The structural change of world trade from 1996 to 2019. A network approach

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Abstract

Global trade suffers a significant contraction in terms of trade flows and economic growth (GDP) as a result 2008 financial crisis. There are questions arising from this fact: Has the structure of international trade changed as a result of the financial turmoil and what has been their recent shape? Inspire by network method and using long coverage data from 1996-2019, we explore the structure of international trade and its dynamics by geometrically analyzing 3 dimensions: the global network with connective features, hierarchical clustering to visualize how the network cluster and centrality analysis to measure the relative importance of countries in the world trade network (WTN). Considering connective topology, results suggest that countries' efforts to multilateral their trade relations have resulted in a network that is increasingly dense, high reciprocal and clustering. However, the network has not yet fully connected. Trade connections are distributed homogeneously among countries, but their intensity (trade value) is highly concentrated in a small set of countries. Although changes in the main connective features stalled after 2008, the crisis did not affect their overall trends. Referring to centrality structure, the financial downturn marks a turning point in the clustering of the WTN from a two main group (led by United States and Germany) to 3 main groups (led by United States, China, and Germany) and declined to 2 main groups (China, Germany) after 2014. Regarding centrality structure, 2008 also witness a change in the top important trade countries from a group of 2 (United States, Germany) to a group of 3 (United States, China, and Germany). Interestingly, while China is hierarchically becoming the most attractive cluster recently implies that more countries are placing this nation as their most priority trading partner, its relative importance surpassed by United States. Centrality analysis also shows that traditional economies remain their leading role in the WTN. Our study provides an intuitive insight for policymakers in establishing or revising trading partners for optimal economic benefit.

JEL Classification: F10, F14, D85
Keywords: world trade, network analysis, minimal spanning tree, PageRank

1 Introduction

The international economy plays an important role in economic development at the level of nations, regions, global and it has experienced crucial changes. For decades, world trade has increased dramatically and trade has been indicated as one of the engines of economic growth. For example, some developing economies in Asia have experienced higher average GDP growth rates in which largely contributed to their notable rising in imports and export [WTO, 2013]. Such a spectacular trend has been achieved not only intensively (i.e through increases in trade flows between countries already trading in the past), but also extensively (i.e newly create trade relationship)[Fagiolo, 2017]

However, the global financial crisis has had far-reaching repercussions on cross-border economic activity. Most literature agreed that the crisis had a negative effect on economic growth in terms of GDP and slowdown /decline of the trade flow. For instance, 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 during the same period [WTO, 2008]. The contraction in exports was especially acute for small open economies, several of whom saw their trade volumes in

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the second half of 2008 fall by up to 30% year-on-year. This trade decline contributed to the spread of recessionary pressures to countries that had little direct exposure to the US subprime mortgage market where the crisis originated. For example, 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].

To comprehensively research the international trade and its structural change by the crisis, countries need to be analyzed systemically, looking at how embedded they are in the complex web of trade relationships, as it is not sufficient to look at each country in isolation or only at their bilateral trade relationships. While bilateral relationships are important channels of interaction between countries [Krugman et al., 1995]. Recent studies have emphasized the importance of directed relationships, suggesting bilateral trade linkages can only explain a small fraction of the impact that economic shock originating in a given country can have another one with which they do not trade [Abeysinghe et al., 2005]. Moreover, bilateral trade relationships may play an important role in linking groups of countries that would have been otherwise disconnected [Fagiolo, 2017]

Over the past few decades, several trade studies have emphasized the use of gravity model, which is often considered the standard-bearer in the analysis of international trade [Ward et al., 2013, Bardhan and Jaffee, 2005]. However, gravity model contains some limitations: it only captures bilateral trade in a multilateral world and attempts to compensate for this by introducing a multilateral resistance term. Multilateral resistance is where the economic distance between two nations is not only based on the bilateral distance but also the weighted average of economic distance to all other trading partners [Anderson and van Wincoop, 2004]. There were some efforts to extend the gravity model to account for this limitation through the use use of multilateral resistance, it still fails to capture different aspects [Olanike Kareem and Kareem, 2014] and does not capture the full interdependencies of trade in the global economy as indicated by trade theory [Koch and Lesage, 2015]. Hence, analysing international trade as a complex network by using network analysis can complement existing techniques to capture the complexity characterizing the global economy

Our research applies network method [BarabaÌsi, 2016] [Newman, 2010b] to the WTN which aims at describing and understanding the system of international trade. The conceptualization of international trade as a network is not new: in economic sociology and political science, Social Network Analysis (SNA) has been applied for nearly forty years to international trade data, mainly to quantitatively test for “world system” or “dependency” theories [Sacks et al., 2016], [Kim and Shin, 2002],[Mahutga, 2006]. It’s only recently, however, that international trade and economics scholars have started to apply network analysis and complex network models mostly rooted in network science to international trade data to quantitatively understand the structure of the international network. Some importance results can be highlight from these contributions: the trade network displays the typical features observed in other complex networks (e.g. the Internet) [Serrano and Boguna, 2003], de Benedictis and Tajoli [2011]. Most literature agreed that the network is becoming much more integrated over time presented by extremely and increasingly dense in connections (Kali and Reyes [2007]Fagiolo et al. [2010]Barigozzi et al. [2009], de Benedictis and Tajoli [2011]Maeng, Seong Eun Choi, Hyung Wooc Lee [2012]De Benedictis et al. [2013], Cepeda-López et al. [2019], in which almost all trade relationships tend to be reciprocated with similar intensities [Serrano and Boguna, 2003]Fagiolo et al. [2010]Barigozzi et al. [2009]. while countries tend to share similar number of connections (homogeneous distribution of links) (Kali and Reyes [2007]Fagiolo et al. [2010]Barigozzi et al. [2009], de Benedictis and Tajoli [2011], [Cepeda-López et al., 2019]), their intensity is particularly right-skewed (i.e.heterogeneous); that is, the bulk of countries holds mainly weak (i.e. low value) trade relations, whereas only a selected set of countries (large economies) holds numerous and intense relations (Fagiolo et al. [2010], [Cepeda-López et al., 2019])[1]. In terms of connectedness, the network does not fit the scale-free [2]connective structure typical of real-world networks, nor a core-periphery [3] network model (de Benedictis and Tajoli [2011],Cepeda-López et al. [2019]). World trade is dominated by a core group of 17 key players, and those core players correspond to the largest countries De Benedictis et al. [2013]. Regarding hierarchical structure, two group hierarchical clustering (US-Germany) to 3 groups (US-Germany-China) Cepeda-López et al. [2019].

There are several things worth mentioning from the literature. Since previous contributions relied on obsolete data sets

[1]However, Serrano and Boguna [2003], De Benedictis et al. [2013] say that both distribution of trade links and values are strong heterogeneity

[2]As explained in a forthcoming section, the scale-free characterization corresponds to networks that display an extremely right-skewed distribution of connections, in the form of a power-law decay. In this type of network, there are a few heavily connected participants and many poorly connected participants, in which there is no typical or representative participant; thus the distribution of connections has no scale, it is scale-free or scale-invariant [León and Berndsen, 2014]

[3]It is crucial to clarify he core-periphery network structure and the customary core-periphery concept in trade literature. The former is related to networks with a densely connected core and a sparse periphery, in which peripheral elements tend not to transact directly with each other –but through the core (see [Fricke et al., 2012] ,[Craig and Von Peter, 2014],). Regarding the latter, the core of world trade consists of countries specialized in capitalintensive and high-tech production, whereas peripheral countries apply themselves to low-valued added, laborintensive products or unprocessed and raw products [Wallerstein, 2011]. In this paper we will refer to the core periphery in the network structure sense.

that were most collected before 2010, the structural change of WTN after 2008 was not fully investigated. Also, analyses on more detailed levels (clustering, centrality) are limited. Given this context, studying the structure of WTN, its dynamics, and how it changed after the financial crisis is an interesting research question from our perspective. This strand of research not only contributes to our understanding of how the financial crisis affects the 'shape' of international economic relations both intensive (trade value) and extensive manner (trade link) but also provides useful reference information for potential next crisis (for example the Covid-19 pandemic). To answer this question, our paper applies network analysis and contributes to the literature on two fronts: data using and methodological design. The former point, we take into account the long coverage of data (1996-2019) which allows us to document the evolution of WTN including the post and after financial crisis periods. Furthermore, unlike most existing literature [Serrano and Boguna, 2003, Kali and Reyes, 2007, Fagiolo et al., 2010]) we do not filter out trade relations by their value nor weight them by size of the exporter or importer and we take into account all possible countries reported (206 countries after ruling out none constantly reported nations). From our best knowledge, this is the largest number compared to previous contributions (106 [Cepeda-López et al., 2019], 159[Fagiolo et al., 2010], 178[De Benedictis et al., 2013]). Considering a larger number of countries allows us to preserve the network's features and provide more accurate analyses of the international trade topological properties. The latter point, we perform analysis on 3 levels of detail to provide a throughout vision of WTN's structure and its dynamic: First, the global network by visualizing the overall WTN and analyzing calculated crucial network topological indicators (density, mean geodesic distance, reciprocity, clustering coefficient, assortativity coefficient by degree, assortativity coefficient by strength, power-law exponent by strength). Second, clustering analysis using Minimal Spanning Tree (MST) method. Finally, centrality measures by PageRank indicator are calculated to analyze the relative importance of nations within the WTN.

Aside from introduction, our paper is organized as follows: the next section explains the methodology and data used. The third section presents and analyses the results. The final section is our conclusion which summarizes the main finding, discuss policy implication and possible further extension.

2 Methodology and data

The first subsection presents network analysis concepts and notations, with the corresponding formulae exhibited in Appendix A[4]. The second subsection describes the dataset and the processing procedure implemented in our research.

2.1 Network method

The network science research literature provides two different approaches for understanding the structure of systems: network analysis and network modeling. As in Börner et al. (2007)(Newman, 2010), the first one is referring to describing and understanding an underlying system, focused on capturing the system's structure. The second attempts to design processes that reproduce empirical data and also serve the purpose of making predictions, focused on model validation. In our framework, we employ the network analysis process (i.e. network sampling, measurement, and visualization).

A network represents a system, which is a set of elements that are related by their connections or links. In the case of WTNs the elements –also known as vertexes or nodes- are the countries, and their connections –also known as edges- are given by their exchanges of goods and services, measured by their exports. As the existence of exports from country A to country B does not imply exports from B to A, the WTN is better portrayed as a directed graph (i.e. in which the direction of the edges is relevant); even if there are exports from A to B and from B to A, it is most likely that their value is not equal, thus a weighted direct graph is convenient as well. Also, as there are no exports from a country to itself, the graph should not display self-edges.

