Hoang *et al. Applied Network Science* (2023) 8:35
https://doi.org/10.1007/s41109-023-00560-9

Applied Network Science

RESEARCH

Open Access

# Reshaping the structure of the World Trade Network: a pivotal role for China?

Vu Phuong Hoang[1*], Carlo Piccardi[2*] and Lucia Tajoli[1*]

*Correspondence:
vuphuong.hoang@polimi.it;
carlo.piccardi@polimi.it; lucia.tajoli@polimi.it

[1] Department of Management, Economics, and Industrial Engineering, Politecnico di Milano, Milan, Italy
[2] Department of Electronics, Information, and Bioengineering, Politecnico di Milano, Milan, Italy

## Abstract

In recent years, the global trade landscape has undergone significant changes, particularly in the aftermath of the 2008 financial crisis and more recently as a consequence of Covid-19 pandemic. To understand the structure of international trade and the impact of these changes, this study applies a combination of network analysis and causal inference techniques to the most extensive coverage of available data in terms of time span and spatial extension. The study is conducted in two phases. The first one explores the structure of international trade by providing a comprehensive analysis of the World Trade Network (WTN) from various perspectives, including the identification of key players and clusters of strongly interacting countries. The second phase investigates the impact of the rising role of China on the global structure of the WTN. Overall, the results highlight a structural change in the WTN, evidenced by a variety of network metrics, around China's rapid growth years. Additionally, the reshaping of the WTN is not only accompanied by a significant increase in trade flows between China and its partners, but also by a corresponding decline in trade among non-China-partner countries. These results suggest that China played a pivotal role in the restructuring of the WTN in the first decades of this century. The findings of this study shed light on the interpretation of the rapidly changing landscape of global trade.

**Keywords:** World trade, Network analysis, Causal inference, China's trade

## Introduction

After decades of sustained and smooth growth, the upward trend in world trade leading to increasing globalization was taken for granted by most countries. Since the 1980 s until the early years of 2000 s, the growth rate of international trade outpaced the world GDP growth rate, and many developing economies especially in Asia experienced a notable increase in imports and exports (WTO 2013), together with GDP growth rates much higher than the world average.

This positive outlook came to a sudden halt in 2008 with the great financial crisis that started in the USA and then spread to many other parts of the world. The global financial crisis had far-reaching repercussions on cross-border economic activity, as it had a dramatic impact on economic growth in terms of GDP and decline of the trade flow. After a sharp and sudden collapse in international trade in the last quarter of 2008, world trade flows declined by about 12% in 2009 (WTO 2013). This exceeded the estimated loss of

5.4% in world GDP (WTO 2009). Such a decline in trade flows was unprecedented since World War II, and therefore generated a widespread debate. The contraction in exports was especially acute for small open economies, many of which saw their trade volumes fall by up to 30% year-on-year in the second half of 2008. This trade decline contributed to the spread of recessionary pressures even to countries that had little direct exposure to the USA subprime mortgage market where the crisis originated. The popular press has provided anecdotal accounts of how manufacturing plants around the world scaled-down production and employment in response to limited export opportunities (Levchenko et al. 2010; Shelburne 2010; Chor and Manova 2010). Unfortunately, this was only the first of a series of turbulences affecting world trade. After the 2008–2009 major shock, the rate of growth of world trade recovered partially, but the upward path became very uneven, affected by some major perturbations in a relatively short time span: the world recession started by the financial crisis, the trade war between USA and China, the Covid pandemic, and most recently the energy crisis following the war in Ukraine.

As mentioned, during the same time frame, since the end of the past century, a greater role of developing countries and especially the rising of China as a key player in global trade was also observed. China's integration into the world economy brought about a mixture of positive and negative impacts (Feenstra and Sasahara 2018). On the one hand, expanded trade with China opened up new avenues of opportunity for many countries, providing access to a rapidly growing market for their goods and services and thereby driving economic growth and employment. Moreover, the increasing role of China as a leading supplier of manufactured goods and raw materials reduced costs for both consumers and enterprises. On the other hand, China's growing economic activity resulted in increased competition for businesses in other countries, particularly in manufacturing and labor-intensive industries, leading to job losses and closures of businesses, particularly in developed economies. Furthermore, China's large trade surplus with numerous nations elicited concerns about its impact on global trade imbalances, while its lack of transparency and adherence to international trade regulations prompted criticism and caused tensions with other countries (Feenstra and Wei 2010). In this context, the rising role of China, generating an effect sometimes named the "China shock" (Feenstra and Sasahara 2018), affected many pre-existing trade patterns, both intensively (i.e., through increases in trade flows between countries already trading in the past) and extensively (i.e., newly created trade relationships) (Fagiolo 2017).

Given the above facts, a relevant question is whether the observed changes in world trade in the past decade are the consequence of random events or instead some structural change occurred in the world trading system. The 2008–2009 trade collapse is often seen as a turning point (e.g., Bems et al. 2013), but in fact, the perturbation it created might have accelerated a deeper, ongoing structural transformation of world trade. In particular, some research questions arise: How did these trade patterns change over time, and what factors influenced these changes? Which countries are the key players in the global marketplace, and what role do they play in shaping trade flows? In order to answer these questions, it is not sufficient to analyze each country in isolation or examine bilateral trade relationships only. As a matter of fact, while bilateral ties are virtual channels of interaction between countries, they can only explain a small fraction of the impact that economic shocks originating in a given country can have on another country, which may not even be a trading partner (Abeysinghe and Forbes 2005). A systemic analysis at the global level is needed to fully understand the complexity of the global trade landscape and its structural changes (Krugman 1995).

Our research employs a combination of network analysis (Newman 2010; Barabasi 2016) and statistical methods for analyzing the structure and organization of the World Trade Network (WTN). The application of Social Network analysis to international trade data has a long history in economic sociology and political science (Sacks et al. 2016; Kim and Shin 2002; Mahutga 2006), but only in relatively recent times have physics methods (in particular Social Physics (Jusup et al. 2022)) and network analysis been used to investigate the international trade network quantitatively. Studies have shown that the trade network has become more and more dense and integrated over time (Serrano and Boguna 2003; Kali and Reyes 2007; Barigozzi et al. 2009). Links are almost evenly distributed across countries, i.e., the network does not exhibit the scale-free degree distribution typically found in a number of real-world networks (Cepeda-López et al. 2019; Fagiolo et al. 2010; De Benedictis and Tajoli 2011). However, in terms of intensity (i.e., total trade of countries) the distribution is highly skewed, with a small group of key players forming a well-connected core (Maeng et al. 2012; De Benedictis et al. 2013; Hoang et al. 2023).

To deeply investigate the structural changes in the WTN we focus on the evolving role of China, as many evidences suggest that the rising role of this country affected the overall WTN (Ianchovichina and Martin 2004; di Giovanni et al. 2014; Feenstra and Wei 2010). In our study we complement network analysis with causal inference, a statistical method that aims at identifying the causal relationship between variables while taking into account the potential confounding factors (Angrist 2010). The goal is understanding how changes in one variable, such as a country's trade policies, affect other variables, such as trade flows or economic growth of other countries, and therefore the entire WTN structure. While causal inference is in principle a powerful tool, its application can be challenging in practice, as it relies on the assumption that all confounding variables are measured. In the case of trade with China, the complexity of the global economy, the variety of industries and trade flows, and the political and geopolitical factors that are also at play, can make it challenging to isolate the effect of China's rising role in trade with other countries. We try to minimize such difficulties by combining causal inference and network analysis, i.e., by including network metrics of countries among the model covariates, together with many other non-network variables.

In this paper, the starting point is our preliminary study of the WTN presented in Hoang et al. (2023), whose results are here summarized, where the evolution of a number of network metrics are discussed for the period 1996–2019. In the first part of the present paper, the above analysis is complemented with a study of the evolution in time of the core-periphery structure of the WTN and of the individual role of each country (centrality). The results are instrumental to the second part of the paper, where the role of China is explored in detail with the tools of causal inference and compared to that of USA, with special attention to the impacts of China evolution on the trade flow of other countries.

## Methodology and data

### Network analysis

In the case of the WTN, nodes correspond to countries and edges model the flows of goods from one country to another. Since the existence of exports from country A to country B does not imply exports from B to A (and, even when exports are bidirectional, their values are in general different), the WTN is modeled as a weighted directed graph, with no self-edges (exports from a country to itself are not considered). If $n$ is the number of countries, the structure of the WTN is described by the $n \times n$ adjacency matrix $A = [A_{ij}]$, with $A_{ij} = 1$ if there is an edge from $i$ to $j$, and $A_{ij} = 0$ otherwise. The *indegree* $k_i^{in} = \sum_j a_{ji}$ (resp. *outdegree* $k_i^{out} = \sum_j a_{ij}$) of node $i$ is defined as the number of incoming (resp. outgoing) edges, i.e., the number of trade partners country $i$ imports from (resp. exports to), and the total degree is defined as $k_i^{tot} = k_i^{in} + k_i^{out}$. The weighted adjacency matrix (or weight matrix) $W = [W_{ij}]$, with $W_{ij} > 0$ if $A_{ij} = 1$, and $W_{ij} = 0$ otherwise, contains the monetary value of the export from $i$ to $j$. The *in-strength* $s_i^{in} = \sum_j w_{ji}$ (resp. *out-strength* $s_i^{out} = \sum_j w_{ij}$) of node $i$ is defined as the aggregate incoming (resp. outgoing) weight, i.e., the total value of the import (resp. export) of country $i$. The total weight $s_i^{tot} = s_i^{in} + s_i^{out}$ is the total import–export value.

