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International Trade and Financial Integration: A Weighted Network Analysis

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International Trade and Financial Integration: A Weighted Network Analysis

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Abstract

In this paper we compare the patterns of trade and financial integration by exploiting network analysis. Our results show that, by combining binary and weighted network analysis, it is possible to deliver more precise and thorough insights on the topological structure and properties of the international trade and financial networks (ITN and IFN). We find that the ITN is more densely connected than the IFN and that the degree of international financial integration varies with asset type. Our results also indicate that richer countries are better linked and form groups of tightly interconnected nodes. This can be seen as a sign of the persistent relevance of local relations. Yet, the growing importance of global links is testified by the disassortative feature of both the ITN and the IFN: poorly connected nodes tend to connect to central ones and use them as hubs to access the rest of the network.

Keywords: International Trade, International Financial Flows, Globalization, Complex Weighted Networks, Dynamics.

JEL Classification: F10, F36, F40, G15.

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1 Introduction

This paper employs complex-network analysis to explore the dynamical patterns of international trade and financial integration. We are interested in investigating (i) whether rich countries are more connected than poor ones in terms of the number and intensity of their trade and financial relationships; (ii) whether well-connected countries entertain trade and financial relationships with partners that are well-connected as well (i.e. whether trade and financial centers are strongly connected among themselves or rather act as hubs to connect peripheral countries to the rest of the world); (iii) whether rich countries tend to trade or exchange mutual claims only with a restricted and relatively closed group of partners; (iv) which countries play the most central role in the trade and financial networks; (v) what has all that to do with the process of globalization.

In the last decades, a large body of empirical contributions has increasingly addressed the study of socio-economic systems in the framework of network theory. 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 bedescribed as networks is not new in the academic literature (Wasserman and Faust, 1994). Indeed, sociologists and psychologists have long been employing social network analysis to explore the patterns of interactions among people or groups.[1] A network approach has been more recently employed to study international trade (Serrano and Boguñá, 2003; Li, Jin, and Chen, 2003; Garlaschelli and Loffredo, 2004, 2005; Kastelle, Steen, and Liesch, 2006). Here the idea is to depict trade relations as a network where countries play the role of nodes and a link indicates the presence of an import/export relation between any two countries (and possibly the intensity of that flow).

A network approach enhances our understanding of international economics because it allows one to recover the whole structure of interactions among countries and to explore connections, paths and circuits. While standard statistics are only able to recover first-order relationships (e.g. import/exports intensity between any two countries), network

[1] 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).

analysis permits to analyze second- and higher-order 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 a set of countries. Knowledge of such topological properties is not only important *per se* (because it improves upon our descriptive knowledge of the stylized facts pertaining to international integration), but it may also be relevant to better understand macroeconomic dynamics. As shown in Kali and Reyes (2005, 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 extend the network approach to the study of international financial relationships. To the best of our knowledge, this is the first attempt in this direction; moreover, and this is the second contribution of the paper, we perform a detailed comparison between the international trade and financial networks (ITN and IFN henceforth). From a purely descriptive perspective, we attempt to single out some robust stylized facts characterizing the ITN and the IFN in order to assess similarities and differences in goods and financial markets integration.

A third important contribution of the paper is methodological, as we employ novel techniques that allow to study the ITN and the IFN as weighted networks (Barrat, Barthélemy, Pastor-Satorras, and Vespignani, 2004). Almost all the relevant literature on international trade networks has indeed studied binary versions of the graph where each 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 the actual amount of trade and asset holding. As our results show, a weighted network analysis allows one to obtain very different conclusions as compared to a binary framework. More specifically, we find that both the ITN and the IFN are symmetric, and the majority of relationships are reciprocated. The majority of countries hold (many) weak links; 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 central nodes tend to connect to peripheral ones but are also involved in relatively highly-interconnected trade triples. In addition, rich countries (in terms of their per capita GDP) form more intense trade links and tend to be more clustered.

The paper is organized as follows: Section 2 gives a brief overview of network analysis, while Section 3 reviews the relevant empirical literature both on network analysis and on financial integration. After a presentation of the data (Section 4), we discuss our results in Section 5. Finally, Section 6 draws some conclusions and offers suggestions for future research.

2 Methodology

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[2].

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". 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).[3]

The most immediate statistic in binary undirected network (BUN) analysis is *node-degree* (ND), which is simply defined as the number of links that a given node has established (i.e., how many connections it holds).

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 (half the sum of all ND) divided by the maximum number of links that there can exist in an undirected graph $(N(N-1)/2)$.

The ND statistics only counts nodes that are directly linked with the one under anal-

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

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

ysis. However, any two nodes with the same ND can acquire a different importance in the network according to whether their partners are themselves very 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.[4] This property can be measured by the *clustering coefficient* (CC), i.e. the percentage of pairs of i's nearest neighbors that are themselves partners. 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 argued, however, that the majority of socio-economic relationships also involve an assessment of how much 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. In many networks (the internet, airline traffic, scientific citations) links are characterized by a non-reducible heterogeneity, due to the fact that different links can carry very different interaction flows. If we use a BUN, we run the risk of considering as equivalent links that instead carry very different 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). The three statistics above (ND, ANND, and CC) 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

[4]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)

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.

To investigate the extent to which each node is characterized by links with homogenous strength, one can associate to each node an Herfindahl strength concentration index, which increases with the heterogeneity in the strength of its relations, i.e. the more across-weight disparity there exists. Furthermore, one can assess how many of the partners of a node display themselves high NS by computing the *average of nearest-neighbor strengths* (ANNS). Once again, any two nodes with the same ANND can end up having very different levels of ANNS. In order to extend the notion of clustering, one can straightforwardly compute a *weighted clustering coefficient* (WCC) by suitably "weight" each triangle using weights w_{ij} associated to its three edges (see Appendix A).

