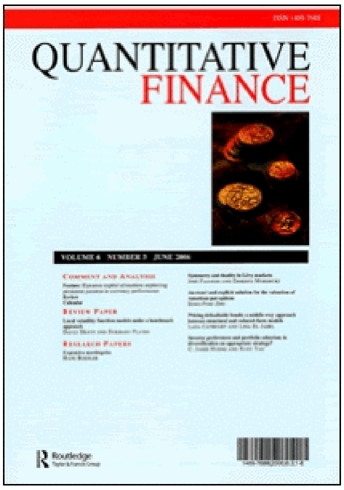

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International trade and financial integration: a weighted network analysis

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The authors analyse patterns of international trade and financial integration using complex network analysis. The combination of both binary and weighted approaches delivers more precise and thorough insights into the topological structure and properties of international trade and financial networks (ITN and IFN). It is found that the ITN is more densely connected than the IFN, while both types of network display a core–periphery structure. This hierarchical organization is more pronounced in financial markets, suggesting that the bulk of trade in financial assets occurs through a handful of countries acting as hubs. High-income countries are better linked and form groups of tightly interconnected nodes. This kind of structure can explain why the recent financial crisis has spread rapidly among advanced countries while reaching emerging markets only in a second phase.

Keywords: International integration; International financial markets; Globalization; Complex weighted networks

1. Introduction

This paper employs complex-network analysis to explore patterns of international trade and financial integration. These structural properties are relevant to understanding aggregate dynamics such as financial contagion or the transmission of shocks through international trade. Network analysis allows us to investigate, for instance: (1) whether high-income countries are beter connected in terms of the number and intensity of trade and financial relationships; (2) which countries play the most central role in trade and financial networks; (3) whether high-income countries tend to trade goods and assets only with a restricted and relatively closed group of partners.

In the last decades, a large body of empirical contributions has increasingly addressed the study of socio-economic systems in the framework of complex network analysis. While the idea is not new, recent works have stressed the ability of this approach to capture the essential characteristics of interacting systems by investigating the whole structure of relations among agents while disregarding their detailed nature.⊥

In this paper, we exploit complex network analysis to compare the degree of international trade and financial integration. While a large literature exists describing trade relationships in terms of a network (see for instance Li *et al*. 2003, Serrano and Boguñá 2003, Garlaschelli and Loffredo 2004, Bhattacharya *et al*. 2008, to quote just a few recent examples), this is the first time bilateral

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⊥Examples of classical studies in the field include Rapoport and Horvath (1961), Milgram (1967), Granovetter (1974), and Padgett and Ansell (1993).

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cross-border trade in financial assets has been analysed using a network approach. Moreover, comparison between the two networks can provide interesting insights into the actual patterns of globalization. From a purely descriptive perspective, we attempt to single out some robust stylized facts characterizing the international trade and financial networks (ITN and IFN henceforth) in order to assess similarities and differences in real and financial market integration. The literature suggests that knowledge of such topological properties is not only important *per se* (because it improves upon our descriptive knowledge of international integration), but it is also relevant for a better understanding of the aggregate dynamics (see for instance Kali and Reyes 2007).

From a methodological point of view, the study is carried out using both binary and weighted analyses. This distinction proves to be useful since, as our results show, a weighted approach allows one to obtain different conclusions as compared to a binary framework. The two approaches complement each other so that we are able to present a much clearer picture of the network characteristics that, we believe, are relevant for a better understanding of the economic effects resulting from trade and financial exchanges.

More specifically, we find that both the ITN and the IFN are highly symmetric, and the majority of relationships are reciprocated. Most countries maintain (many) weak links; yet there exists a group of countries exhibiting a large number of strong relationships, thus hinting at a core–periphery structure. Furthermore, we show that central nodes tend to connect to peripheral ones but are also involved in relatively highly interconnected triples. In addition, rich countries (in terms of their per capita GDP) display stronger ties and tend to be more clustered.

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

2. Methodology

A socio-economic network is usually described by means of a graph, i.e. a collection of N nodes, possibly connected by a set of links.† To characterize a network it is then sufficient to provide an $N \times N$ 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).

In the present context, countries represent nodes that are connected if they exchange either goods or financial assets. A first way to describe international economic integration is to count the number of links maintained by each node: this measure is referred to as *node degree* (ND). If one is instead interested in measuring the overall connectivity of the network, it is possible to look at the density of the graph, which amounts to the number of actual links over the maximum number of possible connections.