Many indicators can be used to globally describe the characteristics of a network (Newman 2010; Barabasi 2016). In this work, we analyzed the evolution of the following network metrics over the time frame considered. The *density* $d = \frac{L}{N(N-1)}$, where $L$ is the number of edges, is the fraction of existing edges (i.e., trade partnerships) over the maximum possible number. The *mean geodesic distance* $l = \frac{1}{N(N-1)} \sum_{i,j} l_{ij}$ is the average number of steps required to connect a pair of nodes $i, j$ along the shortest path. The *reciprocity* $r$ is the fraction of edges $i \rightarrow j$ for which the opposite edge $j \rightarrow i$ exists. The *clustering coefficient* $c$ quantifies how common triads are in the network: it is the average, over all nodes $i$, of the number of edges connecting $i$'s neighbors with respect to the maximum possible number. The *assortativity coefficient by degree* $a_k$ (resp. *by strength* $a_s$) is the (Pearson) correlation between the total degree (resp. total strength) of neighboring nodes, i.e., trade partners. Negative values of $a_k$ (resp. $a_s$) denote the tendency of countries with few partners (resp. small trade volume) to connect with countries with many partners (resp. large trade volume).

We construct the WTN using the BACI-CEPII data set built from data directly reported by each country to the United Nations Statistical Division (Comtrade).[1] Two countries are considered to have a trade connection if there is a link between them in any of the about 5300 commodity sectors, and the total trade value is the aggregate of all sector values. The original dataset provides yearly data from 1996 to 2019. For our analysis, we convert them into biennial periods (i.e., 1996–1997, 1998–1999,....,2018–2019) by averaging two years accordingly. Using biennial periods halves the analytical burden while preserving the dynamics of world trade (Cepeda-López et al. 2019), and enables to maximize the number of links between countries. To avoid potential bias and make comparisons between periods straightforward, we keep the network size (i.e., the number of countries) constant by discarding those countries for which data is unavailable in

[1] http://www.cepii.fr/CEPII/en/welcome.asp.

any period of the dataset. After such a pre-processing, our sample contains 206 countries in 12 biennial periods.

### Causal inference and treatment effect

Moving from the results of the network analysis of the world trading system, that show some relevant changes overtime, we want to identify the possible causes. Causal inference is a statistical approach to examine the impact of one variable on another. It aims to determine and quantify the causal effect while accounting for potential confounding factors. This is done by comparing the outcomes of similar groups that differ only in exposure to the target variable. To study the effect of China's rise on other countries' trade, we use observational data such as trade data from countries with varying levels of trade partnership with China and employ statistical methods to control for other trade-affecting factors like economic growth and exchange rate. In our analysis, we also want to control for some topological characteristics of the WTN, as they can definitely affect trade patterns. Following Rubin's causal model (Angrist 2004; Imbens and Rubin 2010), we introduce the key concepts in causal inference, including the *unit* (the dyad $(i, j)$ of countries $i$ and $j$), the *treatment* (the dyad $(i, j)$ belonging to a set $S$ of countries with strong trade ties to China), and the potential *outcome* (the bilateral trade flow $W_{ij}$ between countries $i$ and $j$). In our study, we define the set $S$ to include countries that have China as their first, second, or third largest trade partner (in terms of averaged imports and exports). Thus the treatment variable $T_{ij}$ is defined as 1 if either country $i$ or $j$ belong to $S$. Our focus is on analyzing the impact of being a strong partner of China in 2001 (resp. 2008) on bilateral trade in 2003 (resp. 2010), corresponding to China's entry into the World Trade Organization (WTO) (resp. the financial downturn). The 2-year lag is allowed to ensure that the treatment is measured before the outcome and not simultaneously. The bilateral trade flow is measured as the logarithm of the average of trade flows for each country dyad (again, the average of the flow from $i$ to $j$, and from $j$ to $i$).

To better assess China's peculiar role, we conducted a comparative study of countries with significant trading relationships with the USA during the time periods 2001–2003 and 2008–2010. A useful requirement to have comparable results in the treatment effect analysis is to have samples in which the relative size of the treated group and the control group are similar. Given the very high number of trade links of the USA since many decades, if we were to include in the treated group all countries with the USA as first, second or third partner, we would have nearly all countries included in the treatment group and a very small control group. This does not occur in the case of China, that became much more recently a relevant trade partner for many countries, allowing to have a reasonable relative size of the treatment group and the control group even including as "treated" countries those who have China as their third partner. This apparently uneven choice allows in fact to have a more even group composition for the two compared cases.

The next step of causal inference analysis is matching. Among the many available methods (Imbens and Rubin 2015), we utilize Inverse Variance Weighting Matching, which is a method of combining multiple studies' estimates of a causal effect, by weighting each study's estimate by its inverse variance, giving higher weight to more precise estimates. This method provides a more accurate overall estimate and is simple to implement. It also allows for combining results of studies with different designs or measurement methods as long as they estimate the same causal effect. In contrast, other methods, e.g., Propensity Score Matching, can only be used for studies with similar design.

In the context of empirical research, the Average Treatment Effect (ATE) is a commonly used statistical measure that quantifies the mean difference in potential outcomes between the treatment group and the control group, averaged over the entire population. In our framework, it is defined as follows:

$$\mathrm{ATE} = \mathrm{E}(W_{ij}|T_{ij} = 1) - \mathrm{E}(W_{ij}|T_{ij} = 0),$$

where $W_{ij}$ represents the trade flow as described previously, $T_{ij}$ represents the treatment status ($T_{ij} = 1$ if the unit receives the treatment and $T_{ij} = 0$ if it does not), and $E()$ denotes expected value.

The Average Treatment Effect is complemented by two additional measures. One is the Average Treatment Effect on Control (ATC), which measures the average difference in expected outcomes among the subset of the population who did not receive the treatment, conditional on the presence or absence of the treatment. In other words, it only focuses on the control group, measuring the difference if they were to receive the treatment. It is defined as:

$$\mathrm{ATC} = \mathrm{E}(W_{ij}|T_{ij} = 0, X_{ij}) - \mathrm{E}(W_{ij}|T_{ij} = 1, X_{ij}),$$

where $X_{ij}$ represents the covariates used in the matching procedure. The second term is clearly not directly observable, but it might be estimated.

Finally, the Average Treatment Effect on the Treated (ATT) measures the effect of the treatment on the subset of the population that received the treatment, compared to what their outcomes would have been if they had not received the treatment. This measure is useful when the treatment is only given to a subset of the population and there may be selection bias that makes the treatment group different from the control group. It is defined as:

$$\mathrm{ATT} = \mathrm{E}(W_{ij}|T_{ij} = 1, X_{ij}) - \mathrm{E}(W_{ij}|T_{ij} = 0, X_{ij}),$$

where $X_{ij}$ represents the covariates used in the matching procedure.

These statistical measures are critical in empirical research as they provide a systematic way of quantifying the effects of a treatment on a population. Unfortunately, we can only observe one of the potential outcomes for each dyad, i.e., either $W_{ij}$ when $T_{ij} = 0$ or $W_{ij}$ when $T_{ij} = 1$, depending on the treatment that is actually received. For each dyad $(i, j)$ we also observe the treatment $T_{ij}$ that was actually received and a set of pre-treatment characteristics, $X_{ij}$, which include background information $B_{ij}$ and network features $C_{ij}$. Based on these characteristics, it is possible to estimate the expected non-observed outcome and compute the above measures.

In particular, $C_{ij}$ contains a few measures obtained from network analysis for countries $i$ and $j$, namely the degree centrality, the PageRank centrality, the local clustering coefficient, and an indicator related to the outcome of community analysis, i.e., which community $i$ and $j$ belong to (all these measures will be discussed in "Results" section). Instead, $B_{ij}$ contains information on the economic, historical and geographical

**Table 1** List of the variables used for causal inference: from $X_0$ to $X_{11}$ are network variables, from $X_{12}$ to $X_{24}$ are economic, historical and geographical background variables

| Code | Label | Description |
|---|---|---|
| $X_0, X_1$ | $C_{Di}, C_{Dj}$ | Degree centrality of countries *i*, *j* |
| $X_2, X_3$ | $C_{Pi}, C_{Pj}$ | PageRank centrality of countries *i*, *j* |
| $X_4, X_5$ | $C_{Ti}, C_{Tj}$ | Clustering coefficient of countries *i*, *j* |
| $X_6, X_7$ | $C_{C1i}, C_{C1j}$ | (binary) 1 if country *i*, *j* belongs to Community 1 |
| $X_8, X_9$ | $C_{C2i}, C_{C2j}$ | (binary) 1 if country *i*, *j* belongs to Community 2 |
| $X_{10}, X_{11}$ | $C_{C3i}, C_{C3j}$ | (binary) 1 if country *i*, *j* belongs to Community 3 |
| $X_{12}$ | lgdp | Log product of real GDPs of countries *i*, *j* |
| $X_{13}$ | lgdppc | Log product of real GDPs per capita of countries *i*, *j* |
| $X_{14}$ | ldist | Log of distance of countries *i*, *j* |
| $X_{15}$ | border | (binary) 1 if *i*, *j* share a land border |
| $X_{16}$ | lareap | Log product of land areas of *i*, *j* |
| $X_{17}$ | island | Number of island nations in the country pair *i*, *j* (0, 1, or 2) |
| $X_{18}$ | landl | Number of landlocked nations in the country pair *i*, *j* (0, 1, or 2) |
| $X_{19}$ | comlang | (binary) 1 if *i*, *j* share a common language |
| $X_{20}$ | comcol | (binary) 1 if *i*, *j* were ever colonies after 1945 with the same colonizer |
| $X_{21}$ | curcol | (binary) 1 if *i* is currently a colony of *j* or viceversa |
| $X_{22}$ | colony | (binary) 1 if *i* ever colonized *j* or viceversa |
| $X_{23}$ | custrict | (binary) 1 if *i*, *j* share the same currency or belong to a currency union |
| $X_{24}$ | regional | (binary) 1 if *i*, *j* belong to a common Regional Trade Agreement (RTA) |

background of countries *i* and *j*, normally used to estimate bilateral trade flows (Kabir et al. 2017). These include population and real GDP (in constant dollars) sourced from the World Development Indicators,[2] as well as data from the Penn World Table Mark 7.1[3] and the IMF's International Financial Statistics.[4] Country-specific variables, such as latitude and longitude, land area, landlocked and island status, physically contiguous neighbors, language, colonizers, and dates of independence, were obtained from the CIA's World Factbook.[5] Information on regional trade agreements was obtained from the World Trade Organization's website.[6] The complete list of background and network covariates is in Table 1.