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 widely 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 the extent to which 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 easily 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 analysis. In a nutshell, they develop an index called *random walk betweenness centrality* (RWBC), which 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 an outgoing 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 BUN and WUN approaches requires the adjacency matrices A and W to be symmetric. However, the majority of interaction relationships that can be captured in network analyses are in principle directed (i.e., not necessary symmetric or reciprocal). 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 (see Fagiolo, 2006). If this happens, the common practice is to symmetrize the original observed network. In the case of BUN, this means that every a_{ij} is replaced by $max\{a_{ij}, a_{ji}\}$, while in WUN one replaces w_{ij} with $0.5(a_{ij} + a_{ji})$.

3 A Glance at the Existing Literature

3.1 Trade and networks

In sociology, there exists a rather long tradition of using social network analysis to investigate international trade relations. 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, with the former appropriating most of the surplus value added produced in the peripheral countries, which are thus prevented from developing. For instance Snyder and Kick (1979) use trade and other criteria to classify countries into one of three groups they identify (core, periphery and semi-periphery). Results for international trade yield a clear-cut three-tiered structure with core countries nearly identified by OECD membership. Breiger (1981) focuses on trade in 4 commodity classes rather than aggregated data. Core countries trade sophisticated industrial goods, while peripheral states trade commodities and row materials. Country classification changes quite a bit when data are weighted, with the emergence of two competing blocks, one dominated by the US (and comprising Canada and Japan) and the other represented by the then young (and much smaller) European Economic Community. Smith and White (1992) investigate the dynamics of the trade network by comparing trade flows in three years, 1965, 1970 and 1980. They document an enlargement of the core over time, a reduction of within-core distance and the progressive marginalization of very peripheral countries.

A couple of recent papers focus on the issue of globalization from a network perspective. Kim and Shin (2002) wish to discover the existence of a core/periphery setup focusing on asymmetric links: core countries are more likely to initiate a trade relation, while peripheral ones to receive it. Centralization has decreased over time, so that globalization seems not to be associated with the emerging of a dominant center, but at the same time the paper highlights that the variance of degrees goes up as globalization is not even and therefore generates more heterogeneity. Kastelle, Steen, and Liesch (2006) perform a binary network analysis over 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 has 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 complex nature of the ITN. Serrano and Boguñá (2003) study import and export flows for 179 counties in 2000 and report evidence of a scale-free degree distribution implying high heterogeneity among actors. There is also a large (0.65) correlation between the number of trade links and per capita GDP. The clustering coefficient depends strongly on the vertex's degree, thus suggesting a hierarchy in the network, a finding that is confirmed by the fact that the average nearest network degree (ANND) depends also on the vertex's degree. The power law distribution of ND is contested by Garlaschelli and Loffredo (2004), who on the other hand still find both disassortativity and hierarchy in the ITN (a clustering coefficient that is decreasing in ND).

Kali and Reyes (2005, 2007) make an important step toward the economic interpretation of network properties: they claim that a country's position in the ITN network has important implications in terms of economic growth and can also explain episodes of financial contagion. On the descriptive side Kali and Reyes (2007) also find that the ITN has a hierarchical structure, notwithstanding a recent increase in the degree of integration of small countries: globalization and regionalization seem therefore to coexist.

3.2 Financial integration

Another stream of literature that is deeply related with the issues discussed in the present paper tries to empirically assess international financial integration.

It must be noticed that a clear-cut consensus has not yet emerged on the actual notion of international financial integration, and above all on its empirical assessment: so for instance (Bekaert and Harvey, 2003, p. 4) claim that integration occurs only when *'assets of identical risk command the same expected return irrespective of their domicile'*. This implies that an expected return model is required to pursue a direct measure of financial integration. Entering this debate is beyond our scope, so in the present section we limit ourselves to report results from two broad groups of studies, the first using price-based indices of integration (therefore being closer to the definition given by Bekaert and

Harvey, 2003), the second measuring it by means of quantity-based indicators.

For what concerns the first group, Goldberg, Lothian, and Okunev (2003) claim that interest rate equalization is the most theoretically appealing definition of financial integration and the one granting the clearer interpretation since it is based on the law of one price. Therefore, to investigate whether financial integration has increased, they study the spreads on bond yields for all possible country pairs in a sample of 6 OECD countries. A more global perspective is taken by Baele, Ferrando, Hördahl, Krylova, and Monnet (2004) who tackle the issue of European financial integration by studying the cross-sectional dispersion of interest rate spreads and of asset returns across euro area members: in this way they manage to check for interest rate equalization on different markets simultaneously. These works tend to find that different market segments display different degrees of integration, while sharing a common tendency toward integration. Still, interest rate equalization is far from achieved even in the case of the EMU where the disappearance of exchange rate risk should have considerably reduced segmentation.

Moving to those studies using quantity-based measures, the presence of a significant home-bias in international portfolios tells that integration has still a long way to go, though the phenomenon is slowly reducing. Recently Milesi-Ferretti and Lane (2006) have adopted a number of quantity-based indicators to describe financial integration. These are derived from the ratios of foreign assets and liabilities over GDP. The ratios are in constant evolution and display a sharp increase since the mid 1990s.

Network analysis clearly belongs to the second family (quantity-based studies), and therefore provides only an indirect measure of integration. Nonetheless it has the additional benefit of bridging the gap between bilateral and multilateral studies. In fact, not only one can infer the total amount of foreign assets (liabilities) held by each country, but it is possible to study their geographical distribution. To gage the relevance of this feature, consider two countries with the same stock of foreign assets: it makes a big difference whether these assets are concentrated among a few partners or rather distributed across a wide range of issuing countries. In terms of network analysis, knowing simultaneously node strength and node degree can provide a better picture of financial integration with respect to standard analysis.

4 Data

Financial data are taken from the IMF Coordinated Portfolio Investment Survey (CPIS). The survey was conducted for the first time in 1997 when only 29 economies participated; it has since then been replicated 4 times in the years 2001–2004 to include 71 countries and five data groups: total assets, equities, and total debt, which is further broken down into long- and short-term debt. We focus our attention on data for the 2001–2004 period, which grant us a sufficiently large number of countries. Although this dataset does not allow one to track the evolution of the IFN over a long time span, it nonetheless provides us with interesting insights on the patterns of financial integration. The CPIS gives information on the amount of assets issued by all partner countries held by each of the 71 reporting countries participating to the survey. In the context of the BUN setup we start from original data and build an adjacency matrix with generic entry $a^t_{kij} = 1$ if at time t country i holds a positive amount of asset type k issued by country j.[5] When we turn to WUN, the generic entry w^t_{kij} represents the actual stock of assets k issued by country j, and held by country i at time t.

