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Topological perturbations on resilience of the world trade competition network

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Network resilience refers to a system's capability to adapt its functions to ensure continuity of essential operations amidst external environmental shifts or internal failures. The resilience of the world trade network faces structural disturbances, such as dynamic changes in the internal and external environments, increasing trade barriers and changes in competition between countries, which is an issue worth exploring. In this study, we introduce a world trade competition network that reflects export competition between two countries. We employ a network dynamics model to assess the resilience of this global trade competition network, focusing on the influence of topological disturbances. The eight distinct types of topological perturbations analyzed include nodes representing countries, links symbolizing inter-country competition, and weights indicative of the intensity of this competition. Our findings reveal that the intensity of export competition between countries significantly influences the resilience of the global trade competition network. Specifically, experimental outcomes indicate that network resilience declines more rapidly when nodes are removed sequentially based on higher weighted degrees than when based on lower ones. Similarly, in link perturbation scenarios, removing links associated with higher competition intensity first leads to a more precipitous decrease in network resilience when the network is otherwise stable. Furthermore, in weight alteration scenarios, networks maintaining a higher ratio of high-intensity competition links demonstrate greater stability compared to those with a reduced proportion of such links. Consequently, sustaining a robust level of export competition between countries is crucial for preserving the stability of the network.

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Introduction

Network resilience is the ability of a system to automatically adjust its activities to maintain essential functions when the external environment changes or when internal failures occur (Liu et al., 2022). In the context of trade networks, it encompasses the network's capacity to adapt, reorganize, and continue functioning effectively in the face of various challenges, such as geopolitical events, economic crises, or natural disasters (Yuan et al., 2022). Network resilience in trade networks is crucial for ensuring the uninterrupted flow of goods, services, and capital across borders, which is essential for global economic stability and growth (Hill and Gochoco-Bautista, 2013). A resilient trade network can absorb and mitigate the impact of disruptions, thereby reducing the risk of trade disruptions cascading into broader economic crises. Nowadays the network resilience of high-dimensional complex network systems has become a major endeavor in many scientific fields (Faggini et al., 2019; Cohen and Havlin, 2000; Scheffer et al., 2001). High-dimensional complex systems include not only socio-economic systems but also power network systems and reciprocal symbiotic ecosystems (Mariani et al., 2019). Gao et al. (2016) proposed a set of natural control and state parameters that can determine multidimensional complex systems, advancing the study of network resilience from a low-dimensional model with few node interactions to a high-dimensional one, which has good applications in ecological networks, gene regulation networks and power system networks. Barzel et al. (2015) found that the microscopic dynamic of complex systems can be inferred by observing the network response to external perturbations. In the field of urban transportation, Zeng et al. (2020) studied the transportation network based on percolation theory and high-resolution GPS dataset to effectively control traffic flow. Ribeiro and Gonçalves (2019) reviewed the studies on how cities respond to and predict external disturbances such as natural disasters or political changes, and reduce the relevant consequences and hazards.

As seen in the study of network resilience of complex systems in various fields, there is a lack of effective instrumental methods for assessing models of network resilience, and high-dimensional networks face multimodal perturbations (Das et al., 2020; Abedi et al., 2019; Gao et al., 2016; Wen et al., 2023). It is necessary to consider different topological perturbations and develop dynamic models to evaluate network resilience. For instance, based on the payment data obtained from the Bank of Sweden, de la Torre et al. (2016) constructed the economic network of Estonia, performed a topological analysis and carried out random or targeted attacks on the network, hence to simulate the network resilience. Another topical issue in social economy is supply chain resilience. Wieland and Durach (2021) sorted out two prominent perspectives on supply chain resilience, namely engineering resilience and socio-ecological resilience. Chen and Jiang (2022) established an urban economic network, and analyzed the relationships between the city's industrial structure and urban network structure systems. McNerney et al. (2022) viewed the economic system as a network of goods, and explored how networks amplify the impact of technological progress as it diffuses along the production process. Saavedra et al. (2014) employed a general Lotka-Volterra model to describe the dynamics in the inter-agent resource-competition network, and investigate the resilient effect of competition level and resource distribution on the global socioeconomic system.

These studies constructed supply chain networks or resource competition networks, and explored the factors that affecting the stability of socio-economic systems in the context of resource competition, supply chains, bank payments, etc. Yet there were few studies working on the network resilience of trade export networks, which is an integral part of the socioeconomic system. Due to the impact of disasters such as the coronavirus pandemic (COVID-19

(Hayakawa and Mukunoki, 2021), changing national policies such as tighter export controls (Hayakawa et al., 2023), and other internal and external perturbations, the overall stability of world trade exports has been affected, as the world trade is in a period of structural adjustment, trade barriers occur from time to time, and export competition among countries is becoming more intense. Previous studies have explored the changes in the network resilience under topological perturbations, i.e., changes in network topological information (Yang et al., 2014). Mon et al. (2019) have found that adjustments in national policies can lead to the occurrence of multiplex network effects, where multiple relations are established between countries. The impact of Preferential Trade Agreement (PTA) networks on export resilience has been assessed, revealing its counter-intuitively negative correlation (Liang, 2023). Following the outbreak of the COVID-19 pandemic, the spread of export disruptions on a state-by-state basis was examined using a social network analysis model (Brienen et al., 2023). In the face of dynamic environment and trade disputes and other perturbations, it is a question worth exploring how the intensity of export competition among countries affects the overall stability of world trade exports.

