administration. However, we obtain an important picture of what would have happened had these effects did not occur. The Granger causality and instantaneous causality are employed to determine the effect mechanism of structural and network-level indicators. Table 4 summarizes the economic insights of the applied methods.

To validate classical Granger causality tests three Bayesian approaches are also applied, such as BVAR with Minnesota Priors (Ni and Sun, 2003), MCMC analysis Bayesian Estimation [jackman2000 estimation] and BFA (Oravecz and Vandekerckhove, 2024).

These four approaches form a comprehensive methodological framework that addresses different aspects of Granger causality analysis while providing mutual validation. The classical Vector Autoregressive (VAR) method establishes the foundational statistical benchmark with its well-understood asymptotic properties, serving as the reference point for comparison. The BVAR approach enhances estimation precision through structured priors, particularly valuable when dealing with limited sample sizes or high-dimensional systems where classical methods may suffer from overfitting. The MCMC Bayesian method provides the most comprehensive uncertainty quantification by generating a full posterior distributions, allowing for nuanced probabilistic statements about causality relationships and their associated uncertainty. Finally, the BFA offers direct model comparison capabilities, providing interpretable evidence measures for competing hypotheses about causal relationships. We considered a relationship to be Granger causal

Table 3
Layer similarity measures with economic interpretations.

Economic dimension	Indicators	Economic meaning and interpretation
Cross-Industry Market Structure and Integration	Node Similarity (NS) Edge Similarity (ES)	Measures the degree of cross-sectoral market integration and trading partner consistency. High NS indicates that countries maintain similar trading partners across different industries, suggesting integrated business relationships, economies of scope, and diversified industrial strategies. This reflects mature economic relationships where countries develop comprehensive trade partnerships spanning multiple sectors. High ES reveals consistent trade flows and partnership intensities across industries, indicating stable supply chain relationships and reduced transaction costs through established business networks. Together, they signal economic integration depth and partnership stability across industrial boundaries.
Industrial Diversification and Risk Management	Pearson Correlation of Degree Centralities (PD) Shortest Path Distance (SP)	Evaluates countries' diversification strategies and vulnerability to sector-specific shocks. High PD suggests that countries maintain similar trade positions across different industries, indicating either successful diversification strategies or concerning over-specialization in similar market niches. This can provide stability through balanced industrial portfolios but may also indicate lack of comparative advantage specialization. Low SP between industries indicates efficient cross-sectoral trade connections, enabling rapid resource reallocation and industrial adaptation during economic transitions. This flexibility is crucial for countries adjusting to technological changes or shifting global demand patterns.
Economic Coherence and Strategic Alignment	Combined Pattern Analysis	When similarity measures move together over time, it indicates increasing economic coherence where countries align their trading strategies across industries, suggesting either successful economic integration policies or concerning loss of competitive differentiation. Increasing similarity patterns may reflect beneficial standardization and efficiency gains through unified trade policies, but could also signal reduced innovation and competitive dynamics. Conversely, decreasing similarity trends may indicate beneficial specialization and comparative advantage development, but could also suggest concerning market fragmentation and reduced economic cooperation, potentially leading to trade inefficiencies and increased vulnerability to external shocks.

Table 4
Comparison of forecasting methods and causality measures: economic interpretation.

Method	Economic purpose	Economic interpretation	Policy implications	Limitations
ARIMA Forecasting	Predict future trade network structures under baseline conditions	Extrapolates historical trends to identify what would happen without external shocks (COVID-19, trade wars, geopolitical conflicts). Provides counterfactual scenarios for policy evaluation.	Enables policymakers to distinguish between natural economic evolution and crisis-induced changes. Helps identify deviations from expected trajectories.	Cannot incorporate structural breaks or unprecedented events
Granger Causality validated by Bayesian approaches	Identify temporal precedence relationships between countries and industries in trade dynamics	Reveals which countries/industries act as "early indicators" of global trade changes. Shows cascade mechanisms where changes in one actor predict changes in others with specific time lags.	Critical for early warning systems. Helps identify which countries to monitor for predicting broader trade disruptions. Informs strategic timing of interventions.	Assumes linear relationships; sensitive to lag selection; correlation $\neq$ true causation
Instantaneous Causality	Capture simultaneous co-movements in trade patterns during economic shocks	Identifies countries and industries that respond synchronously to global economic events. Reveals structural interdependencies and shared vulnerabilities in real-time.	Essential for coordinated policy responses during crises. Helps identify countries that need simultaneous support or face similar risks during global disruptions.	Cannot establish temporal direction of influence; may capture spurious correlations

between two time series at a given lag only if a causal relationship could be demonstrated between the time series by all methods.

The setting of ARIMA and causality analysis is detailed in Appendix D. To analyze the relationships and precedence relations between time series of node properties, layer with respect to similarity values and network properties, we specified a causality graph to depict the relationships among properties, where a node represents a given property, and an edge exists between nodes if causality relations between properties exist. The lags were noted, but we did not use them as weights. Therefore, we obtained a directed unweighted causality graph for Granger causality and an undirected instantaneous causality graph.

3.2.6. Employed clustering and biclustering methods

By clustering the resulting correlation and causal graphs with community-based modularity detection, we determined modules in which communities provide the set of indicators where there are denser causal relationships between nodes than there are between separate modules. We also used a biclustering method to cluster edges between nodes to identify where denser causal relationships exist.

Clustering partitions nodes into communities with denser— than-expected internal ties, whereas biclustering simultaneously groups nodes and the edges between them to uncover edge-dense submatrices. In our directed causality network, community detection (Leiden/Louvain/Infomap) reveals sets of indicators or country— industry

Table 5
Comparison of clustering and biclustering methods: Economic interpretation.

Method	Economic purpose	Economic interpretation	What it cannot capture alone
Modularity-based Community Detection	Identify trade communities and economic blocs based on dense internal connections	Reveals natural economic partnerships and regional trade clusters. High modularity indicates fragmented global trade; low modularity suggests integrated global economy.	Cannot identify temporal dynamics or causal mechanisms within communities. Static view of trade relationships.
Generalized Network-based Dimensionality Analysis (GNDA)	Automatically discover industrial groups with similar temporal trade patterns without pre-specifying cluster numbers	Groups industries by their adaptive capacity and resilience patterns. Identifies which sectors move together during economic cycles and crises.	Cannot reveal why industries cluster together or predict cross-cluster influences.
iterative Binary Biclustering of Gene sets (iBBiG)	Simultaneously cluster countries/industries AND their causal relationships to identify dense interaction patterns	Uncovers hidden economic interdependencies where specific country–industry combinations systematically influence others. Reveals transmission mechanisms of economic shocks.	Cannot determine community structure or long-term temporal trends. Focuses only on causal density.

nodes with concentrated interrelations; iBBiG biclustering complements (Pontes et al., 2015) this by isolating cohesive sets of causal links (origin–target pairs) that co-move and co-predict with similar lags (Castanho et al., 2024). Using both methods allows us identify who forms communities and which specific causal links transmit shocks.

The applied clustering and biclustering methods are briefly introduced in Table 5

By combining (Bayesian-validated) Granger and instantaneous causality with biclustering, we identify edge-dense causal submatrices — i.e., groups of causal relations that co-move and co-predict with coherent lags. Unlike community detection, which clusters nodes, our biclustering clusters the causal links themselves; this exposes concrete propagation channels that static centralities or GVC participation indices cannot be revealed. The joint method tells policymakers not only who is important, but which specific cross-industry/cross-country relations move together and in what temporal order, enabling targeted and time-staged interventions on the small set of links that transmit shocks fastest.

The technical details of community detection and biclustering are in Appendix E.

4. Results

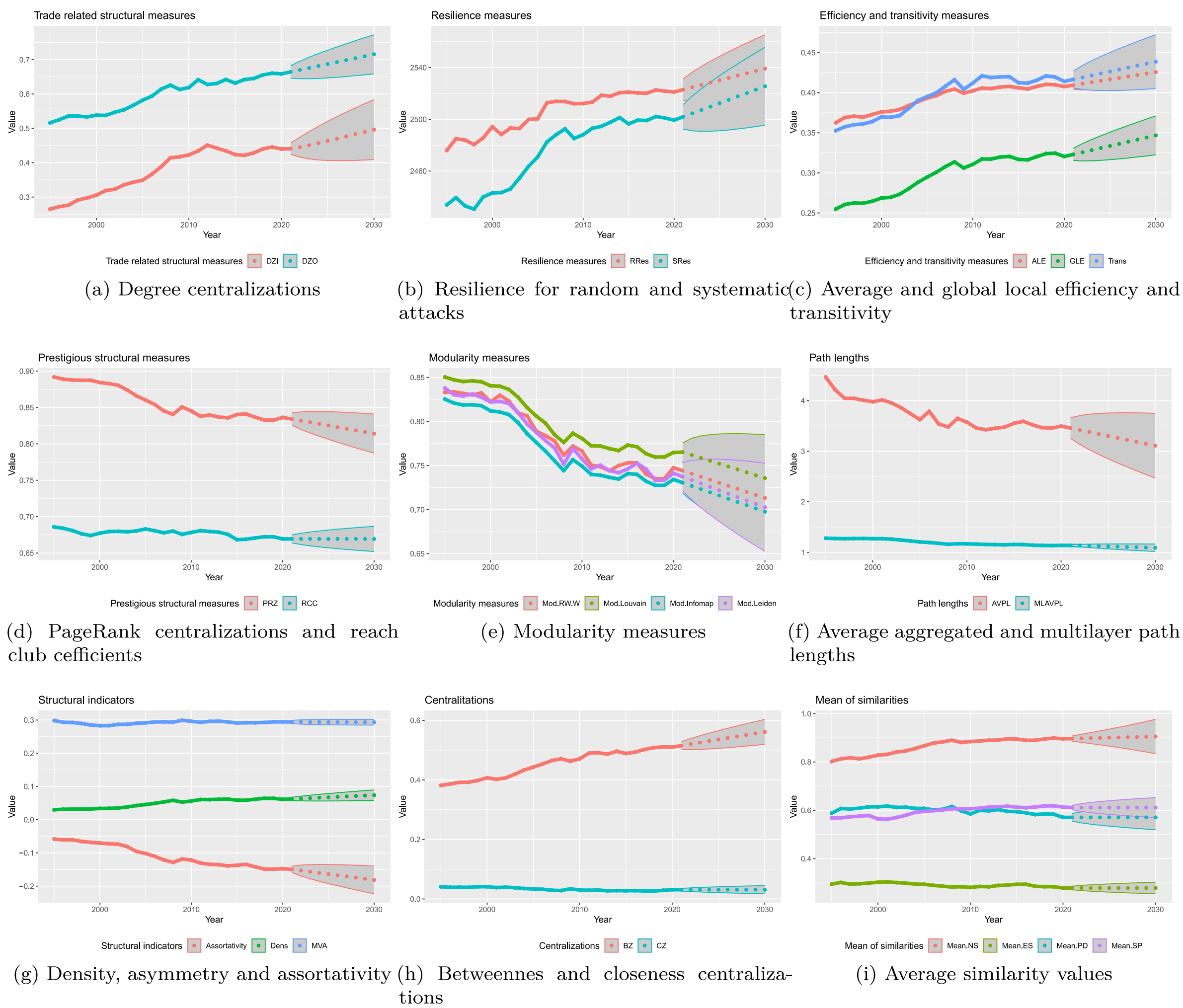
4.1. Temporal analysis of the structure of multilayer dynamic trade networks

Fig. 2 shows the temporal changes in the multilayer network properties. We project the time series of structural indicators utilizing the ARIMA model from 2021 to 2030, and we also establish a 95% confidence interval for prediction. To ensure the prediction, we also calculated the forecasts with Bayesian ARIMA model (see Fig. A.10 in the Appendix). The results of the classical and Bayesian approaches differ only minimally. To layer-specific robustness checks corroborate our main findings, we recomputed the core indicators on the FD- and VA-layers shows to check both demand-driven flows and value-added allocation exhibit the same long-run rise in centralization and the same ebb-and-flow of modular fragmentation identified in the Z-layer. However, in this study, we only compare the sector-specific Value Added (VA) and country-specific FD values with the centrality values calculated on the Z-layers.

Although the forecasts do not show what the impact of, for example, Trump's protective tariffs or the prolongation of the Russia–Ukraine conflict will be, causality analysis can show which structural indicators move at the same time and which ones exhibit a time lag. The causal relationship among the network properties are shown in Fig. 3. Fig. 3(a–b) shows heatmaps and biclusters of Granger (a) and instantaneous (b) causalities according to the network features. The darker reddish cells in Fig. 3(a) indicate longer lags; however, in the context of instantaneous causality, there is no temporal lag, with only significant cells depicted in dark red. In both causalities, two biclusters can be identified, with only the first being significant for both rows and columns. Fig. 3(c) illustrates a directed Granger causality graph with a tree layout. On the basis of this arrangement and clusterings, we create a block diagram, which is illustrated in Fig. 3(e). Fig. 3(d) depicts an undirected graph with instantaneous causality across properties. The color of the nodes signifies the community identified by Leiden's community-based modularity detection technique. The dimensions of the nodes correspond to the DC of each node, with dark red edges representing members of the first bicluster (significant) and dark green edges denoting members of the second bicluster (nonsignificant). In accordance with Granger causality and the specified tree architecture, three levels can be identified to minimize feedback, as shown in Fig. 3(e).

Fig. 3 presents the comprehensive causality analysis framework for multilayer trade network structural indicators from 1995–2020. To determine the effect mechanism of each structural indicator, we initially establish Granger and instantaneous causality (see Fig. 3(a–b)). We cluster the structural features by Leiden's modularity-based community detection (see Fig. 3(c–d)) and by biclustering the relationships (see Fig. 3(a–d)), and finally, we subsequently organize the procedures to minimize the level of feedback among structural elements (see Fig. 3(e)). Ultimately, we obtain a mechanism graph illustrating both the comovements (i.e., ∼instantaneous correlations) and Granger causal linkages (i.e.,∼ precedence) among structural components. The weights in Fig. 3(e) inscribed on the arrows denote the average duration of lags among the structural variables.