Trade data have been assembled from the UN Comtrade database with the target of building a comparable network covering the same period and roughly the same countries as the CPIS. A perfect matching was not possible to achieve, since the CPIS surveys a number of very small economies that are important financial centers (e.g. Cayman Islands, Jersey or Guernsey) but for which no trade data are available. Adjacency matrices are defined in exactly the same fashion as above, while weight matrices are built using average trade flows (more details below).

As reported in Appendix B, the actual sample of countries used to generate the ITN and the IFN varies by year: the number of nodes ranges between 64 and 61 in the case of trade, and between 65 and 61 for CPIS data.

[5]This includes also instances where a positive figure is censored, i.e. we know that cross-holding of that particular asset is positive but we ignore its magnitude.

5 Results

To begin with, we we tested for symmetry of the underlying graphs. First, we measured the proportion of bilateral links in the network. Second, we used a new index based on the difference between the adjacency matrix and its transpose (see Fagiolo, 2006). Results suggest that all networks are sufficiently symmetric not to require a directed analysis. This is easily verified in the case of the binary trade matrix where more than 96% of links are bilateral. Rather high percentages are found also in the case of financial data, with around 75% of connections being reciprocated.[6] For what concerns WUN analysis the asymmetry index is rather low and stable over the period under consideration, confirming that directed analysis is not called for.[7]

Therefore, in order to gage the strength of a trade link in the ITN, the generic weight entry w_{ij}^t is defined as the average between export from i to j and import by i from j (at time t).

Both the trade network and the finance network of total asset holdings have a rather high *density* (see table 1). In particular the ITN is almost fully connected; this is to say that countries in the sample have trade relations with almost everybody else. The percentage of existing links over the maximum possible number of relations reaches 98% for the ITN and ranges between 61% and 70% for the IFN. In this latter case the density of the network has increased between 2001 and 2004.

Table 1: Network density

	trade	total assets	equities	debt	long debt	short debt
2001	0.986	0.615	0.485	0.557	0.549	0.252
2002	0.984	0.631	0.489	0.572	0.564	0.274
2003	0.986	0.660	0.515	0.595	0.590	0.294
2004	0.991	0.692	0.556	0.626	0.614	0.308

Other asset classes display lower densities, in particular the network made up of short-term debt contracts has a density of 25–30% only. Cross-holding of equities is also less

[6]This figure refers to the network generated by total portfolio asset holdings. The minimum proportion of bilateral links (just above 50%) characterizes the IFN generated by short-term debt.

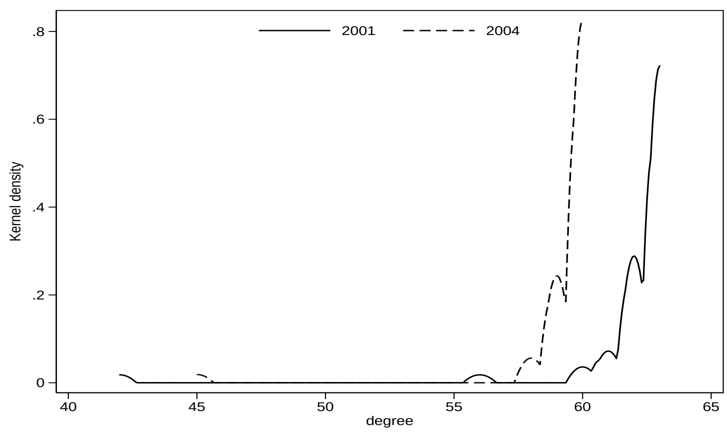
[7]The full set of results on symmetry is available upon request.

pervasive (48–56%), while long-term debt contracts are substantially more widespread. Also, the density of all financial networks has slightly increased during the period under scrutiny.

5.1 Connectivity

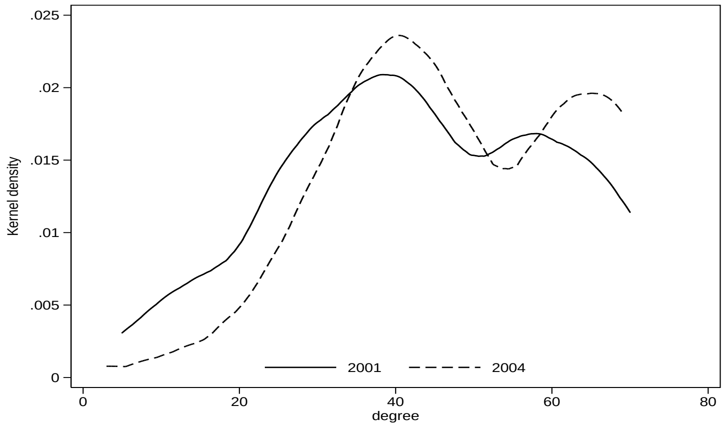
The mean and median ND is very high and stable for the ITN, lower but increasing for the IFN (both for total assets and for each asset class). Figure 1 and 2 display the distribution of node degree for the ITN and the IFN by means of a kernel density plot. The shape of the distributions does not change much over time, but is indeed very different for the two networks.