In this paper, we take into account the topological perturbation scenario simulated by network resilience. First, we calculated the similarity of exports between countries using the ESI (Export Similarity Index) (Finger and Kreinin, 1979), measured the competition intensity between countries and constructed a World Trade Export Competition Network (WTCN). Research on competition intensity in the world trade network focuses only on specific product categories such as global coal (Wang et al., 2021) and iron ore (Hao et al., 2018), but there is no relevant study on the overall export competition intensity worldwide. We have retained the top five countries with the highest competition intensity connected to each country for preprocessing the network (Htwe et al., 2020). Then, based on the general resilient dynamics model, we adopt the ordinary differential equation deformed by the general Lotka-Volterra model (MacArthur, 1970; Harush and Barzel, 2017) to analyze the network resilience. This nonlinear function can effectively simulate the trade export competition in the socio-economic system (Ren et al., 2020; Bishop and Mateos-Garcia, 2019; Arthur, 2021; Ren et al., 2024). Based on the network dynamics model, we explore the impact of network topology perturbation on network resilience of WTCN. We perturb from the three perspectives to understand how network resilience of WTCN changes: the nodes are countries, links are the relationship between countries, and weights represent the competition intensity. Thus, the network resilience changes in the WTCN when perturbation occurs could be unpacked, and the impact of competition intensity on network resilience could be revealed.

Datasets and models

World trade competition network. As shown in Fig.1a, when two countries export the same commodity, they compete for market share in order to gain an advantage in exports. This competitive network relationship is implied from the bipartite network of the country-commodity (Li et al., 2022). The Export Similarity Index (ESI) which depicts the economic structural characteristics or commodity competition, is used to measure the competitive intensity between the two countries. The formula is as Eq.1:

$$ESI_{ij} = \sum_k \min(s_{ik}, s_{jk}) \qquad (1)$$

Among them, s_{ik} is the proportion of national i exported goods k in its total exports. s_{jk} is the proportion of national j exported goods k in its total exports. ESI index is in the range of [0,1], the larger the value, the greater the similarity of the export between
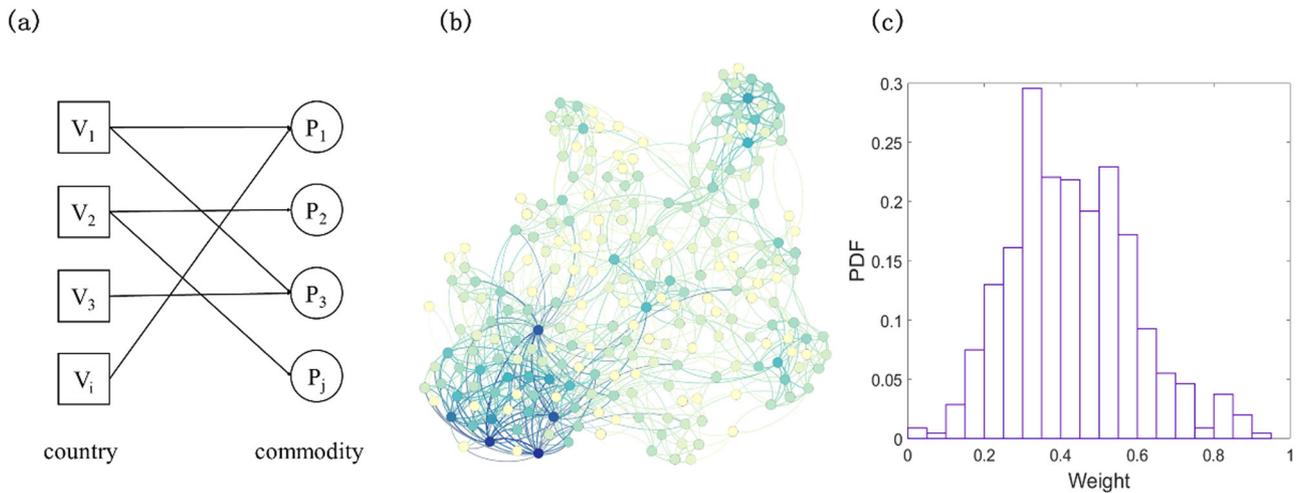
Fig. 1 Construction of world trade competition network (WTCN). a The two maps between the countries and the products. **b** A network diagram of the world trade export competition network built by the average value of trade data from 2016 to 2020. **c** The probability distribution (PDF) of the world trade export competition network constructed by the average value data of 2016–2020.

the two countries and the higher the degree of trade competition. This index can well measure the export competition between two countries, considering the proportion of different commodities and the overall export competition intensity in between the national i and the national j. After measuring the export competition intensity, we built the world trade competition network (WTCN) $G = (V, E)$ using the world trade export data. The WTCN is an undirected weighted network, in which nodes V are the country, links are competitive relationships between countries, and the weights of links are the competitive intensity between the two countries calculated by ESI index.