## Results

### The World Trade Network: basic metrics

Fig. 1 displays the total world trade in the period under study. The almost monotonous upward trend ceases after the 2008 crisis, suggesting structural changes to the system in the subsequent years. The lower panel of the same figure shows that the USA, Germany (DEU), and Japan (JPN) were the dominant trading nations in the first four two-year periods, whereas China (CHN) emerges clearly for the remaining periods: it has

[2] https://databank.worldbank.org/source/world-development-indicators.

[3] https://www.rug.nl/ggdc/productivity/pwt/.

[4] https://data.imf.org/?sk=9D6028D4-F14A-464C-A2F2-59B2CD424B85.

[5] https://www.cia.gov/the-world-factbook/.

[6] https://www.wto.org/.

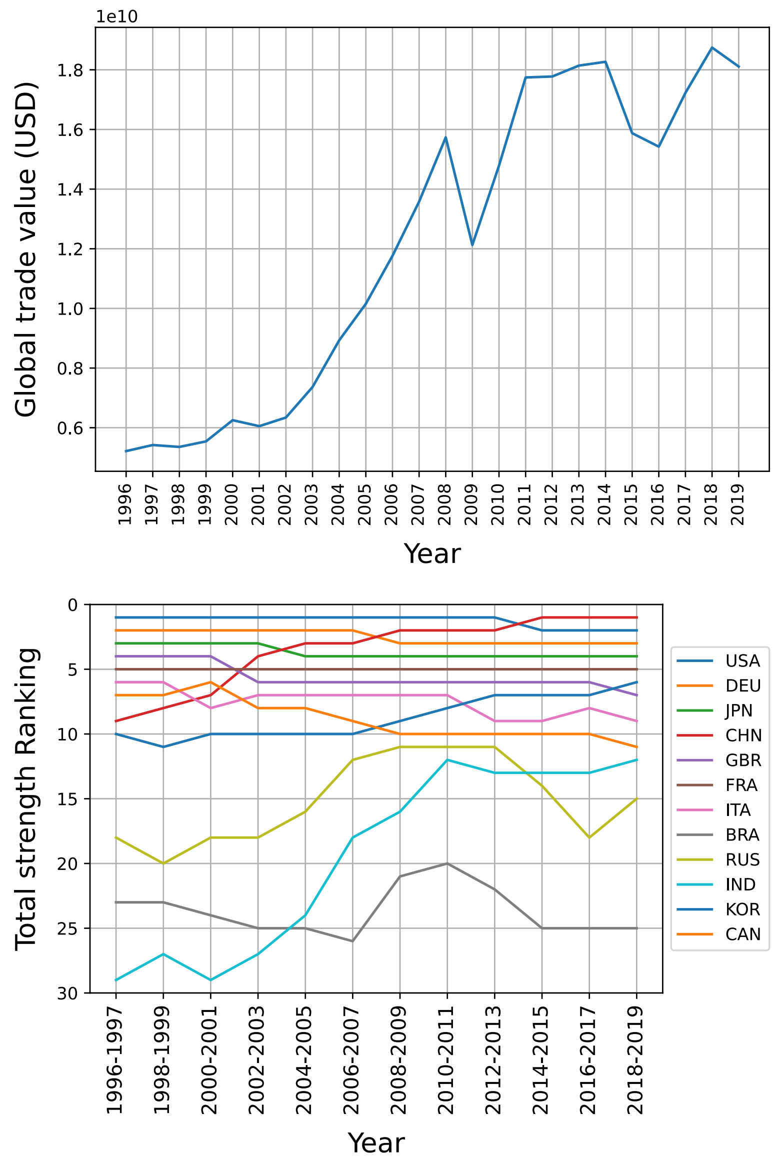


**Fig. 1** Above: Total world trade in the period under study. The increasing trend ceases after the 2008 crisis, suggesting structural changes to the system in the subsequent years. Below: Ranking position for total strength (i.e., total import+export) of a few selected countries. A small group of countries (USA, DEU, JPN, GBR, FRA, ITA) dominate the top positions of the ranking for the entire time period, while CHN improves its position over the years to become the top trader in 2014–2015

the eighth position in the total strength ranking in 1996–1997, but becomes first from 2014–2015 overtaking the USA.

Fig. 2 displays the time evolution of a pool of network metrics for the WTN. In the figure we highlight the 2008–2009 time period, being this the time of the first major trade shock. Indeed, in 2009 world trade collapsed both in value and in volume terms, but this does not necessarily imply a change in the WTN structure. This can be better understood by looking at the evolution of the reported metrics. In the figure, we can see a different pattern before and after 2009, but in many cases the 2008–2009 result occurs within an existing trend, and not as a sudden change, and the turning point of the

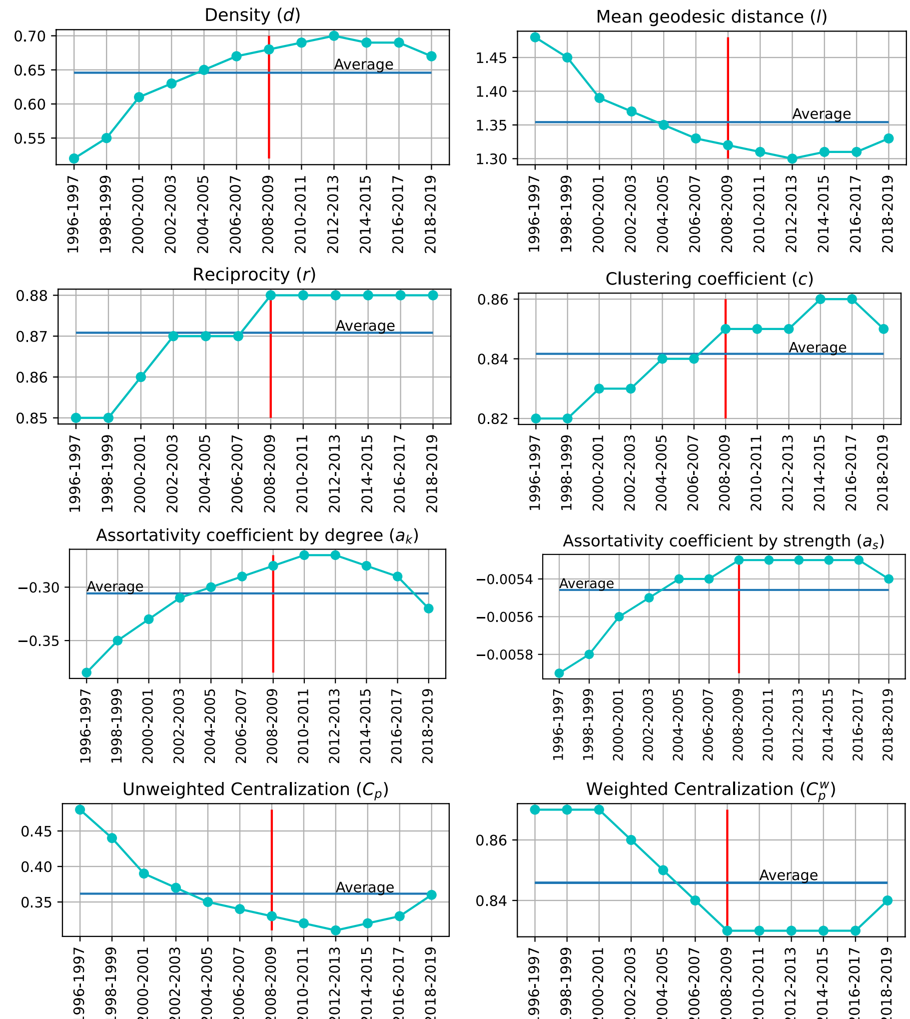


**Fig. 2** Time series of eight network metrics for the WTN. All indicators modify their behavior in the second part of the time frame (after the 2008 financial crisis, see the vertical red line), but the change often occurs gradually, revealing structural changes in the WTN

pattern occurs a few years later. The first two indicators measure how cohesively countries are connected. The figure shows that density is generally very large, with an average of 0.64 across the entire time span. Our findings agree with the literature about the overall increase (resp. decrease) of density (resp. mean geodesic distance) in 1996–2010, when density increased consistently, but from 2010 to 2019 density changed slightly without a clear trend. Instead reciprocity and assortativity stop increasing after 2009, and weighted centralization stops declining. These patterns indeed suggest that at least some of the changes observed in trade in the past decade did not occur as an immediate consequence of the financial crisis shock.