Figure 1: Degree, kernel density plot: trade



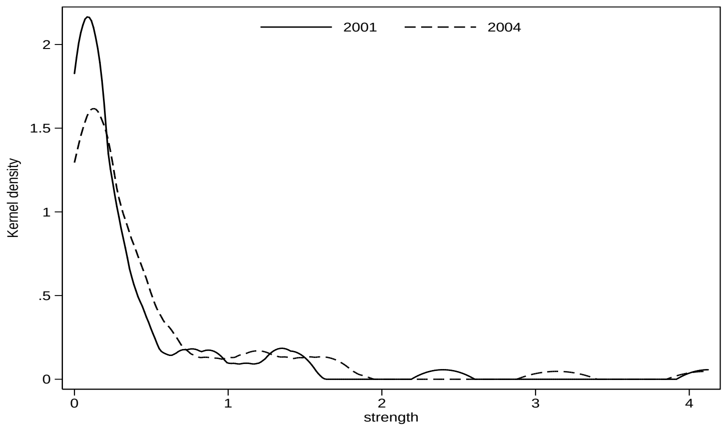
In the case of trade the vast majority of countries have a very large number of partners (due to data availability the maximum number of countries in the ITN is 64 in 2001 and 61 in 2004, which coincides with the mode of the distributions). Consistently with the fact that the network is almost fully connected, the degree distribution has most of the mass on the right tail, as nearly all countries trade with everybody else. For what concern the IFN, figure 2 shows a rather different picture: we see that the distribution of node degree displays some bimodality with a first peak around 40 and a second modal value at the right tail of the distribution. Such a behavior, which is more pronounced in 2004 than at the beginning of the period, suggests the existence of three groups of countries: an *elite* of countries connected with everybody else, a larger group of countries with average connectedness and a periphery of less connected economies.

Figure 2: Degree, kernel density plot: total assets



Comparing the distribution of ND in 2001 and 2004, one has the feeling that at least some peripheral countries have moved to the middle group, which has in fact enlarged its ranks: in 2004 the distribution is more concentrated around the central peak and the left-hand tail is thinner. Moreover, the coefficient of variation of node degree is smaller testifying for a lower dispersion. Yet, given the very short time span of our data, it is very difficult to assess whether this is the result of a temporary shock or a permanent shift.[8]

Figure 3: Strength, kernel density plot: trade

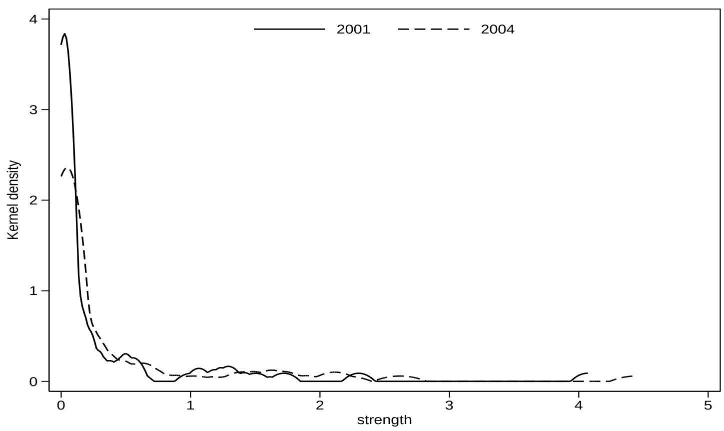


[8]Based on a Kolmogorov-Smirnov test it is not possible to reject the null hypothesis of the two distributions being equal.

The picture changes significantly when we move from BUN to WUN analysis and weight each link by its intensity. Figure 3 shows that the distribution of node strength for the ITN is no longer skewed on the left but rather on the right: a majority of countries holding many weak relationships coexists with a small number of them characterized by more intense links. This feature gets slightly reduced in subsequent years: in 2004 the peak is lower and more mass is distributed at higher values of strength.[9]

Something similar occurs in the case of the IFN (figure 4). As one could possibly guess, the distribution is even more heavily skewed here than in the case of trade, and any bimodality disappears.

Figure 4: Strength, kernel density plot: total assets



Connectivity as measured by ND and NS has increased for all asset types. Apart for total assets, it is highest for debt contracts (total debt and long-term one) and lowest for short-term debt, with cross-border equity holdings somehow in between.

The fact that the ITN is almost fully connected results in the correlation between ND and NS being not significantly different from zero, as ND varies very little. On the contrary, the correlation is positive and significant in the case of the IFN. This means that on average countries with many trading partners tend to hold also more intense relationships.

In the case of WUN, a further important piece of information is represented by *dispar-*

[9]The fact that the number of available countries in the network is smaller in 2004 surely plays a role in determining the reduction in the peak of the distribution.

ity, which tells us whether trade and financial links carry similar weight or rather countries tend to display few tight links and a large number of feeble ones. Table 2 reports the mean values of node disparity for the different types of WUN under scrutiny. One can see that in the case of ITN disparity is low and stable; at the end of the sample period the IFN based on total assets has reached the same value though it started from a higher figure. The behavior of disparity for different asset classes is consistent with what we have found so far, with a higher value for equities, small figures for total and long-term debt and high disparity for short-term debt, again to testify a rather sparse network populated by links carrying very different weights.

Table 2: Node disparity

	trade	total assets	equities	debt	long debt	short debt
2001	0.13	0.207	0.286	0.203	0.2	0.356
2002	0.125	0.215	0.316	0.22	0.215	0.393
2003	0.122	0.159	0.265	0.2	0.198	0.334
2004	0.117	0.117	0.249	0.172	0.182	0.294

This first set of results allows us to make an important methodological point: if the study of the ITN and the IFN is carried out from a BUN perspective, one runs the risk of getting a misleading picture of the underlying phenomena. A weighted network analysis instead allows one to better appreciate how the intensity of the interaction structure is distributed across the population.

5.2 Assortativity

Degree and strength statistics are first-order indicators: they only take into account links to one-step-away partners and do not convey any information on the finer structure of the network. Indeed, it may well happen that countries having many partners are only linked with with poorly-connected countries (we call such a network "disassortative"). Conversely, it may be the case that better connected countries also tend to relate to other well-connected countries (i.e., an "assortative" network). The relation between *average nearest-neighbor degree* (ANND) and ND on one side, and between *average* *nearest-neighbor strength* (ANNS) and NS on the other allows one to assess the degree of assortativity that exists within the network. In other words, whether countries choose as partners nations with the same degree (strength) and whether the relationships with high/low degree/strength countries follow the magnitude of the interaction.