The data is collected from the UN Comtrade Database. We employed a five-year time window from 2016 to 2020 to build the WTCN, as the average data in recent years is more representative. To explore the competition intensity in representative trades, we sorted out the competition intensity for each country and retained the five trade partners with the highest competition intensity (Htwe et al., 2020). At the same time seen in Supplementary Material S1, we also discussed the situation of keeping three and ten trade partners with the highest competition intensity, which does not affect the overall experiments. Figure 1b shows the WTCN built on the average value of trade data from 2016–2020, which means the darker the node color, the higher the trade mean it has. At product level, this study used the classification of international trade standards SITC (Standard International Trade Classification), the second version of which includes 786 products. Figure 1c gives the probability distribution of weight in WTCN constructed by the average value data of 2016–2020.

Network resilience dynamic model. Network dynamics describes the evolution of network participants, such as the variation of gene expression level in gene regulation network, the explosion of species over time and the economic and social system changes in national competition (Liu et al., 2022; Mon et al., 2019). The current resilience function has developed from a low-dimensional model with less node interactions and dynamics, to a high-dimensional complex networks which status parameters can be recognized. The general resilience model proposed in the literature is shown in Eq. 2.,

$$\frac{dx_i}{dt} = F(x_i) + \sum_{j=1}^{N} A_{ij} G(x_i, x_j) \quad (2)$$

In this general model of dynamics, $F(x_i)$ is the self-dynamics of node i, $\sum_{j=1}^{N} A_{ij} G(x_i, x_j)$ is the interaction of node i with its neighboring nodes j. These two items reflect the self-action of network nodes and the interaction between the nodes, respectively. $F(x_i)$ and $G(x_i, x_j)$ are nonlinear functions that follows the laws of dynamics systematically. In this study, an ordinary differential equation deformed from the general Lotka-Volterra model has been used as an elastic dynamics model to measure the resilience of the WTCN (Eq. 3),

$$\begin{cases} F(x_i) = -x_i \\ G(x_i, x_j) = \frac{x_j^2}{x_j^2 + 1} \end{cases} \quad (3)$$

Then the parameter x_{eff} and the parameter β_{eff} to combine dynamics model and structural parameters are introduced by the reference (Scheffer et al., 2001). The following one-dimensional model of the simulation dynamics of the trade system can be obtained as (Eq. 4):

$$f(\beta_{eff}, x_{eff}) = -x_{eff} + \beta_{eff} \frac{x_{eff}^2}{x_{eff}^2 + 1} \quad (4)$$

The parameters x_{eff} and β_{eff} are calculated as:

$$x_{eff} = \frac{\langle s^{out} x \rangle}{\langle s \rangle} \quad (5)$$

$$\beta_{eff} = \frac{\langle s^{out} s^{in} \rangle}{\langle s \rangle} \quad (6)$$

$\langle s \rangle$ is the weighted average degree of the network, s^{out} is the weighted out degree and s^{in} is the weighted in degree of the network nodes. The introduction of these two parameters makes the high-dimensional dynamics model downscaled to a one-dimensional dynamics model, while the two parameters also reflect the network structure. The Eq.4 will continue to explore the simulation of the effect of topological perturbations on the resilience of the WTCN.

