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The Evolution of the World Trade Web

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Abstract

This paper employs a weighted network analysis to study the empirical properties of the world trade web and their evolution over time. We show that most countries are characterized by weak trade links; yet, there exists a group of countries featuring a large number of strong relationships, thus hinting to a core-periphery structure. Also, better-connected countries tend to trade with poorly-connected ones, but are also involved in highly-interconnected trade clusters. Furthermore, rich countries display more intense trade links and are more clustered. Finally, all network properties are remarkably stable across the years and do not depend on the weighting procedure.

Keywords: Networks; World trade web; international trade; weighted network analysis; integration; trade openness; globalization.

JEL Classification: F10, D85.

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1 Introduction

This paper employs network analysis to study the statistical properties of the web of trade relationships among a large set of world countries in the period 1981-2000. We employ data on import and export flows to build, in each year, a network of links between pairs of countries, where each link is weighted by some proxy of the amount of trade flow that it carries. This enables us to apply novel statistical techniques developed in the framework of weighted network analysis and to characterize some robust stylized facts of international trade patterns.

In the last decades, a large body of empirical contributions have increasingly addressed the study of socio-economic systems in the framework of network analysis.[1] A network is a mathematical description of the state of a system at a given point in time in terms of nodes and links.

The idea that real-world socio-economic systems can be described as networks is not new in the academic literature (Wasserman and Faust, 1994). Indeed, sociologists and psychologists have been employing social network analysis since the beginning of the last century to explore the patterns of interactions established among people or groups (Freeman, 1996; Scott, 2000).[2]

More recently, however, the empirical study of networks has flourished thanks to the considerable contribution stemming from physics and computer science. Scholars from such academic disciplines have begun to extensively explore the statistical properties of technological, biological and information networks with new and more powerful statistical tools (Albert and Barabási, 2002; Dorogovtsev and Mendes, 2003; Newman, 2003; Pastos-Satorras and Vespignani, 2004). Fields of application here include – among others – the Internet and the WWW, peer-to-peer networks, power grids, train routes and airline connections, electronic circuits, neural networks, metabolism and protein interactions, and so on.

These new methods have been subsequently applied to social and economic systems (Watts, 1999). As a result, the idea that systems like markets, industries, or the world economy, might be considered as networked structures has become increasingly accepted also among empirical economists.

[1] A survey of this enormous literature is beyond the scope of this paper. The interested reader is referred to Scott (2000), Barabási (2003), Watts (2003), Carrington, Scott, and Wasserman (2005), among others.

[2] Well-known examples of such studies include networks of friendship and social acquaintances (Rapoport and Horvath, 1961; Milgram, 1967), marriages (Padgett and Ansell, 1993), and job-market interactions (Granovetter, 1974).

Furthermore, a network approach has been more recently employed to study international trade (Serrano and Boguñá, 2003; Li, Jin, and Chen, 2003; Garlaschelli and Loffredo, 2004a, 2005; Kastelle, Steen, and Liesch, 2005). Here the idea is to depict the web of trade relations as a network where countries play the role of nodes and a link describes the presence of an import/export relation between any two countries (and possibly the intensity of that flow).

What can a network approach add to our understanding of international trade? Standard statistical techniques treat import/export flows as features of single countries. By doing that, country exports or imports are considered the same way as other country-specific variables, like GDP, consumption or investment. However, import/export flows have to do with both the origin and the target country. A network approach is indeed able to disentangle variables related to how commodities and money flow across countries (through links) from those related to country-specific features. This allows one to recover the whole structure of the web of trade interactions among countries and to explore connections, paths and circuits. Once this world trade web (WTW) has been constructed, it is easy to apply standard network analysis techniques to assess the underlying topological properties of the WTW, its fine structure and the existing correlations between statistical distribution of flows and characteristics of nodes (countries). While standard statistics are only able to recover first-order trade relationships (e.g., import/exports between any two countries), network analysis permits to analyze second- and higher-order trade relationships. For example, one can study trade flows between any two (or more) countries that trade with a given one (i.e., trade relationships which are two-steps away) and to assess the length of trade chains occurring among set of countries.

Knowledge of such topological properties is not only important *per se* (e.g., because it enhances our descriptive knowledge of the stylized facts pertaining to the WTW), but it may also be relevant to better explain macroeconomic dynamics. As shown in Kali and Reyes (2007), the statistical properties of the world-trade networks are able to explain the dynamics of macroeconomic variables related to globalization, growth and financial contagion.

In this paper, we present a detailed study of the WTW for the period 1981-2000 using a weighted network approach. More precisely, from a purely descriptive perspective, we attempt to single out some robust stylized facts pertaining to trade relationships and their evolution over time. We are interested in answering the following questions: Are rich countries more connected than poor ones, in terms of the number and intensity of their trade relationships? Do well-connected countries entertain trade relationships with partners that are well-connected as well (i.e. have many and intense trade relationships)? How large is the likelihood that rich countries tend to trade with countries that preferentially trade only among them? Or, in other words, how large is the probability to find groups of rich countries that form trade clusters? Have the structural properties of the WTW been changing across time? Is the WTW more connected today than in the past (both in terms of number of connections and trade flows)? What has all that to do with the would-be process of globalization?

From a methodological point of view, we employ novel techniques that allow us to study the WTW as a weighted network.[3] Almost all the relevant literature on international trade networks has indeed studied a binary version of the WTW, where each directed link from country i to country j is either in place or not according to whether the trade flow from i to j is larger than a given threshold. On the contrary, we weight the importance of each directed link by using actual trade flows and GDPs.

As our results show, a weighted network analysis allows one to obtain very different conclusions as compared to a binary-network framework. Furthermore, our weighted-network results do not depend on the particular procedure and variables that one employs to weight the links.

More specifically, we find that the WTW is a strongly symmetric network, where the majority of trade relationships (and their intensities) are reciprocated. This implies that one can safely study the WTW as it were an undirected network (i.e., where the direction of links does not matter). Our weighted analysis indicates that weak trade relationships dominate for the vast majority of countries; yet, there exists a group of countries (identifying the core of the network) featuring a large number of strong relationships, thus hinting to a core-periphery structure. Furthermore, we show that better-connected countries tend to trade with poorly-connected ones but are also involved in relatively highly-interconnected trade triples. In addition, rich countries (in terms of their per capita GDP) tend to form more intense trade links and to be more clustered. These cliques are built along the lines of both connectivity and richness and can be seen as a sign of the persistent relevance of local relationships. However,

[3] The analysis of weighted networks was introduced in Barrat, Barthélemy, Pastor-Satorras, and Vespignani (2004); Barrat, Barthélemy, and Vespignani (2005); Barthélemy, Barrat, Pastor-Satorras, and Vespignani (2005), and further developed in Dall'Asta, Barrat, Barthélemy, and Vespignani (2006); Saramaki, Kivelä, Onnela, Kaski, and Kertész (2006); Onnela, Saramaki, Kertész, and Kaski (2005); DeMontis, Barthélemy, Chessa, and Vespignani (2005).

the growing importance of global links is testified by the disassortative feature of WTW: poorly connected nodes tend to connect to central ones and use them as hubs to access the rest of the network. Finally, all structural properties of the WTW display a remarkable stationarity across the years. The stability of the WTW structure suggests that international goods market integration has not increased dramatically over the last 20 years or, viewed from a different vantage point, that despite increased economic integration the core of the WTW has remained mostly unaffected.

The paper is organized as follows. In Section 2 we briefly introduce in a rather informal way the main concepts related to the empirical analysis of networks (more details are contained in Appendix A). Section 3 briefly surveys the relevant literature on international trade networks. Data are described in Section 4. We report our main results in Section 5. Finally, Section 6 concludes and discusses future work.

2 An Introduction to the Statistical Analysis of Weighted Networks

A socio-economic network is usually described by means of a graph, that is a collection of N nodes, possibly connected by a set of links.[4]

The simplest type of graph is binary and undirected. This means that any two nodes can be either connected by a link or not, and link directions do not count. If two nodes are connected, we say that they are "partners" or "nearest neighbors". Thus, links can be represented bi-directional arcs or edges, without arrows denoting the directions of flows. To formally characterize such type of networks, it is sufficient to provide the so-called adjacency matrix, i.e. a symmetric $N \times N$ binary matrix A whose generic entry $a_{ij} = a_{ji} = 1$ if and only if a link between node i and j exists (and zero otherwise).[5]

If the researcher has good reasons to justify her/his empirical analysis by using binary undirected networks (BUNs), the most immediate statistics is the *node-degree* (ND) distribution (and its moments). ND is simply defined as the number of links that a given node has estab-

[4]We refer the reader to Appendix A for more formal definitions and notation.

[5]Self-loops, i.e. links connecting i with itself are not typically considered. This means that $a_{ii} = 0$, for all i.

lished (i.e., how many connections it holds).[6] The shape of the ND distribution can convey a lot of information on the structural properties of a network. For example, BUNs that are created totally at random have unimodal, bell-shaped ND distributions.[7] On the contrary, the so-called scale-free networks (Barabási, 2003) are characterized by right-skewed (power-law) distributions, with a majority of small-ND nodes and a minority of large-ND nodes (i.e., the hubs).

If one is instead interested in a graph-wide measure of the degree of connectivity of the network, a simple way to proceed is to compute the *density* of the graph. The latter is defined as the total number of links that are actually in place divided by the maximum number of links that there can exist in an undirected graph with N nodes.[8].

The ND statistic only counts nodes that are directly linked with the one under analysis. However, any two nodes with the same ND can acquire a different importance in the network to the extent their partners are themselves connected in the network, i.e. if they also have a high ND. To measure how much the partners of node i are themselves very connected in the network, one may compute the *average nearest-neighbor degree* (ANND), that is the average of ND of all partners of i. Nodes with the largest degree and ANND are typically the ones holding the most intense interaction relationships.

A third important feature of network structure concerns the extent to which a given node is clustered, that is how much the partners of a node are themselves partners.[9] This property can be measured by the *clustering coefficient* (Watts and Strogatz, 1998; Szabó, Alava, and Kertész, 2005), that is the percentage of pairs of i's nearest neighbors that are themselves partners[10]. Node clustering is very important, as highly-clustered networks are typically characterized by a strong geographical structure, where short-distance links count more than long-distance ones.

So far, we have only considered binary networks, i.e. graphs where what counts is the mere presence or absence of an interaction between any two nodes. Many researchers have

[6]ND can be also also considered as a measure of centrality of a node in the network, as it can be maintained that the more connections a link has established, the more central it is in the network. More on that below.

[7]In random networks each link is in place with a certain given probability, independently on all the others.

[8]That is: one half the sum of all node degrees over $N(N-1)/2$

[9]Network clustering is a well-known concept in sociology, where notions such as "cliques" and "transitive triads" have been widely employed (Wasserman and Faust, 1994; Scott, 2000). For example, friendship networks are typically highly clustered (i.e. they display high cliquishness) because any two friends of a person are very likely to be friends.