One representation of a network is the adjacency matrix. In our case, due to the directed nature of the WTN, if n is the number of countries, the adjacency matrix A is a square matrix of dimension $n \times n$ with element A_{ij} such that

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$$

The adjacency matrix is binary, in which a 1 represents the existence of an export from i to j, irrespective of the value of the exports. Graphically, an export from i to j is represented by an arrow or directed edge from node i to node j, and its width

[4] A comprehensive fundamental knowledge of the concept and metrics in network analysis is outside the scope of our paper. Reader may refer to [Newman, 2010b]

may be used to represent its contribution to the total value of export. In a weighted network, a weight w_{ij} is assigned to each link. The weighted adjacency matrix W, with element w_{ij},displays the monetary value of the export from i to j such that

$$W_{ij} = \begin{cases} w_{ij} & \text{weight of edge from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$$

In literature, there are numerous metrics or measures related to network analysis, depending on our scope to focus on those that are most commonly used when studying network's connectivity and local structure, namely density, mean geodesic distance, clustering coefficient, assortativity coefficient, and the distribution of degree and strength. The definition and their related economics meaning and notations will be presented as follow, and the mathematical formulas are presented in Appendix A.

Degree (k_i) :Based on adjacency matrix A, it corresponds to the number of edges connected to node i. In directed network, the in-degree (k_i^{in}) and out-degree (k_i^{out}) quantify the number of incoming and outgoing edges, respectively

Strength: Based on weighted adjacency matrix W, it measures the total weight of connections for node i, which provides an assessment of the intensity of its interaction within the network. For directed weighted network, the in strength (s_{in}) and out strength (s_{out}) sum the weight of incoming and outgoing edges, respectively. The total strength is the sum of in strength and out strength.

Density (d): It measures the cohesion of the network. The density of a graph is the ratio of the number of actual edges (m) to the maximum possible number of edges. Density is restricted to the $0 \leq d \leq 1$ range. Networks are commonly labeled as sparse when the density is much smaller than the upper limit ($d \ll 1$), and as dense when the density approximates the upper limit. Real-world networks (e.g. biological, social, and technological) are usually sparse.

Mean geodesic distance (l): Let g_{ij} be the geodesic distance (i.e. the shortest path in terms of number of edges) from node i to j. The mean geodesic distance for node i (l_{ij}) corresponds to the mean of g_{ij}, averaged over all reachable nodes j in the network [Newman, 2010a]. Respectively, the mean geodesic distance or average path length of a network (i.e. for all pairs of nodes) is denoted as l (without the subscript), and corresponds to the mean of l_i over all nodes.

Reciprocity (r): The reciprocity coefficient (r) measures the probability that an edge from i to j is complemented by the reciprocal edge, from j to i. That is, in directed networks, one relation is reciprocal if there are edges in both directions between a pair of vertices; such relation between two vertexes is called dyadic. Reciprocity can be calculated as the fraction of links for which there is a link in the opposite direction in the network. If $r = 1$ then the network is purely bidirectional (i.e. reciprocal), while if $r = 0$ the network is purely unidirectional. From economics viewpoint, high reciprocity implies that most countries both export to and import from most of their trade partners.

Clustering coefficient (c): It corresponds to the property of network transitivity. It measures the average probability that two neighbors of a node are themselves neighbors. The coefficient hence measures the frequency with which loops of length three (i.e a triadic) appear in the network [Newman, 2010a]**.** Real world networks tend to exhibit a large degree of clustering, in the 10 percent and 60 percent range [Newman, 2010a].

Assortativity coefficient by degree (a_k): In the case of assortative mixing by degree ($a_k > 0$), also known as homophily, high-degree (low-degree) nodes tend to be connected to other high-degree (low-degree) nodes. In the case of disassortative mixing by degree ($a_k < 0$) high degree vertexes tend to be connected to low-degree vertexes. The positive and high value of degree correlation reflects that countries with similar number of connections tend to connect to each other.

Assortativity coefficient by strength (a_s): In the case of assortative mixing by strength ($a_s > 0$) high-strength (low-strength) nodes tend to be connected to other high-strength (low-strength) nodes. In the case of disassortative mixing by strength ($a_s <$ 0) low-strength nodes tend to be connected to high-strength nodes and vice versa.

Power-law exponent by strength (γ_s): The power-law distribution suggests that the probability of observing a node with strength s obeys the potential functional form $P_s \propto Z_s^{-\gamma_s}$, where Z is normalizing constant, and γ_s is known as the exponent of the power-law. Non-large values of γ_s suggest a particularly skewed distribution of strength in the network. The right-skewed distribution show that most countries display a low contribution to total value of export, whereas a few countries contribute significantly to the world trade.

There are methods for estimating the coefficient of power-law (γ) and one of them is the ordinary least squares (OLS) regression. However, OLS maybe inaccurate due to large fluctuations in the most relevant part of the distribution (i.e the tail) [Clauset et al., 2009]. Hence in our framework, we apply maximum-likelihood algorithm developed by Clauset et al. [2009] for all estimation of γ.

2.2 Data source and processing

Our analysis begins with the construction of WTN using BACI-CEPII data set which is built from data directly reported by each country to the United Nations Statistical Division (Comtrade). The BACI-CEPII brings more advantages than its original source (Comtrade). First, the CEPII developed a procedure that uses a reconciliation methodology to reduce the number of missing value [De Benedictis et al., 2013]. As a short description, since countries report both their imports and their exports to the United Nations, the raw data we use may have duplicates flows: trade from country i to country j may be reported by i as an export to j and by j as an import from i. The reported values should match, but in practice are virtually never identical, for two reasons: 1) Import values are reported CIF (cost, insurance and freight) while exports are reported FOB (free on board). 2) Mistakes are made, because of uncertainty on the final destination of exports, discrepancies in the classification of a given product, etc...BACI provides a unique, reconciled trade flow by implementing an harmonization procedure whose two main ingredients are: 1) CIF costs are estimated and removed from import values to compute FOB import values. 2) The reliability of each country as a reporter of trade data is assessed. If a reporter tends to provide data that are very different from the ones of its partners, it will be considered as unreliable and will be assigned a lower weight in the determination of the reconciled trade flow value. Under a multi-layer networks' perspective [Bianconi, 2018], the dataset may be conveniently depicted as a multiplex network [5]. Figure 2 depicts the multiplex case for a sample two-sector (A and B) and five countries hypothetical trade network. In this framework, two countries are considered to have trade connection if there is a link between them in any sector and the total trade value is the accumulation of all sectoral values. Hence, since the BACI-CEPII dataset is provided in HS-6 digit [6]sectoral level, we obtain the aggregate trade value from one country to another by summing all commodities trade flow between them.

The original dataset provides annually from 1996 to 2019. To be more convenient for our analysis, we select data from 1996 to 2019 and convert them into biennial periods (i.e 1996-1997, 1998-1999, ...2018-2019) by averaging single year accordingly. Using biennial periods is convenient for some reasons [Cepeda-López et al., 2019]: Firsts, taking into account the non-small number of networks to work with for each period (i.e 24 in our case), working with biennial periods halves the analytical burden while preserving the dynamics of world trade. Second, building biennial networks enable us to maximize the number of trade links to work with and also maximize the number of links that represent trade flow between countries To avoid the case unreported commodities in specific years. Also, to avoid potential bias and to make comparisons between periods straightforward, we keep the network size (i.e the number of countries) constant by discarding those for which data is unavailable in any period of the biennial dataset.

After processing, our sample contains 206 countries, in 12 biennial periods. From the best of our knowledge, our processed data is larger than all previous contributions (([Cepeda-López et al., 2019], [De Benedictis et al., 2013]), and it is close to the number of countries and territories recognized by the UN [7]. Unlike some prior researches on the WTN ([Serrano and Boguna, 2003],[Kali and Reyes, 2007],[Fagiolo et al., 2010]), we do not filter out trade relations by their value nor weight them by the size of the exporter or importer, we attempt to preserve network's features by acknowledging the importance of establishing trade linkages between countries irrespective of their size. Also different from [Cepeda-López et al., 2019] which only focus on export value, we consider the total strength of countries by taking into account both export and import [8]. All data processing and analysis steps in this paper are performed using Python 3.9

3 Results

Results are reported in four subsections. The first subsection presents the overall view of WTNs. The second present their main structural features and dynamics. The third unveils and examines WTN's hierarchical structure. The final one presents centrality analysis which reveals the country's relative importance.

[5] A. Alves et al. [2018] compare different network representations (single layer, multiplex, and multilayer network), their result suggests that using a finer-grained network representation of trade can unmask market structures and sources of heterogeneity in the system that would otherwise remain undetected if values were aggregated across transactions and simpler (and less accurate) structures were used. Hence, multilayer network is certainly appropriate for our framework.

[6] The Harmonized System classification is a six-digit standard, called a subheading, for classifying globally traded products. The larger digit provided more specific commodities. HS-6 approximately in circulation 5,300 HS codes that identify export goods that are broken down into headings along with subheadings.

[7] The original number of countries varies over years reported (213-226). It is also worth noting that there are differences between the number of nations and territories according to different sources. For example, United Stade recognized 196, but the United Nations is 251.

[8] Total strength is the sum of total export and import

3.1 The World Trade Network

Figure 1 exhibits two biennial networks corresponding to the WTN from 1996-1997 to 2018-2019. Nodes correspond to countries, identified by their ISO 3 digit code (see Appendix C). The diameter of each node corresponds to the magnitude of total strength in each biennial period. They are positioned in a circular layout for better visualization. Despite being concealed in the graph, there are arrows of directed edges between countries that follow the direction from exporters to importers, whereas their width represents their contribution to the total exports. Because of overwhelming number of nodes, for graphical convenience and focus on important characteristics, only countries that total strength greater than 90th[9] percentile are displayed at selected 2 biennial periods (1996-1997, 2018-2019)

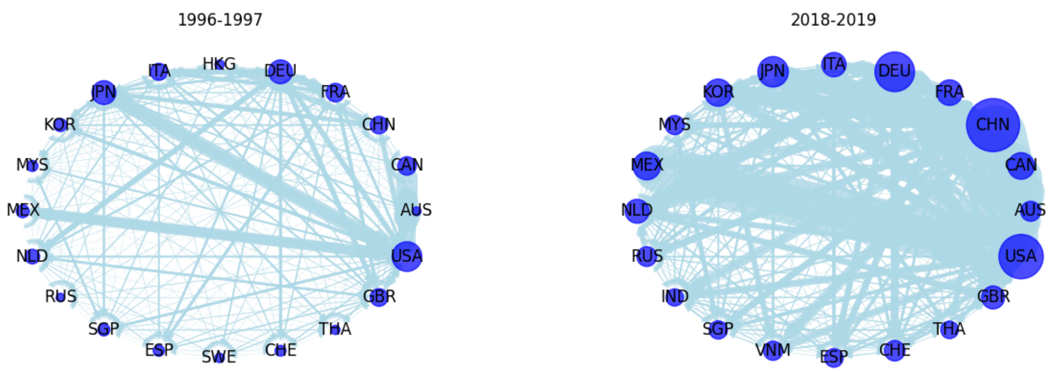


Figure 1: World Trade Network (1996-1997, 2018-2019). Source: Authors' calculations.