Table 3: Correlation between node degree (strength) and ANND (ANNS)

	trade	total assets	equities	debt	long debt	short debt
			BUN: degree – ANND			
2001	-0.705	-0.964	-0.916	-0.946	-0.948	-0.552
2002	-0.661	-0.957	-0.931	-0.979	-0.976	-0.724
2003	-0.572	-0.957	-0.878	-0.948	-0.972	-0.759
2004	-0.659	-0.977	-0.922	-0.967	-0.964	-0.830
			WUN: strength – ANNS			
2001	-0.607	-0.423	-0.401	-0.495	-0.515	-0.323
2002	-0.513	-0.392	-0.418	-0.463	-0.488	-0.277
2003	-0.494	-0.531	-0.459	-0.596	-0.577	-0.373
2004	-0.679	-0.556	-0.485	-0.581	-0.576	-0.376

Table 3 displays the correlation between ND (respectively, NS) and ANND (respectively, ANNS). BUN analysis points toward a strongly disassortative network; this feature remains evident also in the context of WUN, though weaker in magnitude. Serrano and Boguñá (2003) also find that the ITN is a disassortative network, a result that we can now extend to the IFN irrespectively of whether one focuses on total assets, bonds or equities. This implies not only that poorly connected countries preferentially connect to high degree countries (BUN case), sometimes referred to as hubs, but also that this core-periphery structure is maintained also in terms of intensity of interactions.

The behavior of financial links, in particular the strong negative correlation for BUN can probably be explained by the existence of a number of benchmark securities that enter almost every portfolio. When it comes to measuring the importance of such securities though, assets issued by more peripheral countries become appealing in view of diversification, so that weighted financial links become more dispersed and the relevance of hubs diminishes.

5.3 Clustering

Clustering measures the local interconnectivity of the network by computing the number of complete triangles originating from a given country. In other words how many of the partners of country i are themselves connected to each other. The clustering coefficient (CC) for BUNs is almost 1 in the case of the ITN, consistently with the previous finding of a fully connected network, but values are quite high (in the .70–.85 range) for the IFN as well. The CC is very high in all years and, moreover, it is always larger than network density: since in a completely random graph the two are equal, our result implies that the ITN and the IFN are statistically more clustered than if they were random graphs.[10] Therefore, countries tend —on average— to establish trade and financial relationships with partners that are also linked with each other. This sort of "cliquishness" suggests that regional or local ties still play a very relevant role, where localism has not necessarily a geographic meaning, but can well be read as the tendency to interact with traditional partners.[11] These can be member of a regional group, countries with similar degree of development, or simply partners that are historically close.

Does this result hold also if we take into account the intensity or relationships? The answer is no: the weighted version of the CC (WCC) is not only very low, but also smaller than its average value in a random graph. Thus, from a weighted perspective, the ITN and the IFN are on average poorly clustered. 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. It is not difficult to recognize this portrait in the real world, where in each regional group usually a single financial center emerges.

A similar mismatch between BUN and WUN results emerges when we look at the correlation between clustering and node degree or strength. Table 4 shows that while the CC is negatively related to ND, the WCC and NS display a positive correlation.[12] Hence,

[10]See Appendix A.

[11]Although we have no means to check whether geography plays any role in the game, it is nonetheless interesting to note that our picture is consistent both with the idea that distance proxies some information costs (Portes and Rey, 2005), and with the notion that informational asymmetries may depend on investors location (Hau, 2001).

[12]In both cases the correlations are significant at 1%.

we observe that partners of countries characterized by high ND are not very connected among them, while strong relationships do tend to take place within well-defined subset of countries. In other words our analysis of the correlation between clustering and connectivity conveys the idea that hubs (countries with high ND) connect peripheral nodes to the rest of the world; peripheral nodes in turn are not very connected among themselves. On the other hand, strong interactions occur within "clubs": partners of countries with high NS do have high connectivity, something that resembles a "rich club phenomenon".

Table 4: Correlation between node degree (strength) and clustering

	trade	total assets	equities	debt	long debt	short debt
	BUN: degree – clustering					
2001	-0.520	-0.958	-0.926	-0.954	-0.960	-0.199
2002	-0.495	-0.944	-0.907	-0.965	-0.967	-0.501
2003	-0.369	-0.954	-0.873	-0.974	-0.973	-0.566
2004	-0.482	-0.976	-0.911	-0.978	-0.972	-0.629
	WUN: strength – weighted clustering					
2001	0.985	0.973	0.958	0.965	0.969	0.549
2002	0.984	0.963	0.945	0.972	0.983	0.690
2003	0.976	0.977	0.949	0.981	0.986	0.775
2004	0.973	0.979	0.952	0.987	0.983	0.781

Hence, from a BUN perspective one observes a core-periphery, star-shaped structure whereby countries holding a small number of trade and financial relations are connected through hubs rather than in direct contact. Hierarchy is less pervasive in the ITN, probably to testify that hubs play a more relevant role in the financial world.[13] Cliquishness is equally diffused both in the ITN and the IFN (save for the network of short-term debt), consistently with the coexistence of globalization and regionalism. From a methodological point of view, here we see the benefit of combining BUN and WUN analysis, as both of them do convey an important piece of information and allow us to better describe the economic phenomena that underlie network statistics.

[13]Hierarchy is a phenomenon whereby partners of well connected countries are less interconnected than partners of poorly connected ones. A perfectly hierarchical network is one where all relations are unidirectional as in an organizational chart, and would signal the existence of a core-periphery structure.

5.4 Network properties and per capita GDP

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 relationships? Are the rich more clustered? To answer these questions, we study the correlation patterns existing between our network-specific measures (degree, strength, clustering) and country pcGDP.