Specifically, Fig. 3(a) shows Granger causality relationships with lag structure, where darker red cells indicate longer temporal lags (0=no significance, 1–5=year lags) between structural indicators. Key abbreviations: DZI/DZO—measuring trade concentration, BZ—intermediary control, CZ—market accessibility, PRZ—influence concentration, AVPL—trade route efficiency, ALE/GLE—regional/global trade efficiency, Trans (Transitivity—clustering tendency), RRes/SRes—network robustness, MVA—trade balance inequalities, RCC—elite country interactions, Mod.* (Various modularity measures using different algorithms—community structure), Mean.NS/ES/PD/SP—cross-industry integration patterns. Fig. 3(b) displays instantaneous causality (simultaneous co-movements) where dark red dots indicate significant relationships. Fig. 3(c) and (d) present clustered causality graphs with community detection results, where node colors represent different communities identified by Leiden's modularity-based algorithm, and edge colors distinguish significant (dark red) versus nonsignificant (dark green) biclusters. Fig. 3(e) synthesizes the temporal mechanism into a three-tier hierarchical structure: Tier 1 (robustness indicators: Trans, SRes, RCC,



(a) Degree centralizations

(b) Resilience for random and systematic attacks

(c) Average and global local efficiency and transitivity

(d) PageRank centralizations and reach club cefficients

(e) Modularity measures

(f) Average aggregated and multilayer path lengths

(g) Density, asymmetry and assortativity

(h) Betweennes and closeness centralizations

(i) Average similarity values

Fig. 2. Network properties in time (forecast with ARIMA, 95% confidence interval).

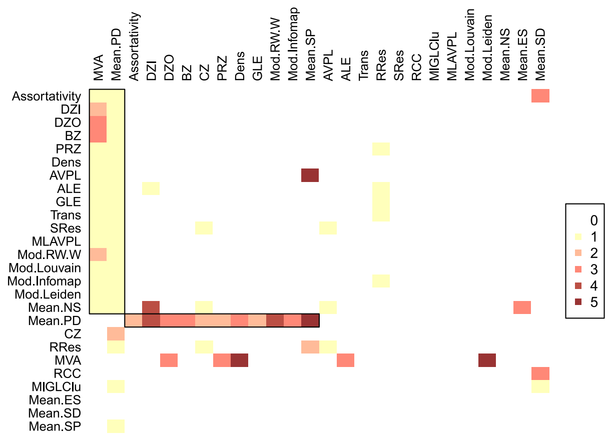
MlGlClu, MLAVPL, Mod.Louvain, Mean.NS) responds first to economic disruptions; Tier 2 (concentration indicators: DZI, CZ, AVPL, RRes, MVA, Mean.ES/PD/SP) follows with 1.35-year average lag; Tier 3 (structural integration indicators: Assortativity, DZO, BZ, PRZ, Dens, ALE, GLE, Mod.RW.W (Modularity random walk (weighted)/Infomap/Leiden, Mean.SP)) responds last with 3.31-year average lag. Bidirectional arrows indicate feedback effects with 1.26-year reverse lag between middle tiers.

4.2. Industrial causality analysis and temporal pattern identification

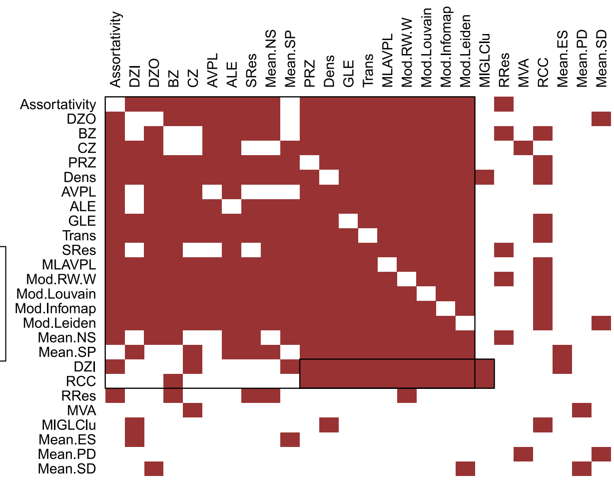
Fig. 4 shows the main centrality values of the top ten industries. The top 10 industries, in this case, are the 10 largest industries with a given centrality. Fig. 4(a) shows the change in export volume, which is expressed in terms of SCO centrality. The change in trade balance, which is the difference between export and import volumes, and expressed in terms of centralities, is SCO-SCI and shown in Fig. 4(c). Additional relative centrality values for the top 10 industries are shown in Fig. 4(b,d–g). The relative centrality for each industry is calculated by dividing the industry centrality value by that of all industries. To validate the results we also calculated the relative sectorial added values (see Fig. 4(h)).

To determine the typical industrial trends, we cluster the node-level indicators by employing the GNDA approach. Fig. 5 shows the temporal patterns of the node-level indicators aggregated by industry. The employed GNDA identifies the number of temporal characteristics (i.e., cluster centers). The temporal patterns of cluster centers shows how the aggregate characteristics of the industries in a given group have changed on average. All industries that belong to such an aggregate (latent) characteristic are listed in the legend. To ensure that the forecasts the Bayesian version of ARIMA models are also shown in Fig. A.11 in Appendix. The results of the classical and Bayesian approaches differ only minimally.

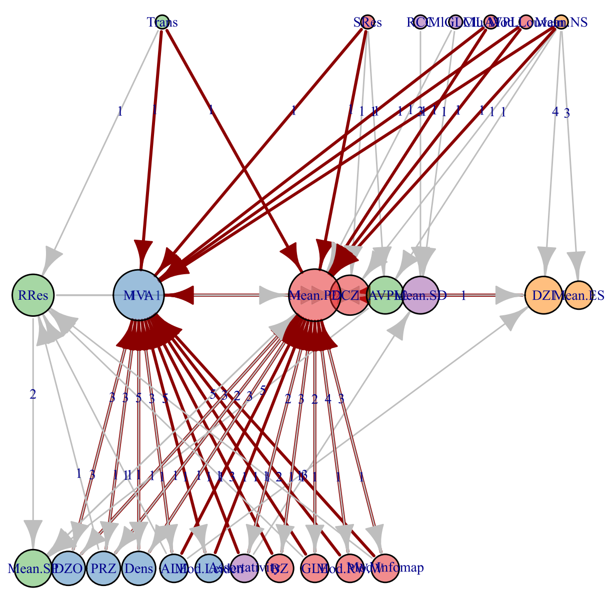
We analyze six indicators. First, DCO illustrates the temporal progression of the quantity of export partners, indicating the average number of buyers a country possesses within an industry (see Fig. 5(a)). The second indicator (see Fig. 5(b)) examined is homophily, which shows what percentages of countries' import and export relationships in a given industry originate from that industry. This indicator characterizes the structure of the industry. The development of homophily over time can show how much the industry is integrated into the international market. If the indicator increases, then it may indicate that the trade relationships between the actors in the given industry are strengthening, while if it decreases, then the opposite situation may occur. The third indicator analyzed is modularity (see Fig. 5(c)). Modularity demonstrates the significant separation of clusters, or modules (communities), inside a network structure. Assessing modularity helps determine the degree to which specific countries create communities within particular industries. The temporal variation in modularity enables the observation of how linkages among industry actors have evolved into communities. Fig. 5 (e–g) illustrate the time evolution of most important industrial centrality indicators, such as EC (e), PRC (f), and BC (g). While EC and PRC demonstrate the role of industries inside



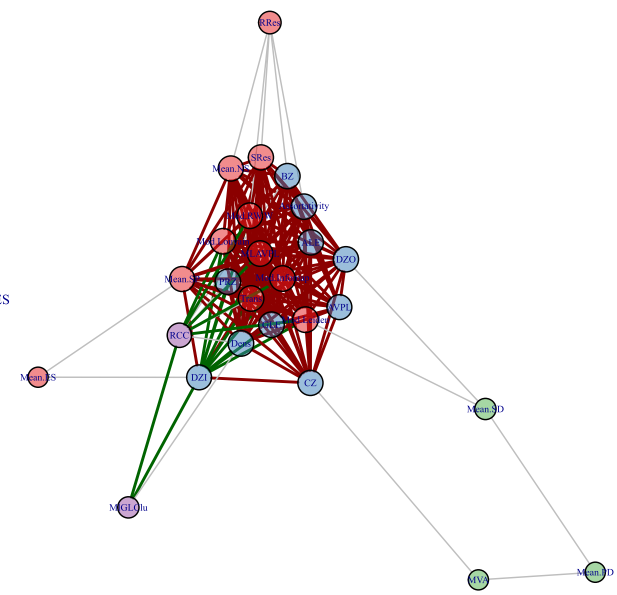
(a) Granger causality (0= no sig., 1-5: year lags)



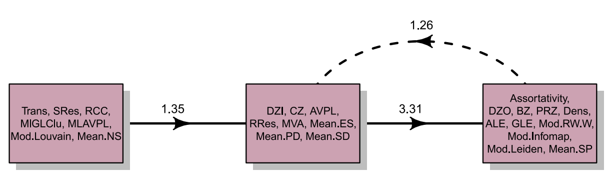
(b) Instantaneous (∘: no sig. •: sig.) causality



(c) Clustered Granger causality graph (⟶: pair of elements in bicluster 1)



(d) Clustered instantaneous causality graph (⟶: pair of elements in bicluster 2)



(e) The effect mechanism (average time lag of precedences)

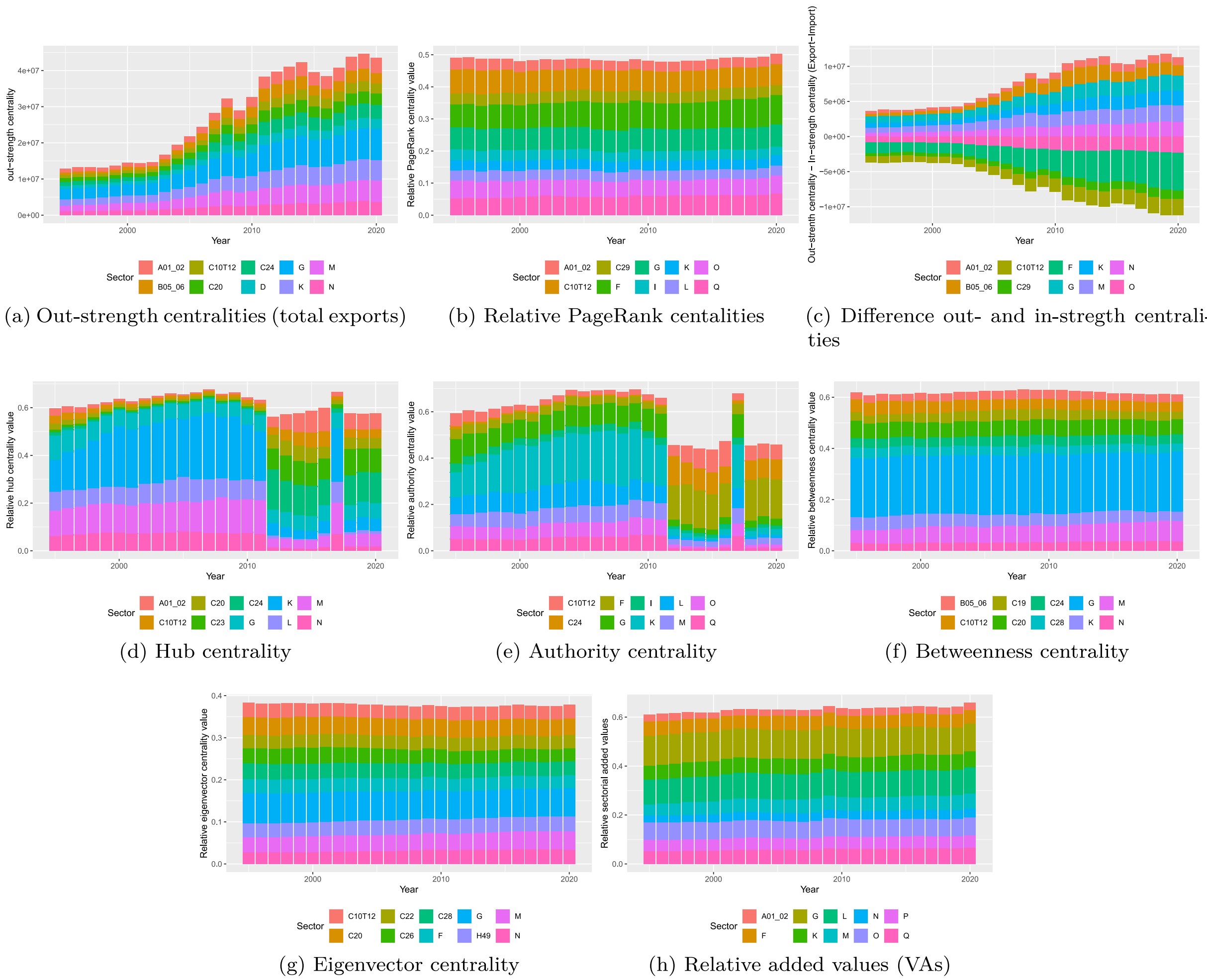
Fig. 3. Causalities between network properties with detailed methodological framework and indicator explanations.

the network, BC illustrates their intermediary function. To validate the change in centrality values the added values are also calculated (h).

The final results of the causality analysis are shown in Fig. 6. This calculation follows the steps of causality analysis on network-level indicators; see Fig. 3. First, the Granger and instantaneous causalities are calculated. Causality graphs are specified and aligned as a tree layout. Each level of trees is grouped into a block, and the average time lag between the pair of elements from a two distinct blocks is calculated.

4.3. Country-level analysis

Fig. 7 shows the top ten countries with the greatest centrality values. The SCO in Fig. 7(a) actually shows the volume of exports considering the ten largest exporters, whereas Fig. 7(c) shows the trade balance SCO-SCI=export-import in time. Fig. 7(b, d–g) shows the ten most important countries with the largest relative PageRank, hub, authority, betweenness and eigenvector centrality values, where the relative centrality value of a given country is calculated by dividing the summed centrality values of all industries of that country by the sum of the centrality values of all industries of all countries. In this way, the sum of the relative centrality values of the top ten countries with the greatest values indicate their role compared to that of all other countries. The change in values over time gives the change in the relative position of the top ten countries. To control the changes in centralities we calculate the changes in FDs (see Fig. 7(h)).