The results in Fig. 2 also show that relationships in the WTN are reciprocal, with a large majority of bidirectional trade relations (see panel Reciprocity ($r$)). In fact, from 1996–1997 to 2018–2019, reciprocity increased from 0.85 to 0.88, a trend that matches that of increasing density. Likewise, the WTN is highly clustered with an average value of 0.84. This level of clustering suggests that it is very likely to find transitive relations (i.e., triads) among countries, and this likelihood has increased parallel to the increase in density: as new relations were built over time, new triads of trade partners were developed. This is the result of large trade openness and new bilateral and multilateral trade agreements.

The evidence of negative assortative mixing by degree (i.e., disassortativity), testified by the negative values of the assortative coefficient $a_k$ throughout the time frame, shows that countries with dissimilar numbers of connections trade with each other. However, their correlations are relatively weak (about $-0.30$ on average) and show an overall decrease in magnitude (from 0.38 to 0.32), which may be due to countries with fewer connections receiving more trade links.

The assortativity mixing coefficient by strength is negative and close to zero. In line with existing contributions (Cepeda-López et al. 2019; Fagiolo et al. 2010; Maeng et al. 2012; De Benedictis et al. 2013), there is no clear connective pattern driven by the intensity of countries' strength, which means that countries search for trading partners irrespective of their contribution to the total value of export. Again, it is arguable that the extensive trade margin prevails on the intensive one, as an increase in density drives this result: most countries maintaining a high number of trading partners should break any tendency to establish connections based on the strength of countries. Export diversification aims at increasing the number of trading partners to avoid concentrating trading relationships.

### Core-periphery analysis

The last two panels of Fig. 2 report the time patterns of the unweighted and weighted centralization index, respectively. For these metrics, we rely on the approach introduced by Della Rossa et al. (2013) for core-periphery analysis, fully applicable to directed and weighted networks. By elaborating the dynamics of a random walker, a curve (the *core-periphery profile*) and a numerical indicator (the *core-periphery score* $C$) are derived. This allows one to quantify to what extent the network is centralized or, inversely, organized in a homogeneous structure. Simultaneously, a coreness value $0 \leq c_i \leq 1$ is attributed to each node, qualifying its position and role: nodes with $c_i = 0$ are the most peripheral, while $c_i \to 1$ for nodes at the center of the core.

We refer the reader to Della Rossa et al. (2013), Piccardi and Tajoli (2018) for further details on core-periphery profile. It is worth noting, however, that the complete network (all-to-all) and the star network represent the extreme cases of the core-periphery profile, as illustrated in Fig. 3. The former has no core-periphery structure as all nodes are equivalent, while the latter is the most centralized network and has $c_i = 0$ for all nodes but the hub, which has $c_i = 1$. Any other network falls somewhere between these extremes: its core-periphery score $C$ is the (normalized) distance of the core-periphery profile from that of the complete network, so that $C = 0$ for the complete (all-to-all) network, and $C = 1$ for the star network: $C$ becomes larger when we consider networks with more pronounced core-periphery structure and stronger centralization.

Figures 2 and 3 show a rather small value of the centralization index, if computed by neglecting weights in WTN and thus only based on the pure topology of connections (unweighted centralization). Indeed, in a core-periphery network, nodes

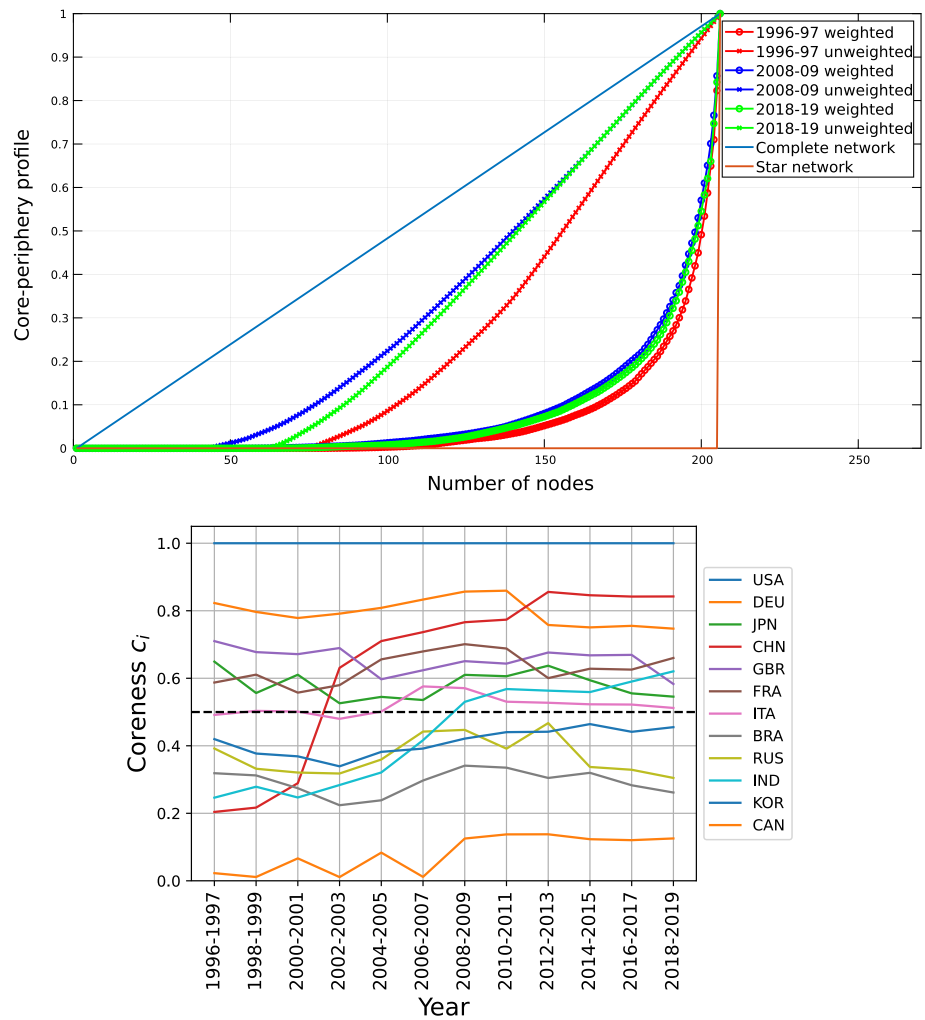


**Fig. 3** Above: The core-periphery profile of the unweighted and weighted WTN in three biennial periods. The unweighted curves are closer to the profile of the complete (all-to-all) network (blue diagonal line), denoting smaller centralization. The weighted curves are closer to the profile of the star network (red angled line), revealing much higher centralization. Below: The time pattern of the weighted coreness $c_i$ for a sample of selected countries. Only very few countries are part of the core (conventionally defined by $c_i > 0.5$) for all or most of the time period (they are USA, DEU, JPN, GBR, FRA, ITA). China displays the most dramatic increase and enters the core of the WTN in 2002–2003

in the periphery should be minimally connected among themselves (Craig and Von Peter 2014; Fricke and Lux 2012), and the high density of the WTN is a signal that a core-periphery connective structure is rather unlikely. In sharp contrast, the intensive trade relationship confirms a high centralization if weights are accounted for (weighted centralization), with a mean value of 0.84 across the time span. This is consistent with the very uneven strength distribution, which shows that the WTN consists of a small group of countries with extensive trade connections, existing alongside small countries with weak trade links connecting each other.

As observed in Fig. 2, the network centralization smoothly decreases until the years 2008–2010, as a consequence of the increasing density due to new forming connections. This trend reverses in the last years of the time frame: this result is consistent

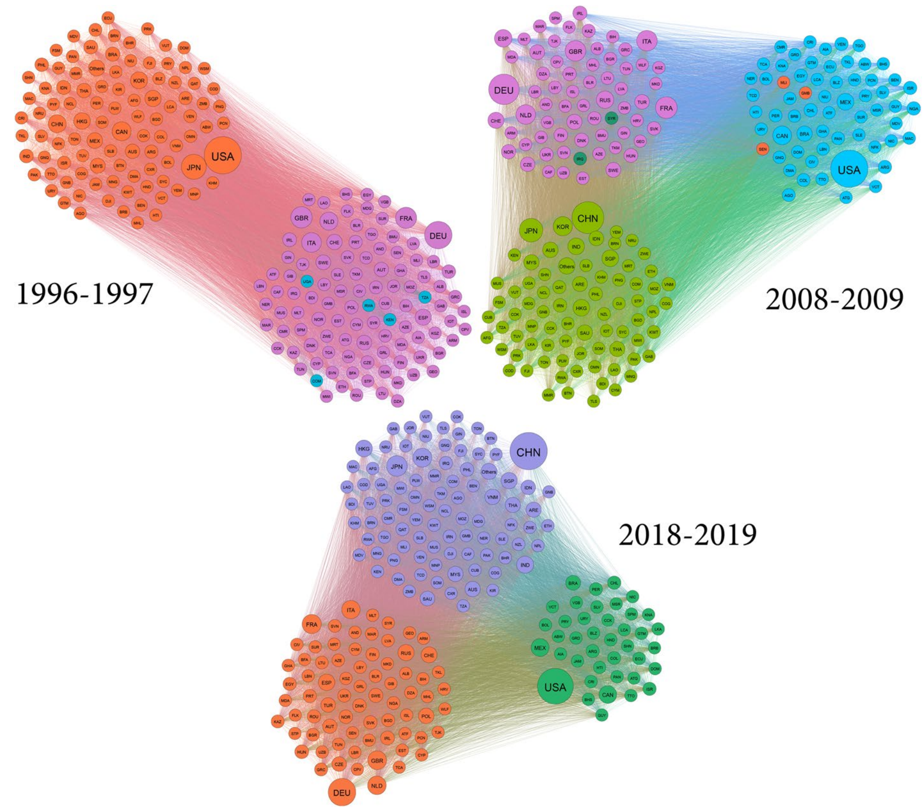


**Fig. 4** Community structure of the WTN in 1996–1997, 2008–2009, 2018–2019. An important structural change is evident from the first to the second graph, with the transition from a 2-group organization (with USA and DEU as leaders) to a 3-group organization (USA, CHN, DEU). The transition takes place around 2002–2003

with an increase in the role of emerging economies such as China and India (Fig. 3) entering the core of the network (here the core is conventionally defined as the set of countries with coreness $c_i > 0.5$).