Table 5: Correlation between node degree/strength and per capita GDP

	trade	total assets	equities	debt	long debt	short debt
			BUN: degree – pcGDP			
2001	0.156	0.015	-0.043	0.037	0.031	-0.045
2002	0.189	-0.027	-0.076	0.008	0.013	-0.017
2003	0.197	0.013	-0.072	0.045	0.035	-0.025
2004	0.182	0.000	-0.093	0.073	0.076	-0.026
			WUN: strength – pcGDP			
2001	0.466	0.577	0.551	0.582	0.584	0.505
2002	0.452	0.579	0.553	0.573	0.570	0.509
2003	0.431	0.569	0.530	0.568	0.569	0.484
2004	0.411	0.576	0.534	0.578	0.573	0.506

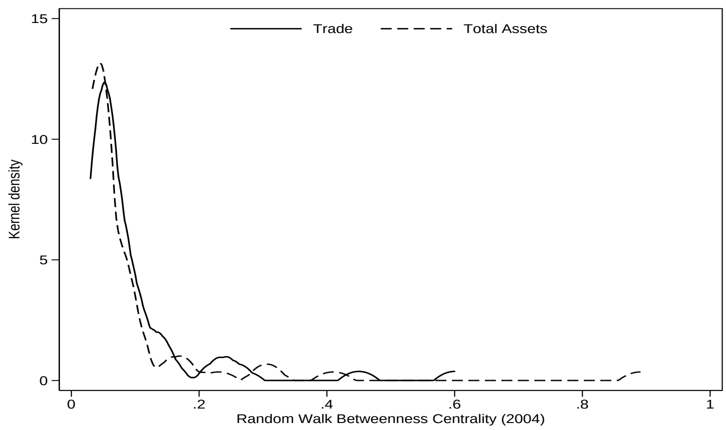
As far as ND is concerned, its correlation with pcGDP is low and never statistically significant (not even for the ITN). Yet, concluding that there is not any relation between the position within the network (connectivity) and pcGDP would be wrong as the latter displays a positive and significant (at 1%) correlation with NS, as reported in the lower panel of table 5. This is to say that once we control for the intensity of trade and financial connections we observe that richer countries are better connected than poorer economies. The correlation is somewhat smaller in the case of the ITN, while different asset types do not display marked differences.

Results for clustering-pcGDP correlations mimic those obtained in the case of clustering and ND/NS. Hence, our BUN analysis suggests the existence of a hierarchical structure in terms of number of partners: rather than on the position within the network this hierarchy is now based on the degree of economic development as measured by per capita income. On the contrary, for what concerns the strength of relations (WUN) we observe some sort of cliquishness: partners of countries with a high pcGDP are more interconnected than those of poorer countries.

5.5 Centrality

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

Figure 5: Random Walk Betweenness Centrality, kernel density plot



We compute *random walk betweenness centrality* (RWBC, see Section 2 and Appendix A) for each of the countries in the ITN and IFN and use the results to classify them as part of the core or of the periphery. It turns out that —due to the high density that characterizes both the ITN and the IFN— the binary version of RWBC displays very little variation and, in addition, it is almost perfectly correlated with ND: as a result, in what follows we will focus only on the weighted version of RWBC.[14]

Figure 5 presents the distribution of weighted RWBC for both the ITN and the IFN of total assets in 2004. The pattern observed for both networks has not changed over the period considered in the study, so that figure 5 gives a good representation of the overall

[14] A second reason 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.

behavior. Similarly, there are no discernable differences across asset types and therefore we focus on the discussion of the results based on total assets. Both distributions are heavily skewed to the right, confirming the hypothesis of a clear-cut core-periphery structure.

Table 6: Composition of the core

2001	2002	2003	2004
	Based on Trade		
USA	USA	USA	USA
UK	UK	UK	UK
Germany	Germany	Germany	Germany
France	France	France	France
Japan	Netherlands	Netherlands	Japan
Italy	Japan	Japan	Italy
Russia	Italy	Italy	
	Based on Total Assets		
USA	USA	USA	USA
UK	UK	UK	UK
Germany	Germany	Germany	Germany
Luxembourg	Luxembourg	Luxembourg	Luxembourg
France	France	France	France
Japan	Japan	Netherlands	Netherlands
Italy	Italy	Japan	

To identify the countries actually belonging to the core we (arbitrarily) impose a threshold at the 90th percentile of RWBC: hence, only countries with a value of the RWBC index within the top 10% are considered core.[15] The number of countries in the core ranges between 7 (2001–2003) and 6 (2004) and its composition is quite stable (see table 6). In fact in the core we find all the "usual suspects" with the only a few exceptions: the presence of Russia in the core of the trade network in 2001 seems occasional as the country drops out from it in following years and actually never comes close to rejoin the group. In both the ITN and the IFN the Netherlands switch in and out of the core, constantly displaying a limit value of centrality. The core of both networks is basically made up of the same countries, with the notable exception of Luxembourg, which plays a central node with respect to financial assets, but not with respect to trade flows.

Finally, the analysis of the correlation between per capita GDP and node betweenness

[15]The same results are obtained once we substitute this relative criterion with an absolute one and attribute core status to those countries displaying values of centrality above the mean plus one standard deviation.

Table 7: Correlation between weighted centrality and per capita GDP

	trade	total assets	equities	debt	long debt	short debt
2001	0.446	0.505	0.509	0.517	0.520	0.515
2002	0.427	0.500	0.493	0.503	0.505	0.234
2003	0.394	0.484	0.463	0.484	0.488	0.493
2004	0.366	0.476	0.453	0.490	0.481	0.513

centrality reveals a similar pattern to that observed for the relationship between node strength and pcGDP.[16] It should be noted that even though the correlation is positive for both networks, it is higher for the IFN, further testifying that international trade integration is more widespread. The results presented in table 7 show that the correlation between pcGDP and RWBC is not only higher for the case of the ITN, but also that it has been steadily declining in the period under scrutiny. This pattern suggests that a higher degree of international economic integration through capital flows is more likely related to a higher pcGDP than a high degree of international economic integration through international trade.

6 Conclusions and Possible Extension

The paper has investigated the properties of the ITN and the IFN using both a binary and a weighted network approach. From a methodological point of view, our paper is the first one —to the best of our knowledge— addressing this issue from a *weighted* network perspective. Indeed, many findings obtained by only looking at the number of relationships that any country maintains are completely reversed if one takes into account the relative intensity of links. Our results show that combining binary and weighted analysis can deliver more precise and thorough insights as far as the topological structure and properties of the ITN and the IFN are concerned. Expectedly, the paper finds that the ITN is more densely connected than the IFN and that the degree of international financial integration varies with asset type: it is highest for long-term debt contracts,

[16] 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.

somewhat lower for equities and rather low for short-term debt, which is characterized by a sparse network.