(a) Out-strength centralities (total exports) (b) Relative PageRank centalities (c) Difference out- and in-stregth centralities

(d) Hub centrality (e) Authority centrality (f) Betweenness centrality

(g) Eigenvector centrality (h) Relative added values (VAs)

Fig. 4. Centrality values of the top 10 industries.

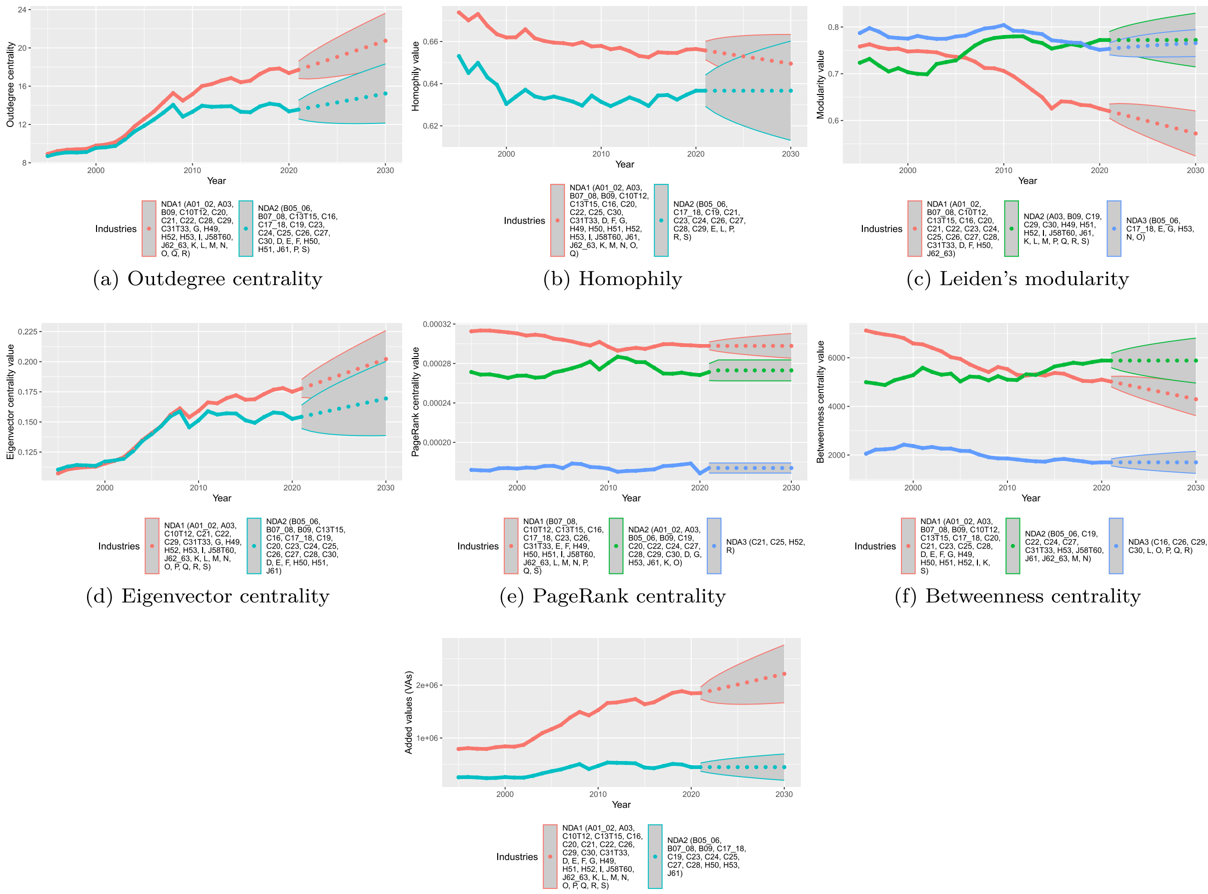
Fig. 8 shows the impact mechanism of changes in all trade activities (import+export with Schwarz Criterion (SC)) measured. The map shows OECD countries. The size of the nodes is proportional to the total trade activity (imports + exports), which is measured via strength centrality. The colors of the nodes indicate the causal group into which each country falls. The first causal relationship is for countries whose trade changes first. The last causal relationship is for countries whose trade changes last. By biclustering the causal relations, one significant group of relationships can be identified, which are indicated by the colors of the arrows.

Fig. 8 maps the temporal propagation of trade volume, which changes across 77 countries from 1995–2020, revealing systematic patterns in how global trade disruptions cascade through different national economies. Fig. 8(a) presents the clustered Granger causality network where nodes represent country size proportionally to total trade activity (imports + exports measured by strength centrality), and node colors indicate causal group membership based on response timing. Dark red arrows represent significant causal relationships (bicluster 1) where changes in one country's trade volume predict changes in another with specific time lags, while light green arrows show nonsignificant relationships (bicluster 2). Fig. 8(b) synthesizes the effect mechanism into four hierarchical tiers with distinct economic characteristics. Fig. 8 shows that the change in trade occurs simultaneously in most countries. Such changes can be divided into four consecutive causal groups in time. Trade changes first appear in Côte d'Ivoire, Estonia, United Kingdom, Hong Kong, China, Croatia, Iceland, Korea, New Zealand, Portugal, Turkey. Afterward, at average, in 2.25 years, the larger set of trade countries is Argentina, Belgium, Bangladesh, Bulgaria, Belarus, Brunei Darussalam, Switzerland, China (People's Republic of), Cameroon, Colombia, Costa Rica, Czechia, Egypt, Finland, Indonesia, Ireland, Israel, Japan, Kazakhstan, Cambodia, Lao (People's Democratic Republic), Lithuania, Morocco, Malta, Myanmar, Malaysia, Nigeria, Pakistan, Peru, Philippines, Romania, Russian Federation, Saudi Arabia, Senegal, Slovakia, Vietnam, rest of the world. A change in a larger group of countries can also be observed, on average, 2.94 years later, such as Australia, Austria, Brazil, Canada, Chile, Cyprus, Germany, Denmark, Spain, France, Greece, Hungary, India, Italy, Jordan, Luxembourg, Latvia, Mexico, Netherlands, Norway, Poland, Singapore, Slovenia, Thailand, Tunisia, Chinese Taipei, United States, South Africa. A backlash can also be observed between the two middle groups with an average delay of 1.92 years. The last group includes a total of 2 countries, namely Sweden, Ukraine, which are those countries where export/import changes in trade appear the latest in the considered period.

5. Discussion

5.1. Structural changes in the trade network

Concentration and market power. The steady rise of importer and exporter centralization and of intermediation power (degree and betweenness centralizations; PageRank centralization; "rich-club" intensity) signals a persistent concentration of global trade in a relatively small set of hub economies. Economically, this implies growing bargaining power for core countries and lead firms, stronger price-setting

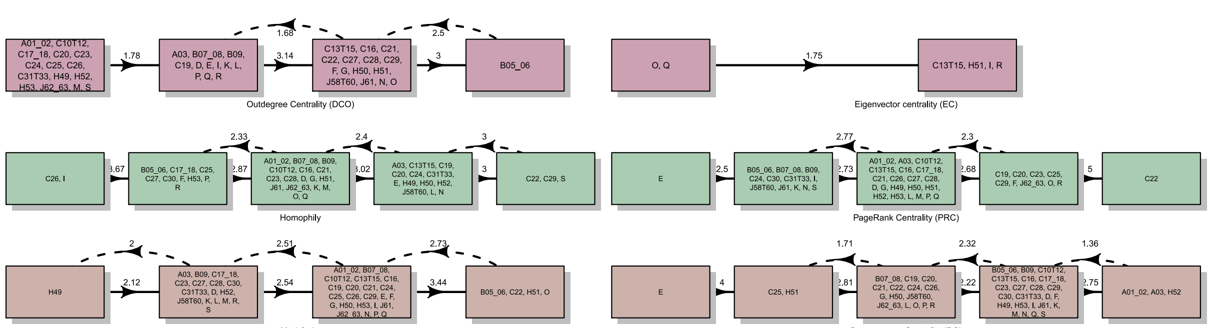


(a) Outdegree centrality (b) Homophily (c) Leiden's modularity

(d) Eigenvector centrality (e) PageRank centrality (f) Betweenness centrality

(g) Added values (VAs)

Fig. 5. Average clustered industrial node-level properties.

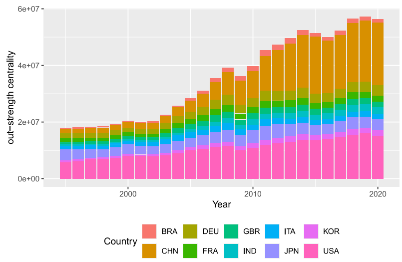


(a) Outdegree centrality, homophily, modularity (b) Eigenvector centrality, PageRank Centrality, Betweenness Centrality

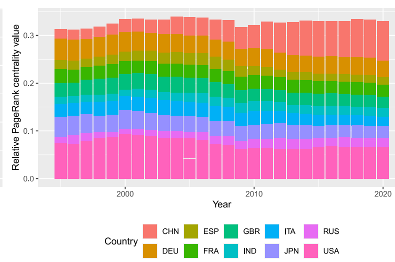
Fig. 6. Industrial effect mechanisms based on causality and cluster analysis with economic interpretation of sectoral groupings.

capacity along GVCs, and a greater potential for policy shocks in a few jurisdictions to transmit widely. The timing is consistent with welldocumented structural drivers: the post-1995 offshoring boom, the 2001 World Trade Organization (WTO) accession of China, and the scaling of platform-type supply chains. Nonnetwork evidence aligns with this pattern: the "export superstars" phenomenon indicates a concentration of exports in a small share of firms (Freund and Pierola, 2015; Rowley, 2024), while the "Great Convergence" describes how Information and Communications Technology (ICT) lowered coordination costs and enabled hub-and-spoke GVCs led by a few economies and firms (Baldwin, 2016). China's increasing systemic centrality in Fig. 2 is consistent with macro evidence on the "China shock" and its broad real-economy repercussions (Autor et al., 2016; Dorn and Levell, 2024).

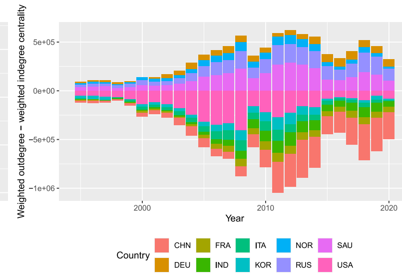
Efficiency, trade costs, and chain architecture. The decline in average (multilayer) path lengths and the rise in local and global efficiency indicate economically shorter and more reliable trade routes, consistent with falling trade costs (logistics, coordination, and information) and the maturation of production sharing. This is precisely what one would expect from containerization, ICT diffusion, and the codification of tasks that enabled fine slicing of value chains (Hummels et al., 2001; Ren, 2024; Baldwin, 2016). The small but persistent increase in density further reflects broadening market access and deeper integration. Microevidence that "time is trade cost" (e.g., delays at the border and in shipping depress trade disproportionately) provides an independent, nonnetwork rationale for the shorter effective distances we observe (Liu and Yue, 2013). In economic terms, Fig. 2 suggests that, up to the



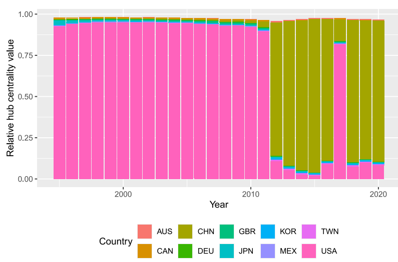
(a) Out-strength centralities (total exports)



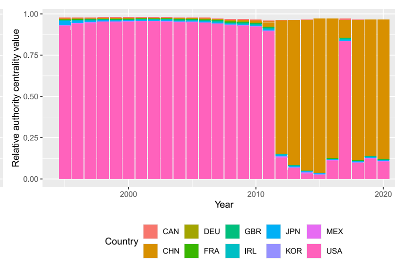
(b) Relative PageRank centalities



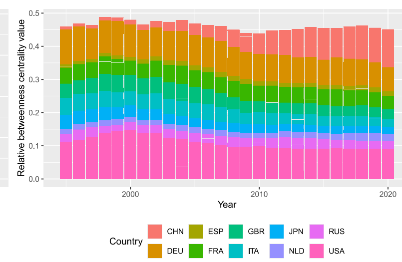
(c) Difference out- and in-stregth centralities



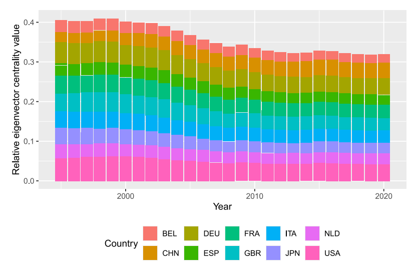
(d) Hub centrality



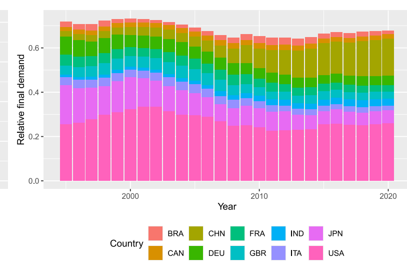
(e) Authority centrality



(f) Betweenness centrality



(g) Eigenvector centrality



(h) Relative final demands (FDs)

Fig. 7. Centrality values of the top 10 countries.