As depicted by nodes diameters in figure 1, there is a significant growth in density as the number of trade link between countries increases. The visualization reveals that a few countries concentrate the total trade values in all periods. Figure 2 and table 1 show that United States (USA), Germany (DEU), and Japan (JPN) are the largest trading nations in the first five periods, whereas the United States, China (CHN), and Germany are for the remaining periods. Correspondingly, those countries concentrate the most intense trade flows (i.e. the weighted edges). Although the intensity of trade flows is rather concentrated, edges appear to be distributed homogeneously among countries

It is also interesting to realize that there has been a change in the ranking of countries as contributors to the total strength –as depicted by the evolution in figure 2 and countries ranking in table 1. The most evident change in this ranking is the rise of China as one of those countries contributing the most to global trade. In 1996-1997 China was the eighth in total strength, whereas since 2006-2007 it has substituted Germany as the second position, only surpassed by the United States.

[9] Since there are 206 countries each year after data processing, the 90^{th} percentile of 206 is $90\% \times 206 = 185.4$ which rounded to the nearest whole number, 185. Thenthere are $206 - 185 = 21$ highest countries. Originally, the set of 21 countries contains "others" which represents for "Other Asia, not elsewhere specified nations". However,we omit it to obtain a list of countries explicitly.

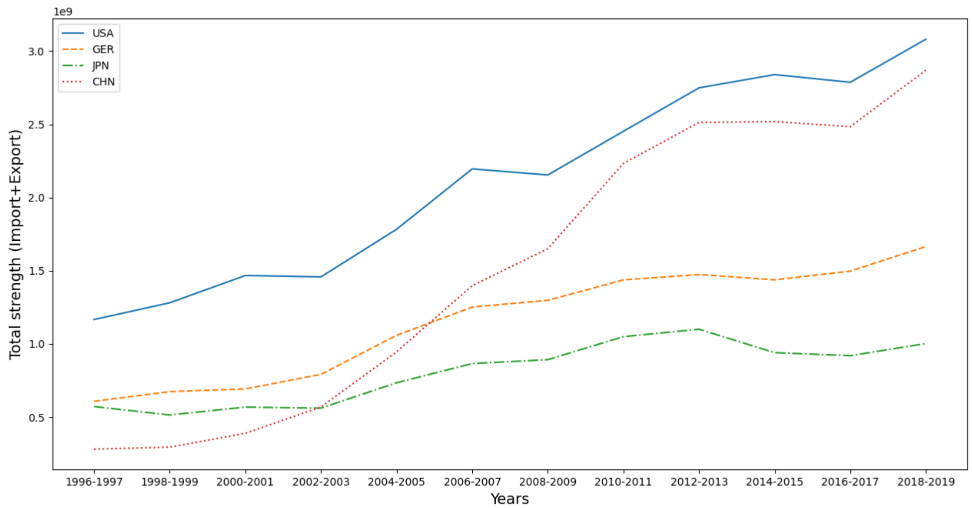


Figure 2: Total strength of United States, Germany, Japan and China from 1996-1997 to 2018-2019. Source: Authors' calculations.

Rank	1996-1997	1998-1999	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019
1	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA
2	DEU	DEU	DEU	DEU	DEU	CHN	CHN	CHN	CHN	CHN	CHN	CHN
3	JPN	JPN	JPN	CHN	CHN	DEU	DEU	DEU	DEU	DEU	DEU	DEU
4	FRA	FRA	GBR	JPN	JPN	JPN	JPN	JPN	JPN	JPN	JPN	JPN
5	GBR	GBR	CAN	GBR	FRA	FRA	FRA	FRA	FRA	CAN	FRA	MEX
6	CAN	CAN	FRA	FRA	CAN	GBR	CAN	CAN	CAN	FRA	CAN	FRA
7	ITA	ITA	CHN	CAN	GBR	CAN	GBR	GBR	KOR	GBR	KOR	KOR
8	CHN	CHN	ITA	ITA	ITA	ITA	NLD	NLD	GBR	KOR	MEX	CAN
9	NLD	NLD	MEX	NLD	NLD	NLD	ITA	KOR	NLD	MEX	GBR	GBR
10	HKG	MEX	NLD	MEX	KOR	KOR	KOR	ITA	HKG	NLD	NLD	NLD
11	KOR	HKG	KOR	KOR	MEX	MEX	MEX	MEX	MEX	HKG	HKG	ITA
12	SGP	ESP	HKG	HKG	HKG	HKG	HKG	HKG	ITA	ITA	ITA	HKG
13	MEX	KOR	ESP	ESP	ESP	ESP	ESP	SGP	CHE	SGP	CHE	CHE
14	ESP	SGP	SGP	CHE	SGP	SGP	RUS	RUS	IND	CHE	SGP	IND
15	CHE	CHE	CHE	SGP	CHE	RUS	CHE	ESP	RUS	IND	ESP	ESP
16	MYS	MYS	MYS	MYS	MYS	CHE	SGP	CHE	SGP	ESP	IND	VNM
17	THA	AUT	IRL	IRL	AUT	MYS	SAU	IND	SAU	RUS	VNM	SGP
18	AUS	SWE	AUT	AUT	RUS	SAU	IND	AUS	AUS	SAU	RUS	AUS
19	SWE	AUS	SWE	SWE	SAU	IND	AUS	MYS	ESP	MYS	THA	RUS
20	RUS	RUS	RUS	RUS	SWE	SWE	BRA	BRA	ARE	ARE	POL	POL

Table 1: List of high strength countries (90^{th} percentile)

Regarding the other BRIC, namely Brazil (BRA), Russia (RUS), and India (IND), in 1996-1997 there was only Russia in the 90th percentile of countries, but in 2009-2010 they were 21, 18 and 15. However, while India slightly improves its position, Russia continuously downgraded its contribution to the total trade from 2014-2015 onward and this concurs with literature due to the US and EU sanctions Russia and Russia counter-sanctions [Fritz et al., 2017]. Correspondingly, some traditional economies have experienced a setback in their role as contributors to total exports, such as Germany, Japan, France (FRA), Great Britain (GBR), and Canada (CAN), among others. Furthermore, it is rather apparent that the most intense edges are now less concentrated than before: in the first period, the most intense trade relations were dominated by the United States, Germany, Japan, Canada, and Mexico, whereas in the last period other countries (e.g. China, Hong Kong) became dominant as well. For Asian nations other than China, South Korea experienced a significant increase in its position, from 11 in 1996-1997 to 7 in 2018-2019.

3.2 The topological feature

Table 2 displays the set of selected metrics for WTN, for each one of the 12 biennial periods in the sample. Concerning how cohesively connected countries are, table 2 shows that density are quite significant with the average of 0.64. From 1996-2019, the density increased consistently, which shows that new trade relations emerged among the fixed set of countries under analysis. From 2009 to 2019, density change slightly without a clear trend, consistent with the trend in trade dynamics during and after 2008-2009 financial crisis Levchenko et al. [2010],Shelburne [2010])[10].

Period	d	l	r	c	a_k	a_s	γ_s
1996-1997	0.52	1.48	0.85	0.82	-0.38	-0.0059	1.48
1998-1999	0.55	1.45	0.85	0.82	-0.35	-0.0058	1.45
2000-2001	0.61	1.39	0.86	0.83	-0.33	-0.0056	1.49
2002-2003	0.63	1.37	0.87	0.83	-0.31	-0.0055	1.94
2004-2005	0.65	1.35	0.87	0.84	-0.30	-0.0054	2.10
2006-2007	0.67	1.33	0.87	0.84	-0.29	-0.0054	2.20
2008-2009	0.68	1.32	0.88	0.85	-0.28	-0.0053	2.31
2010-2011	0.69	1.31	0.88	0.85	-0.27	-0.0053	1.41
2012-2013	0.70	1.30	0.88	0.85	-0.27	-0.0053	2.78
2014-2015	0.69	1.31	0.88	0.86	-0.28	-0.0053	2.75
2016-2017	0.69	1.31	0.88	0.86	-0.29	-0.0053	1.41
2018-2019	0.67	1.33	0.88	0.85	-0.32	-0.0054	2.59
Average	0.64	1.35	0.87	0.84	-0.30	-0.0054	1.99

Table 2: Topological metrics for the world trade network. The metrics displayed are density (d), mean geodesic distance (l), reciprocity (r), clustering coefficient (c), assortativity coefficient by degree (a_k), assortativity coefficient by strength (a_s), power-law exponent by strength (γ_s). Source: Authors' calculations.

The mean geodesic distance (l), which measures the average number of edges between countries, shows a decreasing trend along with the sample. Consistent with the increase in density, the distance between countries decreased markedly between 1996 and 2008; from 2009 onwards the trend is minor and erratic.

It is worth mentioning that although our contribution agrees on the overall increase (decrease) of density (mean geodesic distance) with most existing literature. Our numbers are significantly lower (higher) than findings of [Cepeda-López et al., 2019] for d (l) but concur with the results of [de Benedictis and Tajoli, 2011], which reveal that the network is not yet fully connected. This can be explained by the number of countries we take into account in our data being much larger which corresponds to downward bias due to allowing more countries in the dataset.

Results in Table 2 also show that the relations in the WTN are reciprocal, with more than 8 out of 10 trade relations being bidirectional ($r \geq 0.8$). That is most countries both export to and import from most of their trade partners. From 1996 to 2019 reciprocity increased from 0.85 to 0.88, and the trend matches that of density. Furthermore, from a methodological viewpoint, the high level of reciprocity throughout the sample allows to consider the networks as undirected without any loss of topological information [Serrano and Boguna, 2003]); hence, consistent with findings reported by Fagiolo et al. [2010], the WTN is an extremely symmetric network, which enables us to study it as an undirected network.