[10]More formally, the clustering coefficient of i is given by the ratio between the number of triangles in the network with i as one vertex and the number of all possible triangles that i could have formed. If i has d_i nearest neighbors, this number is equal to $d_i(d_i-1)/2$.

argued, however, that the majority of socio-economic relationships also involve an assessment of how intense is an interaction between two nodes (if any). If one studies such relationships using a BUN approach, it is likely that a lot of important information will be disregarded (see Barrat, Barthélemy, Pastor-Satorras, and Vespignani, 2004, for an introduction). For example, the marriage network (Padgett and Ansell, 1993) can be reasonably studied in a BUN framework. Conversely, in many other networks like the internet, airline traffic, scientific citations, or the WTW, links are characterized by a non-reducible heterogeneity, due to the fact that different links can carry very different interaction flows (e.g., in terms of bytes exchanged, airline passengers, number of citations, export/import value, etc.). If we use a BUN, we run the risk of considering the same way links that instead carry very weak or very strong flows. In those cases, we need to move from a BUN perspective to a weighted (undirected) network (WUN) approach. A WUN is simply defined by means of a symmetric $N \times N$ "weight" matrix W, whose generic entry $w_{ij} = w_{ji} > 0$ measures the intensity of the interaction between the two nodes (and it is zero if no link exists between i and j).[11]

The three statistics above (degree, ANND, and clustering) can be easily extended to a WUN approach. For instance, ND can be replaced by node *strength* (NS) defined as the sum of weights associated to the links held by any given node. The larger the NS of a node, the higher the intensity of interactions mediated by that node. It is easy to see that, given the same ND, any two nodes can be associated to very different NS levels.

Since strength is only an aggregate measure of the interaction intensity mediated by a node, one can also measure the extent to which a node holds links associated with a very dispersed (resp. concentrated) weight profile. To do that, each node i can be associated with the Herfindahl strength concentration index, i.e. the standard Herfindahl concentration index applied to (normalized) weights associated to i's links. The index increases the more a node maintains many low-weight links together with a few high-weight links, i.e. the more across-weight disparity there exists.

One might assess how much the partners of a node are themselves characterized by a high strength by computing either the *weighted average of nearest-neighbor node degrees* (WANND, see Barthélemy, Barrat, Pastor-Satorras, and Vespignani, 2005) or the arithmetic *average of*

[11] Weights are often renormalized to meet the condition that $w_{ij} \in [0, 1]$, e.g. by dividing all original weights by $max\{w_{ij}\}$.

nearest-neighbor strengths (ANNS). Once again, any two nodes with the same ANND can end up having very different levels of ANNS or WANND.

Furthermore, one can straightforwardly compute a *weighted clustering coefficient* by suitably weighting each triangle using weights w_{ij} associated to its three edges (see Appendix A, and Fagiolo, 2007).

Another important notion in network analysis concerns the extent to which a given node is "central" in the graph. However, the meaning of "centrality of a node" is rather vague and has consequently generated many competing concepts and indicators (Scott, 2000). The two most commonly employed definitions of centrality refer to a local notion (a node is central if it has a large number of connections) or to a global notion (a node is central if it has a position of strategic significance in the overall structure of the network). Local centrality can be easily measured by node degree (in BUNs) or node strength (in WUNs). As far as global centrality in BUNs is concerned, the most used indicator is *node betweenness centrality* (BC), defined as the proportion of all shortest paths between any two nodes that pass through a given node. BC thus measures how much a given node acts as intermediary or gatekeeper in the network. It is easy to see that low-ND nodes, which are not locally central, can have a large BC, and therefore be globally central.

Despite its importance, BC is not straightforwardly extendable to WUNs. Therefore, in this paper, we build on recent works by Newman (2005) and Fisher and Vega-Redondo (2006), who have put forward a notion of centrality that nicely fits both BUN and WUN analyses. In a nutshell, they develop an index called *random walk betweenness centrality* (RWBC), which easily captures the effects of the magnitude of the relationships that each node has with its partners as well as the degree of the node in question. Newman (2005) offers an intuitive explanation of this centrality measure. Assume that a source node sends a message to a target node. The message is transmitted initially to a neighboring node and then the message follows a link from that vertex, chosen randomly, and continues in a similar fashion until it reaches the target node. The probabilities assigned to outgoing links can be either all equal (as in BUNs) or can depend on the intensity of the relationship (i.e., link weights in WUNs), so that links representing stronger ties will be chosen with higher probability.

Finally, notice that the "undirected" nature of both BUNs and WUNs approaches requires the matrices A and W to be symmetric. This implies that it is reasonable to assume that binary or weighted relationships are bilateral or reciprocal. However, the majority of interaction relationships that can be captured in network analyses are in principle directed (i.e., not necessary symmetric or reciprocal). For example, the presence/intensity of i's citations of j's work can be very different from j's citations of i's work. Similarly, exports from country i to country j in a given year (e.g., as a share of i's GDP) can be substantially higher or lower than exports from country j to country i (e.g., as a share of j's GDP). As discussed in Fagiolo (2006), deciding whether one should treat the observed network as directed or not is an empirical issue. The point is that if the network is "sufficiently" directed, one has to apply statistics that take into account not only the binary/weighted dimension, but also the direction of flows. As this analysis can often become more convoluted, one ought to decide whether the "amount of directedness" of the observed network justifies the use of a more complicated machinery. There can be several ways to empirically assess if the observed network is sufficiently symmetric or not (cf. Appendix A, and Garlaschelli and Loffredo, 2004b; Fagiolo, 2006). In many cases, networks that can be thought to be asymmetric turn out to appear sufficiently symmetric to justify a BUN/WUN approach (see also below for the WTW). If this happens, the common practice is to symmetrize the original observed network. In the case of BUNs, this means that every a_{ij} is replaced by $max\{a_{ij}, a_{ji}\}$, while in WUNs one replaces w_{ij} with $0.5(w_{ij} + w_{ji})$, see De Nooy, Mrvar, and Batagelj (2005).

3 Related Literature

The idea that international trade flows among countries can be conceptualized by means of a network has been originally put forth in sociology and political sciences. Most of this literature, however, did not address the study of trade networks by using a strategy rooted in the statistical analysis discussed in Section 2. Nevertheless, since the seminal paper by Snyder and Kick (1979), an increasing number of scholars have argued that relational variables are more relevant than (or at least as relevant as) individual country characteristics in explaining the macroeconomic dynamics ensuing from import-export patterns.

This strand of trade-network studies has been deeply influenced by the so-called "world system" or "dependency" theories, i.e. the notion that one can distinguish between core and peripheral countries.[12] In this view, core countries can appropriate most of the surplus value added produced by peripheral ones, which are thus prevented from developing.

For example, Snyder and Kick (1979) study the BUN stemming from aggregate data on trade relationships among 118 countries in 1965 and employ a core-periphery setup to classify countries in three groups (core, semi-core, and periphery). They obtain a clear-cut three-tiered structure for the network, with core countries nearly identified with OECD members. Regression analyses show that the position of a country in the network is able to explain GNP growth, a result interpreted as a sort of confirmation of dependency theories. The importance of network position in explaining growth and development from a core-periphery approach is also stressed by Nemeth and Smith (1985), who apply their analysis to 1970 data of trade flows disaggregated over 5 distinct product classes.[13] A similar approach is followed by Breiger (1981), who studies the composition of trade flows in 1972. Notably, he shows that country classification into blocks is not robust to the introduction of weighted links: if one employs a WUN, where link weights are defined as total trade flows (depurated by average imports and exports for that product class in order to account for size effects), two competing blocks emerge. The first one is dominated by the US (and comprises Canada and Japan), while the second accounts for the (then young and small) European Community. More recently, Smith and White (1992) explore in a dynamic framework the core-periphery approach to network analysis by comparing results in three different years (1965, 1970 and 1980). They document an enlargement of the core over time, a reduction of within-core variability, and a progressive marginalization of very peripheral countries. A binary, directed approach is instead followed by Kim and Shin (2002), who study three snapshots of trade flows (1959, 1975 and 1996) disaggregated over a large set of commodities for 105 countries. They employ 1m and 10m dollars cutoffs to decide if a directed link is present or not. Interestingly, they find that both the density of the network and the variance of ND distributions have increased through time, a result which is associated by Kim and Shin to the globalization process. Moreover, the creation of new links does not appear to be evenly distributed. Core countries are more likely to create outward links (i.e., to initiate an export link), while peripheral countries are more likely to create an inward link (i.e., to receive it), with Asian countries accounting for the majority of

[12]See also Schott (1986) for an application of the gravity model to the trade network.

[13]Sacks, Ventresca, and Uzzi (2001) build a measure of country position in the network based on the concept of "structural autonomy" and show that it has a positive effect on country's per capita GDP.

newly created links.[14] The effects of globalization are further explored by Kastelle, Steen, and Liesch (2005) who perform a binary network analysis on IMF data to test baseline hypotheses on the dynamics of the topological properties of the WTW. They study the period 1938-2003 and find that the evolution of the international trade network has not reached any steady state implying a fully-globalized pattern. Rather, the WTW has been slowly changing and seems to have the potential to continue to do so in the future.

The study of international trade as a relational network has been recently revived in the field of econophysics, where a number of contributions have explored the (notionally) complex nature of the WTW. The common goal of these studies – well in line with the strategy described in Section 2 – is to empirically analyze the mechanics of the international trade network and its topological properties, by abstracting from any social and economic causal relationships that might underlie them (i.e., a sort of quest for theory-free stylized facts). For instance, Serrano and Boguñá (2003) and Garlaschelli and Loffredo (2004a) study the WTW using binary undirected and directed graphs for a few snapshots taken from Gleditsch (2002) international-trade database. They show that the WTW is characterized by a disassortative pattern: countries with many trade partners (i.e., high NDs) are on average connected with countries with few partners (i.e., low ANNDs). Furthermore, partners of well connected countries are less interconnected than those of poorly connected ones, implying some hierarchical arrangements. In other words, a negative correlation emerges between CC and ND distributions. Remarkably, Garlaschelli and Loffredo (2005) show that this evidence is quite stable over time. This casts some doubts on whether economic integration (globalization) has really increased in the last 20 years. Furthermore, the ND distribution appears to be very skewed. This implies the coexistence of few countries with many partners and many countries with only a few partners. Serrano and Boguñá (2003) on one side and Garlaschelli and Loffredo (2004a, 2005) on the other investigate the ND distribution in more details, but while the former report evidence in favor of a power-law (and thus of some degree of complexity), the latter show that this is not actually the case, due to the presence of a sharp cutoff on the right tail of the distribution. Quite interestingly, Garlaschelli and Loffredo (2004a) also find evidence in favor of a hidden-variable model, according to which the topological properties of the WTW can be well explained by a

[14] Very similar results are obtained by Mahutga (2006), who shows that the globalization process has induced structural heterogeneity and thus inequality.

single node-characteristics (in this case country GDP) controlling for the potential ability of a node to be connected.

Both the sociology and the econophysics wave of contributions have had a little impact in the economics arena so far. The main skepticism resided in the fact that the majority of existing works have only aimed at providing another (albeit more powerful) way of *describing* trade patterns, but they have not succeeded in showing how these descriptions can help in *explaining* macroeconomics dynamics. To respond to this critique, a recent paper (Kali and Reyes, 2007) has shown that a country's position in the trade network (e.g., in terms of its node degree) has indeed substantial implications for economic growth and, also, has a good potential for explaining episodes of financial contagion. Furthermore, network position appears to be a substitute for physical capital but a complement for human capital. On the descriptive side, Kali and Reyes (2007) analyze the trade BUN using data from the COMTRADE-UN database and present evidence showing that global trade is still hierarchically structured, with a remarkable core-periphery structure, notwithstanding a recent increase in the degree of integration of small countries. Globalization and regionalization seem therefore to coexist, as trade patterns remain strongly determined by geographical proximity.

4 Data

From a methodological perspective, almost all contributions discussed above share two common key ingredients. First, the empirical analysis of the WTW is carried out using a binary approach. In other words, a link is either present or not according to whether the trade flow that it carries is larger than a given lower threshold.[15] To our knowledge, the only attempt to provide a weighted analysis is in Li, Jin, and Chen (2003).[16] They study a directed version of the WTW where each country is characterized by inward and outward strengths, equal to total imports and exports (as a share of world imports and exports). They explore the shape of such strength distributions, finding evidence in favor of a power-law form. However, the fine

[15]There is no agreement whatsoever on the way this threshold should be chosen. For example, Kim and Shin (2002) use cutoff values of US$ 1 million and 10 million. Kastelle, Steen, and Liesch (2005) endogenously set a cutoff so as to have, in each year, a connected graph. Kali and Reyes (2005) experiment with different lower thresholds defined as shares of country's total exports. On the contrary, other papers (Serrano and Boguñá, 2003; Garlaschelli and Loffredo, 2004a, 2005; Kali and Reyes, 2007) straightforwardly define a link whenever a non-zero trade flow occurs.