## Community analysis

In this section, we study the possible existence of communities in the WTN to understand the evolution in time of economic integration. We obtain communities via modularity maximization (e.g., Barabasi 2016) using Louvain method (Blondel et al. 2008), which iteratively optimizes local communities with perturbations to the current partition, until modularity can no longer be improved. The result we obtain is depicted in Fig. 4 for three of the biennial periods analyzed. In 1996–1997 the network is essentially formed by two communities, the largest one composed by Europe, Middle East and Central Asia, and the other one including North America, East Asia, and Asian Pacific countries. From 2002–2003 on, with the increasing role of China, the network shifts to a 3-community structure, with modules essentially corresponding to Asia, Europe, and America. In terms of key players, the WTN undergoes a change in fragmentation, across the years, from the two-way partition influenced by the USA and Germany, to the three-way organization as a consequence of the rise of China. A large trading partner revision is visible for some regions, while, in contrast, the traditional large economies in Europe have remained strongly interconnected, despite experiencing a decline in the number of small countries depending on trade with them. However, although such communities are fully reasonable in geo-economic terms, the low modularity values (around 0.3 in all biennal periods) reveal that the partition is in fact weak, i.e., communities are not strongly separated the ones from the others and have only a moderate prevalence of intra-community trade.

To summarize, the results obtained so far show that the WTN is characterized by an increasing density but not a fully connected structure, with a compact and clustered configuration, and disassortative mixing by degree. The network has homogeneous degree distribution, which differs from most real-world networks (e.g., social networks), implying that scale-free structures are unlikely to describe the WTN. Instead, the inhomogeneous distribution of trade values gives rise to the core-periphery structure of the network, with a concentration of trade in a few countries. However, such a centralization of the network has declined over time as emerging trade nations increased their role. The observed trends in WTN indicators align with the ongoing globalization and integration of international trade, suggesting that the benefits of expanding and diversifying exports may outweigh the costs of establishing new trade relationships. It seems that a high number of linkages in international trade does not necessarily entail an increase in risk exposure, monitoring costs, or resource depletion. Thus, a high level of connectedness may be a desirable and potentially optimal strategy. Nevertheless, these trends have been hindered in the second half of the analyzed time frame, with limited growth in density and no decrease in distance between countries, and a further consolidation of the network's centralization.

### Centrality analysis

Community analysis provides useful insights on the global organization of the WTN, but its scope in characterizing the individual role of countries is obviously limited. To gain a more comprehensive understanding of the relative importance of countries in the WTN, other factors, such as the significance of neighboring nodes, the intensity of connections between them, and the distance of connections should be taken into account.

Centrality indicators should be able to assess various aspects of the role of the nodes in the WTN. Recent studies (Acemoglu et al. 2012; Carvalho 2014) have proposed eigenvector centrality as an index to determine the influence of firms or sectors on aggregate outcomes or, more in general, to evaluate node influence (Clark and Macdonald 2021). However, it is a measure that could become problematic in directed graphs, because of possible degeneracies due to either network topology (Newman 2010, ch. 7) or extreme imbalance in the node importance (Martin et al. 2014). A viable alternative is the PageRank indicator (e.g., Newman 2010; Barabasi 2016), which is widely applicable and does not suffer from the above problems. The PageRank $x_i$ of country $i$ can be expressed, for the unweighted WTN, as (Barrat et al. 2008, ch. 8):

$$x_i = \alpha \sum_{j=1}^{n} A_{ji} \frac{x_j}{k_j^{out}} + \frac{1-\alpha}{n},$$

while $A_{ji}$ and $k_j^{out}$ are replaced by $W_{ji}$ and $s_j^{out}$, respectively, for the weighted WTN, and the coefficient $\alpha$ is set to the standard value of 0.85. Originally developed for the ranking

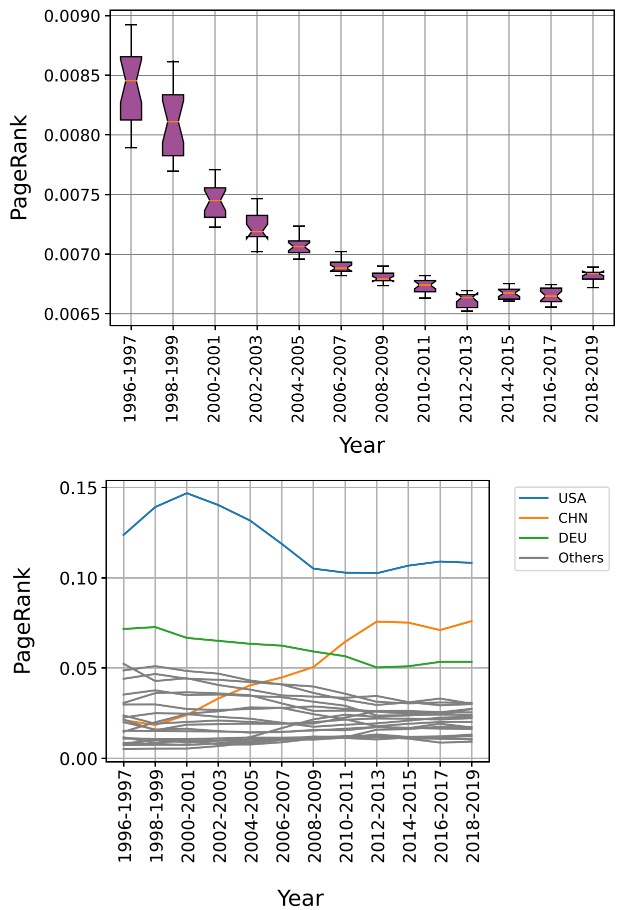


**Fig. 5** Above: Time evolution of the distribution of PageRank values for the unweighted WTN (top 90% countries only). The compression in time of the distribution is a consequence of the homogenization of the connectivity of the countries, in terms of number of trading partners. Below: Time evolution of the PageRank values for the weighted WTN: USA, Germany, and China clearly stand out from the rest of the countries

of web pages, PageRank centrality has found applications in practically all fields (Gleich 2015). In our case, it can effectively consider all relevant factors, such as the number of trading partners, their trade value and their centrality. We compute both unweighted and weighted PageRank, i.e., on the unweighted and weighted WTN, respectively. The results are summarized in Fig. 5.

PageRank values are normalized, in each biennial period, in such a way that the sum over all countries is 1. Therefore, the decline of highest values and the general homogenization observable in Fig. 5 (top panel, unweighted WTN) testify the trend of globalization, consistent with the already observed rise in WTN density and decrease in the mean distance between countries. Small actors increase their relative importance by acquiring more links and trading partners, while traditional large economies experience a decrease in their pivotal role. The observed trend shows a notable stop after 2008, in contrast to its previous rapid decline. This change in trend could conceivably be related to the aftermath of the financial crisis, which may have prompted a more cautious approach towards forging new trade partnerships or imposing trade barriers. However, it is worth noting that the trend partial reversal after 2013 can also be

**Table 2** Top countries by PageRank. Small/medium-sized countries can achieve a relatively high ranking in terms of pure connectivity only (unweighted WTN), but only large economies dominate when trade values are taken into account (weighted WTN)

| Rank | Unweighted WTN | | | Weighted WTN | | |
|---|---|---|---|---|---|---|
| | 1996–1997 | 2008–2009 | 2018–2019 | 1996–1997 | 2008–2009 | 2018–2019 |
| 1 | USA | DEU | GBR | USA | USA | USA |
| 2 | DEU | POL | FRA | DEU | DEU | CHN |
| 3 | FRA | MEX | POL | JPN | CHN | DEU |
| 4 | JPN | DNK | NLD | GBR | FRA | FRA |
| 5 | GBR | CZE | USA | FRA | GBR | GBR |
| 6 | NLD | AUT | ESP | ITA | JPN | JPN |
| 7 | ITA | SVK | DEU | CAN | ITA | NLD |
| 8 | AUT | FRA | NZL | NLD | NLD | IND |
| 9 | ESP | USA | THA | HKG | CAN | CAN |
| 10 | CAN | THA | RUS | ESP | ESP | ITA |

attributed to structural network changes, including the rise of significant new players in the market.

If the intensity of trade is brought back into the analysis by considering the weighted WTN, Fig. 5 (bottom panel) shows that PageRank values are roughly split into two well separated groups, i.e., high and low values, with the former populated by very few countries, namely only two until approximately 2008–2009 (USA and Germany) and three afterwards, after the rapid rise of China which, in terms of PageRank, starts from the 12th position in 1996–1997 to reach the 2nd place in 2018–2019. To complete the above analysis, we report in Table 2 the lists of top-10 countries in terms of PageRank centrality, for three representative biennial periods, and for the unweighted and weighted WTN, separately. It is clearly confirmed that, while small/medium countries may get high ranking in terms of pure connectivity only, large economies have a dominant role when trade values are taken into account.