Topological perturbations in world trade competition network. Eight types of topological perturbations are proposed to explore the dynamics of network resilience of the WTCN, including node
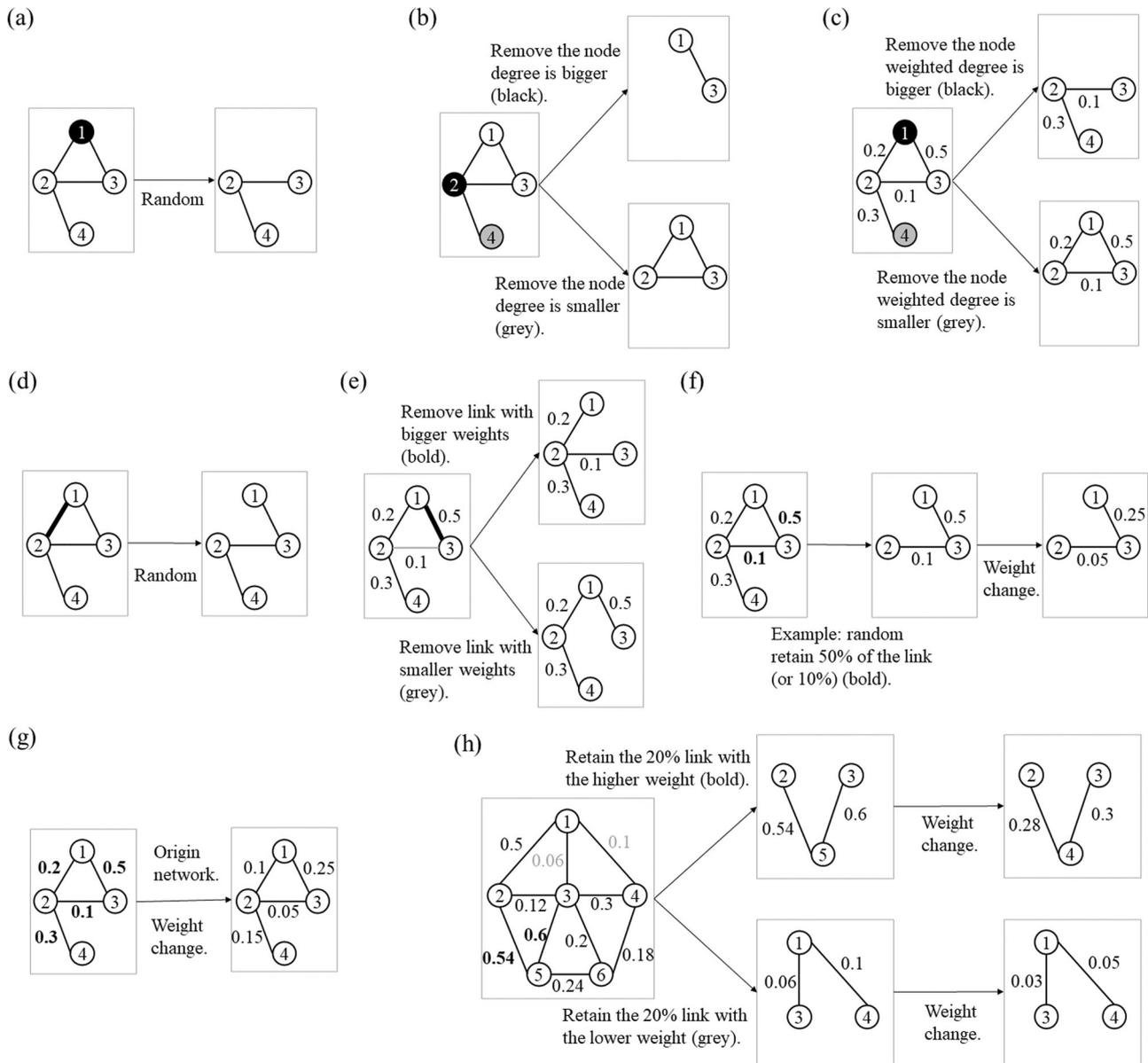
Fig. 2 The eight types of topological perturbation. a Randomly remove nodes. **b** Remove the nodes in order of node degree, black are the nodes with the largest node degree and gray are the nodes with the smallest node degree. **c** Remove nodes in the order of their weighted degree. **d** Random removal links. **e** Remove links in the order of their weight. **f** After randomly retaining the corresponding proportion of network weights, a weight change experiment is performed, with the 50% retention case in the schematic, and the 10% retention case in the same way. **g** The original network is subjected to weight change experiments. **h** The 20% with highest weights and the 20% with lowest weights are retained and then the weight change experiment is performed.

removal, link removal, and weight change. We design three removal strategies for node removal. The first is to remove nodes randomly as shown in Fig. 2a. The second is to remove nodes according to the size of node degree as shown in Fig. 2b, and the third is to remove nodes considering the size of node weighting degree as shown in Fig. 2c. Similarly, we consider two removal strategies for link removal. One is to randomly remove links as seen in Fig. 2d; and the other is to remove according to the weight magnitude, as seen in Fig. 2e. different from nodes and links, for weight change, we first retain the corresponding network weights, then we took different levels of network sparsity into account and explored the impact of network weight change on network resilience. In Fig. 2f and Fig. 2g, we randomly chose nodes with a weight change of 10%, 50%, and 100%, experimented with the weight change and observed the final results. In order to unpack the effect of competitive intensity on weights change, we keep the

20% links with highest or lowest weights to investigate whether higher competitive intensity is more likely to vacillate the network resilience as shown in Fig. 2h. A new network is obtained after considering the retention of the corresponding weights. Before exploring the weight changes, we will re-shuffle the network weights randomly. Though the network position of the weights changes randomly, the existing pattern of the network does not change.