[16]See also Breiger (1981).

properties of the weighted network are not further investigated.

Second, the directed or undirected nature of the observed networks is not thoroughly addressed. In other words, a directed (or undirected) analysis is pursued without statistically assessing the underlying observed nature of the WTW. An exception is the paper by Garlaschelli and Loffredo (2005), who explore the conditions under which one can recover the directed character of a network from its undirected description. However, they fall short from providing a directed analysis using ad-hoc indicators (see for example Fagiolo, 2007).

In this paper, we address these two points in much greater detail. We employ international trade data provided by Gleditsch (2002) to build a sequence of weighted directed networks from 1981 to 2000. Original data report imports and exports from/to a large set of world countries for the period 1950-2000. The choice of the subperiod to be used in the study is driven by three related considerations. First, data for small countries suffer from many missing values, both on trade flow and GDP/population. Second, the number of countries for which we have trade data increases over the years. This might be a problem if one wants to analyze the dynamics of the topological properties of the WTW. Third, the country sample size must be as large as possible to achieve statistical significance. As a result, we decided to build a balanced panel by focussing on $T = 20$ years (1981-2000) and $N = 159$ countries (see Appendix B for more details).

For each country and year, data report trade flows in current US dollars. Whenever exports from country i to j do not match imports of j from i, we averaged the two figures. To build adjacency and weight matrices, we followed the flow of goods. This means that rows represent exporting countries, whereas columns stand for importing countries.

As to link weighting, we proceed as follows. First, in order to avoid any ambiguity stemming from the choice of a particular lower threshold, we define a "trade relationship" by setting the generic entry of the adjacency (binary) matrix $\tilde{a}_{ij}^t = 1$ if and only if exports from country i to country j (labeled by e_{ij}^t) are strictly positive in year t. Second, we note that the usual justification as to why one should not employ weighted trade links is that "it is not clear how these weights should be assigned" (Serrano and Boguñá, 2003). We therefore decided to experiment with a number of economically-meaningful weighting systems and explore the robustness of our results to these alternatives. Our baseline results will refer to weights defined as $\tilde{w}_{ij}^t = e_{ij}^t / GDP_i^t$, i.e. exports over GDP of the exporting country. This weighting procedure allows us to control for exporter country's size and tells us how economy i depends on economy j as a buyer (as j is buying from i). Furthermore, we check if our results change when we divide e_{ij}^t by the importing country's output (GDP_i^t). This can provide information on how economy j depends on economy i as a seller. Finally, we study what happens when we do not scale exports by GDPs and we just weight a link from i to j with exports e_{ij}^t.[17]

For any particular choice of the weighting setup, we end up with a sequence of $N \times N$ adjacency and weight matrices $\{\tilde{A}^t, \tilde{W}^t\}$, $t = 1981, ..., 2000$, which fully describe the evolution of the WTW from a binary and weighted directed perspective.[18]

5 Results

5.1 Global Properties of the WTW

We begin with a quick overview of some global properties of the WTW. From a binary perspective, the WTW appears to be a highly connected network, with an extremely high density, which has been slightly increasing over the years (cf. Figure 1). If one looks at the WTW as a binary directed network (BDN), it is easy to see that the majority of links are reciprocated. For instance, in the second half of the 90's, almost all countries export to partners that in turn export to them.

The almost-symmetric pattern of the WTW is statistically detected also by the S index studied in Fagiolo (2006), which for all years stays very close to zero for both the binary and the weighted version of the WTW, thus strongly testifying in favor of symmetry.[19] If any, the WTW seems to have become more symmetric during the years. This evidence indicates that a directed analysis is not necessary. Therefore, in what follows, we will explore the statistical properties of *symmetrized* versions of the WTW. This means that, in the binary case, any entry a_{ij} of the new adjacency matrix A is set to 1 if and only if either $\tilde{a}_{ij} = 1$ or $\tilde{a}_{ji} = 1$ (and zero otherwise). Accordingly, the generic entry of the new weight matrix W, originally defined as

[17]Notice that for a few small countries total exports are larger than GDP due to re-exports. In those cases we scale by total exports since some of the indicators we adopt require weights to lie in the unit interval.

[18]Of course, adjacency matrices $\tilde{A}^t$ can be recovered from the weight matrices $\tilde{W}^t$ by simply setting to one all non-zero elements of $\tilde{W}^t$.

[19]See Appendix A for the technical details. Note that the corresponding standardized index takes values at least 10 standard deviations below zero.

$\tilde{w}_{ij}^t = e_{ij}^t / GDP_i^t$, is replaced by:[20]

$$w_{ij}^t = \frac{1}{2}(\tilde{w}_{ij}^t + \tilde{w}_{ji}^t) = \frac{1}{2}(\frac{e_{ij}^t}{GDP_i^t} + \frac{e_{ji}^t}{GDP_j^t}). \quad (1)$$

In order to have well-behaved weights, we also employ the convention of dividing all entries in W by their maximum value. This does not introduce any biases in our analysis and ensures that $w_{ij}^t \in [0, 1]$ for all (i, j) and t (Onnela, Saramaki, Kertész, and Kaski, 2005).

5.2 Connectivity

The first issue we address concerns the study of the shape of the degree and strength distributions. More specifically, we explore the extent to which countries are more or less connected (i.e., if they are more or less central in the WTW) both in terms of number of partners (ND) and interaction intensity (NS), and whether these patterns have changed through time.

To begin with, we note that ND distributions do not appear to be as skewed as expected (see Figure 2). In fact, they can hardly be proxied by lognormal or Pareto distributions. A power-law behavior is detected only in the middle of the distribution, as the sharp cutoff reported by Garlaschelli and Loffredo (2005) is present. Remarkably, ND distributions display some bimodality: beside a modal value of 50-100 partners, there is a large group of countries that trade with almost everyone else (hence a second peak around 150). This evidence is more pronounced in the middle of the period. Note also that the shape of the ND distribution remains quite stable over time. Figure 3 displays the time evolution of the first four moments of the ND distribution: average ND has slightly increased over the years, meaning that trade relationships have been weakly but steadily growing during the observed time frame. Moreover, the standard deviation has remained stable, which suggests that integration has increased rather evenly, without resulting in any rise in the heterogeneity of NDs. This conclusion is reinforced by the reduction in both skewness and kurtosis that characterizes the last few years in the sample: the ND distribution has thus become more symmetric and the tails have thinned out to signify that fewer countries now display extreme ND values.

The picture substantially changes when we measure connectivity and centrality in the

[20] Due to the extreme symmetry of the network, results do not change if one symmetrizes the export matrix first and then divides by the GDP of the exporting country.

weighted undirected version of the network (i.e., when links are associated to their weight w_{ij}^t, see eq. 1). The distribution of NS among countries is now much more lognormal than before, see Figure 4, even though in the right tail (high strengths) there seems to be many more countries than a lognormal model would predict. Furthermore, bimodality disappears: strength distributions are more left-skewed, with the majority of countries holding weak trade relationships.

The structural difference between degree and strength distributions can be better appreciated by looking at how the degree-strength correlation varies through time. As Figure 5 (left) shows, this correlation is significantly larger than zero and quite stable around 0.5. This means that *on average* countries with many trade partners tend to hold also more intense trade relationships. However, as shown by the degree-strength scatter plot for 2000, the strength variability for any given degree level is quite high (Figure 5, right). This implies that only a subset of those countries holding many trade relationships (high ND) actually have a very high strength.[21] This is confirmed by average node disparity (i.e. Herfindhal concentration index), which is relatively high for high-degree nodes (not shown). Notice also that the weak increase in ND is not matched by a similar behavior for average NS, which remains quite stable in the period 1981-2000 (Figure 6, left panel). Interestingly, average strength is relatively low (at least in a [0,1] scale) as compared to the relatively high average degree. Finally, the observed drop of skewness and kurtosis of ND distributions does not have a counterpart as far as NS is concerned (compare Figure 3 and 6, right panels). Since this phenomenon is mainly concentrated in the 1990s, it seems to suggest that the recent wave of globalization resulted in an increased number of connections, but did not have any sizable effect on their magnitude. In terms of NS there are many more countries in the tails (namely the left tail) of the distribution, which is also much more skewed than in the case of ND.

This first set of results allows us to make an important methodological point (more on that below). If the study of the WTW is carried out from a BUN perspective, thus loosing a lot of information, one runs the risk of getting a misleading picture of the underlying relational patterns. A weighted network perspective, instead, allows one to better appreciate how the intensity of the interaction structure is distributed across the population.

[21] As the right panel of Figure 5 shows, there seems to be a subset of countries featuring low ND and relatively high strength.

5.3 Assortativity

The foregoing results suggest that the WTW, if viewed as a BUN, is a relatively strongly connected and dense network. On the contrary, if we give weights to these trade links, the picture changes completely: the WTW, now viewed as a WUN, is characterized by relatively weak and more dispersed trades.

Degree and strength statistics, however, are only first-order indicators. In other words, they just take into account links to one-step-away partners and do not convey any information on the finer structure of the WTW. Indeed, it may well happen that countries holding many links only trade with poorly-connected countries (we call such a network "disassortative"). Conversely, it may be the case that better connected countries also tend to trade with other well-connected countries (i.e., an "assortative" network).

In order to explore assortativity in the WTW, let us begin with a BUN perspective and study the behavior of average nearest-neighbor degree (ANND), and how it correlates with other network statistics. As expected, ANND is very high and quite stable in the period considered (Figure 7, left). Average ANND weakly increases from 110 to 120 and stays always above the average degree. However, the degree-ANND correlation pattern clearly indicates a strongly disassortative network: correlation figures are very close to -1 and their magnitude increases over time (Figure 7, right). In the WTW viewed as a BUN, countries that hold many trade relationships definitely trade with poorly-connected countries. This results confirms previous findings by Serrano and Boguñá (2003) and Garlaschelli and Loffredo (2004a).

If the WTW is now studied as a WUN, its disassortative nature remains evident but results are much weaker. As Figure 8 shows, population-averages of both weighted average nearest-neighbor degree (WANND) and average nearest-neighbor strength (ANNS) are quite stable over time and mimic the behavior of degree and strength. However, their correlation with degree and strength is still negative but weaker in magnitude in all years (Figure 9). This means that countries holding a lot of trade relationships do not tend to establish very intense trade links with all their partners. Again, the study of the WTW from a WUN perspective is able to offer a more insightful picture.

The disassortative nature of the WTW implies that countries that are less and more weakly connected tend to form trade relationships with well and more intensively connected countries (i.e., the hubs). This feature is relevant, since it suggests that the WTW has a core-periphery structure not only in terms of existing links, but also in terms of their intensity (as measured by their weights).

To further investigate this property, we plot correlation patterns of ANND, WANND and ANNS vs. node degree and strength. As Figure 10 shows for year 2000, the ANND-ND correlation presents a very limited variability. Conversely, both the WANND-ND and the ANNS-NS scatter plots are characterized by a much more dispersed cloud of points. In particular, there seems to exist a not negligible number of medium/high-degree or medium/high-strength countries that, despite the overall disassortativity, tend to trade with countries that are themselves more and better connected. This seems to support the hypothesis that, within the core-periphery structure of the WTW, there exists an intermediate periphery that is well connected to high degrees nodes (and trades heavily with them).