[10]Literature has found that both cyclical and structural factors may explain the slowdown in trade relative to GDP since the crisis (Central Bank, 2014[Armelius et al., 2014][Francis et al., 2015][Constantinescu et al., 2020])

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 may be explained by larger world trade openness or new bilateral and multilateral trade agreements. Moreover, by construction, a particularly dense network tends to display high clustering because nodes tend to share partners.

The evidence of negative assortative mixing by degree (i.e disassortativity) reflects that countries with dissimilar numbers of connections may connect to each other. However, their correlations are relatively weak (-0.31 on average) and experienced an overall decrease in magnitude (from 0.38 to 0.32) toward uncorrelation (a_k=0). Concur with other results (density, mean geodesic distance) showing that the WTN is not yet fully connected, then there are countries with low connections co-exist with high connective ones and this may explain the negative but weak correlation. As a parallel to the increasing density, countries with fewer connections receive more trade links may lead to a decreasing trend of correlation.

Noting that our result regarding disassortative WTN is similar to some authors (Kali and Reyes [2007], Fagiolo et al. [2010]) which report that the WTN is disassortative mixing by degree, and they suggest that this validates a core-periphery structure of WTN[11] but contradict with [Cepeda-López et al., 2019] which state that the expected distinctive real-world connective pattern of a few heavily connected countries and many sparsely connected countries are absent. Moreover, as in a core-periphery network structure nodes in the periphery should be minimally connected among them [Craig and Von Peter, 2014], [Fricke et al., 2012]). Cepeda-López et al. [2019] also suggested that WTN's high density may already signal that a core-periphery connective structure is rather unlikely. However our density result is not particularly high as reported by Cepeda-López et al. [2019], for this reason, we omitted analysis for core-periphery in our framework because of the lack of coherent results.

The assortativity mixing by strength coefficient (a_s) is negative and close to zero. As agreed with existing contributions, 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 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.

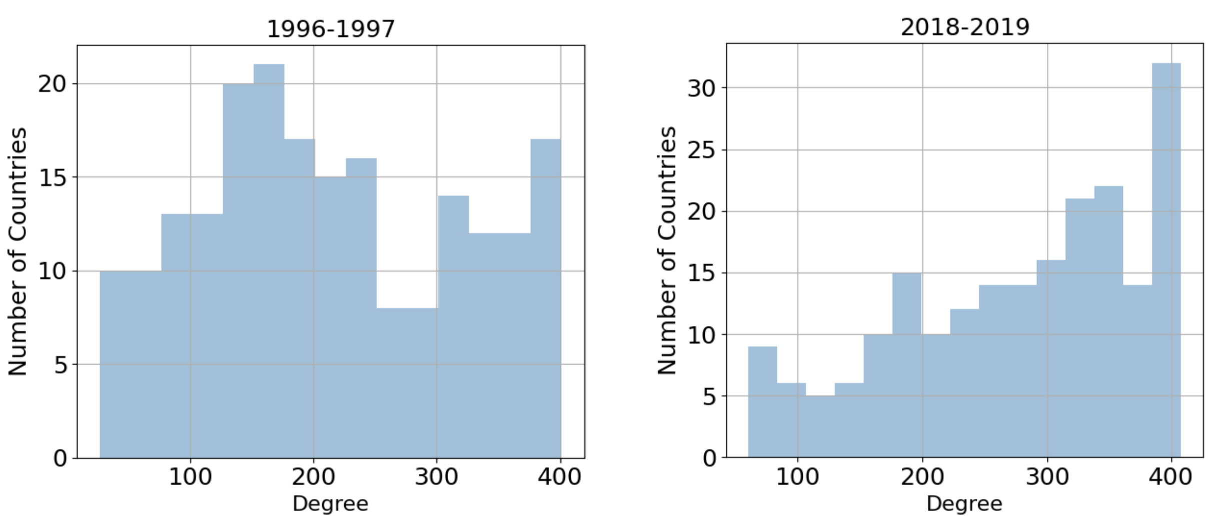


Figure 3: Total degree distribution (1996-1997, 2018-2019). Source: Author's calculation

[11]However, as stated before, recent literature ([Csermely et al., 2013][Li et al., 2014]) argues that core-periphery is a feature that is not related to disassortative mixing by degree only.

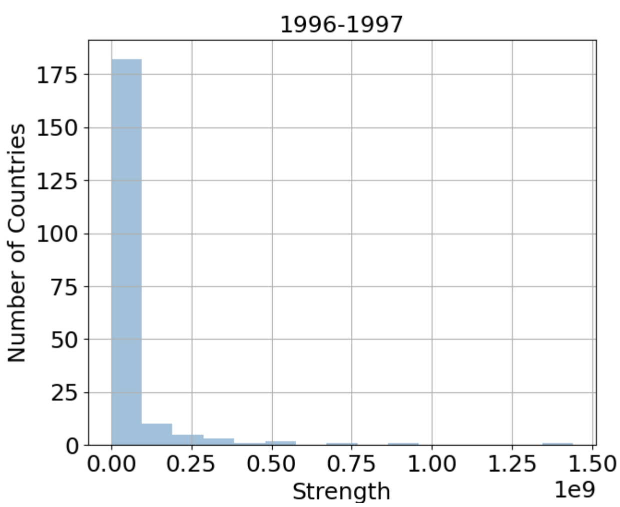


Figure 4: Total trength distribution (1996-1997, 2018-2019). Source: Author's calculation

As depicted in figures 3 and 4, the expectation that WTN may represent a real-world network with only a few heavily connected countries and many sparsely connected countries is unsatisfied. On a contrary, the intensity of connections is dominated by a few nations. These traits of the distribution of degree (figure 3) and strength (figure 4) are consistent along the sample. The distribution of degree is not right-skewed but left-skewed, with most countries displaying high trading partners, with a clear decline in the number of countries with very few connections. Hence, both the power-law coefficient and the visualization of degree distribution suggest that the WTN does not fit the scale-free connective structure typical of a real-world network. This result is similar to the findings by Kali and Reyes [2007], Fagiolo et al. [2010], Barigozzi et al. [2009], Cepeda-López et al. [2019] but contradict with Serrano and Boguna [2003], De Benedictis et al. [2013]. On the other hand, the average value of γ_s shown in table 2 reveal that as agree with most contributions, the distribution of strength is strongly right-skewed ($\gamma_s = 1.99 < 3$): Most countries experience a low contribution in terms of total trade volumes of the world trade network, whereas a few countries contribute much higher. Noting that in this paper we apply the maximal-likelihood algorithm proposed by Clauset et al. [2009] to estimate all γ. The power-law fitting visualization is displayed in figure 5.

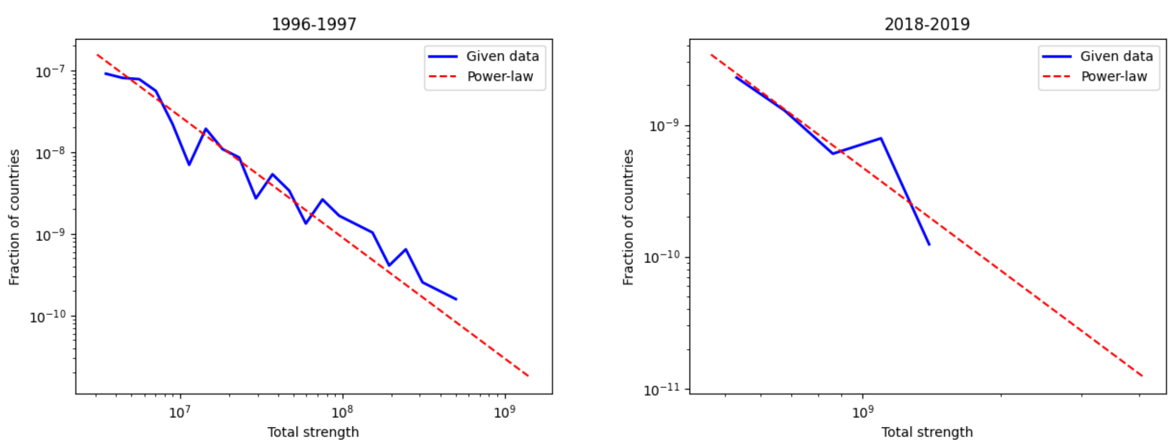


Figure 5: Power law fitting of total strength distribution

The scale-free connective structure of some real-world networks has been related to preferential attachment dynamics [Barabási and Albert, 1999], in which nodes tend to connect to strongly connected nodes. Therefore, finding a dense and homogeneous distribution of links suggests that countries do not show a clear preference to establish relations with a small set of well-connected countries, but a preference to maximize their trade partners. Likewise, dense and homogeneous distribution of links contravenes a key driver of core-periphery network structures, namely the tendency of elements (i.e. countries) to restrict the set of potential trading partners due to decreasing returns to connectedness [Hojman and Szeidl, 2008, Fricke et al., 2012]. Furthermore, consistent with the reduction of trade costs and with the benefits inherent to international trade, it is arguable that establishing trade relations with an additional country does not necessarily require weakening or neglecting prior trade relations, thus maximizing the number of trading partners may be an optimal strategy. Consequently, from a network optimization viewpoint [Cancho and Solé, 2003, Hojman and Szeidl, 2008], our results suggest that the structure of the WTN is driven by the benefits of establishing trading relations for countries (e.g. fostering and diversifying exports, spurring economic growth), with those benefits not exhibiting a strong marginal decrease as the number of trade partners increase amid falling trade costs and frictions[12]

In summary, attained results enable us to summarize the WTN as relatively dense, compact (low distance among countries), high reciprocal and clustered, disassortative mixing by degree, homogeneous distribution by degree, and inhomogeneous by strength. In this vein, the dynamics of the WTN network tend to oppose most real-world networks (e.g social and financial networks), which tend to share common features such as sparseness and inhomogeneous connective structures. Despite not yet being fully connected, there is evidence that suggests scale-free structures seem implausible for characterizing the WTN. Finally, it is fair to say that WTN's connective structure and dynamics may be explained by the potential benefits of increasing and diversifying exports outweighing the costs of establishing new trade relations. Unlike some strands of trading relations literature (e.g interbank lending [13]), increasing the number of linkages in international trade does not entail a direct increase in risk exposure or monitoring costs or the depletion of finite resources, therefore high connectedness is a plausible and -potentially-optimal strategy [Cepeda-López et al., 2019].