It should be emphasized that, while China's rise to prominence as the major trading nation is evident from raw data (see Fig. 1), its centrality remains dominated by the USA. This discrepancy can be attributed to China's propensity in dealings with smaller and developing economies, compared to the USA' transactions with are mostly devoted to major economies, including China itself, which have significant centrality. The different role of these two economies, and the impact on their partners, is the subject of the next section.

## Causal inference: the pivotal role of China

Moving from the evidence highlighted in the previous section, attention is now directed towards the impact of China on the pattern of trade flow among nations through an exhaustive evaluation of two key periods, specifically from 2001 to 2003 and from 2008 to 2010. The former period corresponds to the time when China joined the World Trade Organization in 2001, and was therefore able to access world markets with lower barriers, with a lag period of two years to allow the growing influence to take effect. The latter period pertains to the start of the economic recession of 2008, and the two-year

**Table 3** Treatment effect estimate of China and USA (2001–2003). China's impact is indicated by positive and statistically significant values of ATT, ATC and ATE. Conversely, negative values associated with the USA suggest a negative impact over this period

| | est. | st.err. | $z$ | $P > \|z\|$ | 95% C.I. | |
|---|---|---|---|---|---|---|
| **China 2001–2003** | | | | | | |
| ATE | 0.388 | 0.104 | 3.744 | 0.000 | 0.185 | 0.590 |
| ATC | 0.433 | 0.115 | 3.770 | 0.000 | 0.208 | 0.658 |
| ATT | 0.147 | 0.113 | 1.304 | 0.192 | − 0.074 | 0.368 |
| **USA 2001–2003** | | | | | | |
| ATE | − 0.315 | 0.132 | − 2.394 | 0.017 | − 0.573 | − 0.057 |
| ATC | − 0.321 | 0.143 | − 2.254 | 0.024 | − 0.601 | − 0.042 |
| ATT | − 0.312 | 0.170 | − 1.841 | 0.066 | − 0.645 | 0.020 |

lag was applied to allow the effects to build. For the analysis of the period 2001–2003, a sample size of 6324 units (i.e., dyads of countries) was selected as the control group and 1190 units as the treatment group. The average outcome for the treatment group was 2.508, whereas it was 2.265 for the control group, resulting in a raw difference of 0.243. To account for potential confounding variables, a standardised mean difference (SMD) was calculated (Cohen 1998). A standardized difference larger than 0.1 and around 0.2 is normally considered indicative of a small but significant effect (Austin 2011), and most of our covariates have values above 0.2–0.3.[7]

This study employs a matching estimator approach to address the issue of covariate imbalance. Treatment and control units are paired based on their proximity in terms of confounding variables that are standardized using a weighting matrix, such as the inverse variance matrix. The resulting unit-level treatment effects are averaged to obtain the overall treatment effect. However, the matching procedure may introduce bias due to differences in covariate values, which is addressed using an Ordinary Least Squares (OLS) estimation method.

The results presented in Table 3 display a positive and statistically significant average treatment effect (ATE) of 0.388 for nations that have China as a major trading partner. This result suggests that China's expanding integration into the global trade network has a pronounced impact on the trade flow among countries, particularly for those nations where China is a substantial trading partner or forming stronger connections with China. The positive effect is confirmed by the Average Treatment Effect in Control (ATC) and Average Treatment Effect in Treated (ATT) measures when focusing separately on the effect of treatment on the control or treated group, respectively. Specifically, for the control group, if they supposedly would have strong connections with China, they may expose a higher trade level compared to when they are not significantly connected to China. A similar argument applies to ATT focusing on the treated group only. This outcome implies that China's expanding integration into the global trade network has a pronounced impact on the trade flows among countries.

To provide a comparative perspective, the same methodology and time frame were applied to the USA and its main partners. The results, as indicated by ATE, ATC, and

[7] Results of the pre-treatment statistical analysis are available from the authors upon request.

**Table 4** Treatment effect estimate of China and USA (2008–2010) China's impact is indicated by positive and statistically significant values of ATT, ATC and ATE. Conversely, negative values associated with the USA suggest a negative impact over this period

| | est. | st.err. | *z* | $P > \|z\|$ | 95% C.I. | |
|---|---|---|---|---|---|---|
| **China 2008–2010** | | | | | | |
| ATE | 0.154 | 0.074 | 2.088 | 0.037 | 0.009 | 0.298 |
| ATC | 0.093 | 0.103 | 0.907 | 0.364 | − 0.108 | 0.294 |
| ATT | 0.222 | 0.080 | 2.772 | 0.006 | 0.065 | 0.379 |
| **USA 2008–2010** | | | | | | |
| ATE | − 0.092 | 0.082 | − 1.114 | 0.265 | − 0.253 | 0.070 |
| ATC | − 0.058 | 0.087 | − 0.659 | 0.510 | − 0.229 | 0.114 |
| ATT | − 0.117 | 0.115 | − 1.013 | 0.311 | − 0.343 | 0.109 |

ATT values in Table 3, suggest that countries that identify the USA among their primary trading partners experienced a marked decrease in trade value in comparison to other nations.

This trend continued during the period 2008–2010 (Table 4), as the 2008 financial crisis originating in the USA hit especially the more advanced economies and much less China. Economies with significant connections to China continued to display higher levels of trade relative to the rest of the world, suggesting that China's growing presence in international trade had a positive impact in fostering trade flows between other nations in the post–2001 period and also played a role in mitigating the negative effects on trade of the 2008 economic downturn.[8]

## Concluding remarks

In this study, we investigated the structural changes in the World Trade Network (WTN) and the pivotal role of China using data spanning from 1996 to 2019. Our research employed a combination of network analysis and causal inference techniques to gain a comprehensive understanding of the WTN architecture, dynamics, and complex relationships between nations, as well as to quantify China's impact on the network.

Our findings confirmed previous literature in that the WTN is a dense network with a small group of countries having strong trade connections, while many countries have numerous weak trade relations. Our analysis revealed that the network has become increasingly dense, reciprocal, and compact, however, it has not yet achieved full connectivity, i.e., not all possible country-to-country trade connections have been established. The WTN has characteristics such as clustering, disassortative mixing by degree, inhomogeneity by strength, and homogeneity by degree. This latter feature, together with the high density, make it differ from typical real-world networks, which are often very sparse and inhomogeneous in degree (Newman 2003). Our network analysis suggested that the benefits of increasing and diversifying exports outweigh the costs of establishing new trade relations. However, since the 2008 trade shock, but even more

[8] From Tables 3 and 4 it is worth noting that the ATT value is remarkably lower than ATE or ATC in the case of China 2001–2003, suggesting that at that time the influence of China was still weak. The opposite occurs in 2008–2010, when China's trading power was greatly increased. This result may also occur because the treatment effect (i.e., being a partner of China) is not homogeneous for all countries in the treated group, as China can be their first, second, or third trading partner.

clearly after 2012–2013, we observe a slower growth of the network, resulting in a small decrease in the density of trade connections and increase in the distances between countries, and a consolidated centralization of the network. This might be originated by the disruption generated by the financial crisis and the subsequent economic downturn but, as discussed in the paper, also by the important modifications in the network structure as a consequence of the increasing role of China.

Such a network reconfiguration becomes clear also from the community analysis. Our results reveal that the WTN has undergone a significant change after 2002–2003, when China disrupted the two-group hierarchical organization of world trade, led by the USA and Germany, and emerged as the leader of a new cluster in the following period. Furthermore, China continues to appear as the most attractive trade nation as it is getting more connections. A revision of preferred trade partners is visible and geographic realignment has become sustained in some regions (Asia-Pacific, South America). In contrast, the traditional large economies in Europe have remained highly interconnected.

Our study highlights a significant shift in the centrality of countries in the second half of the time period analyzed. The analysis, based on the PageRank indicator, shows that China joined the USA and Germany as one of the few countries of highest importance in the WTN, while the USA still held a superior position. The findings also emphasize the overall resilience of the position of traditional economies in the WTN: the study suggests that liberalization has led to a denser and more homogeneous WTN, but also indicates that the most intense trade relations remain concentrated among a few countries. The shift in the clustering structure and centrality of the WTN presents opportunities for developing economies to enhance the benefits of trade by carefully selecting or revising their trade partners.

Finally, our new approach combining network analysis and causal inference indicates that China's growing integration into the WTN had a significant impact on the flow of trade between countries. In particular, countries with China as their main trading partner tend to have a higher level of trade with each other than the rest of the countries. This reshaping of the structure of the global trade network was further amplified by the 2008 financial crisis, which decreased trade between countries with links to the USA. However, economies with strong ties to China continued to trade more than the rest of the world. Therefore, China's growth in trade played a key role in promoting trade flows among other countries in the period after 2001, and played a role in balancing the negative effects of the economic crisis in 2008. Our results indicate that China it is not only a major player in the WTN, but also an important hub connecting other countries and reshaping the global trade structure. Overall, this research highlights the important role China plays in the global trade network and the need for other countries to adapt to this changing landscape.

It is essential to acknowledge that the study has certain limitations, including the complexities of factoring in influences such as interference between country dyads and politics/geopolitics, which can hinder a comprehensive examination of China's rising role in trade with other nations. However, the study serves as a solid foundation for further research, including the examination of the impact of the Covid-19 pandemic on the international trade network, an issue that has not been explored in this paper due to data availability limitations. Additionally, future studies could delve deeper by examining the trade network at a sectoral level, analyzing the evolution of trade specialization, and investigating the transmission of shocks and the resilience of the network.