As compared to standard international-trade statistical investigations, network analysis allows the researcher to explore not only first-order phenomena associated to the patterns of trade and financial integration of any given country (e.g. the degree of openness to trade or the share of foreign assets in the portfolio), but also second- and higher-order empirical facts. In particular, we show that richer countries tend to be better linked and to form groups of tightly connected economies. 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 relations. However, the growing importance of global links is testified by the disassortative feature of both the ITN and the IFN: poorly connected nodes tend to connect to central ones and use them as hubs to access the rest of the network.

For what concerns future research, a natural extension of our work entails exploring the role of geographic proximity in shaping the ITN and the IFN: this might allow us to better determine the relative importance of global and local links, and whether the two act as substitutes or rather complement each other. Along this line, an interesting question concerns the impact of regional integration (trade agreements, but also monetary integration) on the characteristics of the network. Second, along the line of Kali and Reyes (2007), we would like to match topological properties with country-specific variables to see how the structure of the ITN and IFN is shaped by (and shapes) macroeconomic dynamics.

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References

Baele, L., A. Ferrando, P. Hördahl, E. Krylova and C. Monnet (2004), "Measuring European Financial Integration", Occasional Paper 14, ECB.

Barrat, A., M. Barthélemy, R. Pastor-Satorras and A. Vespignani (2004), "The architecture of complex weighted networks", *Proceedings of the National Academy of Sciences*, 101: 3747–52.

Bekaert, G. and C. Harvey (2003), "Emerging markets finance", *Journal of Empirical Finance*, 10(1-2): 3–56.

Breiger, R. (1981), "Structure of economic interdependence among nations", in Blau, P. M. and R. K. Merton (eds.), *Continuities in structural inquiry*, pp. 353–80. Sage, Newbury Park, CA.

Fagiolo, G. (2006), "Directed or Undirected? A New Index to Check for Directionality of Relations in Socio-Economic Networks", *Economics Bulletin*, 3: 1–12, available on-line at http://economicsbulletin.vanderbilt.edu/2006/volume3/EB-06Z10134A.pdf.

Fisher, E. and F. Vega-Redondo (2006), "The Linchpins of a Modern Economy", Working paper, Cal Poly.

Garlaschelli, D. and M. Loffredo (2004), "Fitness-Dependent Topological Properties of the World Trade Web", *Physical Review Letters*, 93: 188701.

Garlaschelli, D. and M. Loffredo (2005), "Structure and evolution of the world trade network", *Physica A*, 355: 138–44.

Goldberg, L., J. Lothian and J. Okunev (2003), "Has International Financial Integration Increased?", *Open Economies Review*, 14: 299–317.

Granovetter, M. (1974), *Getting a Job: A Study of Contracts and Careers*. Cambridge, MA, Harvard University Press.

Hau, H. (2001), “Location Matters: An Examination of Trading Profits”, *Journal of Finance*, 56(5): 1959–83.

Kali, R. and J. Reyes (2005), “Financial contagion on the International Trade Network”, Unpublished Manuscript.

Kali, R. and J. Reyes (2007), “The Architecture of Globalization: A Network Approach to International Economic Integration”, *Journal of International Business Studies*, Forthcoming.

Kastelle, T., J. Steen and P. Liesch (2006), “Measurig globalisation: an evolutionary economic approach to tracking the evolution of international trade”, Paper presented at the DRUID Summer Conference on Knowledge, Innovation and Competitiveness: Dynamycs of Firms, Networks, Regions and Institutions - Copenhagen, Denemark, June 18–20.

Kim, S. and E.-H. Shin (2002), “A Longitudinal Analysis of Globalization and Regionalization in International Trade: A Social Network Approach”, *Social Forces*, 81: 445–71.

Li, X., Y. Y. Jin and G. Chen (2003), “Complexity and synchronization of the World trade Web”, *Physica A: Statistical Mechanics and its Applications*, 328: 287–96.

Milesi-Ferretti, G. M. and G. M. Lane (2006), “The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970-2004”, IMF Working Papers 06/69, International Monetary Fund.

Milgram, S. (1967), “The small world problem”, *Psychology Today*, 2: 60–67.

Newman, M. (2005), “A measure of betweenness centrality based on random walks”, *Social Networks*, 27: 39–54.

Onnela, J., J. Saramaki, J. Kertész and K. Kaski (2005), “Intensity and coherence of motifs in weighted complex networks”, *Physical Review E*, 71: 065103.

Padgett, J. and C. Ansell (1993), “Robust action and the rise of the Medici, 1400-1434”, *American Journal of Sociology*, 98: 1259–1319.

Portes, R. and H. Rey (2005), "The determinants of cross-border equity flows", *Journal of International Economics*, 65: 269–96.

Rapoport, A. and W. Horvath (1961), "A study of a large sociogram", *Behavioral Science*, 6: 279–291.

Scott, J. (2000), *Social Network Analysis: A Handbook.* London, Sage.

Serrano, A. and M. Boguñá (2003), "Topology of the World Trade Web", *Physical Review E*, 68: 015101(R).

Smith, D. and D. White (1992), "Structure and Dynamics of the Global Economy: Network Analysis of International Trade, 1965-1980", *Social Forces*, 70: 857–93.

Snyder, D. and E. Kick (1979), "Structural position in the world system and economic growth 1955-70: A multiple network analysis of transnational interactions", *American Journal of Sociology*, 84: 1096–126.

Wasserman, S. and K. Faust (1994), *Social Network Analysis. Methods and Applications.* Cambridge, Cambridge University Press.

Appendix A: Statistical Analysis of Binary and Weighted Networks

In this appendix, we present some more formal definitions of the statistics introduced in Section 2 for both binary and weighted networks.

Consider a 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 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, and $X^{[k]}$ as the matrix obtained from X by raising to k each entry.