5.4 Clustering

We now turn to exploring clustering patterns, and their relations with connectivity. This entails asking whether more and better connected countries tend to build trade relationships with pairs of countries that themselves trade with each other (they are partners and/or they hold more intense relations).

Figure 11 (left) shows the behavior of the average CC for the BUN description of the WTW. Average CC is very high in all years. Furthermore, it is always larger than network density (cf. Figure 1). Since in a completely random graph the expected CC is equal to network density, this result implies that the WTW (viewed as a BUN) is statistically more clustered than if it were random. Therefore, countries tend to form – on average – trade relationships with partners that also trade with each other. This sort of "cliquishness" suggests that regional or local ties still play a very relevant role, where localism does not not necessarily have a geographic meaning, but can very well be read as a tendency to interact with traditional partners.[22] These can be members of a regional group, countries with similar degree of development, or simply partners that are historically close.

Does this result hold also when we take into account that trade relationships may be very

[22]This interpretation is further corroborated by the fact that typically highly-clustered networks are characterized by a strong "geographical" structure whereby short-distance links count more than long-distance ones.

heterogeneous in their intensity? The answer is no. Indeed, the weighted version of the CC, albeit quite stable over time, is very low. Moreover, it is significantly smaller (from a statistical point of view) than its average value in a random graph, see Figure 11 (right).[23] Thus, from a weighted perspective, the WTW is poorly clustered on average. Out of the network jargon, this implies that there is some heterogeneity within each group or clique of countries, consistently with the idea of the existence of a prominent center acting as an hub.

If one looks at the correlation between clustering and degree/strength, a similar mismatching emerges. Indeed, as found also by Serrano and Boguñá (2003) and Garlaschelli and Loffredo (2005), countries that hold more trade partners (high degree) are less clustered than those holding few partners. The correlation is very strong and negative, as it is close to -0.96 throughout the whole period (Figure 12, left panels). From a BUN perspective, thus, a core-periphery, star-shaped trade network seems to be in place. Countries that hold a small number of trade relationships do not trade with each other but are connected to the hubs. Again, if one takes into account the actual trade intensities associated to these connections, the conclusion is reversed (Figure 12, right panels). The correlation between the weighted CC and strength is now positive, statistically-significant, and sharply increasing across time. Therefore, countries with high-intensity trade relationships are typically involved in highly-interconnected triples, a pattern that somewhat reminds the "rich club phenomenon" (where "richness" is now interpreted in terms of intensity of trade relationships). Although the overall clustering level is not significantly larger than zero, the fact the the magnitude of the CC-strength correlation is increasing through time suggests that the "rich club phenomenon" continues to be an issue for international trade.

5.5 WTW Properties and Country Wealth

An interesting issue to explore concerns the extent to which network-specific indicators correlate with country wealth. For example, do countries with a higher per-capita GDP (pcGDP) maintain more and stronger trade relationships? Are the rich more clustered? To answer these questions, we study the correlation patterns existing between our network-specific measures (degree, strength, clustering coefficients) and country pcGDP.

[23] In a random graph the expected value of weighted clustering equals $\frac{27}{48}$ of network density; see Appendix A for the details.

As far as degree and strength are concerned, the outcomes are very clear: there seems to be a relatively high and persistent positive correlation between connectivity levels and pcGDP (Figure 13). This is generally true both in terms of the number of trade partners a country holds and in terms of the intensity of its trade interactions. However, the correlation strength-pcGDP appears to be stronger than the degree-pcGDP one.[24] Therefore, richer countries tend to hold more, and more intense, trade relationships.

Results for clustering-pcGDP correlations mimic instead those obtained for the correlation between clustering and degree/strength. Richer countries tend to be less clustered from a BUN point of view, while they are more clustered (and increasingly so over the years) from a weighted perspective (Figure 14). This result seems to support the "rich club phenomenon" interpretation discussed above. The fact that this correlation is increasing over the years suggests that cliquishness among richer countries has been augmenting such that, as long as the strength of trade relations is concerned, further integration for the overall network can be attributed to stronger ties among advanced countries.

5.6 Centrality

So far we have treated nodes as if they were anonymous, not considering which countries display higher or lower network properties. Now we address the role each country plays in the WTW by means of a measure of *centrality*. By doing so, we will be able to explicitly characterize the core and the periphery of the network, whose existence is hinted at by our results, and to compare them.

We compute *random walk betweenness centrality* (RWBC, see Section 2 and Appendix A) for each of the countries in the sample and use the results to classify them as part of the core and or of the periphery. It turns out that – due to the high density that characterizes the WTW – the binary version of RWBC is almost perfectly correlated with ND[25]: as a result, in what follows we will focus only on the weighted version of RWBC. A second reason to look at weighted RWBC only is that so far weighted indicators seem to give a better representation of the network structure, and in particular to hint more directly to a core-periphery structure.

[24] Also the shape of the underlying relation is different. While degree seems to be linearly related to pcGDP, a log-log relation holds between strength and pcGDP. This means that pcGDP influences more heavily strength than it does with degree.

[25] The correlation between the two indicators is not statistically different from 1.

Figure 15 presents the distribution of weighted RWBC for 1981, 1990, and 2000. The observed patterns have not changed over time and are indeed very similar to those characterizing node strength (see Figure 4): the distributions are heavily skewed to the right, confirming the hypothesis of a clear-cut core-periphery structure. To identify the countries actually belonging to the core we (arbitrarily) impose a threshold at the 95th percentile of RWBC: hence, only countries with a value of centrality within the top 5% are considered core.[26] Table 2 displays the 8 countries forming the core between 1981 and 2000. Interestingly, this simple information turns out to be very powerful in describing the evolution of international trade integration in the last two decades of the XXth century, and can actually trace a number of relevant economic episodes. For instance, unification allows Germany to overcome Japan in this special ranking and gain the second place, whereas the dissolution of Soviet Union marked the exit from the core, as Russia (which took its place in the sample) never comes close to reaching the first 5% of the sample. Moreover, the 1981 peak in oil prices that followed the second shock and the beginning of the Iran –Iraq war results in Saudi Arabia being briefly included into the core, though it drops quickly out of it and further away in the following years as the price of crude oil drops down.

More recently, the increasing importance acquired by Asian countries - most notably China, but also South Korea - in international trade is captured by our centrality index. Both countries have become part of the core in 2000, after having been close to achieve this already in 1995. Other Asian countries such as Malaysia, India and (above all) Thailand have experienced a remarkable increase in their RWBC over the last twenty years. On the contrary, Latin American countries (i.e., another classical group of emerging markets) did not manage to climb the ranking as fast as their Asian counterparts. For instance, Brazil displays a very stable measure of centrality, whereas Mexico and Argentina are characterized by wide fluctuations both in the absolute value of the RWBC index and in the relative position in the ranking. Among Latin American countries only Chile and, to a lesser extent, Colombia do appear to improve their status within the WTW network, although they have remained quite peripheral.

Finally, the analysis of the correlation between per capita GDP and node betweenness centrality reveals a similar pattern to that observed for the relationship between node strength

[26] A very similar result is obtained if one attributes the core status to those countries displaying values of RWBC above the mean plus one standard deviation.

and pcGDP.[27] Figure 16 shows that the relation between RWBC and pcGDP is very stable over time and attains values around 0.50.

5.7 Robustness

All results obtained so far refer to a particular weighting procedure. To recall, each directed link from node i to j is weighted by total exports of country i to country j and then divided by the country i's GDP (i.e., the exporter country). Such a weighting setup allows one to measure how much economy i depends on economy j as a buyer.

Are our findings robust to alternative weighting schemes? To address this issue, we consider the two alternative setups discussed in Section 4. In the first setup, we still remove size effects from trade flows, but we now divide by the GDP of the *importer* country (j's GDP, in the above example). In the second setup, we retain the size effect and we simply define the weight of link (i, j) as total exports from i to j.

All our main results are surprisingly robust to all these alternatives.[28] This is an important point, as a weighted graph analysis might in principle be sensible to the particular choice of the weighting procedure.

As an illustration, Figure 17 reports the correlation structure between ANNS, clustering, node strength and pcGDP across years.[29] Left panels refer to the first alternative weighting scheme (exports scaled by importer GDP) whereas right panels shows what happens under the second alternative setup (no GDP scaling at all). All previous results are confirmed. Notice that if we do not scale exports, an even stronger correlation emerges in all years between weighted clustering and strength.

6 Concluding Remarks

In this paper, we have begun to explore the statistical properties of the world trade web (WTW) in the framework of empirical network analysis. Following a stream of recent literature

[27]This is expected since one of the interpretations of node strength is related to the degree of influence that a given node has on the network or to what extent other nodes depend on a given node; also, the correlation between RWBC and NS is very high.

[28]As mentioned, we have also experimented with another weighting scheme where we have symmetrized the graph before dividing by exporter (or importer) GDP. All these alternatives did not result in any significant change of our main findings.

[29]More detailed results are available from the authors upon request.

we have conceptualized the web of trade relationships across world countries as a weighted network where countries play the role of nodes, and trade flows are represented by links between nodes. To that end, we have studied imports/exports flows between all pairs formed out of 159 countries, from 1981 to 2000.

From a methodological point of view, our paper is the first one – to our best knowledge – to address a thorough empirical investigation of the statistical properties of the WTW as a *weighted* network. This means that instead of accounting for the mere presence/absence of a trade relationship between any two countries, we estimate the intensity of any trade relationship by some function of the value of import/export flow carried by that link. Our results show that a weighted analysis can deliver more precise insights as far as the topological structure and statistical properties of the WTW are concerned. Indeed, many findings obtained by only looking at the number of trade relationships that any country maintains are completely reversed if one takes into account the relative intensity of trade links. Furthermore, we show that all our main results do not dramatically change if one experiments with different link weighting schemes.

From a descriptive point of view, this paper can be considered as an attempt to single out some robust stylized facts pertaining to the evolution of the WTW topological structure. As compared to standard international-trade statistical investigations, network analysis allows the researcher to explore not only first-order phenomena associated to import-export patterns of any given country (e.g., the degree of openness to trade) but also second- and higher-order empirical facts concerning, for example, the extent to which highly connected countries tend to trade with highly connected countries, the likelihood that trade partners of highly connected countries are themselves parters, and so on.

Our statistical exercises show that the WTW is an extremely symmetric network, where almost all trade relationships tend to be reciprocated with similar intensities. This allows one to study the WTW as if it were a weighted *undirected* network.

Notwithstanding a very high density, the average strength of nodes is rather poor. Indeed the majority of countries holds mainly weak relationships, whereas only a selected core on nodes combine high degree and high strength. This hints to a core-periphery (scale-free) structure for the weighted WTW. This insight is confirmed by the finding regarding the "disassortative" nature of the WTW: our data show that countries holding many (and more intense) trade relationships preferably trade with poorly-connected countries.

Furthermore, while the average number of trade relationships has increased through time, their average intensity has remained quite stable. More generally, all structural properties of the WTW display a remarkable stationarity across the years. This stability implies that trade integration has not increased dramatically over the last 20 years or, in other words, that its change has not had a significant impact on the structure of the WTW. A possible explanation is that trade integration has been steadily growing since the 1950s and the bulk of it had been achieved before the period under consideration here.

We also find that the WTW, viewed as a binary directed network, is highly clustered. Moreover, countries that hold more trade partners (high degree) are less clustered than those holding few partners. These conclusions are completely different when we account for the importance of each link. Indeed, the weighted version of the WTW displays a very weak clustering level and countries with high-intensity trade relationships are typically involved in highly-interconnected trade triples.

Finally, we have studied the relationships between network properties and country wealth. We have shown that richer countries tend to form more (and more intense) trade links and to be more clustered (and increasingly so over the years).