## Appendix: Summary statistics for causal inference analysis

See Tables 5, 6, 7 and 8

**Table 5** Summary statistics for China (2001–2003)

| Variable | Controls ($N_c = 6324$) | | Treated ($N_t = 1190$) | | Raw-diff |
|---|---|---|---|---|---|
| | Mean | St.dev. | Mean | St.dev. | |
| Y | 2.265 | 3.046 | 2.508 | 2.992 | 0.243 |
| **Variable** | **Controls ($N_c = 6324$)** | | **Treated ($N_t = 1190$)** | | **SMD** |
| | **Mean** | **St.dev.** | **Mean** | **St.dev.** | |
| X0 | 1.387 | 0.488 | 1.259 | 0.498 | − 0.259 |
| X1 | 0.985 | 0.414 | 1.037 | 0.459 | 0.118 |
| X2 | 0.016 | 0.026 | 0.012 | 0.021 | − 0.18 |
| X3 | 0.003 | 0.005 | 0.006 | 0.008 | 0.334 |
| X4 | 0.662 | 0.156 | 0.703 | 0.158 | 0.263 |
| X5 | 0.662 | 0.156 | 0.703 | 0.158 | 0.263 |
| X6 | 0.238 | 0.426 | 0.192 | 0.394 | − 0.114 |
| X7 | 0.186 | 0.389 | 0.097 | 0.296 | − 0.26 |
| X8 | 0.251 | 0.434 | 0.462 | 0.499 | 0.452 |
| X9 | 0.303 | 0.460 | 0.595 | 0.491 | 0.614 |
| X10 | 0.511 | 0.500 | 0.346 | 0.476 | − 0.337 |
| X11 | 0.510 | 0.500 | 0.308 | 0.462 | − 0.420 |
| X12 | 50.277 | 2.566 | 50.604 | 2.555 | 0.128 |
| X13 | 17.958 | 1.793 | 17.423 | 1.769 | − 0.300 |
| X14 | 8.036 | 0.884 | 8.139 | 0.738 | 0.126 |
| X15 | 0.032 | 0.176 | 0.036 | 0.187 | 0.022 |
| X16 | 23.876 | 3.244 | 24.709 | 3.503 | 0.247 |
| X17 | 0.318 | 0.528 | 0.139 | 0.347 | − 0.399 |
| X18 | 0.309 | 0.517 | 0.235 | 0.470 | − 0.149 |
| X19 | 0.189 | 0.392 | 0.161 | 0.367 | − 0.075 |
| X20 | 0.091 | 0.288 | 0.077 | 0.267 | − 0.050 |
| X21 | 0.000 | 0.013 | 0.000 | 0.000 | − 0.018 |
| X22 | 0.018 | 0.132 | 0.010 | 0.100 | − 0.066 |
| X23 | 0.016 | 0.125 | 0.027 | 0.162 | 0.077 |
| X24 | 0.104 | 0.305 | 0.057 | 0.232 | − 0.172 |

**Table 6** Summary statistics for USA (2001–2003)

| Variable | Controls ($N_c = 2209$) | | Treated ($N_t = 5305$) | | Raw-diff |
|---|---|---|---|---|---|
| | Mean | St.dev. | Mean | St.dev. | |
| Y | 1.818 | 2.954 | 2.506 | 3.051 | 0.688 |
| **Variable** | **Controls ($N_c$=2209)** | | **Treated ($N_t$=5305)** | | **SMD** |
| | **Mean** | **St.dev.** | **Mean** | **St.dev.** | |
| X0 | 1.266 | 0.510 | 1.409 | 0.478 | 0.291 |
| X1 | 0.943 | 0.371 | 1.014 | 0.440 | 0.173 |
| X2 | 0.014 | 0.030 | 0.016 | 0.024 | 0.076 |
| X3 | 0.002 | 0.003 | 0.004 | 0.007 | 0.389 |
| X4 | 0.704 | 0.166 | 0.653 | 0.150 | − 0.322 |
| X5 | 0.806 | 0.115 | 0.773 | 0.133 | − 0.267 |
| X6 | 0.062 | 0.241 | 0.301 | 0.459 | 0.653 |
| X7 | 0.062 | 0.241 | 0.301 | 0.459 | 0.653 |
| X8 | 0.197 | 0.398 | 0.321 | 0.467 | 0.285 |
| X9 | 0.249 | 0.433 | 0.391 | 0.488 | 0.308 |
| X10 | 0.741 | 0.438 | 0.378 | 0.485 | − 0.785 |
| X11 | 0.727 | 0.446 | 0.375 | 0.484 | − 0.755 |
| X12 | 49.474 | 2.338 | 50.685 | 2.574 | 0.493 |
| X13 | 17.696 | 1.912 | 17.947 | 1.746 | 0.137 |
| X14 | 7.596 | 0.85 | 8.242 | 0.795 | 0.785 |
| X15 | 0.049 | 0.216 | 0.026 | 0.159 | − 0.121 |
| X16 | 23.761 | 2.419 | 24.111 | 3.599 | 0.114 |
| X17 | 0.117 | 0.330 | 0.361 | 0.550 | 0.540 |
| X18 | 0.487 | 0.620 | 0.218 | 0.434 | − 0.502 |
| X19 | 0.124 | 0.330 | 0.210 | 0.407 | 0.230 |
| X20 | 0.120 | 0.326 | 0.076 | 0.265 | − 0.150 |
| X21 | 0.000 | 0.000 | 0.000 | 0.014 | 0.019 |
| X22 | 0.005 | 0.074 | 0.021 | 0.144 | 0.138 |
| X23 | 0.033 | 0.178 | 0.011 | 0.106 | − 0.146 |
| X24 | 0.134 | 0.341 | 0.081 | 0.273 | − 0.172 |

**Table 7** Summary statistics for China (2008–2010)

| Variable | Controls ($N_c = 4523$) | | Treated ($N_t = 4012$) | | Raw-diff |
|---|---|---|---|---|---|
| | **Mean** | **St.dev.** | **Mean** | **St.dev.** | |
| Y | 2.266 | 3.243 | 3.15 | 3.232 | 0.884 |
| **Variable** | **Controls ($N_c = 4523$)** | | **Treated ($N_t = 4012$)** | | **SMD** |
| | **Mean** | **St.dev.** | **Mean** | **St.dev.** | |
| X0 | 1.456 | 0.471 | 1.500 | 0.462 | 0.095 |
| X1 | 1.146 | 0.430 | 1.171 | 0.466 | 0.057 |
| X2 | 0.012 | 0.019 | 0.013 | 0.018 | 0.084 |
| X3 | 0.004 | 0.004 | 0.006 | 0.010 | 0.317 |
| X4 | 0.724 | 0.139 | 0.709 | 0.139 | − 0.110 |
| X5 | 0.815 | 0.116 | 0.804 | 0.133 | − 0.086 |
| X6 | 0.250 | 0.433 | 0.307 | 0.461 | 0.127 |
| X7 | 0.235 | 0.424 | 0.231 | 0.422 | − 0.009 |
| X8 | 0.526 | 0.499 | 0.258 | 0.438 | − 0.571 |
| X9 | 0.479 | 0.500 | 0.231 | 0.422 | − 0.536 |
| X10 | 0.224 | 0.417 | 0.435 | 0.496 | 0.461 |
| X11 | 0.287 | 0.452 | 0.538 | 0.499 | 0.528 |
| X12 | 50.224 | 2.392 | 51.276 | 2.615 | 0.420 |
| X13 | 18.350 | 1.696 | 18.007 | 1.794 | − 0.197 |
| X14 | 7.958 | 0.888 | 8.275 | 0.735 | 0.389 |
| X15 | 0.029 | 0.166 | 0.027 | 0.163 | − 0.007 |
| X16 | 23.181 | 3.140 | 24.728 | 3.258 | 0.483 |
| X17 | 0.306 | 0.518 | 0.299 | 0.514 | − 0.012 |
| X18 | 0.372 | 0.551 | 0.262 | 0.476 | − 0.215 |
| X19 | 0.172 | 0.378 | 0.180 | 0.384 | 0.019 |
| X20 | 0.080 | 0.272 | 0.092 | 0.290 | 0.043 |
| X21 | 0.000 | 0.015 | 0.000 | 0.000 | − 0.021 |
| X22 | 0.019 | 0.138 | 0.009 | 0.093 | − 0.091 |
| X23 | 0.031 | 0.174 | 0.014 | 0.117 | − 0.117 |
| X24 | 0.286 | 0.452 | 0.112 | 0.315 | − 0.447 |