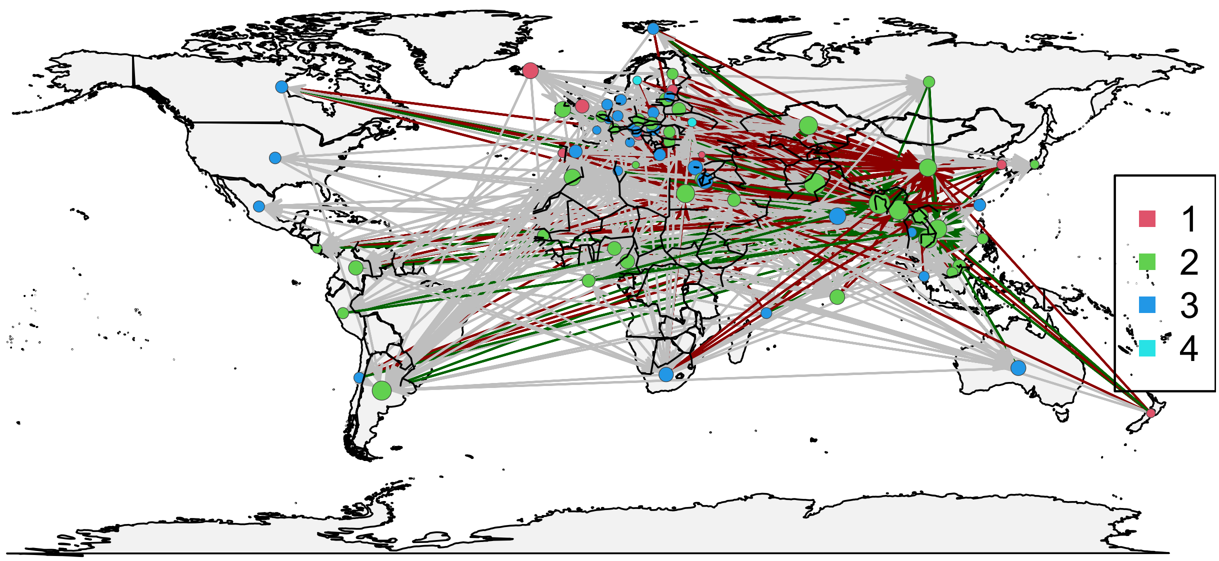
mid-2010s, firms optimized to minimize coordination and leadtime risk while leveraging larger supplier networks.

Regionalization vs. global integration. Modularity and assortativity patterns capture the tension between regionalization and global integration. Assortativity trending more negative is consistent with a hub-and-spoke, core–periphery architecture: highly connected hubs transact extensively with less connected periphery nodes — a hallmark of lead-firm GVCs. Modularity dynamics point to an ebb and flow between global integration and the re-emergence of regional blocs. The post-2008 "slowbalization" debate emphasized both cyclical (demand, finance) and structural (policy, technology) drivers of a slower trade elasticity (Constantinescu et al., 2020). Fig. 2 is consistent with a period of re-regionalization around the mid-to-late 2010s as trade policy frictions rose (Evenett, 2019), even as the underlying technology and logistics fundamentals continued to support efficient cross-border production. Put differently, the economic forces pushing toward integration (falling trade costs) and the policy forces pushing toward fragmentation (tariffs, screening, compliance divergence) coexisted during this period.

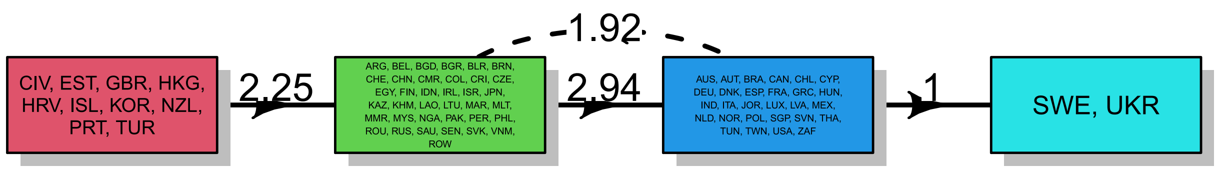
Resilience and systemic risk. Improvement in random failure resilience together with the more modest gains (or plateaus) in targeted-attack resilience imply that while the trade system became better at absorbing idiosyncratic disturbances, it remained vulnerable to shocks concentrated on hubs (e.g., a targeted tariff or a chokepoint disruption). This is an economic tradeoff familiar in the supply chain management: efficiency gains from scale and centralization raise exposure to hub-specific risks. The literature on supply chain risk similarly warns that the very forces that made GVCs efficient – supplier consolidation, just-in-time inventories, and hub concentration – also magnifies systemic vulnerability to policy and logistical shocks (Baldwin and Freeman, 2022). The patterns in Fig. 2 therefore square with an economic interpretation in which firms optimized for cost and speed during "normal times", while policy shocks and crises reveal the nonlinear losses associated with central-node disruptions.

The counterfactual outlook lacks recent shocks. The ARIMA-based projections (2021–2030) are a baseline, "no-new-shock" counterfactual. Economically, the forecast of continued efficiency gains (shorter effective distances), slight additional densification, and mild declines in modular segmentation suggests that, the absence of new protectionist measures or large geopolitical events, the gravitational pull of technology, scale, and learned coordination would have continued to deepen integration and diffuse influence marginally away from the very top players. This counterfactual complements non-network assessments that attribute much of the post-2016 deceleration to policy and uncertainty rather than to a reversal of the technological and organizational underpinnings of GVCs (Constantinescu et al., 2020). In other words, Fig. 2's forecasts imply that the observed fragmentation of recent years is not inevitable; it is contingent on policy and shock realizations rather than being dictated by economic fundamentals alone (Milberg et al., 2024).

As shown in Fig. 3 most structural changes occur instantaneously and collectively, with causal mechanism analysis organizing these relationships into three consecutive hierarchical groups. These findings align with Baldwin and Lopez-Gonzalez (2015)'s observation of "deep integration" in global value chains, where interconnected production networks create simultaneous adjustment patterns across multiple economic dimensions. The first tier comprises structural indicators reflecting network robustness – transitivity, global clustering coefficients, and



(a) Clustered Granger causality graph (⟶: bicluster 1 (significant), ⟶: bicluster 2 (non significant))



(b) Effect mechanism

Fig. 8. Country-level causality effect mechanism of strength centrality (total trade volume) with geographic and economic development patterns.

systematic resilience measures – which change earliest in response to economic disruptions. This pattern mirrors Autor et al. (2016)'s findings on the "China shock", where initial trade policy changes first affected the structural integrity of manufacturing networks before cascading to other sectors. From an economic policy perspective, this suggests that policymakers should monitor network robustness indicators as early warning signals for broader structural changes, as these measures capture the fundamental stability of trade relationships before concentration or community patterns begin to shift.

The second tier encompasses centralization and similarity indicators, reflecting changes in market concentration and trading partner alignment patterns, which respond with an average lag of 1.35 years after robustness changes. This delayed response supports Melitz (2003)'s heterogeneous firm trade model, where aggregate trade patterns emerge from firm-level adjustments that take time to manifest in network-wide concentration measures. The third tier includes community structure indicators (modularity and assortativity) with an average lag of 3.31 years, representing the longest-term structural adjustments in trading bloc formation and partnership preferences. This temporal sequencing contradicts the immediate adjustment assumptions of standard trade models (Krugman et al., 1980; Mansouri, 2022) but supports more recent dynamic trade literature emphasizing gradual adjustment processes (Eaton et al., 2016; Atsebi et al., 2024). Bidirectional causality between the second and third tiers (with a 1.26-year reverse lag) indicates that community structure changes can also influence concentration patterns, suggesting that trade bloc formation can reshape market power dynamics—a finding consistent with Hofmann et al. (2019)'s analysis of preferential trade agreements' effects on multilateral trade patterns. These results provide crucial guidance for crisis management: robust early intervention during the first phase can prevent cascading effects, whereas delayed responses may require addressing all three structural dimensions simultaneously at much higher economic and political costs.

5.2. Industrial changes and restructuring

The centrality values shown in Fig. 4 reveal remarkable structural stability in global trade hierarchies despite major economic disruptions, suggesting that fundamental comparative advantages and industrial specialization patterns exhibit strong persistence over time. The dominance of wholesale and retail trade (G), financial services (K), and basic metals (C24) in export volumes and centrality measures aligns with Hausmann and Hidalgo (2011)'s economic complexity theory, which predicts that countries and industries with established capabilities maintain their positions in global value networks. This stability contradicts the "creative destruction" hypothesis of Schumpeter (2013), which would predict more dramatic industrial reshuffling following major crises such as the 2008 financial crisis. From a trade theory perspective, these findings support the Heckscher–Ohlin model's prediction of persistent specialization patterns based on factor endowments (Leamer et al., 1995), while challenging newer models that emphasize rapid industrial transformation through technology adoption (Grossman and Helpman, 1993; Helpman, 2025). The absence of significant restructuring in PageRank, betweenness, and eigenvector centralities indicates that core industries maintain their intermediary roles and influence positions within global supply chains, suggesting that established trade relationships create substantial switching costs and network externalities that preserve existing hierarchies even during periods of economic turbulence. As shown in Fig. 4, industries with high centrality measures (such as agriculture financial services) also tend to exhibit high and growing value-added contributions. Nevertheless, the top 10 value added industries incorporate professional scientific and technical activities (M), public administration and defense (O), and human health and social works (Q) which are also selected in the calculation of the top 10 eigenvector-centralities. This correlation suggests that an industry's position in the trade network is often reflective of its economic importance in terms of value creation, which is further strengthened by similar industry characteristics in terms of both centrality and added value (compare Fig. 4(b, g) with Fig. 4(h)), as well as the high average correlation between VAs and the employed out-strength ($\rho = 0.96$) centrality values.

However, the observed shifts in hub and authority centralities reveal more nuanced adjustments in industrial leadership and trust relationships within the global economy. Financial and insurance sector's declining hub centrality after 2011 – overtaken by basic materials and construction – reflects a fundamental reorientation of global economic priorities following the financial crisis, consistent with Reinhart and Rogoff (2009)'s and Kose et al. (2022)'s documentations of postcrisis shifts toward tangible asset sectors and infrastructure investment. This transition aligns with Rodrik (2016)'s argument about "premature deindustrialization", where developing economies increasingly prioritize manufacturing and construction over financial services. The rise of basic materials in authority centrality suggests growing recognition of resource-rich countries and commodity-production industries as reliable trading partners, supporting Venables (2016)'s analysis of the "resource curse" reversal in countries that successfully leveraged commodity booms for broader economic development. These changes in authority reflect evolving trust patterns in international trade, where countries increasingly view suppliers of essential materials as more dependable than financial intermediaries—a shift that has profound implications for supply chain resilience and strategic economic partnerships. The construction sector's emergence in authority centrality likely reflects the global infrastructure boom, particularly in emerging markets, consistent with the Group (2017)'s emphasis on infrastructure investment as a driver of sustainable development (Knack et al., 2025).

According to Fig. 5, both the network indicators and VAs of industries can be clearly classified into 2–3 distinguishable clusters, which are similarly separated for most centrality and the VA measures, revealing fundamental economic stratification patterns that align with established theories of industrial organization and sectoral heterogeneity. Most of the industrial node-level centrality measures are affected by the 2008 financial crisis, but the extent of this impact varies significantly across clusters, reflecting differential economic resilience capacities that correspond to varying degrees of market concentration, capital intensity, and global integration. The DCO and EC centralities characterizing the multiplicity of export partners show very similar patterns, and in the case of both centralities, two main characteristics whose trajectory after the 2008 financial crisis is completely different can be identified, demonstrating that these sector groupings exhibit distinct adaptive capacities in the wake of global disruptions. The results are also validated by clustering according to VA. We can see a similar sectoral breakdown, where the trends are the same as those seen with DCO and EC centralities. This finding is consistent with Carvalho (2014) sectoral shock propagation theory, which suggests that industries with different network positions respond heterogeneously to aggregate shocks. Industries in the first cluster, such as agriculture, food products, and IT, demonstrate resilience and continue strengthening postcrisis, albeit at a slower pace, which economically reflects their essential nature and lower cyclical sensitivity, supporting Acemoglu et al. (2012a) reported that upstream sectors and those providing basic necessities tends to be less volatile during economic downturns. These sectors are characterized by stronger integration and robust export partnerships, allowing them to sustain growth despite adverse conditions, which are consistent with Rauch and Watson (2003) and Roner and Tomasi (2025) evidence that differentiated product industries maintain more stable trade relationships. In contrast, industries in the second cluster, including mining, construction, and education, exhibit stagnation, potentially due to their higher cyclical sensitivity and dependence on domestic demand cycles, which aligns with Davis and Haltiwanger (2001) and Goswami and Paul (2025) studies of procyclical employment patterns in construction and resource extraction sectors. The forecasts suggest expansion in export partnerships across both clusters, hinting at gradual recovery and broader network involvement, reflecting the economic principle of market adjustment through diversification strategies as described by Melitz (2003). Homophily and modularity patterns further underscore the structural economic differences between these industry clusters, with lower homophily values in the second cluster indicating greater cross-sectoral dependencies, consistent with input–output analysis showing that certain industries serve as critical intermediate suppliers (Leontief, 1986; De Mesnard, 2024). However, the predictions suggest convergence in homophily indicators between the two clusters, potentially reflecting ongoing structural transformation toward more integrated global production networks, supporting Baldwin (2016)'s concept of the "great convergence" in industrial structures. The significant decrease in modularity observed in the first cluster, while the concentration stagnates in the other clusters, economically suggests that leading industries are becoming more integrated into global markets while others remain relatively isolated, consistent with Autor et al. (2016) findings on the heterogeneous impacts of globalization across sectors. Decreasing betweenness centrality in the first cluster suggests that the intermediary role of these industries is weakening, while that of the second cluster, which includes several transport industries, is strengthening, reflecting a fundamental shift in the global division of labor where traditional manufacturing centers are being replaced by logistics and service hubs, supporting Gereffi (2017) analysis of the global value chain governance transitions.

Economically, the complementary grouping tools clarify why specific sectors co-locate and how that maps into preparedness and policy design. Time-profile partitioning (GNDA; Fig. 5) reveals a fast-moving "input–coordination" constellation – farm and food systems, chemicals and advanced materials, semiconductors/electronics, freight and storage, digital infrastructure, and professional/technical services – whose joint motion arises from common choke-point inputs (e.g., fertilizers, rare earths, specialty chemicals, chips) and tight synchronization of logistics and data; actionable safeguards here include upstream buffer capacity for those inputs, narrowly scoped duty exemptions on bottleneck components, pre-cleared "green lanes" for cargo and data, and supplier spreads across at least three regions. A second, investment-sensitive "build-and-utilities" constellation – extraction and basic materials with building and energy/water services – clusters because capital-expenditure cycles bind them; counter-cyclical public orders, regional reserves of key materials, and rules-of-origin that reward dual sourcing dampen volatility. A slow-adjusting "social and knowledge" constellation – education, health, and cultural/publishing – moves together via income channels rather than input ties, calling for income smoothing and service-continuity contracts rather than border measures. Using multiple grouping lenses is essential: modularity-based partitions on indicator graphs highlight system levers; GNDA identifies who moves together and when; binary biclustering (iBBiG; Table 5) pinpoints dense origin–target dyads that actually carry transmission. Overlaying lead–lag evidence from the causality tests onto these biclusters (Fig. 6) marks which dyads ignite cascades and the typical delay, enabling a tiered playbook: sentinel dashboards on the fast-moving constellations trigger narrow waivers and logistics fast-tracks; if the build-and-utilities constellation lights up next, deploy material swap lines and diversification mandates; if the slow constellation activates, pivot to demand-side stabilizers. This integrated reading turns otherwise technical groupings into precise, time-sequenced resilience and trade actions.