As mentioned, this work is an admittedly preliminary step towards a better understanding of the topological properties of the WTW and its dynamics. The agenda of interesting issues to address in the future is therefore quite rich. Firstly, one would like to explore in more details the topological properties of the WTW, both cross-sectionally and time-series. Meaningful questions here concern the role of geographical proximity in shaping the structure of international trade, the degree of fragility of the network, and so on. Furthermore, trade flows could be disaggregated across product classes to explore how trade composition affects network properties.

Secondly, one could abstract from aggregate statistical properties and analyze at a finer level the role of single countries in the network structure. For instance, how does the dynamics of degree, strength, clustering, etc. behave for single relevant countries in different World regions? Do country-specific network indicators display the same time-stationarity of their aggregate counterparts?

Finally, more in line with Kali and Reyes (2007), one can ask whether the topological properties of the WTW, viewed as a weighted network, are able to explain the macroeconomic dynamics of growth and development.

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Appendix A: Statistical Analysis of Binary and Weighted Networks

Preliminaries

In this appendix, we present some more formal definitions of the statistics introduced in Section 2 for both binary and weighted networks, and we provide a compact matrix-notation useful to compute them (see also Albert and Barabási, 2002; Newman, 2003; Fagiolo, 2007, for an introduction).

Consider a notionally-directed and possibly weighted network composed of N nodes. Let $\tilde{W} = \{\tilde{w}_{ij}\}$ be a $N \times N$ weight matrix (not necessarily symmetric), where $\tilde{w}_{ij} \in [0,1]$ and $\tilde{w}_{ii} = 0$ for all i. The binary case will imply that $\tilde{w}_{ij} \in \{0,1\}$. We assume that a directed link from i to j exists if and only if $\tilde{w}_{ij} > 0$. The adjacency $N \times N$ matrix $\tilde{A} = \{\tilde{a}_{ij}\}$, where $\tilde{a}_{ij} \in \{0,1\}$, is thus defined from $\tilde{W}$ by letting $\tilde{a}_{ij} = 1$ iff $\tilde{w}_{ij} > 0$ (and zero otherwise).

In what follows, we will also define $X_{(i)}$ as the i-th row of matrix X; $X^{[k]}$ as the matrix obtained from X by raising to k each entry; and $\frac{\{\mathbf{u}\}}{\{\mathbf{v}\}}$ as the vector obtained by dividing the two vectors entry by entry.

Checking for Symmetry

To check if an empirically-observed weighted network W is sufficiently symmetric to justify an undirected analysis, we employ the index developed in Fagiolo (2006). The index is based on the following idea. If a network is symmetric then any norm of the (suitably normalized) difference between $\tilde{W}$ and $\tilde{W}^T$ (i.e., its transpose) should vanish.

To build the index, define, without loss of generality:

$$Q = \{q_{ij}\} = \tilde{W} - (1 - \tilde{W})I_N, \tag{2}$$

where I_N is the $N \times N$ identity matrix. Notice that $q_{ij} = \tilde{w}_{ij}$ for all $i \neq j$, while now $q_{ii} = 1$ for all i[30].

Consider then the square of the Frobenius (or Hilbert-Schmidt) norm:

$$\|Q\|_F^2 = \sum_i \sum_j q_{ij}^2 = N + \sum_i \sum_{j \neq i} q_{ij}^2, \tag{3}$$

where all sums (also in what follows) span from 1 to N. The index used to check for symmetry is defined as:

$$\widetilde{S}(Q) = \frac{\|Q - Q^T\|_F^2}{\|Q\|_F^2 + \|Q^T\|_F^2} = \frac{\|Q - Q^T\|_F^2}{2\|Q\|_F^2} = \frac{1}{2}\left[\frac{\|Q - Q^T\|_F}{\|Q\|_F}\right]^2. \tag{4}$$

It is easy to see that:

$$\widetilde{S}(Q) = 1 - \frac{\sum_i \sum_j q_{ij} q_{ji}}{\sum_i \sum_j q_{ij}^2}. \tag{5}$$

Furthermore, the scaled version of $\widetilde{S}(Q)$

$$S(Q) = \frac{N+1}{N-1}\widetilde{S}(Q), \tag{6}$$

ranges from 0 (full symmetry) to 1 (full asymmetry). In order to use the index as a statistically-sound check for symmetry, let us suppose that entries in $\tilde{W}$ are independently and identically distributed as a uniform random variable defined in the unit interval. In that case, one can find coefficients $(m_B(N), s_B(N))$, which depend both on N and on the binary (B) vs. weighted (W) nature of the underlying graph (i.e. of $\tilde{W}$), such that

[30] The need for recovering self-loops is only required to have an index which is strictly increasing in the degree of asymmetry of the underlying graph, see Fagiolo (2006) for details.

$$S_B(Q) = \frac{S(Q) - m_B(N)}{s_B(N)} \tag{7}$$

$$S_W(Q) = \frac{S(Q) - m_W(N)}{s_W(N)} \tag{8}$$

are distributed as a standardized Normal random variable. This can help one in assessing the extent to which an empirically-observed binary/weighted graph is directed or not. Positive (respectively, negative) values of the standardized index (e.g., $k = 1, 2, ...$ standard deviations away from zero) would suggest that the graph is directed (respectively, undirected).

Notice that, in the case the notionally-directed graph $\tilde{W}$ turns out to "look" as an undirected graph, common practice calls for a symmetrization of binary/weighted links. In the case of binary graph, we will let:

$$A = \{a_{ij}\} = max\{\tilde{a}_{ij}, \tilde{a}_{ji}\}, \tag{9}$$

whereas if the graph is weighted we define:

$$W = \{w_{ij}\} = \frac{1}{2}(\tilde{w}_{ij} + \tilde{w}_{ji}). \tag{10}$$

Binary Undirected Networks, BUNs

Let us suppose that the underlying graph is binary and undirected and let A be its adjacency matrix.

The degree of node i (or node degee, ND) is defined as

$$d_i = \sum_j a_{ij} = A_{(i)}\mathbf{1}, \tag{11}$$

where $\mathbf{1}$ is the N-vector made of all ones.

Similarly, the average nearest-neighbor degree (ANND) of node i reads:

$$annd_i = d_i^{-1} \sum_j a_{ij} d_j = d_i^{-1} \sum_j \sum_h a_{ij} a_{jh} = \frac{A_{(i)} A \mathbf{1}}{A_{(i)} \mathbf{1}}. \tag{12}$$

Finally, node i's clustering coefficient (CC), defined as the ratio of the number of triangles with i as one vertex, to the maximum number of triangles that node i could have formed given its degree (Fagiolo, 2007), is equal to:

$$C_i(A) = \frac{\frac{1}{2} \sum_{j \neq i} \sum_{h \neq (i,j)} a_{ij} a_{ih} a_{jh}}{\frac{1}{2} d_i (d_i - 1)} = \frac{(A^3)_{ii}}{d_i (d_i - 1)}. \tag{13}$$

Notice that in a random graph where links are in place, independently of each other, with a probability $p > 0$, the expected value for the CC is equal to p.

Weighted Undirected Networks, WUNs

Let us now assume that the underlying graph is weighted and undirected and let W be its weight matrix.

Firstly, node strength of i is defined as :

$$s_i = \sum_j w_{ij} = W_{(i)}\mathbf{1}. \tag{14}$$

Furthermore, the average nearest-neighbor strength (ANNS) of i is computed as the arithmetic mean of strengths of i's neighbors as follows:

$$anns_i = d_i^{-1} \sum_j a_{ij} s_j = d_i^{-1} \sum_j \sum_h a_{ij} w_{jh} = \frac{A_{(i)} W \mathbf{1}}{A_{(i)}\mathbf{1}}. \tag{15}$$

Similarly, the weighted average of nearest-neighbor degrees (WANND) of i reads:

$$wannd_i = s_i^{-1} \sum_j w_{ij} d_j = s_i^{-1} \sum_j \sum_h w_{ij} a_{jh} = \frac{W_{(i)} A \mathbf{1}}{W_{(i)}\mathbf{1}}. \tag{16}$$

Sometimes, it is also useful to define "node disparity" among (concentration of) i's weights as follows:

$$h_i = \frac{(N-1)\sum_j \left(\frac{w_{ij}}{s_i}\right)^2 - 1}{N-2} = \frac{(N-1)\frac{1}{s_i^2}\sum_j w_{ij}^2 - 1}{N-2} = \frac{(N-1)\frac{W_{(i)}^{[2]}\mathbf{1}}{(W_{(i)}\mathbf{1})^2} - 1}{N-2} \tag{17}$$

As far as the weighted version of the CC for WUNs is concerned, we focus here on the extension of the CC to WUNs originally introduced in Onnela, Saramaki, Kertész, and Kaski (2005):

$$\tilde{C}_i(W) = \frac{\frac{1}{2}\sum_{j\neq i}\sum_{h\neq(i,j)} w_{ij}^{\frac{1}{3}} w_{ih}^{\frac{1}{3}} w_{jh}^{\frac{1}{3}}}{\frac{1}{2} d_i(d_i-1)} = \frac{(W^{[\frac{1}{3}]})^3_{ii}}{d_i(d_i-1)}, \tag{18}$$

where we define $W^{[\frac{1}{k}]} = \{w_{ij}^{\frac{1}{k}}\}$, i.e. the matrix obtained from W by taking the k-th root of each entry. As discussed in Saramaki, Kivelä, Onnela, Kaski, and Kertész (2006), the index $\tilde{C}_i$ ranges in $[0,1]$ and reduces to C_i when weights become binary. Furthermore, it takes into account weights of all edges in a triangle (but does not consider weights not participating in any triangle) and is invariant to weight permutation for one triangle. The expected value of the weighted CC in a random graph where links are in place, independently of each other, with a probability $p > 0$, is equal to $(\frac{3}{4})^3 p$.

Random-Walk Betweenness Centrality (RWBC)

Suppose the underlying graph, interpreted as a current circuit, is a weighted undirected network and let W be its weight matrix and s the $N \times 1$ strength vector. Following Newman (2005) and Fisher and Vega-Redondo (2006), consider a generic node i for which we want to compute the RWBC and an impulse generated from node h (the source) and working its way to node k (the target). Let $f(h,k)$ be the "source" $N \times 1$-vector such that $f_i(h,k) = 1$ if $i = h$, $f_i(h,k) = -1$ if $i = k$, and 0 otherwise. Define by $v(h,k)$ the $N \times 1$-vector of node voltages. Newman (2005) shows that Kirchoff's law of current conservation implies that:

$$v(h,k) = [D - W]^{-1} f(h,k), \tag{19}$$

where $D = diag(s)$, where s is the node-strength vector, and $[D-W]^{-1}$ is computed using the Moore-Penrose pseudo-inverse.

This in turn implies that the current (i.e. intensity of interaction) flowing through node i, originated from h and getting to k, is given by:

$$I_i(h,k) = W \cdot |v(h,k) - \mathbf{1} v_i(h,k)|, \tag{20}$$

where W is the weight matrix, $I_h(h,k) = I_k(h,k) = 1$, and $\mathbf{1}$ is the conformable unit vector.

It is then straightforward to define node-i RWBC as:

$$RWBC_i = \frac{\sum_h \sum_{k \neq h} I_i(h,k)}{N(N-1)}. \tag{21}$$

Appendix B: Countries in the Balanced Panel (1981-2000)

The dataset provided by Gleditsch (2002) includes 196 countries for which there are data on trade flows from 1948 to 2000. However, trade data contain many missing (or badly reported) values before 1970. In addition, there are some countries with zero total exports in some years.

Notice also that our analysis requires to match trade data with real GDP (both in levels and per capita). This is because: (i) weights are defined as exports divided by GDP; (ii) one wants to cross-sectionally correlate network measures with country-specific variables like per-capita GDP.