3.3 Cluster analysis

Although the WTN visualization and topological analysis are informative in analyzing the connective structure of the WTN, the dimensionality of the WTN, namely its large number of elements (i.e. countries) and their interactions (i.e. linkages), obscures its hierarchical structure. As highlighted by Maeng, Seong Eun Choi, Hyung Wooc Lee [2012], when analyzing the densely connected WTN, it is particularly difficult to identify the important trading partner of a country or the overall network structure. A simple yet illuminating method suitable for examining the hierarchical structure of WTN is the minimal spanning tree (MST). This dimensionality reduction technique, which consists of choosing the minimal weights (i.e. shortest distances) of a connected system of n nodes in such a way that the resulting system is an acyclic network (i.e. without loops) with $n-1$ links that minimize the system's weight [León and Berndsen, 2014], delivers a filtered version of the original system that retains its most salient features. Hence, the MST is also referred to as the "skeleton" or "backbone" inside the network [Wu et al., 2006].

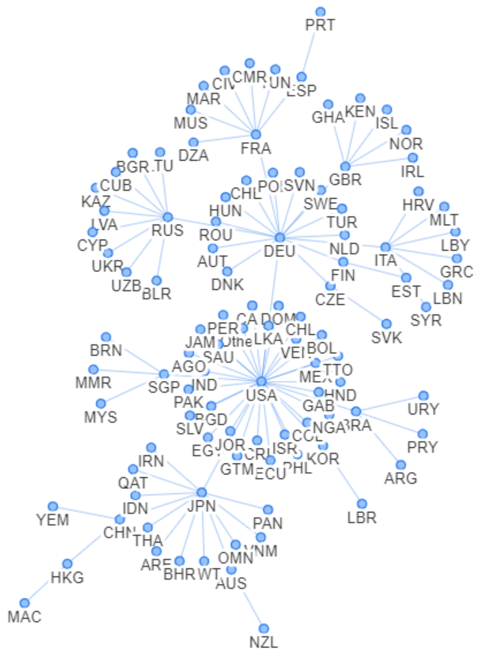
We generate the MST from the densely connected WTN. We set the strength of a link as $g_{ij} = 1/w_{ij}$ where w_{ij} is the trade value from country i to country j. Then extracting the MST by using Kruskal's algorithm: we firstly arrange the link as ascending order respect to strength and select the mimimal one. When obtaining the minimal link, we keep on selecting the link with the least strength. A similar procedure is repeated for the remaining links until we arrive $n-1$ nodes, we stop the selection process. Also noting that the MST only applied for the undirect network, then we symmetrizing adjacency matrix of our directed network by taking the average $\tilde{g_{ij}} = \frac{1}{2}(g_{ij} + g_{ji})$ and this is reasonable due to the high reciprocity of our WTN as a result of topological section ([Maeng, Seong Eun Choi, Hyung Wooc Lee, 2012],[Serrano and Boguna, 2003],[Fagiolo et al., 2010]).

Figure 6 displays the MST for selected 5 biennial periods (1996-1997, 2006-2007, 2008-2009, 2014-2015, 2018-2019). As before, nodes correspond to countries, identified by their ISO three-letter code (see Appendix D). Edges between countries in the MST correspond to the most important trade link for each country –after avoiding loops in the network. Nodes are positioned in a tree layout, which attracts adjacent vertexes and repulses distant ones. The figure displays countries that

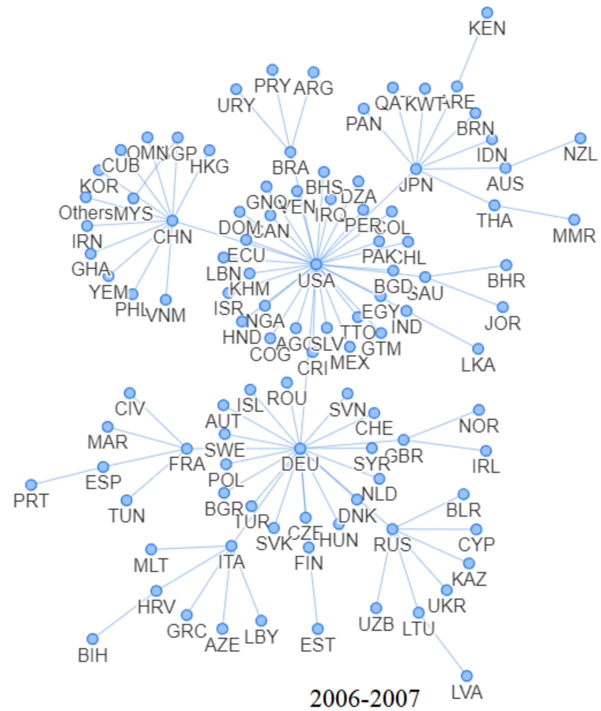
[12]Network optimization literature suggests that real-world networks' sparse and inhomogeneous connective structures (e.g. scale-free, core-periphery) may result from a tradeoff between the benefits from connections and their related costs [Hojman and Szeidl, 2008]. For instance, financial networks' literature suggests that their sparse and inhomogeneous structure may be driven by a tradeoff, either between maximizing the availability of liquidity and minimizing the exposure to counterparty risk [Castiglionesi and Wagner, 2013],[Castiglionesi and Eboli, 2018],[León-Rincón and Sarmiento, 2016] or between maximizing linkages to fit counterparties (i.e. preferential attachment) and preserving finite resources (i.e. homeostasis), as in [León and Berndsen, 2014]

[13]Trading relations literature on interbank lending has flourished after the 2007-2008 crisis [Cocco et al., 2009]

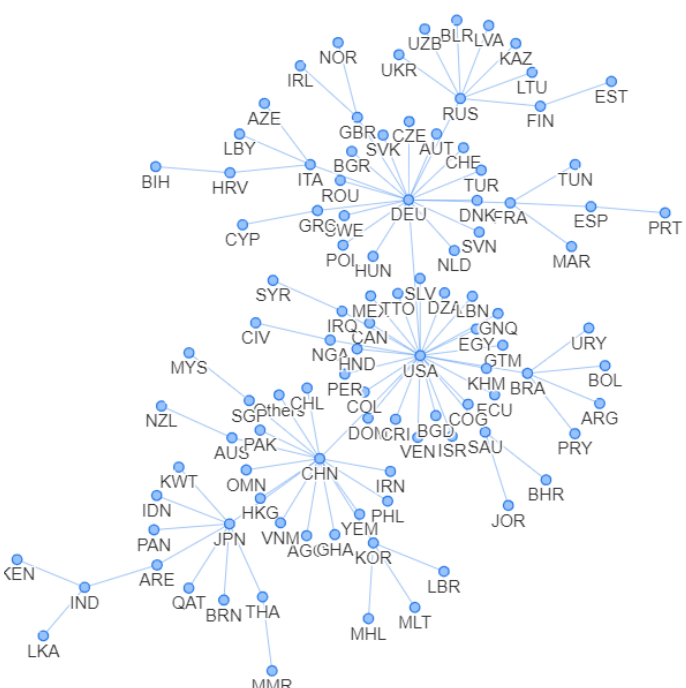
pertain to percentile 50th of strength (i.e. those contributing lower than 50th percentile are excluded).



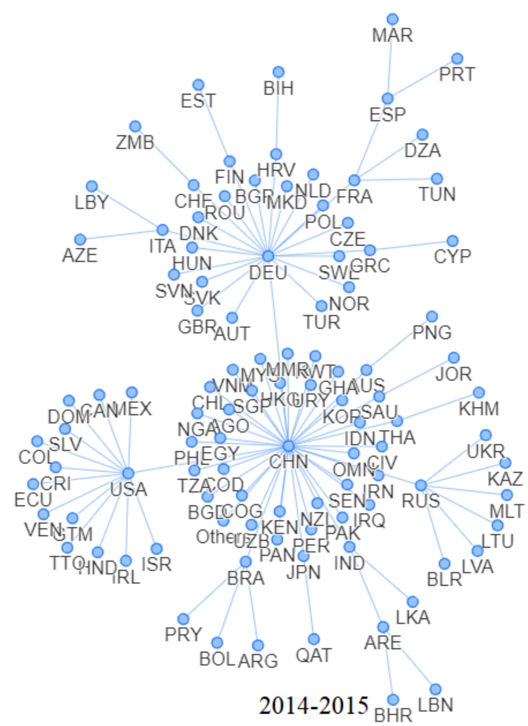
1996-1997



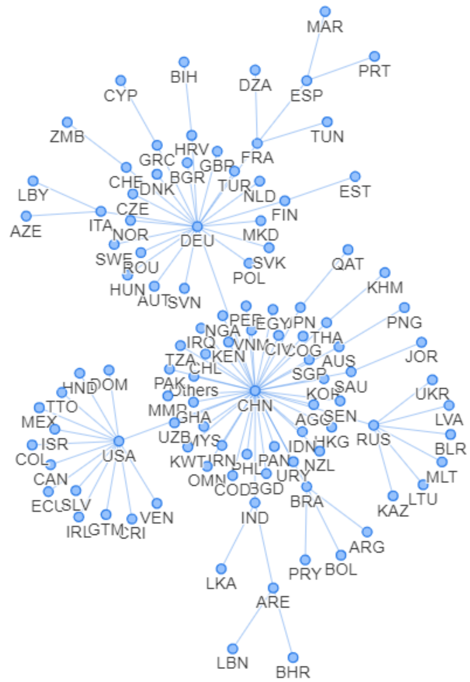
2006-2007



2008-2009



2014-2015



2018-2019

Figure 6: World trade minimal spanning trees. Source: Author's calculation

The most manifest feature of the first five periods (1996-1997, 1998-1999 . . . 2006-2007) is that the WTN exhibits a two-group hierarchical structure, with the United States (US) and Germany (DEU) as the leaders of such hierarchy. Geographical clustering is rather evident for these six periods: most countries trailing the United States belong to America and South East Asia & Pacific, whereas most countries trailing Germany belong to Europe & Central Asia). In these five periods, Japan (JPN) leads a group that is composed by a handful of countries from East Asia & Pacific, but this group tends to cluster under United States' influence. Moreover, the hierarchical structure in these first five periods is consistent with gravity models of international trade, which predict that bilateral trade flows are proportional to the economic mass of both countries (i.e. their size measured by GDP) and inversely proportional to the distance between them. In this vein, visual inspection reveals that those countries that lead the main groups (United States, Germany) and subgroups from 1996 to 2007 correspond to the large economies (e.g. Japan, Great Britain, France, Italy), and most of their periphery nodes correspond to proximate countries (by border, distance, language, political allies, former colonies, etc). A similar view for the group led by Russia and Commonwealth of Independent States (CIS) nations [14].