The observed temporal differentiation in industrial responsiveness patterns reflects fundamental economic structural characteristics that determine adjustment speeds to global trade disruptions. Early-responding industries—primarily agriculture and food products (A01_02), electronics (C26), financial services (K), and telecommunications (J61)-exhibit characteristics associated with rapid market adjustment capabilities: high technology intensity, short production cycles, and immediate consumer demand sensitivity (Acemoglu et al., 2012b; Autor et al., 2020). These sectors typically operate with lower capital intensity and higher labor mobility, enabling swift reallocation of resources during economic shocks, consistent with Melitz and Redding (2014) findings on firm heterogeneity in trade adjustment. The early responsiveness of the electronics sector aligns with Timmer et al. (2014)'s and Kordalska et al. (2025)'s studies of rapid global value chain reconfiguration in technology-intensive industries, where modular production processes facilitate quick supplier switching and geographic relocation. Conversely, late-responding industries – construction (F), basic materials (C24), and utilities (D, E) – are characterized by high capital intensity, long investment horizons, and substantial sunk costs that create adjustment rigidities (Decker et al., 2020). These upstream and midstream industries face structural constraints including long-term contracts, specialized infrastructure, and regulatory frameworks that impede rapid reconfiguration, supporting Antràs and Chor (2013) theory of sequential production and adjustment costs in global supply chains. The intermediate timing of manufacturing industries (C20, C28, C29) reflects their position in value chains where adjustment speeds depend on both upstream input availability and downstream demand patterns, creating moderate response lags that correspond to inventory cycles and production planning horizons (Alfaro et al., 2019). This sectoral stratification suggests that trade policy interventions should be temporally sequenced: immediate support for technology-intensive and service sectors, medium-term assistance for manufacturing, and long-term structural programs for capital-intensive industries, recognizing that cross-country variations within the same industry may reflect differences in technological sophistication, market structure, and institutional frameworks (Caselli et al., 2020; Conteduca et al., 2025).

These results indicate that the systematic lag between the initial disruptions and their broader economic consequences. While changes in homophily (as an indication of a change in the industry trade structure) and centrality indicators (as an indication of the changed role of industries) emerges early in sectors such as computing, electronics, finance, and telecommunications, cascading effects reach industries such as education, social work, publishing, and construction much later. This delayed response underscores how crises often unfold in waves, first impacting direct trade and financial hubs and then trickling down to peripheral sectors. If a crisis escalates, then industries dependent on discretionary spending, such as arts, entertainment, and recreation, will likely suffer the most prolonged instability. Ultimately, these patterns emphasize the importance of proactive policy measures and diversified trade strategies to mitigate vulnerabilities across industrial sectors, ensuring resilience in the face of global economic upheavals.

5.3. Reorganization of countries' positions in international trade

The primary takeaway from Fig. 7 is that the global dominance of leading countries is declining, while leadership roles are being significantly rearranged (compare Fig. 7(a–g) to Fig. 7(h)). The results are illustrated in Fig. 7 underscore the changing dynamics of global trade networks, particularly the rising significance of dominating states, especially China. During the examined timeframe, China's rise is characterized by a steady growth in export quantities, centrality metrics across all sectors (see Fig. 7(b, d–f)), and FDs (see Fig. 7(h)), in stark contrast to the declining relative centrality values of other prominent countries. This trend highlights China's strategic emphasis on augmenting its involvement in commerce and supply chains (see Fig. 7(d–e)), establishing itself as a pivotal mediator of global trade. The shift in dominance from the US to China, as indicated by metrics such as PageRank (see Fig. 7(b)), hub (d), authority centralities (e), and FDs (h), signifies a significant reconfiguration of trade relations and underscore China's increasing power and essential role in global supply chains. The present Trump administration's China policy appears to be a rational measure; nonetheless, importantly, owing to global interconnection, the ramifications of the tariff conflict extend beyond China and may negatively influence the entire trade framework.

The observed grouping of countries' trade based on Granger causality analysis highlights the temporal dynamics of trade interactions, suggesting underlying economic interdependencies and responsiveness among nations. The first group, which includes Estonia, the United Kingdom, and several Asian countries, indicates that these economies are quick to respond to shifts in trade, owing to their export-driven growth strategies and integration in global supply chains. The subsequent grouping, emerging after an average of 2.25 years, encompasses a more diverse array of countries, suggesting a broader economic network that reacts to initial changes in trade by adapting their exports and imports accordingly, reflecting the interconnectedness of global trade flows. The notable lag of 2.94 years for the third group underscores the delayed response of larger, often more established economies such as the US and Germany, which may be less agile owing to their size and complexity but significant in world trade dynamics. The observed causal relationships between the two middle groups, with an average lag of 1.92 years from the countries in the third group, suggests that if changes do occur in the third group, then they will also affect countries in the second group, as is likely the case with the current US–Europe tariffs. Finally, Sweden and Ukraine belong to the group of late responders, which suggests that the effects of potential crises appear the latest here or that they are able to adequately mitigate their effects. These findings emphasize the intricate and varied nature of global trade interactions, highlighting the importance of considering temporal dynamics in economic analyses to better understand the causal relationships among countries in terms of trade.

A large tariff increase would initially hit nations that are heavily integrated into global trade flows – especially those in the second group – such as Japan, China, and Belgium, which would struggle with rising costs and shrinking competitive advantages. Additionally, disruptions would severely affect economies with strong industrial dependence, such as Germany and the US, triggering delayed but significant consequences for trade relationships worldwide. These findings align with industry-level causality results, where sectors such as agriculture, electronics, transportation, and public services show the earliest structural adjustments to trade dynamics.

Ultimately, the causality of industry shifts and trade transformations is intrinsically linked. Early-reacting countries are home to industry that are the first to undergo structural changes, reinforcing the idea that economic shocks propagate through industrial sectors before expanding to national trade policies. As trade adjustments appear to follow cascading patterns – with an initial group reacting first, which is followed by broader economic shifts –; thus, it becomes crucial for policymakers and businesses to anticipate disruptions on the basis of industrial vulnerabilities. By understanding the interconnectedness of trade and industry responses, nations can develop more resilient economic strategies, thus minimizing risks from potential crises and ensuring the stability of global commerce.

China and the US play pivotal roles in global trade dynamics, acting as central hubs that influence broader economic shifts. Based on causality analysis, both countries fall within the third causal group, meaning that their trade fluctuation, in the case of a global crisis, occurs slightly later than do those in early-responding nations, but due to interconnectedness and causal mechanisms, trade in almost all economies disruptions if any radical change occurs in these countries. If more serious tariff measures were implemented in Chinese or US trade; then it would disrupt supply chains, increase production costs, and force countries to restructure their trade dependencies. Nations heavily integrated with these economies – such as Germany, Japan, and Mexico – would face immediate trade disruptions, leading to price volatility and slower economic growth. Industries reliant on Chinese manufacturing or US consumer demand would struggle, prompting shifts toward regional trade agreements or diversification in sourcing strategies. The ripple effects could restructure global trade hierarchies, potentially accelerating economic fragmentation and forcing adaptation at key industrial sectors.

6. Summary and conclusion

This paper presents a thorough analysis of global trade networks utilizing the OECD's ICIO figures from 1995 to 2020. This study utilizes sophisticated methodologies, including temporal analysis of multilayer networks, clustering, biclustering, and causality analysis, to evaluate structural indicators such as degree centralization, resilience, transitivity, and modularity. The study's principal methodological advancements encompass the utilization of Granger causality to elucidate the effect mechanism and temporal dynamics among network features, alongside the implementation of modularity-based community detection strategies to delineate clusters within the calculated causality networks. This study, by examining networks across diverse industries and nations, uncovers emerging dynamics and patterns in global trade, emphasizing changes in resilience, concentration, and the importance of significant players, particularly China and the US. Individual research is interrelated, examining various aspects of global trade linkages and enhancing the comprehensive understanding of how economic disturbances affect trade patterns. This research is essential for policymakers and business leaders, highlighting the need for adaptive methods to improve resilience in the face of persistent global economic fluctuations and crises, thereby promoting informed decision-making and sustainable economic development.

The research questions of this study – what causal patterns can be identified in multilayer trade network structures and how these patterns reveal the roles of specific countries and industries as drivers of change in global trade dynamics – have been comprehensively addressed through an in-depth temporal analysis of multilayer trade networks. The findings reveal significant shifts in structural indicators (see Contribution $\mathbf{C}_1$), such as increasing concentration and rising transitivity within trade networks, particularly highlighting the evolving roles of major players such as China and the US. This study contributes to the literature by unearthing the nuanced causal relationships between trade dynamics and economic disruptions, particularly emphasizing the interconnectedness of countries and industries in the face of global economic change (see Contribution $\mathbf{C}_2$). By employing advanced methodologies such as Granger causality and modularity-based community detection, this research adds a unique layer of understanding to how industrial shifts propagate through trade networks, allowing for the better anticipation of such shifts in the future. Ultimately, this study underscores the importance of proactive policy measures, arguing for diversified trade strategies to enhance resilience against potential crises, thereby providing valuable insights for policymakers and economic strategists in navigating the complexities of global trade systems (see Contribution $\mathbf{C}_3$).

6.1. Implications for scholars

This study highlights the importance for scholars to utilize a variety of methodologies – such as biclustering, network analysis, and causality methods – when intricate trade linkages are being examined. Each method offers distinct insights; network analysis uncovers the comprehensive structural characteristics of trade interactions, biclustering identifies the concentrated causal relationships within particular subsets of nodes, and causality techniques clarify the temporal precedence and influences among various properties. Analyzing multilayered networks are crucial for comprehending the complex interconnections within industry partnerships, enabling a more detailed examination of node interactions across several trade aspects. Excluding any of these approaches may result in an incomplete understanding; for example, without causality analysis, correlations may be erroneously interpreted as causation, and disregarding biclustering may overlook crucial relational dynamics that differ across contexts. This thorough methodology strengthens the validity of the results, enabling academics to formulate better informed conclusions regarding the changing dynamics of global commerce and its ramifications for economic policy.

This study demonstrates that examining complex trade networks requires a *multimethodological approach* that combines network analysis, causality testing, and clustering techniques to capture different dimensions of trade relationships. Each method provides unique analytical insights: network analysis reveals structural characteristics and centrality patterns, Granger causality identifies temporal precedence relationships between variables, and biclustering uncovers concentrated causal relationships within specific subsets of nodes and edges. Scholars should recognize that *methodological complementarity* is essential rather than optional when studying complex economic systems. Future research should avoid methodological reductionism – the tendency to rely on single analytical approaches – as this inevitably leads to an incomplete understanding of multifaceted phenomena such as global trade dynamics.

The application of Granger causality testing to network structural indicators represents a significant methodological advancement that scholars should incorporate it into longitudinal trade studies. This research reveals that traditional cross-sectional network analysis fails to capture the *temporal ordering of structural changes*, missing critical insights into how disruptions propagate through trade systems. Scholars should adopt *dynamic network analysis frameworks* that explicitly model time-dependent relationships between network properties, moving beyond static snapshots to understand evolutionary processes. Identification of three-tier causal mechanisms – from robustness to concentration to community structure – provides a template for future research examining how economic shocks cascade through different levels of network organization.

Methodologically, our findings motivate an edge-centric pipeline: estimate temporal precedence via Granger/Bayesian tests to form a binary causal adjacency, then biclusters this matrix to recover heterogeneous "causal regimes"—cohesive sets of relations sharing effect direction and lags. This complements node-level community detection by revealing multiplex shock-transmission pathways that are invisible in centralities or GVC indices. The approach yields reproducible templates for early-warning screens and scenario design that hinge on the link-level co-causality rather than aggregate node importance.

The multilayer network approach employed in this study offers superior analytical depth compared to single-layer trade network studies, enabling simultaneous examination of industry-specific and cross-industry trade relationships. Scholars should recognize that *layer interdependencies* in trade networks cannot be adequately captured through aggregated or isolated industry analyses. Future research should extend multilayer network theory to incorporate additional dimensions such as temporal layers, institutional layers (formal vs. informal trade relationships), and geographic layers (bilateral vs. multilateral trade agreements). This multidimensional approach is particularly crucial for understanding how policy interventions in one industry or region propagate across the entire trade ecosystem.

This study introduces biclustering methodology to trade network research, revealing *simultaneous clustering of both nodes and relationships* that traditional clustering methods cannot identify. Scholars should recognize biclustering as a powerful tool for uncovering hidden patterns in economic networks, particularly for identifying which specific relationships drive broader structural changes. The iterative Binary Biclustering of Gene sets (iBBiG) method adapted for trade networks provides a template for future applications in economic research. Scholars should explore biclustering applications in other economic domains, such as financial networks, innovation ecosystems, and supply chain relationships, where understanding both actor groups and relationship patterns is crucial for comprehensive analysis.

The application of multiple community detection algorithms (Leiden, Louvain, Infomap) reveals that *different modularity measures capture distinct aspects of trade network structure*, suggesting scholars should employ multiple algorithms rather than relying on a single community detection methods. This research demonstrates that community structures in trade networks are not static but evolve in response to economic and political changes, requiring dynamic community detection approaches. Future research should develop *temporal community detection methods* specifically designed for economic networks, incorporating economic theory about trade relationship formation and dissolution into algorithmic design.

While Granger causality testing provides valuable insights into temporal precedence relationships, scholars must acknowledge its limitations when applied to relatively short economic time series. This study's adaptation of Granger causality to 26-year trade data demonstrates the need for *modified causality testing frameworks* that account for the specific characteristics of economic data, including structural breaks, policy interventions, and cyclical patterns. Scholars should develop *economic-specific causality measures* that incorporate domain knowledge about trade relationship formation, policy implementation lags, and economic adjustment processes. Additionally, future research should explore alternative causality frameworks such as transfer entropy or convergent cross-mapping that may be more suitable for economic network data.