We have therefore selected countries in such a way to have: (i) a time horizon and a country sample size as long as possible; (ii) no missing values in trade data and GDP (both in levels and per capita); (iii) non-zero total exports.

By applying conditions (i) and (ii) we get only 83 countries from 1960-2000. This number becomes 138 for the period 1970-2000; 152 for the period 1970-2000; 163 for the period 1981-2000; and 168 for the period 1990-2000. We thus decided to select the time interval 1981-2000 using 163 countries. However, 4 of them (San Marino, Andorra, Liechtenstein, Monaco) have total exports equal to zero in some years. This leaves us with N=159 countries, whose list is in Table 1.

Table 1: List of Countries in the Balanced Panel.

Id	Acro	Name	Id	Acro	Name	Id	Acro	Name	Id	Acro	Name	Id	Acro	Name	Id	Acro	Name
2	USA	United States	150	PAR	Paraguay	395	ICE	Iceland	520	SOM	Somalia	678	YEM	Yemen	910	PNG	Papua
20	CAN	Canada	155	CHL	Chile	402	CAP	Cape Verde	522	DJI	Djibouti	690	KUW	Kuwait	920	NEW	New Zealand
31	BHM	Bahamas	160	ARG	Argentina	403	STP	Sao Tome	530	ETH	Ethiopia	692	BAH	Bahrain	935	VAN	Vanuatu
40	CUB	Cuba	165	URU	Uruguay	404	GNB	Guinea-Bissau	540	ANG	Angola	694	QAT	Qatar	940	SOL	Solomon's
41	HAI	Haiti	200	UKG	United Kingdom	411	EQG	Eq. Guinea	541	MZM	Mozambique	696	UAE	Arab Emirates	950	FJI	Fiji
42	DOM	Dominican Rep.	205	IRE	Ireland	420	GAM	Gambia	551	ZAM	Zambia	698	OMA	Oman	970	KBI	Kiribati
51	JAM	Jamaica	210	NTH	Netherlands	432	MLI	Mali	552	ZIM	Zimbabwe	700	AFG	Afghanistan	971	NAU	Nauru
52	TRI	Trinidad/Tobago	211	BEL	Belgium	433	SEN	Senegal	553	MAW	Malawi	710	CHN	China	972	TON	Tonga
53	BAR	Barbados	212	LUX	Luxembourg	434	BEN	Benin	560	SAF	South Africa	712	MON	Mongolia	973	TUV	Tuvalu
54	DMA	Dominica	220	FRN	France	435	MAA	Mauritania	570	LES	Lesotho	713	TAW	Taiwan			
55	GRN	Grenada	225	SWZ	Switzerland	436	NIR	Niger	571	BOT	Botswana	731	PRK	North Korea			
56	SLU	Saint Lucia	230	SPN	Spain	437	CDI	Cote DIvoire	572	SWA	Swaziland	732	ROK	South Korea			
57	SVG	St. Vincent	235	POR	Portugal	438	GUI	Guinea	580	MAG	Madagascar	740	JPN	Japan			
58	AAB	Antigua	260	GFR	Germany	439	BFO	Burkina Faso	581	COM	Comoros	750	IND	India			
70	MEX	Mexico	290	POL	Poland	450	LBR	Liberia	590	MAS	Mauritius	760	BHU	Bhutan			
80	BLZ	Belize	305	AUS	Austria	451	SIE	Sierra Leone	591	SEY	Seychelles	770	PAK	Pakistan			
90	GUA	Guatemala	310	HUN	Hungary	452	GHA	Ghana	600	MOR	Morocco	771	BNG	Bangladesh			
91	HON	Honduras	325	ITA	Italy	461	TOG	Togo	615	ALG	Algeria	775	MYA	Myanmar			
92	SAL	El Salvador	338	MLT	Malta	471	CAO	Cameroon	616	TUN	Tunisia	780	SRI	Sri Lanka			
93	NIC	Nicaragua	339	ALB	Albania	475	NIG	Nigeria	620	LIB	Libya	781	MAD	Maldives			
94	COS	Costa Rica	345	YUG	Yugoslavia	481	GAB	Gabon	625	SUD	Sudan	790	NEP	Nepal			
95	PAN	Panama	350	GRC	Greece	482	CEN	Centr African Rep.	630	IRN	Iran	800	THI	Thailand			
100	COL	Colombia	352	CYP	Cyprus	483	CHA	Chad	640	TUR	Turkey	811	CAM	Cambodia			
101	VEN	Venezuela	355	BUL	Bulgaria	484	CON	Congo	645	IRQ	Iraq	812	LAO	Laos			
110	GUY	Guyana	360	RUM	Rumania	490	DRC	Congo (Zaire)	651	EGY	Egypt	816	DRV	Vietnam			
115	SUR	Surinam	365	RUS	Russia	500	UGA	Uganda	652	SYR	Syria	820	MAL	Malaysia			
130	ECU	Ecuador	375	FIN	Finland	501	KEN	Kenya	660	LEB	Lebanon	830	SIN	Singapore			
135	PER	Peru	380	SWD	Sweden	510	TAZ	Tanzania	663	JOR	Jordan	840	PHI	Philippines			
140	BRA	Brazil	385	NOR	Norway	516	BUI	Burundi	666	ISR	Israel	850	INS	Indonesia			
145	BOL	Bolivia	390	DEN	Denmark	517	RWA	Rwanda	670	SAU	Saudi Arabia	900	AUL	Australia			

Table 2: Countries in the core

1981	1985	1990	1995	2000
USA	USA	USA	USA	USA
Japan	Japan	Germany	Germany	Germany
Germany†	Germany†	Japan	Japan	Japan
UK	UK	France	France	France
France	France	UK	UK	UK
USSR	USSR	Italy	Italy	China
Italy	Italy	USSR	Belgium	Italy
Saudi Arabia	Netherlands	Netherlands	Netherlands	Korea

† Up to 1989 data refers to West Germany only.

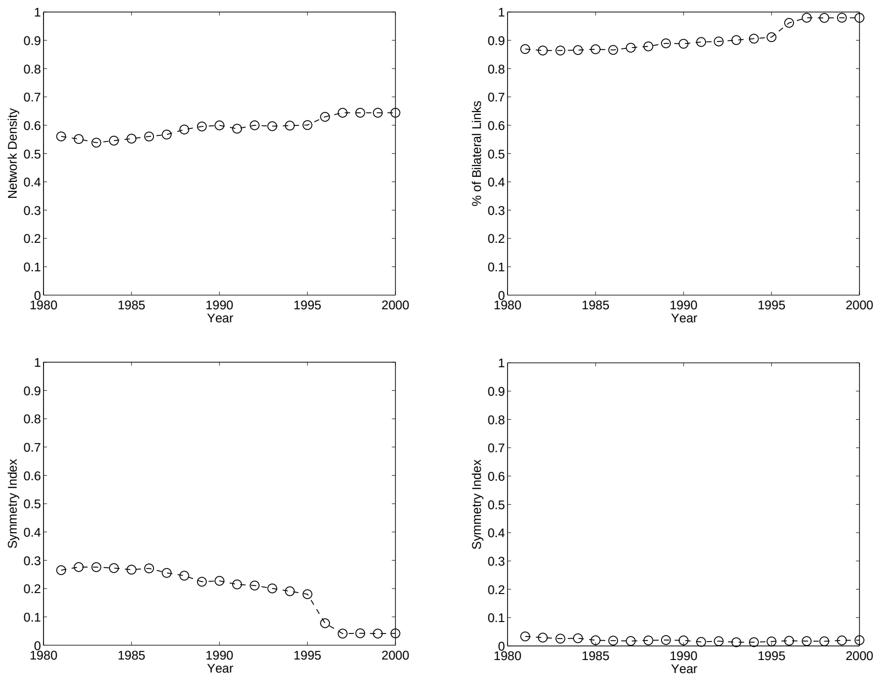
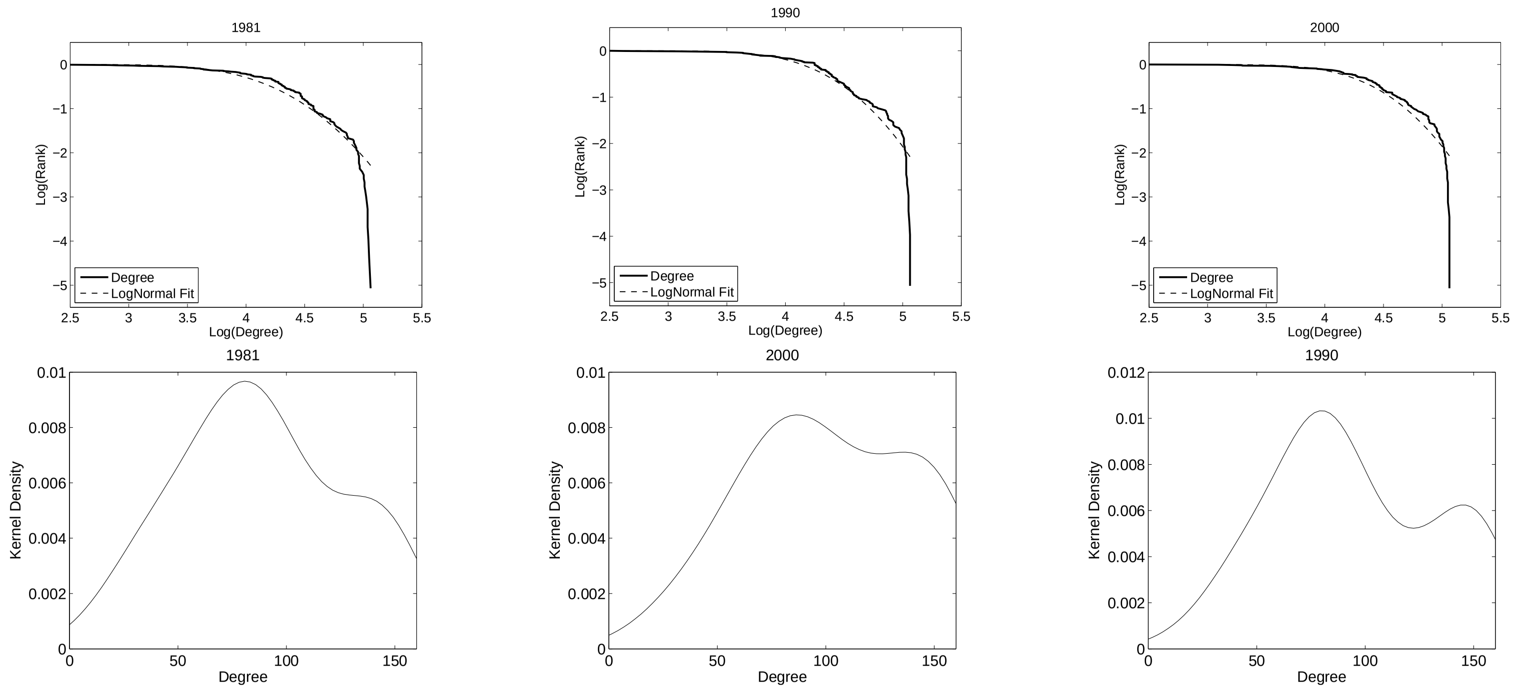


Figure 1: Global network indicators vs. years. Top-left: Network density. Top-right: Percentage of bilateral links. Bottom-left: S index (not standardized) for BUNs. Bottom-right: S index (not standardized) for WUNs.

Figure 2: The WTW as a BUN. Degree distributions in 1981, 1990, 2000. Top panels: Size-rank plots (dashed line: lognormal fit). Bottom panels: Kernel density estimates.



Note. Size-rank plots. X-axis: log of degree. Y-axis: Log of rank of x-axis observation.