In the experimental setup, we conduct 100 independent repeated experiments to avoid the influence of randomness on the experimental results. And both node removal by node degree size and link removal by weight size is removed in a fixed order, so there is no need for multiple simulation experiments to eliminate randomness. Therefore, the results are presented as a single curve. In the node removal experiments, we set the number of nodes removed at a time to 1, as the number of network nodes

is small and removing one node at a time shows a significant contrast. In weight change experiment, after obtaining the retained network we set the number of random exchanges of network weights to 300 times, thus to represent the network variation before the weight change perturbations. In order to maintain the rationality of the overall number of runs, the change of network weights is set to reduce by 2% each time after the initial perturbation, therefore, the overall changes in the network resilience can be observed.

Results

We explored the effect of topological perturbations on the network resilience of the WTCN according to the order of experimental design. We simulate topological perturbations from node removal, link removal and weight change, different removal strategies are adopted for the three topological perturbations.

Node removal. The effect of node removal strategy on the network resilience of the WTCN are reported in Fig. 3. First, we randomly remove nodes from the WTCN and 100 simulations have been performed to reach the results. Figure 3a shows the network resilience is gradually lost along with the random removal of nodes. Next, we remove the nodes in accordance with the degree value to obtain a new simulation, which is shown in Fig. 3b. It can be seen that the network resilience decreases faster when nodes with larger degree are removed first. A collapse of the network resilience is shown when 40% nodes are removed. We further explored the collapse state. As the nodes are gradually removed, it appears that some network nodes do not have any connections with other nodes, so the former isolated nodes would be reduced from the network. At this point, more stray node pairs would emerge. These stray node pairs are not connected to majority of other nodes but are not removed as isolated nodes, so network resilience is reduced and leads to network collapse. More details are elaborated in Supplementary Material S2. The third removal strategy considers node weighted degree and removes nodes in the order from higher weighted degree and from lower weighted degree. As shown in Fig. 3c, network resilience changes differently according to different removal orders. The average network resilience will decrease faster when nodes with higher

weighted degree are removed first. On the contrary, the network resilience will decrease more slowly when nodes with lower weighted degree are removed first. It can be obtained from Fig. 3b, c, showing how node degree and node weighted degree in WTCN affect network resilience. It is inferred that larger node degree and weighted degree have greater impact on network resilience. Therefore, when more the world's leading trading powers iterates their internationalization strategy, it would generate a greater impact on the entire trade network.

Link Removal. We also consider two link removal strategies: random removal and removal in the order of higher and lower weights in the situation of topological perturbation. As shown in Fig. 4a, when links are randomly removed from the network, network resilience decreases and no special cases occur. Figure 4b shows that network resilience decreases faster when links with higher weights have been removed first. So, it is inferred that among WTCN when competition intensity between two countries is greater, it has greater influence to the network resilience of the entire network.