Binary undirected networks

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

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

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

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

$$annd_i = d_i^{-1} \sum_j a_{ij} d_j = d_i^{-1} \sum_j \sum_h a_{ij} a_{jh} = \frac{A_{(i)} A \mathbf{1}}{A_{(i)}\mathbf{1}}. \tag{2}$$

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, is equal to:

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

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

Let us now assume that the underlying graph is weighted and undirected and let W be its weight matrix. First, node strength of i is defined as:

$$s_i = \sum_j w_{ij} = W_{(i)}\mathbf{1}. \tag{4}$$

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

$$anns_i = d_i^{-1} \sum_j a_{ij} s_j = d_i^{-1} \sum_j \sum_h a_{ij} w_{jh} = \frac{A_{(i)} W \mathbf{1}}{A_{(i)}\mathbf{1}}. \tag{5}$$

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

$$h_i = \frac{(N-1)\sum_j \left(\frac{w_{ij}}{s_i}\right)^2 - 1}{N-2} = \frac{(N-1)\frac{1}{s_i^2}\sum_j w_{ij}^2 - 1}{N-2} = \frac{(N-1)\frac{W_{(i)}^{[2]}\mathbf{1}}{(W_{(i)}\mathbf{1})^2} - 1}{N-2}. \tag{6}$$

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

$$\tilde{C}_i(W) = \frac{\frac{1}{2}\sum_{j\neq i}\sum_{h\neq(i,j)} w_{ij}^{\frac{1}{3}} w_{ih}^{\frac{1}{3}} w_{jh}^{\frac{1}{3}}}{\frac{1}{2}d_i(d_i-1)} = \frac{(W^{[\frac{1}{3}]})_{ii}^3}{d_i(d_i-1)}, \tag{7}$$

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. 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 WUN 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:

$$v(h,k) = [D-W]^{-1} f(h,k), \tag{8}$$

where $D = diag(s)$ 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:

$$I_i(h,k) = \frac{1}{2} \sum_j |v_i(h,k) - v_j(h,k)|, \tag{9}$$

where $I_h(h,k) = I_k(h,k) = 1$.

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

$$RWBC_i = \frac{\sum_h \sum_{k \neq h} I_i(h,k)}{N(N-1)}. \tag{10}$$

Appendix B: Countries in the sample

		4c—Trade				CPIS			
code	Country	2001	2002	2003	2004	2001	2002	2003	2004
213	Argentina	x	x	x	x	x	x	x	x
314	Aruba	x	x	–	–	x	x	–	–
193	Australia	x	x	x	x	x	x	x	x
122	Austria	x	x	x	x	x	x	x	x
313	Bahamas, The	x	x	x	–	x	x	x	–
419	Bahrain	x	x	x	x	x	x	x	x
316	Barbados	x	x	x	x	x	x	x	x
124	Belgium	x	x	x	x	x	x	x	x
223	Brazil	x	x	x	x	x	x	x	x
918	Bulgaria	x	x	x	x	x	x	x	x
156	Canada	x	x	x	x	x	x	x	x
228	Chile	x	x	x	x	x	x	x	x
233	Colombia	x	x	x	x	x	x	x	x
238	Costa Rica	x	x	x	x	x	x	x	x
423	Cyprus	x	x	x	x	x	x	x	x
935	Czech Republic	x	x	x	x	x	x	x	x
128	Denmark	x	x	x	x	x	x	x	x
469	Egypt	x	x	x	x	x	x	x	x
939	Estonia	x	x	x	x	x	x	x	x
172	Finland	x	x	x	x	x	x	x	x
132	France	x	x	x	x	x	x	x	x
134	Germany	x	x	x	x	x	x	x	x
174	Greece	x	x	x	x	x	x	x	x
532	Hong Kong SAR	x	x	x	x	x	x	x	x
944	Hungary	x	x	x	x	x	x	x	x
176	Iceland	x	x	x	x	x	x	x	x
536	Indonesia	x	x	x	x	x	x	x	x
178	Ireland	x	x	x	x	x	x	x	x
115	Isle of Man	–	–	–	–	x	x	x	–
436	Israel	x	x	x	x	x	x	x	x
136	Italy	x	x	x	x	x	x	x	x
158	Japan	x	x	x	x	x	x	x	x
916	Kazakhstan	x	x	x	x	x	x	x	x
542	Korea, Republic	x	x	x	x	x	x	x	x
446	Lebanon	x	x	x	x	x	x	x	x
137	Luxembourg	x	x	x	x	x	x	x	x
546	Macao SAR	x	x	–	–	x	x	–	–
548	Malaysia	x	x	x	x	x	x	x	x
181	Malta	x	x	x	x	x	x	x	x
684	Mauritius	x	x	x	x	x	x	x	x
273	Mexico	x	x	x	x	x	x	x	x
138	Netherlands	x	x	x	x	x	x	x	x
196	New Zealand	x	x	x	x	x	x	x	x
142	Norway	x	x	x	x	x	x	x	x
564	Pakistan	x	x	x	x	x	x	x	x
283	Panama	x	x	x	x	x	x	x	x
566	Philippines	x	x	x	x	x	x	x	x
964	Poland	x	x	x	x	x	x	x	x
182	Portugal	x	x	x	x	x	x	x	x
968	Romania	x	x	x	x	x	x	x	x
922	Russian Fed	x	x	x	x	x	x	x	x

(*continued on next page*)

		Trade				CPIS			
code	Country	2001	2002	2003	2004	2001	2002	2003	2004
576	Singapore	x	x	x	x	x	x	x	x
936	Slovak Republic	x	x	x	x	x	x	x	x
199	South Africa	x	x	x	x	x	x	x	x
184	Spain	x	x	x	x	x	x	x	x
144	Sweden	x	x	x	x	x	x	x	x
146	Switzerland	x	x	x	x	x	x	x	x
578	Thailand	x	x	x	x	x	x	x	x
186	Turkey	x	x	x	x	x	x	x	x
926	Ukraine	x	x	x	x	x	x	x	x
112	United Kingdom	x	x	x	x	x	x	x	x
111	United States	x	x	x	x	x	x	x	x
298	Uruguay	x	x	x	x	x	x	x	x
846	Vanuatu	x	x	x	x	x	x	x	x
299	Venezuela	x	x	x	x	x	x	x	x
number of countries		64	64	62	61	65	65	63	61

x available; – not available (or not used)