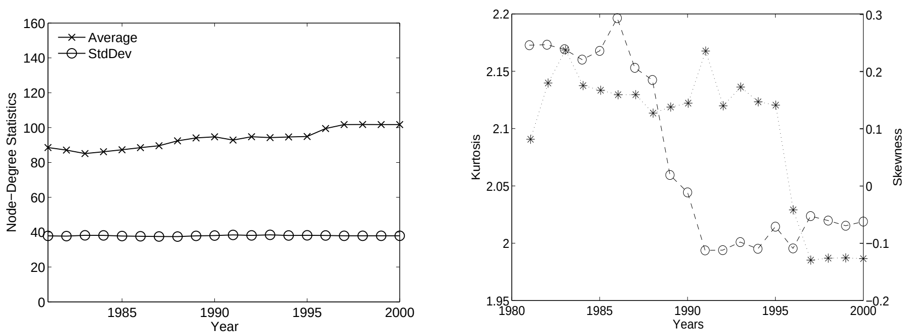
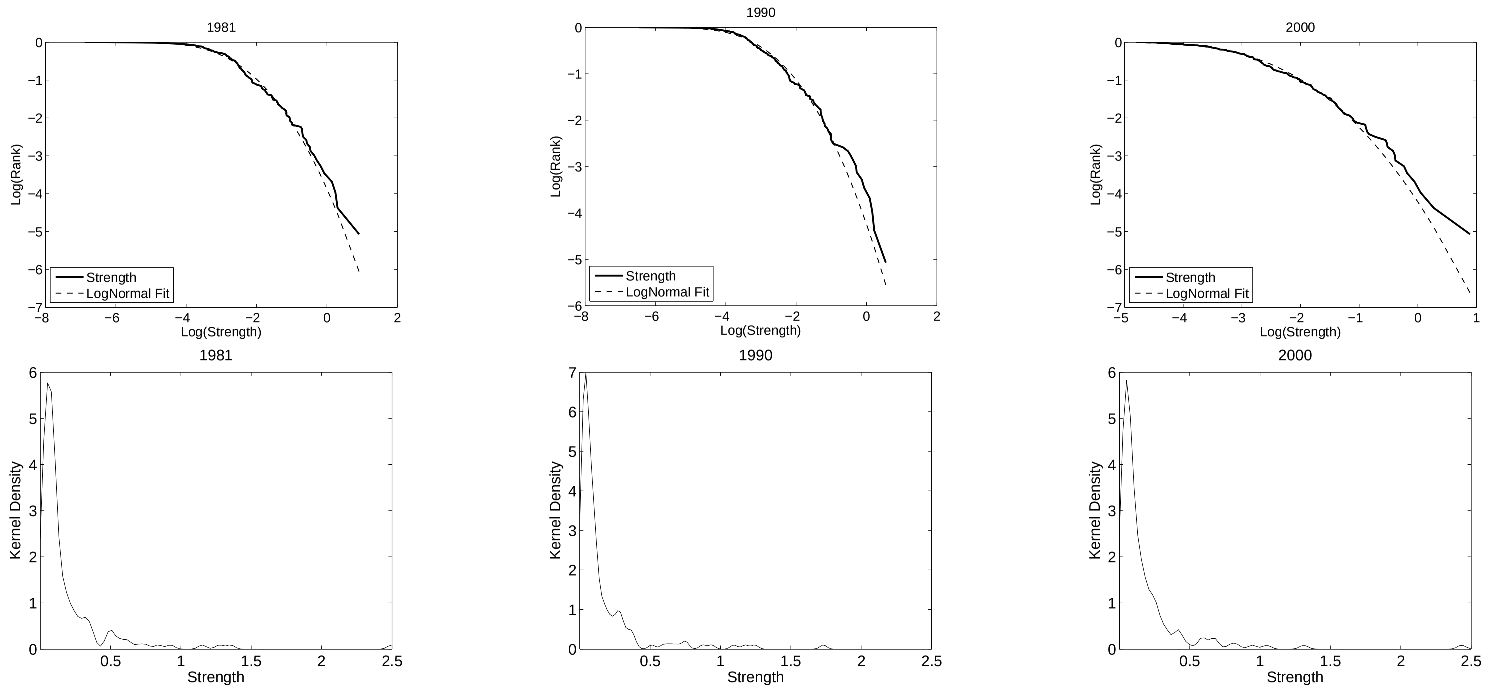


Figure 3: The WTW as a BUN. Left panel: Average and standard deviation of degree distributions. Right panel: kurtosis (circles) and skewness (asterisks) of degree distributions.

Figure 4: The WTW as a WUN. Strength distributions in 1981, 1990, 2000. Top panels: Size-rank plots (dashed line: lognormal fit). Bottom panels: Kernel density estimates.



Note. Size-rank plots. X-axis: log of strength. Y-axis: Log of rank of x-axis observation.

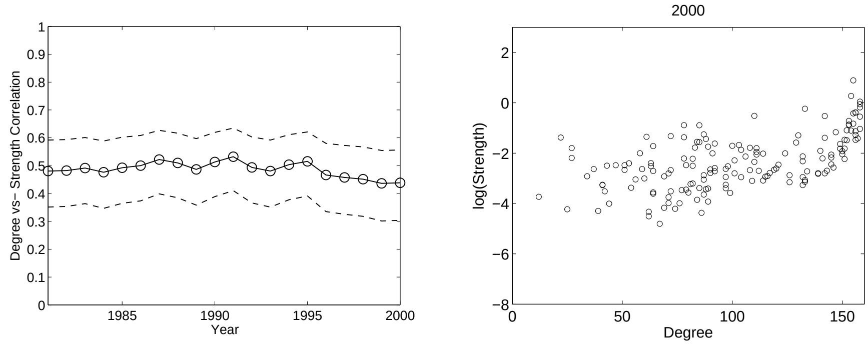


Figure 5: BUN vs. WUN. Left panel: Degree-strength correlation vs. years (dashed lines: 5% and 95% confidence intervals). Right panel: Degree-strength scatterplot in 2000.

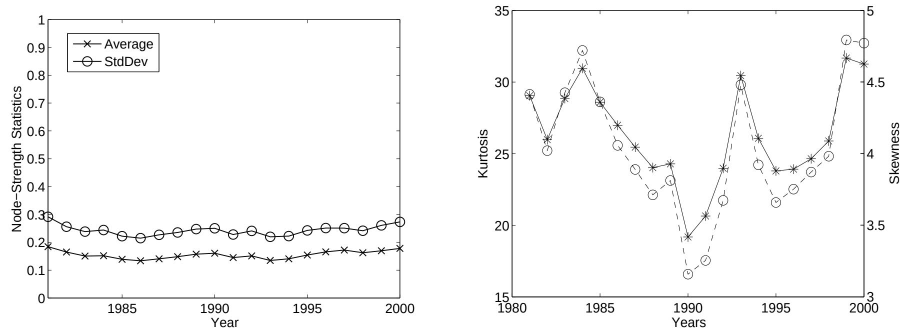


Figure 6: The WTW as a WUN. Left panel: Average and standard deviation of strength distributions. Right panel: kurtosis (circles) and skewness (asterisks) of strength distributions.

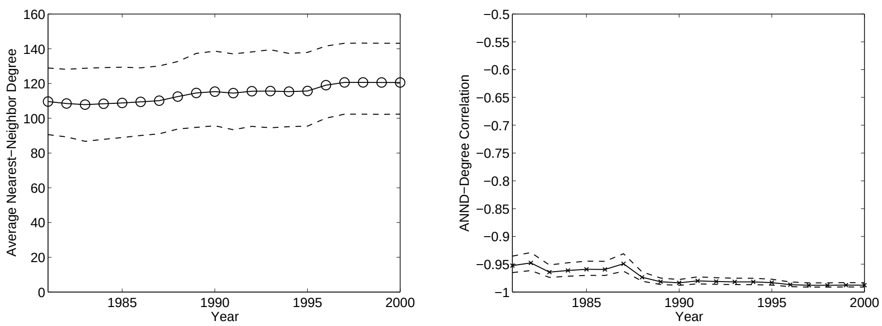


Figure 7: Average Nearest-neighbor degree (ANND). Left: Population average vs. years. Right: Correlation between (ANND) and degree vs. years. Dashed lines: 5% and 95% confidence intervals.

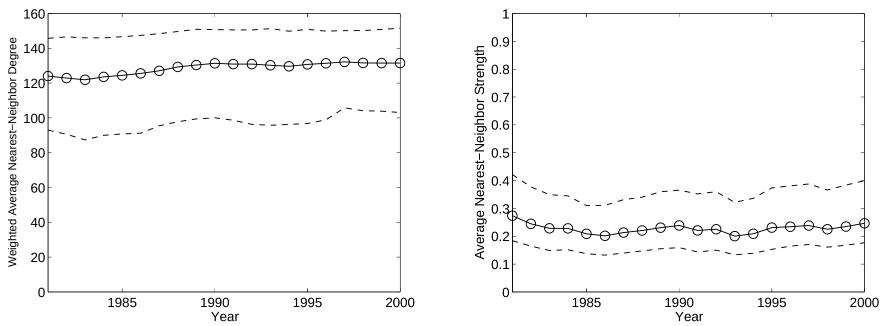


Figure 8: Left: Population-average of weighted average nearest-neighbor degree (WANND) vs. years. Right: Population-average of average nearest-neighbor strength (ANNS) vs. years. Dashed lines: 5% and 95% confidence intervals.

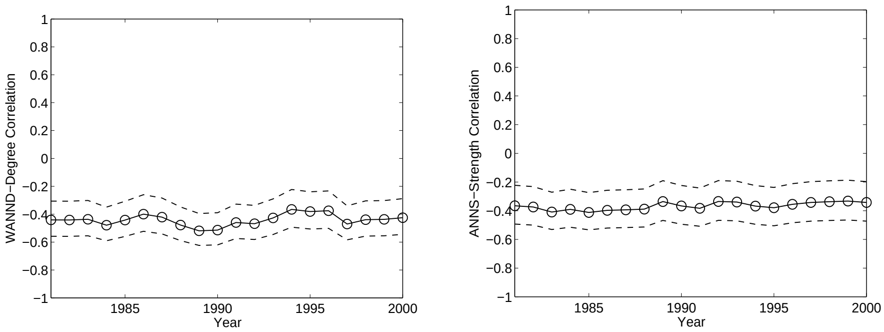


Figure 9: Left: WANND-degree correlation vs. years. Right: ANNS-strength correlation vs. years. Dashed lines: confidence intervals.

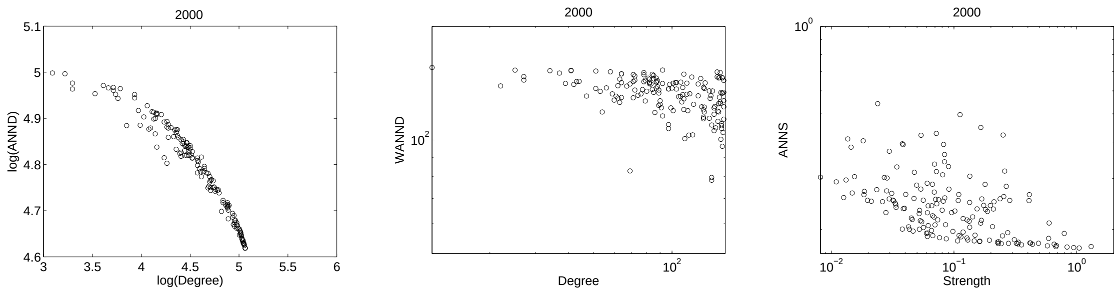


Figure 10: Left: ANND-degree scatter plot. Mid: WANND-degree scatter plot. Right: ANNS-strength scatter plot. Year: 2000.