This research demonstrates the importance of the *bridging network science methodologies with economic theory* to generate meaningful insights for policy and practice. Scholars should avoid purely methodological applications of network analysis that lack economic theoretical grounding, as this can lead to technically sophisticated but economically meaningless results. Future research should develop *theoretically-informed network metrics* that capture economically relevant concepts such as comparative advantage, trade complementarity, and economic complexity. The integration of network centrality measures with economic concepts such as export sophistication and economic fitness represents a promising direction for future theoretical development.

The reliance on OECD ICIO data highlights both opportunities and constraints for trade network research. Scholars should recognize that *data aggregation choices significantly impact the analytical results*, and future research should systematically examine how different levels of sectoral and temporal aggregation affect network structure and causal relationships. The development of robustness testing frameworks for network-based economic analysis is essential, including sensitivity analysis for parameter choices in community detection algorithms, stability testing for biclustering results, and cross-validation approaches for causality testing. Scholars should also explore alternative data sources and develop methods for integrating multiple datasets to overcome the limitations of any single data source.

The application of ARIMA models to network structural indicators represents an initial step toward *predictive network analysis in trade research*. Scholars should develop more sophisticated forecasting frameworks that incorporate network structure into prediction models, moving beyond univariate time series approaches to multivariate network-based forecasting. Future research should explore machine learning approaches specifically adapted for network data, including graph neural networks and network-aware ensemble methods. The development of *scenario-based forecasting models* that can simulate the impact of different policy interventions on trade network evolution represents a crucial area for future methodological development.

6.2. Implications for policymakers

This research underscores the importance of the trade network interdependencies and their vulnerabilities for policymakers in an increasingly interconnected global economy. This research illustrates that trade networks frequently operate in unison, indicating that alterations in one nation can trigger swift transformations throughout the entire network, hence increasing the degree of vulnerability of countries during crises. If a major power, such as China or the US, were to impose punitive tariffs, then it could disrupt supply chains and provoke economic consequences that reverberate across global trade environment, especially impacting countries closely linked to these economies. This analysis indicates that sanctions or tariffs may trigger cascading effects, resulting in significant alterations in trade connections and economic frameworks. Consequently, comprehending the interdependence of trade connections is essential; a uniform approach to sanctions may prove counterproductive, resulting in unforeseen repercussions for both the imposing and targeted nations. Policymakers must acknowledge the complex dynamics inside trade networks and design sophisticated measures that consider these interrelations to reduce the degree of vulnerability and bolster economic resilience against potential disruptions.

Causal analysis reveals that certain industries – particularly agriculture and food products, electronics, transportation, and public services – act as early indicators of structural change and exhibit strong cascading effects throughout the trade network. This finding necessitates *sector-specific resilience strategies* tailored to each industry's role in the causal chain. For industries identified as early responders, policymakers should implement *strategic stockpiling programs* for critical inputs. For instance, in the electronics sector, governments should maintain strategic reserves of rare earth elements and semiconductors, while in agriculture, seed and fertilizer stockpiles should be established. Additionally, *supplier diversification mandates* should be introduced for companies in these critical sectors, requiring them to maintain relationships with suppliers from at least three different geographic regions to prevent single-source dependencies.

The modularity analysis demonstrates strong regional clustering patterns within the global trade network, with communities exhibiting denser internal connections than external ones. This structural characteristic suggests that policymakers should prioritize *deepening regional trade agreements* and establishing *bloc-level coordination mechanisms*. Specifically, regions should develop integrated payment systems to reduce dependence on dominant global currencies, create joint strategic reserve programs for critical commodities, and harmonize regulatory frameworks to facilitate rapid trade rerouting during crises. For example, European policymakers should strengthen energy cooperation mechanisms and develop common procurement strategies for critical raw materials, whereas Asian economies should enhance supply chain integration through standardized logistics protocols and shared early warning systems.

Centrality analysis reveals increasing concentration of trade power, particularly the rising dominance of China and the relative decline of other major economies. To counteract this vulnerability, policymakers must implement *active diversification strategies* that reduce excessive dependence on dominant trade partners. This requires establishing *reshoring and nearshoring incentive programs* that provide tax benefits, subsidies, and regulatory fast-tracking for companies that relocate the production of strategic goods closer to home markets. Furthermore, governments should launch *industrial upgrading initiatives* focused on moving up the value chain in sectors where they currently serve as low-value suppliers, particularly in technology-intensive industries where supply chain control translates to economic leverage.

The identification of distinct causal groups among countries – with early responders such as Estonia, the UK, and South Korea signaling changes before they cascade to larger economies – provides a roadmap for developing *predictive monitoring systems*. Policymakers should establish *real-time trade network dashboards* that track key structural indicators including centrality measures, modularity coefficients, and resilience metrics. These systems should automatically trigger policy responses when threshold values are exceeded. For instance, when betweenness centralization increases beyond historical norms, this should activate contingency plans for alternative trade route development. Similarly, declining modularity values should prompt enhanced regional cooperation mechanisms.

The three-tier causal mechanism identified in this study – where robustness changes first, followed by concentration and fragmentation patterns, and finally community structures – provides a framework for *graduated crisis response protocols*. In the first phase, when network robustness indicators decline, policymakers should activate protective measures for critical infrastructure and essential supply chains. During the second phase, characterized by changes in centralization patterns, governments should implement trade route diversification measures and activate alternative supplier networks. In the third phase, when community structures begin to shift, focus should turn to long-term structural rebuilding and establishing new trade partnerships to replace disrupted relationships.

Temporal causality analysis reveals that countries occupy different positions in the global response hierarchy, requiring *differentiated strategic approaches*. Early-responding countries should maintain high flexibility and rapid adaptation capabilities, investing in diverse economic portfolios and maintaining excess capacity in critical sectors. Late-responding countries such as Sweden and Ukraine should leverage their stability to serve as *shock absorbers* for regional networks, developing capabilities to maintain trade flows when other partners are disrupted. Large economies in the middle tier, including Germany and the United States, must recognize their *systemic importance* and implement responsible trade policies that consider global spillover effects, including gradual rather than sudden policy changes and advance consultation with trading partners.

Industry-level causality patterns reveal that sectors such as basic materials and construction have gained prominence while financial services have declined in hub centrality. This suggests that policymakers should *rebalance industrial policies* to reflect changing structural importance. Countries should develop *critical industry protection programs* for sectors identified as central to network stability, including preferential access to capital, workforce development programs, and regulatory protection from hostile takeovers. Simultaneously, policies should encourage the development of *industrial redundancy* in critical supply chains, supporting the maintenance of alternative production capabilities even when they may not be immediately cost-competitive.

The strong interconnections revealed between technology sectors indicate vulnerabilities that require *strategic technological autonomy measures*. Policymakers must launch comprehensive *technology sovereignty programs* that build domestic research and development capabilities in critical areas including semiconductors, artificial intelligence, and renewable energy technologies. This involves creating innovation clusters that link universities, research institutions, and industry, establishing sovereign patent pools for critical technologies, and developing domestic alternatives to foreign-controlled technology platforms. Additionally, governments should implement *technology supply chain mapping initiatives* to identify and address critical dependencies before they become sources of vulnerability during crises.

7. Limitations and directions for future work

Notwithstanding the abovementioned constraints, this methodology offers a comprehensive framework for analyzing intricate trade networks. A significant restriction is the dependability of causality tests when utilized on short-term time-series data, shown by the 26-year timeframe examined in this work; the constrained data length may result in misleading correlations and compromise the precision of the projections. The dependence on the OECD's The ICIO tables presents data constraints, as this dataset may fail to encompass all intricacies of trade dynamics or the complete spectrum of industries involved. Moreover, the aggregation of sectors might impede comprehensive analysis, as it conceals differences within subsectors and may neglect essential causal pathways. Excluding any of the utilized approaches, such as biclustering or network analysis, would result in the forfeiture of critical insights and might culminate in an inadequate understanding of the complexities inherent in trade interactions and structural transformations. The integration of various techniques is crucial for understanding the intricacies of global trade dynamics and for establishing a refined foundation for future analysis and policy suggestions.

Future research derived from this study might concentrate on broadening the temporal examination of multilayer trade networks beyond the 1995–2020 period to include more recent developments, such as the enduring effects of the COVID-19 pandemic and geopolitical conflicts. Moreover, researchers could investigate the integration of more detailed data to mitigate the constraints linked to sectoral aggregation, facilitating a more profound understanding of certain subsector dynamics and their trading patterns. Future research might examine the influence of developing technologies on trade dynamics and the contributions of digital trade in transforming global economic relations. Moreover, analyzing the impact of diverse policy interventions on real-time trade networks could furnish policymakers with prompt insights to formulate more effective strategies. Utilizing machine learning or sophisticated statistical methods to improve the outcomes of the causal analysis of emerging trends might deepen the understanding of these complex networks, hence enabling more precise forecasting and scenario planning.

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Appendix A. Additional figures and tables

See Figs. A.9–A.11.

Appendix B. List of employed node-level indicators

Table B.6 shows the employed node-level centrality measures, for a given (fixed) year. where $\sigma_{i,k}(c_{jp})$ is the number of shortest paths between nodes c_{ip} and c_{kr} that pass through node c_{jq}. $\sigma_{i,k}$ is the total number of shortest paths between countries a_i and a_k; $d(c_{jq}, c_{ip})$ is the shortest distance from country j in industry q to country i in industry p; λ is the eigenvalue of the adjacency matrix used to compute eigenvector centrality; d is a damping factor used in PageRank calculations, typically set to around 0.85; HOM^C_{jq} is a relative centrality or Homophily measure for a given centrality measure C for country j in industry q, $C(c_{jq})|_{I_q}$ is a given centrality measure restricted to the industry q; $C(c_{jq})$ is an arbitrary centrality value without any industrial restriction.

Appendix C. Employed network-level indicators

Table C.7 lists the employed network-level indicators for a fixed year.

where N is the total number of nodes (countries), M is the total number of edges, N_p^{retain} is the number of nodes in the largest component in sector p, $A_{ip,jq}$ is the (supra) adjacency matrix entry indicating connections between nodes i and j in sector p and sector q, $|N_{ip}|$ is the number of reachable nodes from node i in sector p, and Clu^p is the clustering coefficient in industry p.

(a) Indegree centrality

(b) Outdegree centrality

(c) Homophily

(d) Leiden's modularity

(e) Sectorial added vales (VAs)

Fig. A.9. Sectorial network properties.

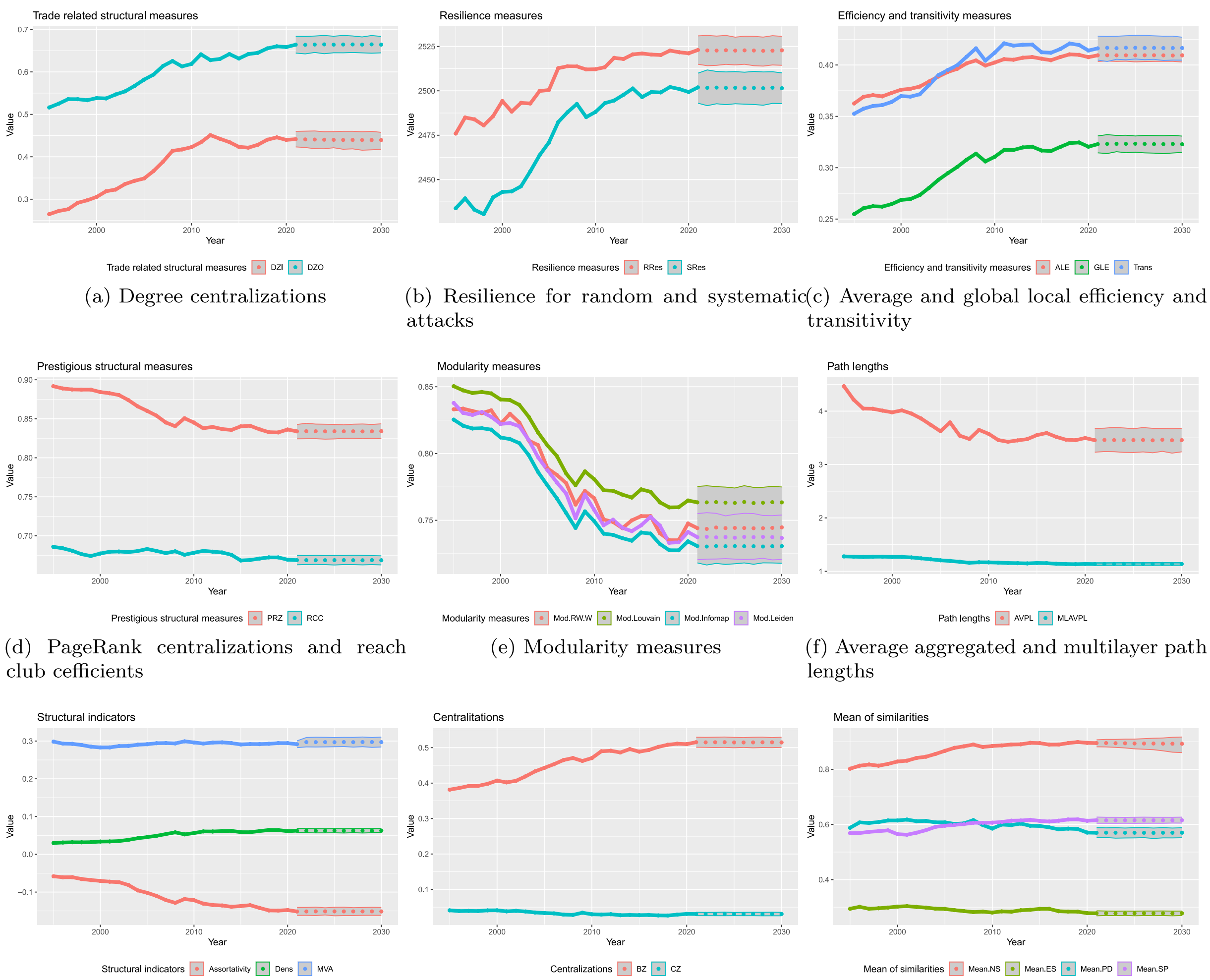
Appendix D. The setting of ARIMA and causality analysis

The ARIMA model is a widely used statistical technique for forecasting time-series data. The ARIMA model is characterized by three parameters—(p, d, q), where p is the number of autoregressive terms, d is the degree of differencing needed to make the time series stationary, and q is the number of lagged forecast errors in the prediction equation.