In 2008-2009, the hierarchical structure of the WTN suffers a noticeable shift: China disrupts the two-group hierarchical organization of world trade. In 2007 China moved away from the United States with a group of about ten countries from East Asia & Pacific, including Japan. Afterward, China preserves a dominant position along United States and Germany, in which these three large countries lead three easily recognizable geographical clusters, namely South East Asia & Pacific, America, and Europe & Central Asia, respectively.Remarkably, the group led by China has attracted several countries that were close to the United States before 2007, including some that are geographically closer to the United States than to China (e.g. Argentina, Brazil, and Chile). Likewise, some countries have fled the Europe & Central Asia group and clustered with –the more distant- China (e.g. subgroup led by Russia and some CIS countries changing the trade dominant from Germany to China. Some features of this shift in the hierarchical structure contradict geographical clustering. However, this shift in the world trade hierarchy is consistent with gravity models of international trade because i) China has surpassed Germany as the second-largest economy since 2007; ii) the size gap between China and the United States has narrowed, and iii) the distance effect has decreased as trade costs have diminished in the last decades. Also, consistent with empirical evidence regarding

[14] Also known as SNG countries

the strong influence of trading partners' growth on a country's economic growth [Arora et al., 2005], it is fair to say that fast-growing countries (e.g. China) should be more likely to attract trade flows as well.

The period from 2008-2009 onward experienced the group dominated by China turn into the most prominent cluster. More interestingly, the WTN witnessed a structural change from the group of 3 countries (USA, China, Germany) back to the group of 2 (China, Germany) from 2014-2015. China has replaced United States as the largest cluster while group led by United States gradually lose its position and tend to form a subgroup that connects to China in 2018-2019. This is consistent with the fact that China has been the world's largest exporting country since 2009. Moreover, it may also relevant to China's Belt and Road initiative (BRI) adopted in 2013 which invests in nearly 70 countries and international organizations [World Bank, 2018]. The result conforms with existing literature [OECD, 2018] which stated that before 2000, exports to the OECD as a share of Chinese exports were around 61% while, for the BRI-participating economies, it was 19%. Subsequently, the trend in the share of BRI-participating economies has been continually upwards, reaching 34% in 2016, while that for the OECD declined gradually to around 49%, and through this route many small and developing economies in the BRI corridor consider China to be their most important trading partner. Finally, except for Germany, this period also witnessed the setback of clusters relevant to some other traditional large economies (Great Britain, France, Italy, Japan), whereas emerging nations other than China (BRICs) start to reveal their role in WTN structure as more visible subgroups connect to China.

3.4 Centrality analysis

Despite providing useful information, the cluster analysis has not covered all the crucial factors to characterize the role of countries in the WTN: i) Cluster analysis only analyzes the trade value of links, ignoring weak links. ii) Relative importance of countries is not only measured by weight, but also by many other factors. As an addition to cluster measure, it is possible to highlight other characteristics that could be taken into account to measure the relative importance of countries: i) Consider the relative importance of neighbor nodes and the intensive of connection between those neighbors to the underlying node ii) Consider the distance of connections[15][Cerina et al., 2015].

In network literature, there are a number of centrality indicators which measure different aspects of characterizing nodes and their role in the WTN. To summarise, centrality measures can be classified into four main groups [Jackson, 2010]: i) Degree centrality measuring how a node is connected to others (with strength centrality as a weighted version) ii) Closeness centrality showing how easily a node can be reached by other nodes. iii) Betweenness centrality describing how important a node is in terms of connecting other nodes. iv) Eigenvector centrality measure, associates node's centrality to the node neighbors' characteristics, directly referring to how important, central, influential or tightly clustered a node's neighbors are.

Recently, several studies such as [Acemoglu et al., 2012], [Carvalho, 2014] proposed theoretical models in which the influence of individual firms or sectors on aggregate outcomes is determined by their eigenvector centrality and eigenvector is an index that matches our criteria. This indicator, however, is problematic because the importance of some peripheral nodes may be overestimated if they have only an insignificant connection with the real important one. Another issue of the eigenvector method is that it does not penalize the distant connections [Cerina et al., 2015]. More importantly, eigenvector centrality is not applicable to directed graphs. In our pattern, a node is important if it is connect with another important node, and in turn it do not have other significant connection. Also, a suitable metric should contain a damping factor that penalizes the distance connection and it is applicable to a directed graph. To fulfill these shortcomings, the PageRank indicator [Page and Brin, 1998] which is originally developed to evaluate the ranking of web pages is employed. The detail of algorithm and formulae are displayed in Appendix B.1 and B.2. Deducing from these formulas, the PageRank centrality for country i becomes higher if :1) the number of country i partner increase 2) country i's trade increase 3) PageRank for country i's partner increase. In our paper, we apply two version of PageRank: non-weighted and weighted which the former only consider trade links and the latter consider trade value of connections.

[15]In reality, more distance connections are more likely to incur transaction loss. Here we focus on network distance, not a geographical one

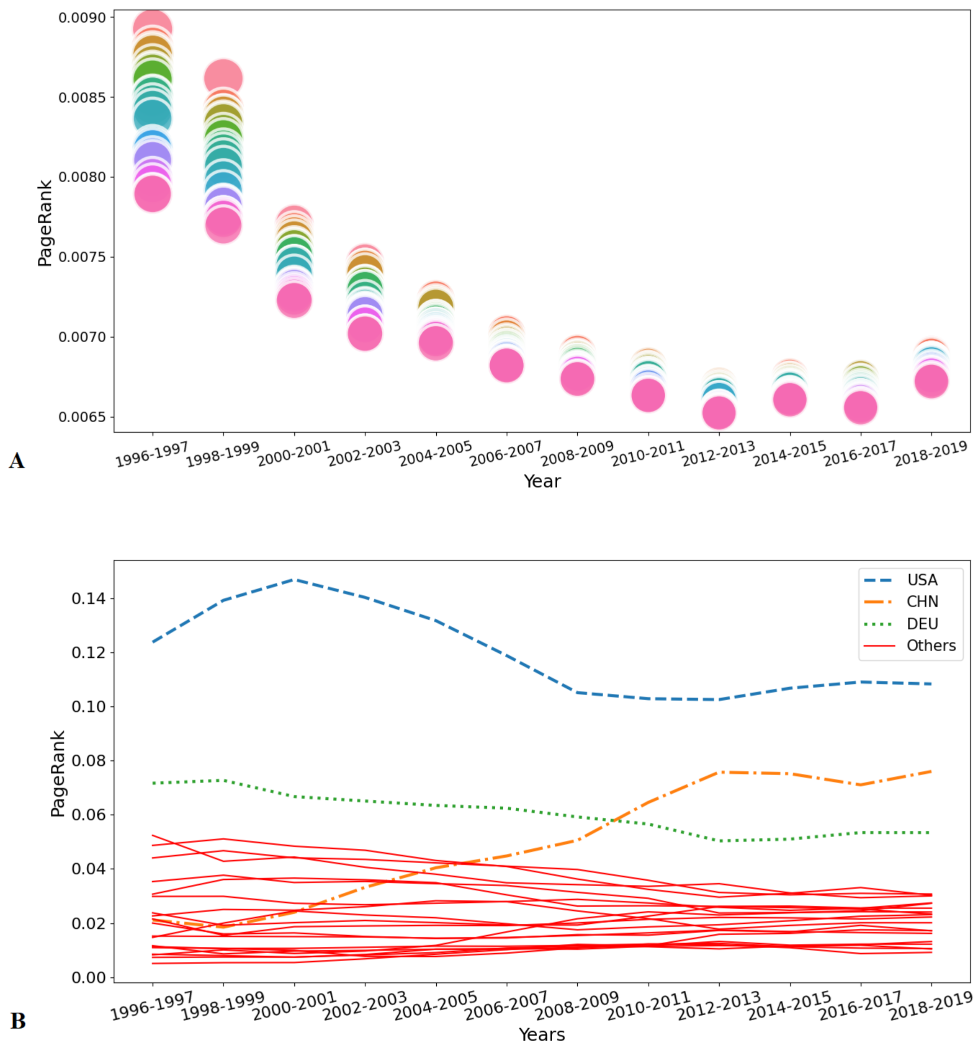


Figure 7: PageRank of countries (90th percentile) from 1996 to 2019. A) non-weighted PageRank. B) weighted PageRank. Source: Author's calculation

The centrality value of connectivity shows an overall decline along the sample and it is minor and erratic from 2008 onward. As depicted in figure 9A, countries tend to share similar values overtime. It is arguable that the globalization trend may lead to the PageRank distribute more homogeneous between nations and it is reasonable with the increase in WTN density and the narrowing mean distance between countries, where smaller trade countries increase their relative importance by receiving more links and trade partners, while traditional large economy set back their role[16]. However, this trend has slowed down after the 2008 economic crisis, possibly because countries are more cautious in establishing new trading partners, or trade barriers are erected to prevent establishing new trade partners to limit the contagion impact of the crisis.

Also depicted from figure 7, the weighted PageRank from 1996-2008 reveals that countries are divided into 2 groups representing high and low-ranking nations. More specifically from 1996-1997 to 2008-2009, group 1 includes the US and Germany as the two elevated economies. The period 2008-2009 marked the point which group 1 from 2-country-group (USA, Germany) to a group of 3 countries (USA, China, Germany) where China experienced a rapid promotion from 12th position in 1996-1997 to 2nd place in 2018-2019. The values of other nations in the second group are slightly decreased

[16]The calculated values are normalized that sum of all countries PageRank equal to 1

and more homogeneous. However, unlike the non-weighted version, the significant collapse in values of countries within the 90th percentile list is not observed in the weighted measure. Furthermore, tables 3 and 4 reveal that while smaller countries appear relatively frequent in the top rankings in terms of connective central, the traditional large economies remain intensively important when taking into account trade values. The full tables of 90^{th}percentile countries are presented in Appendix B.3.