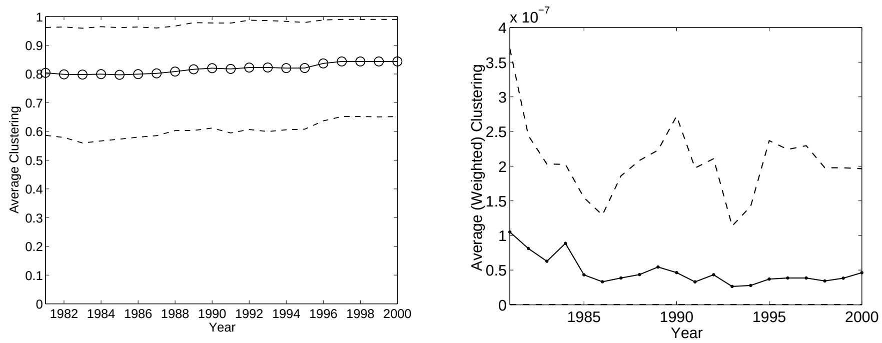


Figure 11: Left: Average of BUN (binary) clustering coefficient vs. years. Right: Average of WUN (weighted) clustering coefficient vs. years. Dashed lines: 5% and 95% confidence intervals.

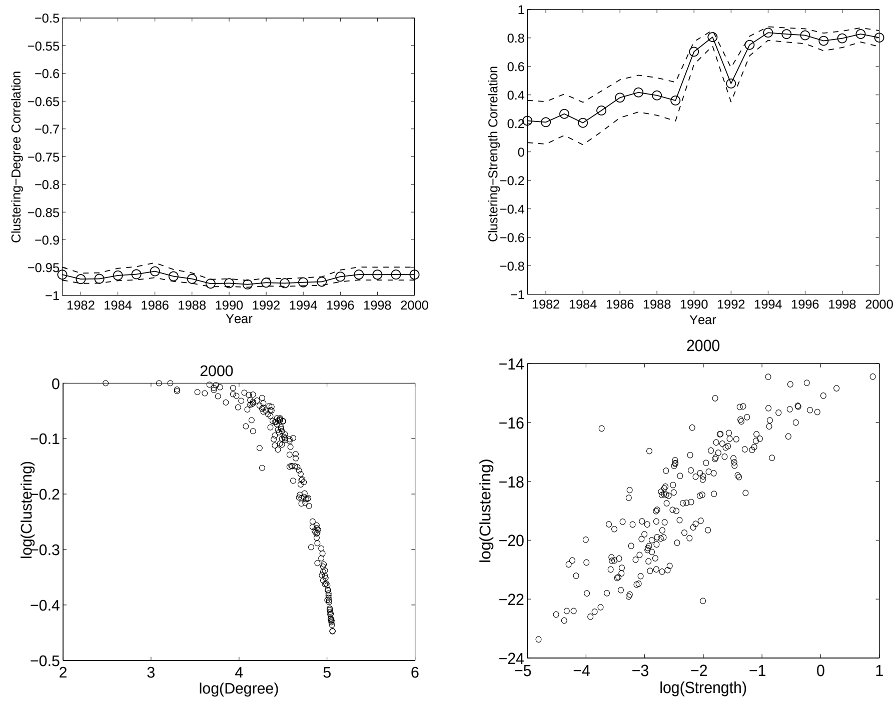


Figure 12: Top-left: Correlation between (binary) clustering coefficient and degree vs. years. Top-right: Correlation between (weighted) clustering coefficient and strength vs. years. Dashed lines: 5% and 95% confidence intervals. Bottom-left: Scatter plot of (binary) clustering coefficient and degree in year 2000. Bottom-right: Scatter plot of (weighted) clustering coefficient and strength in year 2000.

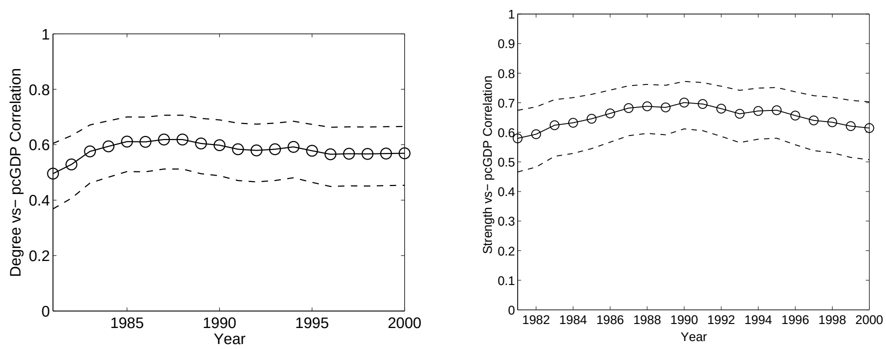


Figure 13: Correlation between degree-pcGDP and strength-pcGDP vs. years. Dashed lines: 5% and 95% confidence intervals.

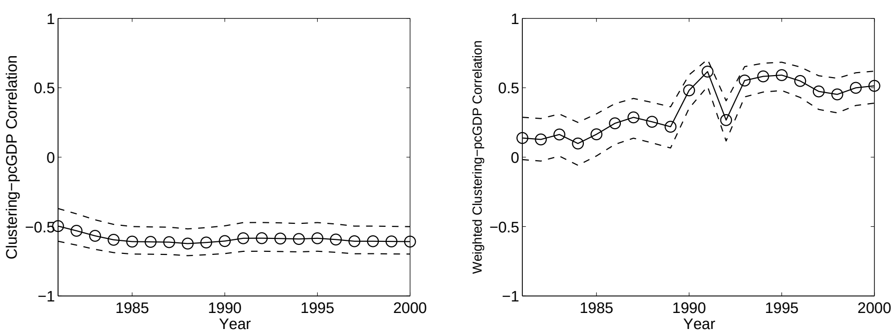
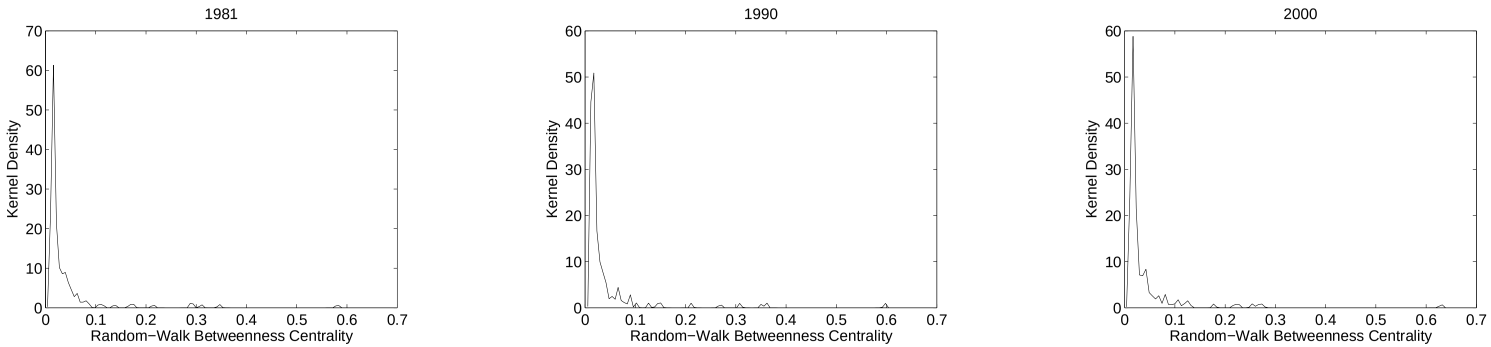


Figure 14: Left: Correlation between clustering and pcGDP in a BUN vs. years. Right: Correlation between clustering and pcGDP in a WUN vs. years. Dashed lines: 5% and 95% confidence intervals.

Figure 15: Random Walk Betweenness Centrality distributions in 1981, 1990, 2000: Kernel density estimates.



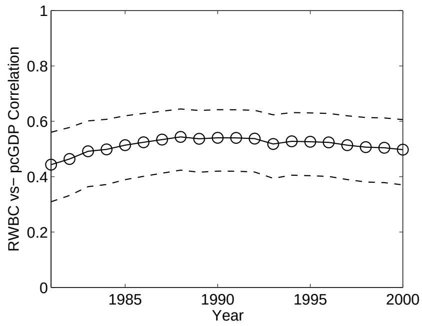


Figure 16: Correlation between Random Walk Betweenness Centrality and pcGDP. Dashed lines: 5% and 95% confidence intervals.

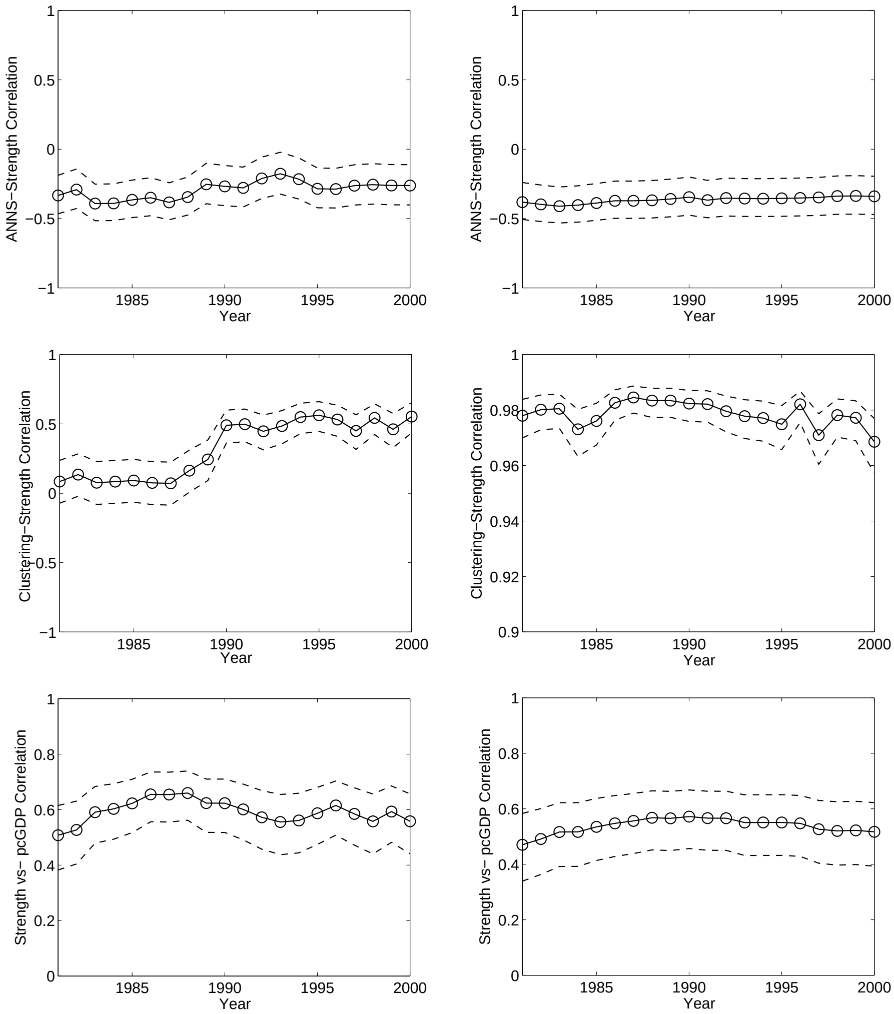


Figure 17: Alternative weighting schemes. Left panels: Exports divided by importer country GDP. Right panels: Exports not scaled by any country size measure. Top: Correlation between strength and ANNS vs. years. Mid: Correlation between clustering and strength vs. years. Bottom: Correlation between strength and pcGDP. Dashed lines: 5% and 95% confidence intervals.