**Table 8** Summary statistics for USA (2008–2010)

| Variable | Controls ($N_c = 3517$) | | Treated ($N_t = 4692$) | | Raw-diff |
|---|---|---|---|---|---|
| | Mean | St.dev. | Mean | St.dev. | |
| Y | 2.716 | 3.118 | 2.899 | 3.226 | 0.182 |
| **Variable** | **Controls ($N_c = 3517$)** | | **Treated ($N_t = 4692$)** | | **SMD** |
| | **Mean** | **St.dev.** | **Mean** | **St.dev.** | |
| X0 | 1.486 | 0.478 | 1.503 | 0.440 | 0.039 |
| X1 | 1.161 | 0.450 | 1.182 | 0.435 | 0.047 |
| X2 | 0.013 | 0.020 | 0.013 | 0.018 | 0.024 |
| X3 | 0.004 | 0.005 | 0.005 | 0.009 | 0.216 |
| X4 | 0.715 | 0.144 | 0.709 | 0.132 | − 0.043 |
| X5 | 0.810 | 0.125 | 0.804 | 0.123 | − 0.05 |
| X6 | 0.113 | 0.317 | 0.383 | 0.486 | 0.657 |
| X7 | 0.105 | 0.307 | 0.331 | 0.471 | 0.569 |
| X8 | 0.515 | 0.500 | 0.329 | 0.470 | − 0.382 |
| X9 | 0.490 | 0.500 | 0.256 | 0.436 | − 0.500 |
| X10 | 0.372 | 0.483 | 0.288 | 0.453 | − 0.180 |
| X11 | 0.405 | 0.491 | 0.413 | 0.492 | 0.017 |
| X12 | 50.345 | 2.516 | 50.918 | 2.582 | 0.225 |
| X13 | 18.035 | 1.956 | 18.281 | 1.648 | 0.136 |
| X14 | 7.890 | 0.853 | 8.226 | 0.809 | 0.405 |
| X15 | 0.037 | 0.189 | 0.024 | 0.153 | − 0.076 |
| X16 | 23.950 | 3.131 | 23.942 | 3.440 | − 0.002 |
| X17 | 0.235 | 0.458 | 0.344 | 0.545 | 0.217 |
| X18 | 0.408 | 0.570 | 0.222 | 0.443 | − 0.363 |
| X19 | 0.123 | 0.328 | 0.220 | 0.414 | 0.260 |
| X20 | 0.103 | 0.304 | 0.075 | 0.263 | − 0.099 |
| X21 | 0.000 | 0.000 | 0.000 | 0.015 | 0.021 |
| X22 | 0.011 | 0.105 | 0.018 | 0.134 | 0.060 |
| X23 | 0.028 | 0.165 | 0.016 | 0.125 | − 0.083 |
| X24 | 0.213 | 0.410 | 0.136 | 0.343 | − 0.204 |

**Abbreviations**

GDP Gross domestic product
RTA Regional trade agreement
WTN World Trade Network

**Acknowledgements**
Not applicable

**Author contributions**
VPH, CP and LT conceived the research, conducted the experiments, wrote and reviewed the manuscript.

**Funding**
Not applicable.

**Availability of data and materials**
WTN data are publicly available at http://www.cepii.fr/CEPII/en/welcome.asp.

## Declarations

**Competing interests**
The authors declare that they have no competing interests.

Received: 11 March 2023 Accepted: 5 June 2023
Published online: 16 June 2023

**References**

Abeysinghe T, Forbes K (2005) Trade linkages and output-multiplier effects: a structural VAR approach with a focus on Asia. Rev Int Econ 13(2):356–375
Acemoglu D, Carvalho VM, Ozdaglar A, Tahbaz-Salehi A (2012) The network origins of aggregate fluctuations. Econometrica 80(5):1977–2016
Angrist JD (2004) Treatment effect heterogeneity in theory and practice. Econ J 114:52–83
Angrist JD (2010) Microeconometrics. In: Durlauf SN, Blume LE (eds.) Treatment effect, Palgrave Macmillan UK, London, pp 329–338. https://doi.org/10.1057/9780230280816_36
Austin PC (2011) An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar Behav Res 46(3):399–424
Barabasi AL (2016) Network science. Cambridge University Press, Cambridge
Barigozzi M, Fagiolo G, Garlaschelli D (2009) The multi-network of international trade: a commodity-specific analysis. Technical report. https://ideas.repec.org/p/ssa/lemwps/2009-09.html
Barrat A, Barthélemy M, Vespignani A (2008) Dynamical processes on complex networks. Cambridge University Press, Cambridge
Bems R, Johnson RC, Yi K-M (2013) The great trade collapse. Ann Rev Econ 5(1):375–400
Blondel VD, Guillaume JL, Lambiotte R, Lefebvre E (2008) Fast unfolding of communities in large networks. J Stat Mech Theory Exp 2008(10):10008
Carvalho VM (2014) From micro to macro via production networks. J Econ Perspect 28(4):23–48
Cepeda-López F, Gamboa-Estrada F, León C, Rincón-Castro H (2019) The evolution of world trade from 1995 to 2014: a network approach. J Int Trade Econ Dev 28(4):452–485
Chor D, Manova K (2010) Off the cliff and back? Credit conditions and international trade during the global financial crisis. Technical report, National Bureau of Economic Research, Cambridge, MA. http://www.nber.org/papers/w16174.pdf
Clark RA, Macdonald M (2021) Identification of effective spreaders in contact networks using dynamical influence. Appl Netw Sci 6(1):5
Cohen J (1998) Statistical power analysis for the behavioral sciences, 2nd edn. Routledge, New York
Craig B, Von Peter G (2014) Interbank tiering and money center banks. J Financ Intermed 23(3):322–347
De Benedictis L, Tajoli L (2011) The world trade network. World Econ 34(8):1417–1454
De Benedictis L, Nenci S, Santoni G, Tajoli L, Vicarelli C (2013) Network analysis of world trade using the BACI-CEPII dataset. Technical report. https://econpapers.repec.org/RePEc:cii:cepidt:2013–24
Della Rossa F, Dercole F, Piccardi C (2013) Profiling core-periphery network structure by random walkers. Sci Rep 3(1):1–8
di Giovanni J, Levchenko AA, Zhang J (2014) The global welfare impact of China: trade integration and technological change. Am Econ J Macroecon 6(3):153–83
Fagiolo G, Reyes J, Schiavo S (2010) The evolution of the world trade web: a weighted-network analysis. J Evol Econ 20(4):479–514
Fagiolo G (2017) The international trade network. In: Victor JN, Montgomery AH, Lubell M (eds) The Oxford handbook of political networks, vol 1. Oxford University Press, Oxford, pp 669–688
Feenstra RC, Sasahara A (2018) The 'China shock', exports and U.S. employment: a global input-output analysis. Rev Int Econ 26(5):1053–1083
Feenstra RC, Wei S-J (2010) China's growing role in world trade. Technical report. https://www.nber.org/books-and-chapters/chinas-growing-role-world-trade
Fricke D, Lux T (2012) Core-periphery structure in the overnight money market: Evidence from the e-mid trading platform. Kiel Working Paper 1759. http://hdl.handle.net/10419/55868
Gleich DF (2015) Pagerank beyond the web. SIAM Rev 57(3):321–363
Hoang VP, Piccardi C, Tajoli L (2023) A network analysis of world trade structural changes (1996–2019). In: Cherifi H, Mantegna RN, Rocha LM, Cherifi C, Micciche S (eds) Complex networks and their applications XI. Springer, Cham, pp 490–501
Ianchovichina E, Martin W (2004) Impacts of China's accession to the World Trade Organization. World Bank Econ Rev 18(1):3–27
Imbens GW, Rubin DB (2015) Causal inference for statistics, social, and biomedical sciences: an introduction. Cambridge University Press, Cambridge
Imbens GW, Rubin DB (2010) Microeconometrics. In: Durlauf SN, Blume LE (eds) Rubin Causal Model, pp. 229–241. Palgrave Macmillan UK, London. https://doi.org/10.1057/9780230280816_28
Jusup M, Holme P, Kanazawa K, Takayasu M, Romic I, Wang Z, Gecek S, Lipic T, Podobnik B, Wang L, Luo W, Klanjscek T, Fan J, Boccaletti S, Perc M (2022) Social physics. Phys Rep 948:1–148
Kabir M, Salim R, Al-Mawali N (2017) The gravity model and trade flows: recent developments in econometric modeling and empirical evidence. Econ Anal Policy 56:60–71
Kali R, Reyes J (2007) The architecture of globalization: a network approach to international economic integration. J Int Bus Stud 38(4):595–620
Kim S, Shin EH (2002) A longitudinal analysis of globalization and regionalization in international trade: a social network approach. Soc Forces 81(2):445–471
Krugman P (1995) Growing world trade: causes and consequences. Brook Pap Econ Act 26(1):327–377

Levchenko A, Lewis L, Tesar L (2010) The collapse of international trade during the 2008–2009 crisis: In: search of the smoking gun. Technical report, National Bureau of Economic Research, Cambridge, MA. http://www.nber.org/papers/w16006.pdf
Maeng SE, Choi HW, Lee JW (2012) Complex networks and minimal spanning trees in international trade network. In: International journal of modern physics: conference series, vol 16, pp 51–60
Mahutga MC (2006) The persistence of structural inequality? A network analysis of international trade, 1965–2000. Soc Forces 84(4):1863–1889
Martin T, Zhang X, Newman MEJ (2014) Localization and centrality in networks. Phys Rev E 90(5):052808
Newman MEJ (2003) The structure and function of complex networks. SIAM Rev 45(2):167–256
Newman MEJ (2010) Networks: an introduction. Oxford University Press, Oxford
Piccardi C, Tajoli L (2018) Complexity, centralization, and fragility in economic networks. PLoS ONE 13(11):1–13
Sacks MA, Ventresca MJ, Uzzi B (2016) Global institutions and networks: contingent change in the structure of world trade advantage, 1965–1980. Am Behav Sci 44(10):1579–1601
Serrano MA, Boguna M (2003) Topology of the world trade web. Phys Rev E 68(1):015101
Shelburne R (2010) The global financial crisis and its impact on trade: the world and the European emerging economies. Technical report. https://ideas.repec.org/p/ece/dispap/2010_2.html
WTO (2013) World Trade Report 2013—Factors shaping the future of world trade. Technical report. https://www.wto.org/english/res_e/booksp_e/world_trade_report13_e.pdf
WTO (2009) World Trade Report 2009—Trade policy commitments and contingency measures. Technical report. https://www.wto.org/english/res_e/booksp_e/anrep_e/world_trade_report09_e.pdf

## Publisher's Note