Rank	1996-1997	1998-1999	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019
1	USA	USA	FRA	DEU	DEU	FRA	DEU	FRA	NLD	FRA	FRA	GBR
2	DEU	DEU	USA	FRA	POL	POL	POL	ESP	FRA	POL	ESP	FRA
3	FRA	FRA	DEU	AUT	MEX	MEX	MEX	POL	CZE	IND	SGP	POL
4	JPN	AUT	ESP	USA	FRA	CZE	DNK	CZE	GBR	ESP	CZE	NLD
5	GBR	GBR	GBR	KOR	USA	DEU	CZE	MEX	PAK	NLD	SVK	USA
6	NLD	ITA	KOR	DNK	CZE	AUT	AUT	SYC	THA	SGP	POL	ESP
7	ITA	JPN	CAN	ESP	SVN	KOR	SVK	NLD	MEX	THA	THA	DEU
8	AUT	CAN	CZE	THA	ITA	USA	FRA	GBR	CHE	CZE	KOR	NZL
9	ESP	NLD	THA	ITA	HRV	DNK	USA	THA	USA	KOR	NLD	THA
10	CAN	CHE	CHE	CAN	ESP	SVK	THA	USA	ESP	USA	USA	RUS

Table 3: Top 10 centralized countries by non-weighted PageRank. Source: Author's calculation

Rank	1996-1997	1998-1999	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019
1	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA
2	DEU	DEU	DEU	DEU	DEU	DEU	DEU	CHN	CHN	CHN	CHN	CHN
3	JPN	GBR	GBR	GBR	GBR	CHN	CHN	DEU	DEU	DEU	DEU	DEU
4	GBR	FRA	JPN	FRA	FRA	FRA	FRA	FRA	JPN	JPN	GBR	FRA
5	FRA	JPN	FRA	JPN	CHN	GBR	GBR	JPN	FRA	GBR	FRA	GBR
6	ITA	ITA	CAN	CAN	JPN	JPN	JPN	GBR	GBR	FRA	JPN	JPN
7	CAN	CAN	ITA	ITA	CAN	ITA	ITA	ITA	CAN	CAN	CAN	NLD
8	NLD	NLD	NLD	CHN	ITA	CAN	NLD	NLD	HKG	HKG	NLD	IND
9	HKG	ESP	ESP	NLD	ESP	NLD	CAN	CAN	NLD	NLD	HKG	CAN
10	ESP	MEX	MEX	ESP	NLD	ESP	ESP	IND	ITA	ITA	IND	ITA

Table 4: Top 10 centralized countries by weighted PageRank. Source: Author's calculation

It is interesting to note that while China impressively become the most significant trading country shown in cluster analysis, its relative importance was surpassed by United States. This could be explained by China trades in large volumes with small and medium-sized developing economies, whereas United States trades with major economies (including China itself) which have high centrality. This finding may be relevant to the difference between low and high trade barriers of China and United States.

4 Concluding remarks

We analyze the structure change of WTN based on data available from 1996 to 2019 using network analysis. Unlike traditional method, our approach is able to capture the complexity arising from the numerous interaction among countries, hence it allows for a better description and analysis of world trade [Serrano and Boguna, 2003, Fagiolo et al., 2010]. Using long coverage data in both time and geographical dimensions, we perform a comprehensive representation of the WTN's structure before and after the financial crisis in 3 aspects: global network with connective measures, cluster, and centrality analyses.

Our main findings come in the form of an updated and enhanced characterization of the connective structure of the WTN. Concurring with most existing literature, it is fair to state that the WTN is a relatively dense network that consists of a large number of countries holding numerous weak (i.e. low value) trade relations, and a small set of countries holding both numerous and intense relations. Our results point out that the WTN may be characterized as increasingly dense, reciprocal, compact (i.e. with low distances among countries). However, different from the conclusion of other authors[Fagiolo et al., 2010, Cepeda-López et al., 2019, Maeng, Seong Eun Choi, Hyung Wooc Lee, 2012]), our density and distance values show that the world has not yet close to fully connected. The WTN is also clustered, disassortative mixing by degree, homogeneous by degree, and inhomogeneous by strength. Therefore, we find evidence that the WTN does not conform to the main features exhibited by real-world networks (e.g. social and financial networks). Also, from a network optimization viewpoint, we suggest that the connective structure of the WTN may be explained by the potential benefits of increasing and diversifying exports outweighing the costs of establishing new trade relations.

Additionally, using minimal spanning trees (MST), we avoid the overcrowding issue of WTN. This enabled us to examine the hierarchical structure of world trade, which unveiled several interesting features. For instance, we identify that the WTN experienced a major shift after 2008 when China disrupted the two-group hierarchical organization of world trade led by the United States and Germany and completely replace USA in 2019 as the most significant cluster. Due to the rise of China as the second-largest economy –surpassing Germany and closing the gap with the United States- and to the declining costs of trade, we suggest that this shift in the WTN hierarchy is consistent with traditional gravity models of international trade. Furthermore, China continues to be expected as the most attractive trade nation as it is receiving more connections and this finding is expected to be reinforced when Regional Comprehensive Economic Partnership (RCEP)[17] agreement to enter into force on 1 January 2022.

Finally, the year 2008 also marked the change of top importance countries from a group of 2 (United States, Germany) to the group of 3 (United States, China, Germany). Interestingly, although more and more countries are placing China as their most priority trading partner by cluster result, the centrality analysis shows that it is surpassed by the United States and other traditional economies remain their important role in the WTN. Regarding the policy implications, it is worth highlighting that our results provide new insights for analyzing and understanding the world and regional trade. For instance, results suggest that liberalization has produced an increasingly dense and homogeneous WTN, but they also suggest that most intense relations are still concentrated in a few countries. Also, due to the shift in the clustering structure and centrality of world trade after 2007-08 and the evidence of growth spillover effects induced by trade (Arora et al., 2005), results point out that an appropriate selection or revision of countries' trade partners could enhance the benefits of trade –especially for developing economies. Furthermore, our study also provides useful information for developing countries in establishing free trade agreements (FTA), especially with the China and United States to achieve optimal economic benefits with the objective of balancing fast economic growth (infrastructure, GDP) and sustainable development (environment, working condition, labor forces)[18].

Several ideas for further research were readily formed. For an instant, the impact of Covid-19 pandemic on the architecture of the international trade network has not yet been investigated due to data availability issues. At a more fractioned level, examining a multi-layered network formed by sectoral connections within and across nations is definitely useful for mesoscale (country-sector) analysis. Also, investigating the evolution of sectors over time is meaningful for analyzing patterns in trade specialization. Likewise, the propagation of shocks and resilience of the network could provide new information on how potential crises could affect global production and supply chains. Finally, due to the importance of tradeable services and the high correlation between service and products, we acknowledge the relevance of examining and analyzing this sector in forthcoming research.

[17]The Regional Comprehensive Economic Partnership (RCEP) is a free trade agreement (FTA) between the ten member states of the Association of Southeast Asian Nations (ASEAN) (Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Vietnam) and its five FTA partners (Australia, China, Japan, New Zealand and Republic of Korea). It is considered the world's largest free trade agreement, as it covers nearly a third of the global population and about 30 per cent of its global gross domestic product (GDP)

[18]Readers can refer to Chile's case study in handling FTAs with United States and China from the perspective of a developing country [Sotiriou and Rodríguez-Pose, 2021]

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Appendix

A Network analysis formulae

Let the number of nodes be n. We denote the adjacency matrix as A:

$$A = \begin{pmatrix} a_{11} & \dots & a_{1j} & \dots & a_{1n} \\ \vdots & \ddots & \vdots & & \vdots \\ a_{i1} & & a_{ij} & & a_{in} \\ \vdots & & \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nj} & \dots & a_{nn} \end{pmatrix}$$

where:

$$a_{ij} = \begin{cases} 1 & \text{if there is a link from node } i \text{ to node } j \\ 0 & \text{otherwise} \end{cases}$$

Network analysis formulae	
$k_i^{in} = \sum_{j=1}^{n} A_{ji}$ In degree	$k_i^{out} = \sum_{j=1}^{n} A_{ij}$ Out degree
$s_i^{in} = \sum_{j=1}^{n} W_{ji}$ In strength	$s_i^{out} = \sum_{j=1}^{n} W_{ij}$ Out strength
$d = \frac{m}{n(n-1)}$ Density	$l_i = \frac{1}{(n-1)} \sum_{j(j \neq i)} g_{ij}$ Mean geodesic distance of a node
$l = \frac{1}{n} \sum_i l_i$ Mean geodesic distance of a network	$c = \frac{(\text{number of triangles}) \times 3}{\text{number of connected triples}}$ Clustering coefficient
$r_k = \frac{\sum_{ij} (A_{ij} - k_i k_j / 2m) k_i k_j}{\sum_{ij} (A_{ij} \delta_{ij} - k_i k_j / 2m) k_i k_j}$ Degree correlation[a]	$c_i = \frac{\text{pairs of neighbors of } i \text{ that are connected}}{\text{pairs of neighbors of } i}$ Local clustering coefficient
Where A_{ij} is a directed adjacency 3 matrix: $A_{ij} = \begin{cases} 1 & \text{if there is an adge from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$ W_{ij} is a directed and weighted adjacency matrix n is the number of participants in the network, m is the number of edges g_{ij} is the shortest path (i.e geodesic distance) between two nodes i and j $\delta_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$	
[a]To compute the strength correlation the k_i and k_j variable outside the parenthesis should be replaced by $s_i$and s_j respectively.	

Table 5: Network analysis formulae. For a more comprehensive review, please refer to [Newman, 2010b]

B Centrality analysis

B.1 Non-weighted PageRank

Let the Pagerank centrality be PR_i for country i at time t. Then it is defined as

$$PR_i = \psi \sum_{j=1}^{n} a_{ij} \frac{PR_j}{k_j} + \chi$$

Where ψ and χ are positive constants and k_j is the outdegree
Conventionally, we set $\psi = 0.85$ and $\chi = 1$.
The PageRank is normalised such that their total sum is equal to 1

B.2 Weighted PageRank

The weighted PageRank formula is given as

$$PR_i = (1-\psi) + \psi \sum_{j=1}^{n} PR_j.w_{ij}w_{ji}$$

Here, PR_i refers to the Weighted PageRank of node i
ψ is the damping factor, we let $\psi = 0.85$ in our framework
w_{ij} is the weight of link from node i to node j
w_{ji} is the weight of link from node j to i