Weight change. Figure 5 shows the effect of topological perturbation of weight change on the resilience of the WTCN. In our experiments, we considered two strategies to explore the perturbation of weight change: network sparsity and competition intensity. First, we retained different percentages of weights (10, 50, and 100%) to explore the effect of weight change on network resilience at different levels of network sparsity. Second, we retained links with top and bottom 20% competition intensity to explore whether greater competition intensity has a greater impact on the overall weight change that disrupts network resilience. In Fig. 5a, when we randomly retained 10% weights, after simulating the network 100 times, we can see that the maximum mean of network resilience reduced slightly, but the overall fluctuations are drastic. Along with the gradual reduction of the weights, the network resilience becomes larger, reflecting that the network at this time is very unstable and may collapse at any time. When we randomly retained 50% weights in the network, corresponding to the horizontal axis in Fig. 5b, we can see that the overall reduction size of network weights is about 10%, and
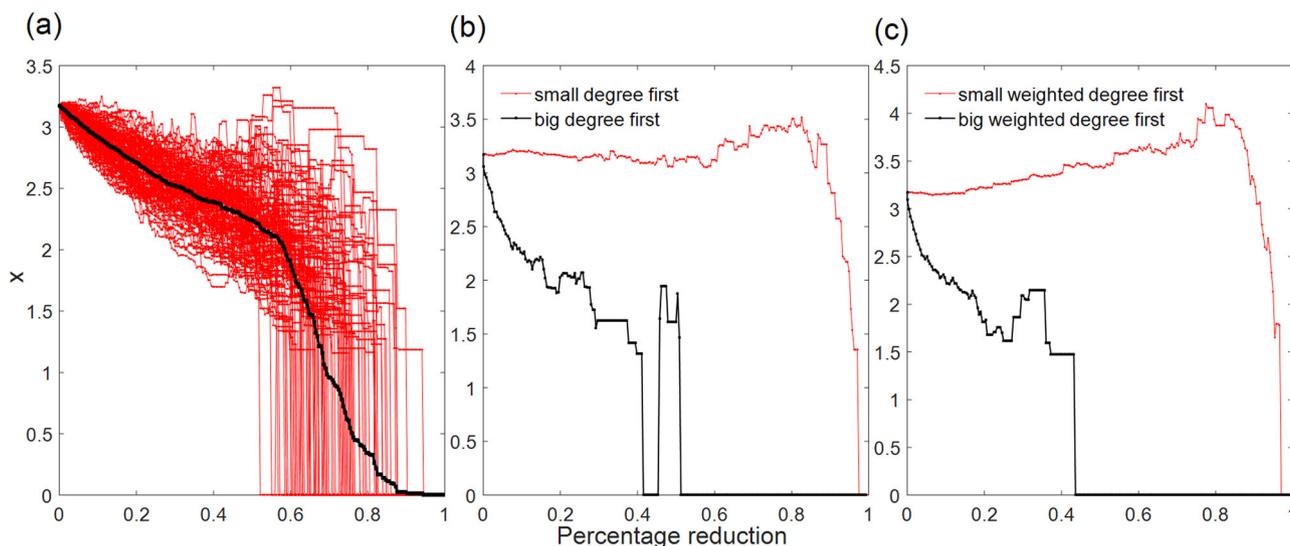