The general formulation of the ARIMA model can be expressed as:

$$\Phi(B)(1-B)^d y_t = \Theta(B)\epsilon_t \tag{D.1}$$

where y_t represents the time series data, B is the backshift operator, $\Phi(B)$ is the autoregressive polynomial of order p, $(1-B)^d$ signifies the differencing operation (where d represents the number of differences taken to achieve stationarity), $\Theta(B)$ is the moving average polynomial



(a) Degree centralizations
(b) Resilience for random and systematic attacks
(c) Average and global local efficiency and transitivity
(d) PageRank centralizations and reach club cefficients
(e) Modularity measures
(f) Average aggregated and multilayer path lengths
(g) Density, asymmetry and assortativity
(h) Betweennes and closeness centralizations
(i) Average similarity values

Fig. A.10. Network properties in time (forecast with Bayesian ARIMA, 95% confidence interval).

of order q, and ϵ_t denotes white noise error terms. By identifying appropriate values for p, d, and q through the analysis of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), one can construct an optimal ARIMA model tailored to the characteristics of the time series data.

Prior to applying the ARIMA model, ensuring that the time series data is stationary. Therefore, we assessed the results through tests such as the Augmented Dickey-Fuller (ADF) test, which examines the null hypothesis that a unit root is present in the time series. If the p-value obtained from the ADF test is below a predetermined significance level (commonly 0.05), the null hypothesis can be rejected, indicating that the series is stationary. If the data require differencing (i.e., $d > 0$), this process is usually repeated until a suitable level of stationarity is achieved. Following differencing, diagnostic checks using the ACF and PACF plots help in identifying the optimal parameters p and q. Finally, model validation can be performed using metrics such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), along with residual analysis to ensure the reliability and robustness of the ARIMA model. The parameters of the ARIMA model were determined by the `auto.arima` function of the `forecast` package. However, the ACF and PACF values and the stationarity of the time series were also double checked. Stationarity was tested using ADF tests, while the terms were determined using ACF and PACF functions.

The objective of investigating causal relationships is to determine how alterations in the structure of the trade network or the roles of countries and industries influence other entities over time. The employed Granger causality, a concept named after the econometrician Clive Granger (Granger, 1969), refers to a statistical hypothesis test that determines whether one time series can predict other time series on the basis of their historical values. Formally, time series Y is said to *Granger-cause* time series X if past values of Y provide significant information about future values of X, given that past values of X alone do not provide the same level of predictive power. This can be mathematically expressed in a VAR framework, where one might quantify the relationship as follows:

$$X_t = a_0 + \sum_{i=1}^{p} a_i X_{t-i} + \sum_{j=1}^{q} b_j Y_{t-j} + \epsilon_t \tag{D.2}$$

$$Y_t = c_0 + \sum_{i=1}^{p} c_i Y_{t-i} + \sum_{j=1}^{q} d_j X_{t-j} + \eta_t \tag{D.3}$$

If the coefficients b_j are statistically significant, we can conclude that Y Granger-causes X. A key aspect of Granger causality is that it does not imply true causality in the philosophical sense; rather, it establishes a *predictive relationship* on the basis of temporal precedence. Therefore, we use the precedence between time series rather than causality relationships.

To select the appropriate lag for Granger causality testing, several methods such as AIC, BIC, or SC were employed and it is tested with BVAR methods. These criteria evaluate the goodness of fit of models with varying lags, penalizing for complexity to prevent overfitting. Additionally, an F test was used to ascertain the significance of the

(a) Outdegree centrality (b) Homophily (c) Leiden's modularity

(d) Eigenvector centrality (e) PageRank centrality (f) Betweenness centrality

(g) Added values (VAs)

Fig. A.11. Average clustered industrial node-level properties forecasting by Bayesian ARIMA models.

Granger causality results at different lag structures, ensuring that one appropriately captures the underlying temporal dynamics. To cross-validate the results and lags of Granger causality analysis we also calculated several Bayesian approaches.

The BVAR method employs a structured prior distribution to address the curse of dimensionality in multivariate time series models. For a bivariate VAR(p) model $\mathbf{y}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{y}_{t-i} + \epsilon_t$, the Minnesota prior assumes that each variable follows a random walk, with prior mean $\mathbb{E}[A_{ij}^{(l)}] = \delta_i \delta_{ij}$ where $\delta_i = 1$ and δ_{ij} is the Kronecker delta. The prior covariance structure is $\mathrm{Var}[A_{ij}^{(l)}] = \frac{\lambda^2}{l^2} \frac{\sigma_i^2}{\sigma_j^2}$, where λ controls overall tightness and l represents the lag order. This method provides stable parameter estimates even with limited data by shrinking coefficients toward economically meaningful values, making it particularly suitable for Granger causality analysis where parameter precision is crucial for reliable inference.

The MCMC approach provides full posterior distributions for all parameters through Gibbs sampling, offering comprehensive uncertainty quantification. For the VAR system $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{E}$ where $\mathbf{E} \sim MN(\mathbf{0}, \boldsymbol{\Sigma}, \mathbf{I}_T)$, we specify the following conjugate priors $\boldsymbol{\beta}|\boldsymbol{\Sigma} \sim MN(\mathbf{B}_0, \boldsymbol{\Sigma}, \mathbf{V}_0)$ and $\boldsymbol{\Sigma} \sim IW(\mathbf{S}_0, \nu_0)$. The Gibbs sampler alternates between drawing $\boldsymbol{\beta}^{(i)}|\boldsymbol{\Sigma}^{(i-1)}, \mathbf{Y} \sim MN(\hat{\mathbf{B}}, \boldsymbol{\Sigma}^{(i-1)}, \hat{\mathbf{V}})$ and $\boldsymbol{\Sigma}^{(i)}|\boldsymbol{\beta}^{(i)}, \mathbf{Y} \sim IW(\hat{\mathbf{S}}, \hat{\nu})$, where the hat notation denotes posterior parameters. Granger causality is assessed by computing the posterior probability $P(\gamma_j \neq 0|\mathbf{Y})$ for the coefficients of the causal variable. This method captures the full parameter uncertainty and provides probabilistic statements about causality relationships.

The BFA method provides direct model comparison by computing the ratio of marginal likelihoods between competing hypotheses. For testing whether x_1 Granger-causes x_2, we compare models M_1 (unrestricted) and M_0 (restricted) through $BF_{10} = \frac{p(\mathbf{y}_2|M_1)}{p(\mathbf{y}_2|M_0)}$, where the marginal likelihood under conjugate Normal-Gamma priors is $p(\mathbf{y}|M) = \frac{\Gamma(\alpha_n)}{\Gamma(\alpha_0)} \frac{(\beta_0)^{\alpha_0}}{(\beta_n)^{\alpha_n}} \frac{|\mathbf{V}_n|^{1/2}}{|\mathbf{V}_0|^{1/2}} (2\pi)^{-T/2}$, with $\alpha_n = \alpha_0 + T/2$, $\beta_n = \beta_0 + \frac{1}{2}(\mathbf{y}^T\mathbf{y} + \mathbf{b}_0^T \mathbf{V}_0^{-1} \mathbf{b}_0 - \mathbf{b}_n^T \mathbf{V}_n^{-1} \mathbf{b}_n)$, and $\mathbf{V}_n^{-1} = \mathbf{V}_0^{-1} + \mathbf{X}^T\mathbf{X}$. The posterior probability of causality is then $P(M_1|\mathbf{y}) = \frac{BF_{10}}{1+BF_{10}}$ assuming equal prior model probabilities. This approach provides direct evidence quantification for competing causal hypotheses.

The synergistic value of employing all four methods lies in their complementary strengths and the robustness achieved through methodological triangulation. Convergent results across frequentist and Bayesian paradigms strengthen confidence in causal inferences, whereas divergent results signal the need for deeper investigation. The classical approach provides computational efficiency and familiar statistical interpretation, while Bayesian methods offer richer uncertainty characterization and more flexible modeling assumptions. The BVAR method connects classical and fully Bayesian approaches, offering improved finite-sample properties without the computational intensity of MCMC. The BFA provides the most direct hypothesis testing framework, yielding clear evidence statements about relative model support. Together, these methods create a robust analytical framework that captures different dimensions of statistical evidence, computational efficiency, and interpretive clarity, ultimately leading to more reliable and nuanced conclusions about causal relationships in time series data.

To establish a strong consensus across the four methodological approaches, we must first standardize the diverse outputs into a common evidence scale $[0, 1]$, where 0 indicates no evidence for causality and 1 represents maximum evidence. Let $E_i \in [0, 1]$ denote the standardized evidence measure from method i, where $i \in \{1, 2, 3, 4\}$ corresponds to

Table B.6
Employed node-level indicators in the multilayer trade network.

Abbr.	Node-Level Indicator	Formula	Meanings
DCI	Indegree centrality	$DCI(c_{jq}) = \sum_{c_{ip}\in V} e_{ip,jq}$	The number of exporters to country j in industry q.
DCO	Outdegree centrality	$DCO(c_{jq}) = \sum_{c_{ip}\in V} e_{jq,ip}$	The number of importers from country j in industry q.
DC	Degree centrality	$DC(c_{jq}) = DCI(c_{jq}) + DCO(c_{jq})$	The number of trade partners of country j in industry q.
SCI	Instrength centrality	$SCI(c_{jq}) = \sum_{c_{ip}\in V} w(e_{ip,jq})$	The volume of exports to country j in industry q.
SCO	Outstrength centrality	$SCO(c_{jq}) = \sum_{c_{ip}\in V} w(e_{jq,ip})$	The volume of imports from country j in industry q.
BC	Betweenness centrality	$BC(c_{jq}) = \sum_{c_{ip}\neq c_{jq}\neq c_{kr}} \frac{\sigma_{i,k}(c_{jp})}{\sigma_{i,k}}$	Which a country acts as a bridge along the shortest paths between other countries in the trade network.
CC	Closeness centrality	$CC(c_{jq}) = \frac{1}{\sum_{c_{ip(t)}\in V} d(c_{jq},c_{ip})}$	How quickly a country can access other countries in the trade network based on the shortest paths.
EC	Eigenvector centrality	$EC(c_{jq}) = \frac{1}{\lambda} \sum_{c_{ip}\in V} w(e_{ip,jq})EC(c_{ip})$	Country's influence in the trade network by considering not just the number of connections but the importance of those connections.
AUT	Authority centrality	$AUT(c_{jq}) = \sum_{c_{ip}\in V} HUB(c_{ip})$	The country's reputation or significance as a trusted source of exports within a particular industry. High authority scores indicate that a country is seen as a primary destination for trade.
HUB	Hubness centrality	$HUB(c_{jq}) = \sum_{c_{ip}\in V} AUT(c_{ip})$	The ability of a country to direct trade toward other significant trading partners.
PRC	PageRank centrality	$PRC(c_{jq}) = (1-d) + d \sum_{c_{ip}\in V} \frac{PRC(c_{ip})}{DCO(c_{ip})}$	The importance of a country based on the trade volume and connectivity of its trading partners.
HOM	Homophily	$HOM^{C}_{jq} = C(c_{jq})\% = \frac{C(c_{jq})\vert_{I_q}}{C(c_{jq})}$	Relative centrality value restricted to industry q.

BVAR, Classical VAR, MCMC analysis, Bayesian, and BFA approaches, respectively.

For the Granger causality based on classical VAR method, we transform the p-value p using the monotonic transformation:

$$E_1 = 1 - p \tag{D.4}$$

For the BVAR, we utilize the Forecast Error Variance Decomposition (FEVD) proportion $\phi \in [0,1]$ that variable x_1 contributes to the variance of variable x_2 at horizon h:

$$E_2 = \frac{\mathrm{FEVD}_{x_1\to x_2}(h)}{\sum_j \mathrm{FEVD}_{j\to x_2}(h)} \tag{D.5}$$

For the MCMC Bayesian method, we directly use the posterior probability of causality:

$$E_3 = P(\gamma \neq \mathbf{0}|\mathbf{Y}) \tag{D.6}$$

where γ represents the vector of coefficients for the causal variable in the target equation.

For the BFA, we convert the Bayes factor BF_{10} to posterior probability assuming equal prior model probabilities:

$$E_4 = \frac{BF_{10}}{1 + BF_{10}} \tag{D.7}$$

For the strong consensus, significant causality ($p < 0.01$), high posterior probability ($Prob(> 0.85)$), strong FEVD ($FEVD > 0.15$), and strong $BF_{10} > 5$ were assumed Granger causality between two time series. This careful approach is essential in economic modeling, where misidentified causal relationships could lead to misguided policy recommendations or investment strategies.

Conversely, instantaneous causality is a more immediate concept, which refers to the relationship between variables at the same point in time. Such causality assesses whether two variables are correlated at a specific moment, typically measured via correlation coefficients. Mathematically, if two variables X_t and Y_t have their correlation is expressed as follows:

$$cor(X_t, Y_t) = \frac{cov(X_t, Y_t)}{\sigma_X \sigma_Y} \tag{D.8}$$

where cov denotes covariance and σ represents the standard deviations of X and Y, then, instantaneously, changes in one variable may be associated with changes in the other variables at the same time. Unlike Granger causality, instantaneous causality does not attempt to evaluate the temporal influence of one variable on another variable. When comparing the two concepts, Granger causality focuses on the predictive capacity of a variable over time, whereas instantaneous causality examines the correlation at a single point in time. Both concepts can coexist in an analysis; one may find that two variables are instantaneously correlated but does not exhibit a Granger-causal relationship, indicating that while they move together, one does not predict the other.

Despite their advantages, Granger causality and instantaneous causality analyses have several limitations. These analyses assume linear relationships between variables and can be sensitive to the choice of lags and the presence of outliers. Furthermore, these analyses may lead to spurious results in the presence of confounding variables or nonstationary data, which necessitates pretesting for stationarity through tests such as the ADF test. However, despite these limitations, Granger causality and instantaneous causality can be incredibly useful in analyzing a 26-year trade network in terms of deriving insights into the dynamic relationships among trading countries, industries, and economic indicators. By applying appropriate preprocessing steps, such as differencing and cointegration analysis, researchers can enrich their understanding of how trade dynamics change over time and which factors truly influence these changes in a temporally structured manner, shedding light on policy implications and future trends in international trade. However, when analyzing relatively short-term time-series data, such as a 26-year period (1995–2020), Granger causality emerges as an ideal choice because advanced causality methods require longer-term time series.