B.3 List of highest Pagerank countries

Rank	1996-1997	1998-1999	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019
1	USA	USA	FRA	DEU	DEU	FRA	DEU	FRA	NLD	FRA	FRA	GBR
2	DEU	DEU	USA	FRA	POL	POL	POL	ESP	FRA	POL	ESP	FRA
3	FRA	FRA	DEU	AUT	MEX	MEX	MEX	POL	CZE	IND	SGP	POL
4	JPN	AUT	ESP	USA	FRA	CZE	DNK	CZE	GBR	ESP	CZE	NLD
5	GBR	GBR	GBR	KOR	USA	DEU	CZE	MEX	PAK	NLD	SVK	USA
6	NLD	ITA	KOR	DNK	CZE	AUT	AUT	SYC	THA	SGP	POL	ESP
7	ITA	JPN	CAN	ESP	SVN	KOR	SVK	NLD	MEX	THA	THA	DEU
8	AUT	CAN	CZE	THA	ITA	USA	FRA	GBR	CHE	CZE	KOR	NZL
9	ESP	NLD	THA	ITA	HRV	DNK	USA	THA	USA	KOR	NLD	THA
10	CAN	CHE	CHE	CAN	ESP	SVK	THA	USA	ESP	USA	USA	RUS
11	KOR	ESP	AUT	CHE	NLD	NZL	Others	AUT	IRL	IRL	NZL	KOR
12	CHE	IDN	AUS	BGD	KOR	IRL	IND	CHE	POL	SVN	SWE	CZE
13	IDN	THA	IRL	NLD	IRL	ITA	HRV	IND	BRA	BRA	AUS	SVK
14	IRL	GRC	ITA	GBR	AUT	ESP	NLD	KOR	KOR	RUS	IRL	BRA
15	SVN	SGP	Others	JPN	CAN	NLD	GBR	IDN	CAN	GBR	SVN	Others
16	THA	DNK	JPN	AUS	AUS	GBR	KOR	Others	SVK	PAK	GBR	IDN
17	DNK	KOR	SVN	SVN	PAK	HRV	BGR	BRA	TUR	TUR	PAK	IRL
18	CZE	IRL	NGA	IDN	THA	SVN	IRL	AUS	IDN	Others	BHR	SGP
19	PRT	CZE	IDN	CZE	GBR	IND	AUS	HRV	DNK	DEU	ITA	SVN
20	GRC	AUS	DNK	SVK	DNK	CHE	ITA	ITA	IND	CAN	TUR	SWE
21	FIN	MEX	NLD	IRL	CHE	THA	ESP	IRL	SVN	AUS	IDN	IND

Table 6: 90^{th} percentile non-weighted PageRank countries

Rank	1996-1997	1998-1999	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019
1	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA	USA
2	DEU	DEU	DEU	DEU	DEU	DEU	DEU	CHN	CHN	CHN	CHN	CHN
3	JPN	GBR	GBR	GBR	GBR	CHN	CHN	DEU	DEU	DEU	DEU	DEU
4	GBR	FRA	JPN	FRA	FRA	FRA	FRA	FRA	JPN	JPN	GBR	FRA
5	FRA	JPN	FRA	JPN	CHN	GBR	GBR	JPN	FRA	GBR	FRA	GBR
6	ITA	ITA	CAN	CAN	JPN	JPN	JPN	GBR	GBR	FRA	JPN	JPN
7	CAN	CAN	ITA	ITA	CAN	ITA	ITA	ITA	CAN	CAN	CAN	NLD
8	NLD	NLD	NLD	CHN	ITA	CAN	NLD	NLD	HKG	HKG	NLD	IND
9	HKG	ESP	ESP	NLD	ESP	NLD	CAN	CAN	NLD	NLD	HKG	CAN
10	ESP	MEX	MEX	ESP	NLD	ESP	ESP	IND	ITA	ITA	IND	ITA
11	KOR	HKG	CHN	MEX	MEX	MEX	IND	HKG	IND	IND	ITA	HKG
12	CHN	CHN	HKG	HKG	HKG	HKG	KOR	ESP	KOR	KOR	MEX	MEX
13	SGP	SGP	KOR	KOR	KOR	KOR	HKG	KOR	MEX	MEX	KOR	KOR
14	Others	KOR	SGP	SGP	Others	IND	MEX	MEX	ESP	ESP	ESP	ESP
15	CHE	Others	Others	CHE	CHE	SGP	CHE	SGP	SGP	SGP	CHE	ARE
16	RUS	CHE	CHE	Others	SGP	RUS	SGP	CHE	CHE	CHE	ARE	CHE
17	MEX	AUT	AUS	AUS	IND	CHE	RUS	RUS	ARE	ARE	SGP	SGP
18	MYS	RUS	MYS	SWE	AUS	Others	Others	Others	RUS	Others	Others	POL
19	THA	SWE	SWE	RUS	RUS	AUS	ARE	BRA	Others	RUS	THA	THA
20	BRA	AUS	BRA	THA	TUR	POL	AUS	AUS	THA	THA	POL	Others
21	AUS	BRA	AUT	MYS	THA	TUR	POL	ARE	AUS	POL	TUR	RUS

Table 7: 90^{th} percentile weighted PageRank countries

C List of country code

Country name	ISO 3 digit
Afghanistan	AFG
Albania	ALB
Algeria	DZA
American Samoa	ASM
Andorra	AND
Angola	AGO
Antigua and Barbuda	ATG
Azerbaijan	AZE
Argentina	ARG
Australia	AUS
Austria	AUT
Bahamas	BHS
Bahrain	BHR
Bangladesh	BGD
Armenia	ARM
Barbados	BRB
Belgium	BEL
Belgium-Luxembourg	BEL
Bermuda	BMU
Bhutan	BTN

Plurinational State of Bolivia	BOL
Bosnia Herzegovina	BIH
Botswana	BWA
Brazil	BRA
Belize	BLZ
British Indian Ocean Territories	IOT
Solomon Islands	SLB
British Virgin Islands	VGB
Brunei Darussalam	BRN
Bulgaria	BGR
Myanmar	MMR
Burundi	BDI
Belarus	BLR
Cambodia	KHM
Cameroon	CMR
Canada	CAN
Cabo Verde	CPV
Cayman Islands	CYM
Central African Republic	CAF
Sri Lanka	LKA
Chad	TCD
Chile	CHL
China	CHN
Christmas Islands	CXR
Cocos Islands	CCK
Colombia	COL
Comoros	COM
Mayotte	MYT
Congo	COG
Democratic Republic of the Congo	COD
Cook Islands	COK
Costa Rica	CRI
Croatia	HRV
Cuba	CUB
Cyprus	CYP
Czechoslovakia	CSK
Czechia	CZE
Benin	BEN
Denmark	DNK
Dominica	DMA
Dominican Republic	DOM
Ecuador	ECU
El Salvador	SLV
Equatorial Guinea	GNQ
Former Ethiopia	ETH
Ethiopia	ETH
Estonia	EST
Falkland Islands (Malvinas)	FLK
Fiji	FJI
Finland	FIN
France, Monaco	FRA
French Polynesia	PYF

French South Antarctic Territories	ATF
Djibouti	DJI
Gabon	GAB
Georgia	GEO
Gambia	GMB
State of Palestine	PSE
Germany	DEU
Former Democratic Republic of Germany	DDR
Former Federal Republic of Germany	DEU
Ghana	GHA
Gibraltar	GIB
Kiribati	KIR
Greece	GRC
Greenland	GRL
Grenada	GRD
Guam	GUM
Guatemala	GTM
Guinea	GIN
Guyana	GUY
Haiti	HTI
Honduras	HND
China, Hong Kong Special Administrative Region	HKG
Hungary	HUN
Iceland	ISL
Indonesia	IDN
Iran	IRN
Iraq	IRQ
Ireland	IRL
Israel	ISR
Italy	ITA
Côte d'Ivoire	CIV
Jamaica	JAM
Japan	JPN
Kazakhstan	KAZ
Jordan	JOR
Kenya	KEN
Democratic People's Republic of Korea	PRK
Republic of Korea	KOR
Kuwait	KWT
Kyrgyzstan	KGZ
Lao People's Dem. Rep.	LAO
Lebanon	LBN
Lesotho	LSO
Latvia	LVA
Liberia	LBR
Libya	LBY
Lithuania	LTU
Luxembourg	LUX
China, Macao Special Administrative Region	MAC
Madagascar	MDG
Malawi	MWI
Malaysia	MYS

Maldives	MDV
Mali	MLI
Malta	MLT
Mauritania	MRT
Mauritius	MUS
Mexico	MEX
Other Asia, not elsewhere specified	N/A
Mongolia	MNG
Republic of Moldova	MDA
Montenegro	MNE
Montserrat	MSR
Morocco	MAR
Mozambique	MOZ
Oman	OMN
Namibia	NAM
Nauru	NRU
Nepal	NPL
Netherlands	NLD
Netherlands Antilles	ANT
Curaçao	CUW
Aruba	ABW
Saint Maarten (Dutch part)	SXM
Bonaire, Saint Eustatius and Saba	BES
New Caledonia	NCL
Vanuatu	VUT
New Zealand	NZL
Nicaragua	NIC
Niger	NER
Nigeria	NGA
Niue	NIU
Norfolk Islands	NFK
Norway, Svalbard and Jan Mayen	NOR
Northern Mariana Islands	MNP
Federated State of Micronesia	FSM
Marshall Islands	MHL
Palau	PLW
Pakistan	PAK
Panama	PAN
Papua New Guinea	PNG
Paraguay	PRY
Peru	PER
Philippines	PHL
Pitcairn	PCN
Poland	POL
Portugal	PRT
Guinea-Bissau	GNB
Timor-Leste	TLS
Qatar	QAT
Romania	ROU
Russian Federation	RUS
Rwanda	RWA
Saint Barthélemy	BLM

Saint Helena	SHN
Saint Kitts and Nevis	KNA
Anguilla	AIA
Saint Lucia	LCA
Saint Pierre and Miquelon	SPM
Saint Vincent and the Grenadines	VCT
San Marino	SMR
Sao Tome and Principe	STP
Saudi Arabia	SAU
Senegal	SEN
Serbia	SRB
Seychelles	SYC
Sierra Leone	SLE
Europe EFTA, not elsewhere specified	N/A
India	IND
Singapore	SGP
Slovakia	SVK
Viet Nam	VNM
Slovenia	SVN
Somalia	SOM
South Africa	ZAF
Southern African Customs Union	ZAF
Zimbabwe	ZWE
Spain	ESP
South Sudan	SSD
Sudan	SDN
Former Sudan	SDN
Suriname	SUR
Swaziland	SWZ
Sweden	SWE
Switzerland, Liechtenstein	CHE
Syria	SYR
Tajikistan	TJK
Thailand	THA
Togo	TGO
Tokelau	TKL
Tonga	TON
Trinidad and Tobago	TTO
United Arab Emirates	ARE
Tunisia	TUN
Turkey	TUR
Turkmenistan	TKM
Turks and Caicos Islands	TCA
Tuvalu	TUV
Uganda	UGA
Ukraine	UKR
The Former Yugoslav Republic of Macedonia	MKD
Former USSR	SUN
Egypt	EGY
United Kingdom	GBR
United Republic of Tanzania	TZA
USA, Puerto Rico and US Virgin Islands	USA

US Miscellaneous Pacific Islands	N/A
Burkina Faso	BFA
Uruguay	URY
Uzbekistan	UZB
Venezuela	VEN
Wallis and Futuna Islands	WLF
Samoa	WSM
Yemen	YEM
Serbia and Montenegro	SCG
Zambia	ZMB

Table 9: Countries in the sample