Fig. 3 The effect of node removal on the network resilience of WTCN. The horizontal coordinate indicates the percentage of nodes removed and the vertical coordinate indicates the average state of network resilience. **a** Nodes were randomly removed and 100 simulations were performed. The black curve represents the average of 100 simulations. **b** Remove nodes in the order of larger and smaller node degree. **c** Remove nodes in the order of larger and smaller weighted degree.
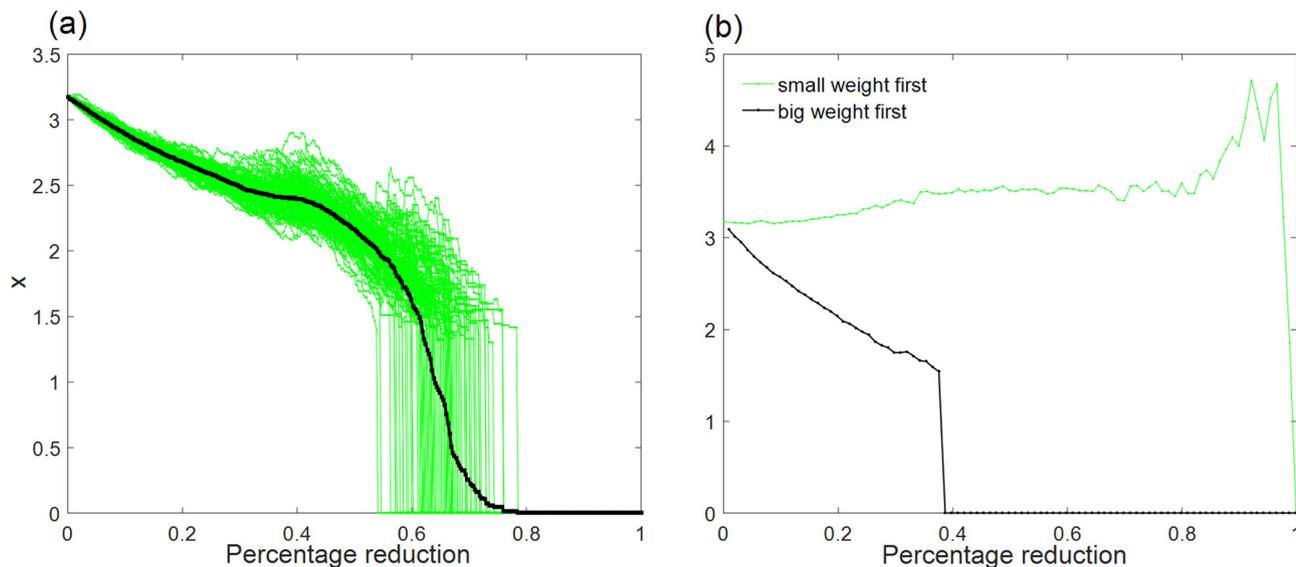
Fig. 4 The effect of link removal on the network resilience of WTCN. a Randomly remove links for 100 random simulations. The black curve represents the average of 100 simulations. **b** Consider link weight order for removal.
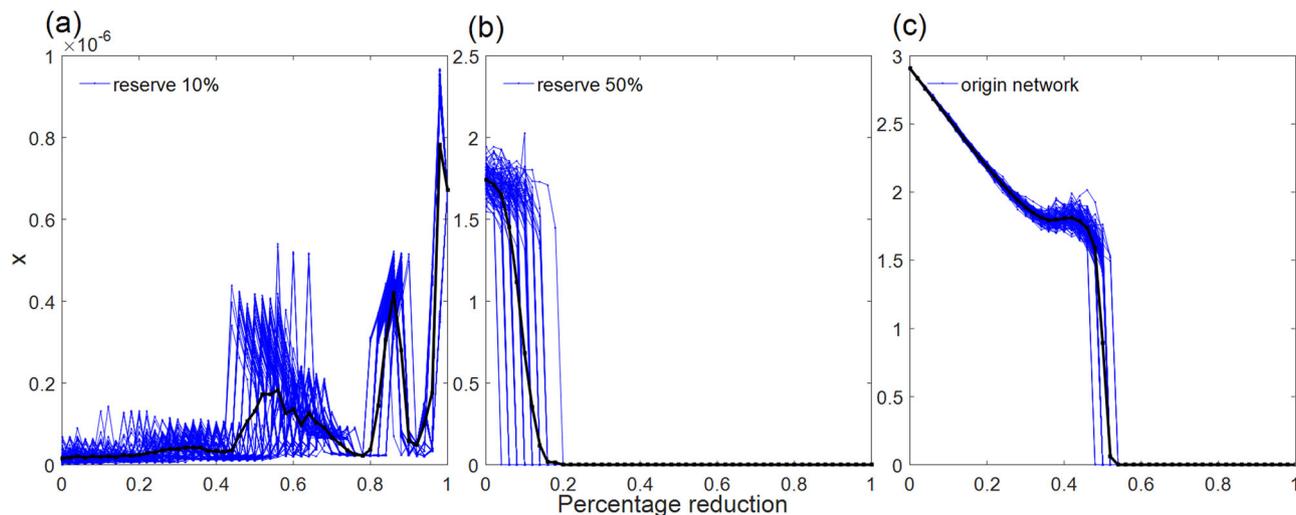
Fig. 5 The effect of weight change on the network resilience of WTCN. The horizontal coordinate is the overall percentage reduction in weights, each time by 2%, and the vertical coordinate is the average network resilience state. The black curve represents the average of 100 simulations. **a** 10% of the weights are randomly retained and the rest are marked as 0. The weight positions are then randomly exchanged. **b** 50% of the weights are randomly retained and the rest are marked as 0. The weight positions are then randomly exchanged. **c** The original network.