Table C.7
Network-level indicators in the multilayer trade network.

Abbr.	Network-level indicator	Short mathematical formula	Interpretation
Assort	Assortativity	$Assort = \frac{\sum_{ip}(DC(c_{ip})\cdot DC(c_j q))-\frac{1}{M}\left(\sum_{ip}(DC(c_{ip}))\right)^2}{\frac{1}{M}\sum_i(DC(c_{ip}))^2-\frac{1}{E}\left(\sum_{ip}(DC(c_{ip}))\right)^2}$	Describes the tendency of countries to connect with others that have similar trade volumes or degrees, indicating whether trade relationships promote balance or disparity.
Dens	Density	$Dens = \frac{M}{N(N-1)}$	Quantifies the proportion of possible trade connections that are realized, indicating how interconnected the countries are overall.
AVPL	Average Path Length	$AVPL = \frac{1}{N(N-1)}\sum_{c_{ip}\neq c_{jq}} d(c_{ip}, c_{jq})$	Represents the average number of steps needed to connect any two countries, reflecting the efficiency of trade routes.
MLAVPL	Multilayer Average Path Length	$MLAVPL = \frac{1}{\sum_k \lvert L_k\rvert}\sum_k AVPL^{l_k}$	Assessing the average path length across multiple layers shows how efficiently connections can be made through different industries.
Tra	Transitivity	$Tra = \frac{3\times\text{Triangles}}{\text{Connected triplets}}$	Indicates the likelihood that countries sharing a common trading partner also trade with each other, reflecting the degree of clustering in trade relationships.
DZI	Indegree centralization	$DZI = \frac{1}{N-1}\left(\frac{\sum_{ip}(DCI(c_{ip})-DCI_{max})}{(N-1)(DCI_{max}-DCI_{min})}\right)$	Measures the inequality in the incoming trade connections across countries, indicating dependence on a few major importers.
DZO	Outdegree Centralization	$DZO = \frac{1}{N-1}\left(\frac{\sum_{ip}(DCO(c_{ip})-DCO_{max})}{(N-1)(DCO_{max}-DCO_{min})}\right)$	Indicates how concentrated outgoing trade relationships are, reflecting how few countries dominate as exporters.
BZ	Betweenness Centralization	$BZ = \frac{1}{(N-1)(N-2)}\sum_{ip} BC(c_{ip})$	Highlights the extent to which countries act as intermediaries in trade, facilitating connections between others and controlling trade flows.
CZ	Closeness Centralization	$CZ = \frac{1}{N}\sum_{ip} CC(c_{ip})$	Reflects the overall accessibility of countries to each other in the network, indicating the efficiency of trade connections.
PRZ	PageRank Centralization	$PRZ = \frac{1}{N}\sum_{ip} PRC(c_{ip})$	Measures the overall influence of countries based on their trade volume and the significance of their trading partners.
MVA	Mean Vertex Asymmetries	$MVA = \frac{1}{N}\sum_{ip} \lvert DCI(c_{ip}) - DCO(c_{ip})\rvert$	Provides insights into the balance between imports and exports across countries, highlighting structural inequalities in trade.
RRes, SRes	Resilience for Random/ Systematic Attack	$\sum_p N_p^{retain}$	Measures the ability of the network to maintain connectivity under random/systematic removals of countries, indicating robustness of trade relationships.
Mod	Modularity Value	$Mod = \frac{1}{2M}\sum_{ip,jq}(A_{ip,jq} - DCI(c_{ip})DCO(c_{jq}))\delta(C_i, C_j)$	Identifies the degree to which the network can be divided into modules, or communities, with dense internal connections and sparse external ones, indicating trade groupings.
RCC	Reach Club Coefficient	$RCC = \frac{1}{N}\sum_{ip} \lvert N_{ip}\rvert$	Measures the efficiency of trade reachability across the network, indicating how well countries can connect with each other.
MLGLClu	Multilayer Global Clustering	$MLGLClu = \frac{1}{M}\sum_p Clu^p$	Captures the clustering tendency across different industries, reflecting the propensity for countries to develop strong trade ties within and between layers.

Appendix E. The application of community-based clustering and biclustering methods

Modularity-based community detection algorithms minimize Eq. (E.1) as follows:

$$M = \frac{1}{2L}\sum_{i,j}\left(r_{i,j} - \gamma\hat{r}_{i,j}\right)\delta(C_i, C_j), \tag{E.1}$$

where M is the modularity value, $r_{i,j}$ is the edge weight between nodes i and j, $\hat{r}_{i,j}$ is the expected weight based on the null model of Newman (2006), L is the total weight in the network, γ is a constant (default 1), and δ equals 1 if nodes i and j belong to the same community and 0 otherwise. For directed similarity graphs, Eq. (E.2) must be minimized.

$$M = \frac{1}{L}\sum_{i,j}\left(r_{i,j} - \gamma\hat{r}_{i,j}\right)\delta(C_i, C_j), \tag{E.2}$$

The result of community detection is a partition of the graph. By further developing this method, by specifying a given distance measure, it is possible to search for modules and, thus, indicator groups between variables and data (Kosztyán et al., 2022). This procedure is adopted in the GNDA method, which does not require us to specify the number of clusters in advance. In real and synthetic tests, the method correctly estimated the number of clusters (Kosztyán et al., 2024a), and thus, we also used this approach to separate the time series of industry patterns.

Conversely, biclustering goes a step further by allowing for The simultaneous clustering of both rows and columns in an adjacency matrix, a capability that is particularly useful when dealing with data that have inherent multidimensional characteristics. In the context of a directed trade network, where nodes represent various node or network properties and edges signify the causal relationships between these properties, biclustering can provide a more nuanced analysis. This approach allows for the identification of subgroups of nodes that exhibit similar behaviors or properties across specific conditions or timeframes while also revealing which causal relationships (the edges) are most significant within those groupings.

We employed the iBBiG method, which assumes that the utilized dataset is binary.

This algorithm balances the homogeneity (in this case, entropy) of the selected submatrix with the size of the league. Formally, the iBBiG algorithm maximizes the following target function if the binarized dataset with a given threshold tr is denoted as B_{tr}:

$$\max \leftarrow score := (1 - H_{\mathcal{B}})^{\alpha}\begin{cases} \sum_i\sum_j [\mathcal{B}]_{i,j} & \text{, if } Me(\mathcal{B}) > \tau \\ 0 & \text{, if } Me(\mathcal{B}) \leq \tau, \end{cases} \tag{E.3}$$

where $score$ is the score value of the submatrix (bicluster, league) $\mathcal{B} \in B_{tr}$. $H_{\mathcal{B}}$ is the entropy of submatrix $\mathcal{B}$, with a given threshold tr, $Me(\mathcal{B})$ is the median of bicluster $\mathcal{B}$, $\alpha \in [0,1]$ is the exponent, and τ is the cutting value. If tr, τ or α is increased, then we obtain a smaller but more homogeneous submatrix. To strengthen the significance, stability and reliability, previous studies (see, e.g., Gusenleitner et al., 2012; Kosztyán et al., 2019) recommend that the balance exponent (α) be set to 0.3 while the cutoff threshold (τ) be set to 0.5.

Identifying biclusters is a heuristic method. Therefore, in addition to conducting significance tests both for rows and columns, we must calculate the stability of the biclusters. Typically, a bootstrapping algorithm is used to calculate the stability of biclusters. This method ignores rows and columns and evaluates the changes within biclusters Lee et al. (2011). Stability is also calculated for both rows and columns. We say

Table F.8
Employed similarity measures in the multilayer trade network.

Abbrev.	Similarity indicator	Formula	Interpretation
NS	Node similarity	$NS(p,q) = \frac{1}{A}\sum_i \frac{\lvert N(c_{ip}) \cap N(c_{iq})\rvert}{\lvert N(c_{ip}) \cup N(c_{iq})\rvert}$	Measures the extent to which a country share common neighbors in different industries, indicating their relational similarity based on direct trade links.
ES	Edge similarity	$ES(p,q) = \frac{1}{A}\sum_i \frac{\lvert T(e_{ip}) \cap T(e_{iq})\rvert}{\lvert T(e_{ip}) \cup T(e_{iq})\rvert}$	Assesses the similarity between two edges based on their incident nodes and trade volumes, reflecting how closely two trade relationships mirror each other.
PD	Pearson correlation of degree centralities	$PD(p,q) = cor(DC(c_{ip}), DC(c_{iq}))$	Examines the linear correlation between the degree centralities of countries across two different industries, indicating the consistency of trade relationships across those industries.
SP	Shortest path distances	$SP(p,q) = \frac{1}{A}\sum_i(\min\{d(c_{ip}, c_{iq})\})$	Represents the minimum number of edges that must be traversed to connect two countries, highlighting the efficiency of trade routes and potential connectivity between them.

Table G.9
List of countries.

ID	ISO3	Country	ID	ISO3	Country
1	ARG	Argentina	**40**	KAZ	Kazakhstan
2	AUS	Australia	**41**	KHM	Cambodia
3	AUT	Austria	**42**	KOR	Korea
4	BEL	Belgium	**43**	LAO	Lao (People's Democratic Republic)
5	BGD	Bangladesh	**44**	LTU	Lithuania
6	BGR	Bulgaria	**45**	LUX	Luxembourg
7	BLR	Belarus	**46**	LVA	Latvia
8	BRA	Brazil	**47**	MAR	Morocco
9	BRN	Brunei Darussalam	**48**	MEX	Mexico
10	CAN	Canada	**49**	MLT	Malta
11	CHE	Switzerland	**50**	MMR	Myanmar
12	CHL	Chile	**51**	MYS	Malaysia
13	CHN	China (People's Republic of)	**52**	NGA	Nigeria
14	CIV	Côte d'Ivoire	**53**	NLD	Netherlands
15	CMR	Cameroon	**54**	NOR	Norway
16	COL	Colombia	**55**	NZL	New Zealand
17	CRI	Costa Rica	**56**	PAK	Pakistan
18	CYP	Cyprus	**57**	PER	Peru
19	CZE	Czechia	**58**	PHL	Philippines
20	DEU	Germany	**59**	POL	Poland
21	DNK	Denmark	**60**	PRT	Portugal
22	EGY	Egypt	**61**	ROU	Romania
23	ESP	Spain	**62**	RUS	Russian Federation
24	EST	Estonia	**63**	SAU	Saudi Arabia
25	FIN	Finland	**64**	SEN	Senegal
26	FRA	France	**65**	SGP	Singapore
27	GBR	United Kingdom	**66**	SVK	Slovakia
28	GRC	Greece	**67**	SVN	Slovenia
29	HKG	Hong Kong, China	**68**	SWE	Sweden
30	HRV	Croatia	**69**	THA	Thailand
31	HUN	Hungary	**70**	TUN	Tunisia
32	IDN	Indonesia	**71**	TUR	Turkey
33	IND	India	**72**	TWN	Chinese Taipei
34	IRL	Ireland	**73**	UKR	Ukraine
35	ISL	Iceland	**74**	USA	United States
36	ISR	Israel	**75**	VNM	Vietnam
37	ITA	Italy	**76**	ZAF	South Africa
38	JOR	Jordan	**77**	ROW	Rest of the World
39	JPN	Japan			

that a bicluster is significant (stable) if it is significant (stable) for both rows and columns. We calculated both the significance and stability of each bicluster.

Appendix F. List of employed similarity indicators

Table F.8 lists the employed similarity measures comparing industries.

where A is the number of actors where each country is considered only once. $N(c_{ip})$ is the set of neighbors (trading partners) for country i in industry p, and $T(e(i_p))$ is the set of trade relations for edges $e(i_p, i_q)$ and $e(i_q, i_p)$.

Appendix G. List of country and industrial codes

See Tables G.9 and G.10.

Data availability

All data and all code can be included into the final version. The entire source codes and data sources of the paper including calculations can be downloaded here: https://github.com/kzst/ICIO/.

Table G.10
List of industries (sectors).

ID	Old code	Code	Industry
1	D01T02	A01_02	Agriculture, hunting, forestry
2	D03	A03	Fishing and aquaculture
3	D05T06	B05_06	Mining and quarrying, energy producing products
4	D07T08	B07_08	Mining and quarrying, non-energy producing products
5	D09	B09	Mining support service activities
6	D10T12	C10T12	Food products, beverages and tobacco
7	D13T15	C13T15	Textiles, textile products, leather and footwear
8	D16	C16	Wood and products of wood and cork
9	D17T18	C17_18	Paper products and printing
10	D19	C19	Coke and refined petroleum products
11	D20	C20	Chemical and chemical products
12	D21	C21	Pharmaceuticals, medicinal chemical and botanical products
13	D22	C22	Rubber and plastics products
14	D23	C23	Other non-metallic mineral products
15	D24	C24	Basic metals
16	D25	C25	Fabricated metal products
17	D26	C26	Computer, electronic and optical equipment
18	D27	C27	Electrical equipment
19	D28	C28	Machinery and equipment, nec
20	D29	C29	Motor vehicles, trailers and semi-trailers
21	D30	C30	Other transport equipment
22	D31T33	C31T33	Manufacturing nec; repair and installation of machinery and equipment
23	D35	D	Electricity, gas, steam and air conditioning supply
24	D36T39	E	Water supply; sewerage, waste management and remediation activities
25	D41T43	F	Construction
26	D45T47	G	Wholesale and retail trade; repair of motor vehicles
27	D49	H49	Land transport and transport via pipelines
28	D50	H50	Water transport
29	D51	H51	Air transport
30	D52	H52	Warehousing and support activities for transportation
31	D53	H53	Postal and courier activities
32	D55T56	I	Accommodation and food service activities
33	D58T60	J58T60	Publishing, audiovisual and broadcasting activities
34	D61	J61	Telecommunications
35	D62T63	J62_63	IT and other information services
36	D64T66	K	Financial and insurance activities
37	D68	L	Real estate activities
38	D69T75	M	Professional, scientific and technical activities
39	D77T82	N	Administrative and support services
40	D84	O	Public administration and defence; compulsory social security
41	D85	P	Education
42	D86T88	Q	Human health and social work activities
43	D90T93	R	Arts, entertainment and recreation
44	D94T96	S	Other service activities
45	D97T98	T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

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