the average state of the network resilience is completely zero. It indicates the network has completely lost resilience. The maximum network resilience of WTCN increased comparing with Fig. 5a. It means that links will increase the maximum network resilience. Figure 5c shows that the network with all link weights retained has a greater maximum resilience, while network resilience is only completely lost when weights are reduced by about 50%. So, it indicates that retaining more links would slow down the impact of weight size on network resilience.

After considering the effect of network sparsity on weight change, we next consider the effect of the magnitude of competition intensity. From the above results of retaining 10%, the network appears to be in an unstable state. We therefore retain the top 20% of links with higher weight and the 20% with smaller weight respectively to avoid a network that is too sparse or unstable. The network weight positions are then randomly transformed to perform a gradual reduction in weights. Figure 6a

shows that the overall maximum network resilience is extremely small when retaining links with lower network weights. As the network weights gradually decrease, the average state of network resilience keeps fluctuating rather than gradually decreasing, indicating that the network is unstable. But as shown in Fig. 6b, the resilience decreases as the weight decreases and finally loses its resilience. The fluctuations are not as large as those in Fig. 6a, indicating that the higher competitive intensity makes the network more stable.

The topological perturbation fits with the network resilience dynamics model. After an experimental study of the network resilience from three types of topological perturbations on the WTCN, we explained how the three perturbations could fit with the network resilience dynamics model. The dynamics function (Eq. 3) predicts a single first-order excess at $\beta_{eff}^c = 2$, which is
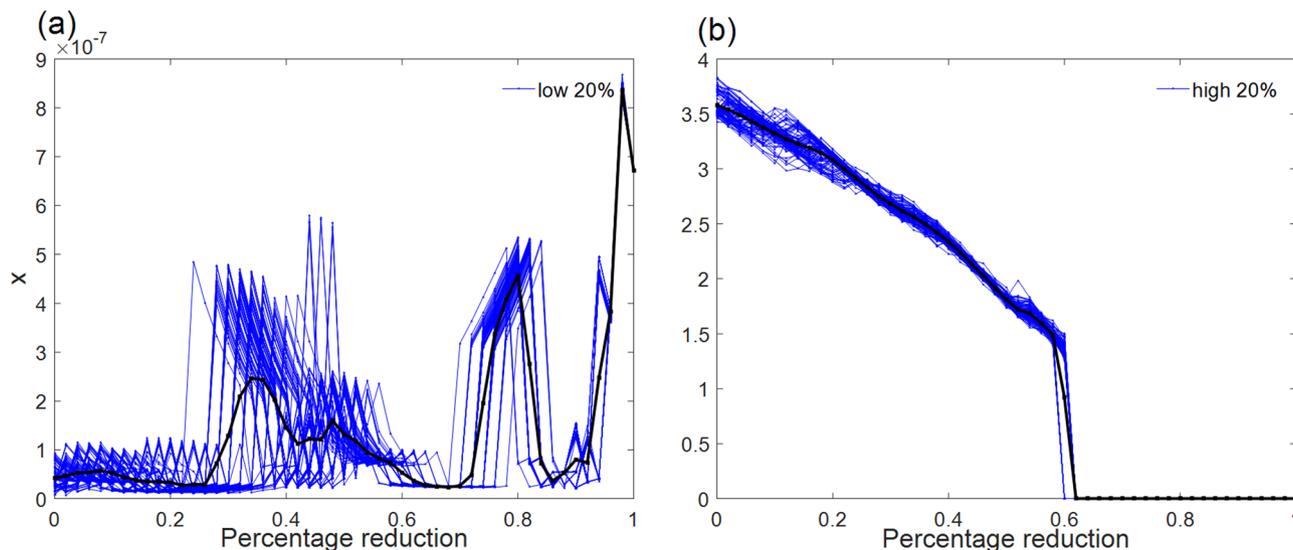
Fig. 6 Resilience of retention of lower or higher weights on the world trade export competition network. The black curve represents the average of 100 simulations. **a** Retain the lower 20% after weight ranking. **b** Take the top 20% of links after retaining the higher weight ranking. The new networks are obtained separately for simulation.
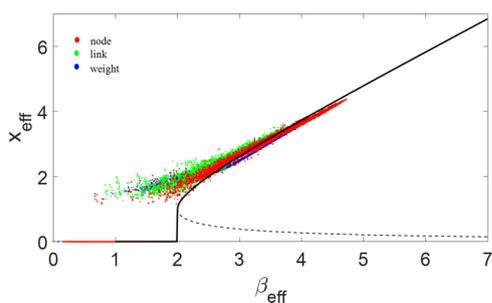
Fig. 7 The results of node removal, link removal, and weight change are mapped on β-space. The red scatter represents the result of node perturbation, the green scatter represents the result of link perturbation, and the blue scatter represents the result of weight change perturbation.

entirely determined by the dynamics function and is independent of the A_{ij} of the network. Furthermore, we show the two-dimensional coordinates with horizontal axis β_{eff} and vertical axis x_{eff}, and show the experimental results and dynamical function curves in the graph. As shown in Fig. 7, all observed data points caused by node removal, link removal, and weight changes collapse to the same curve regardless of the micro details of the network. The curve is similar to the generic resilience function (black solid line) predicted by the analysis. The results demonstrate that our dynamical function model can be well fitted to the world trade export competition network we constructed.

Conclusions and discussions

In this paper, we first constructed a world trade competitive network (WTCN) based on world trade export data and the theoretical support of dynamical resilience function to respond to the intensity of trade competition among countries. We then analyzed eight types of topological perturbations (node, link, and weight) that affect the network resilience of WTCN. The experimental results show that removing nodes after random removal under node perturbation gradually decreases WTCN's network resilience. The difference between 100 random simulations is insignificant, and the overall volatility of randomly

removed nodes is not affected by randomness. Therefore, we continue to remove nodes in order of larger and smaller degree. The results show that network resilience decreases more quickly when nodes with larger degree are removed first. Similarly, when we remove nodes in order of higher or lower weighted degree respectively, the network resilience decreases rapidly when we remove with larger weighted degrees first. This suggests that higher competition intensity has a greater impact on network resilience. The link perturbation, WTCN's network resilience decreases gradually with the removal of links when links are randomly removed. However, it decreases faster when links with higher weights are removed first, which shows that higher export competition intensity between two countries leads to a significant reduction in resilience.

Some of the study findings correspond to real situations in the world trade exports. The node perturbation corresponding to perturbations to countries shows that world trade export data does not contain countries all over the world. When new countries join the world trade export market, the competitive pattern and stability of the world trade export competition network will certainly be affected. If a country no longer exports a certain commodity when a WTCN is constructed based on a commodity industry, this country withdraws from the WTCN. According to the experimental results, the network resilience of the WTCN decreases when nodes are orderly removed. When a country has large degree and weighted degree, the network resilience decrease more rapidly. For example, the trade dispute between China and the United States in the Sino-US trade war will also lead to competition intensity change between China and the United States in the WTCN, which could also affect the stability of the overall network (An empirical analysis is seen in Supplementary Material S3).

The experimental model proposed in this study fits well with the WTCN. Therefore, the conclusions can provide effective suggestions for maintaining the stability of real-world trade exports. This paper not only helps us understand the perturbations affecting the stability of the WTCN, but also reveals that the competition intensity between countries affects the stability of world trade to a large extent. When countries or links in the network are perturbed in different sequences, the stability of the overall WTCN is altered to varying degrees. We deform the

ordinary differential equations of the general Lotka-Volterra model to use as the resilient dynamics model applied to our WTCN that responds to national export competition. Despite the changes in network resilience of the WTCN under node, link, and weight change perturbations are explored, future studies could explore multiple factors that affect network resilience in the complex world trade networks.

Data availability

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