Following Serrano and Boguñá (2003) and Garlaschelli and Loffredo (2004) we also investigate whether low-degree nodes have the tendency to establish relations with partners characterized by high (or low) degree. The literature suggests that this feature is relevant for the diffusion of information, diseases or whatever flows through the network. In our case then, it can provide us with useful insights into the processes of contagion in the aftermath of an economic shock or a financial crisis. The correlation between the degree of a node and the average degree of its partners (*average nearest neighbour degree*, or ANND) delivers the statistical information on this characteristic of the network. If the correlation is positive, one is in the presence of an assortative graph, where nodes tend to establish links with partners with a similar level of connectivity; otherwise the network is said to be disassortative.

Another important feature of network structure concerns the extent to which a given node is clustered, that is how many partners of a node are themselves partners. The *clustering coefficient* (CC) of node i measures the percentage of pairs of i's partners that are connected among themselves: this can be seen as the number of complete triangles originating from each country (over all possible triangles given the number of existing links). A large number of networks display a tendency for link formation between neighbouring vertices: these highly clustered graphs are often characterized by a strong geographical structure, where short-distance links are more relevant than more distant ones.

Trade and financial links are expected to be characterized by strong heterogeneity in their intensity. To take this into account, we need to discriminate between strong and weak links: we do so by weighting each connection by its intensity. The three statistics above (ND, ANND and CC) can be extended and applied to a weighted version of the network. *Node strength* (NS) is the sum of weights associated with the links maintained by any node. The larger the strength of a node, the stronger its participation in international markets. To investigate the amount of heterogeneity in economic relationships, we can associate with each node a Herfindahl concentration index, which increases with the heterogeneity of link intensity shares. Furthermore, we study the degree of network assortativity from a weighted perspective by looking at the correlation between strength and *average nearest neighbour strength* (ANNS). This tells us whether high-strength countries tend to establish links with partners that are also very active in international markets or not. The extension of the clustering coefficient to weighted networks can be done in several ways (Saramaki *et al.* 2007). Here we focus on the methodology proposed

†We refer the reader to Fagiolo *et al.* (2009) for more formal definitions of network concepts.

by Onnela *et al.* (2005), who suggest using average triangle intensities to quantify the importance of each triad.† The correlation between vertex strength and the *weighted clustering coefficient* (WCC) provides additional information on the patterns of international economic integration, as it tells whether high-trade-volume countries engage in strong relationships with each other. In the real world, economies of scale in the processing of information imply the emergence of a few leading financial centres that are likely to be linked by strong ties.‡

The last question we address relates to the role played by each country in the two networks. To do so, we compute a measure of centrality (*random walk betweenness centrality*, or RWBC) proposed by Newman (2005) and Fisher and Vega-Redondo (2007), which provides information on the position of each node relative to all other nodes. In fact, two countries with the same number of partners (ND) or the same engagement in world markets (NS) may have different centrality (and therefore may play a different role) depending on how their partners are connected, how the partners of their partners are connected, and so on and so forth.

3. A glance at the existing literature

In sociology and political science there exists a long tradition of using network analysis to investigate international trade relations. These studies have been influenced by the so-called 'dependency' theories, according to which there exists a small number of countries (the core) that exploits the rest of the world, which is thus prevented from developing. Network analysis has then been traditionally used to classifying countries into a core and a periphery (see for instance Snyder and Kick 1979, Breiger 1981, Smith and White 1992), but more recent applications exist that have studied the impact of the recent wave of globalization on the structure of the world trade (e.g. Kim and Shin 2002).

The web of international trade relations has also been widely used as a case study in a number of papers in the physics domain (Serrano and Boguñá 2003, Garlaschelli and Loffredo 2004, Serrano *et al.* 2007). These works typically adopt a binary analysis and their results suggest that both ANND and clustering depend on node degree, thus confirming the presence of a hierarchy in the network. Recently, some papers have started using a weighted approach (Saramaki *et al.* 2007, Bhattacharya *et al.* 2008) though the focus of all these contributions rests more with the topological properties of the network than with their economic underpinning.

Two interesting applications of network analysis are proposed by Kali and Reyes (2007, 2009), who show that a country's position in the ITN has important implications in terms of economic growth and can also explain episodes of financial contagion.

To the best of our knowledge, no attempt has been made so far to apply complex network analysis to assess the degree of international financial integration. In truth, the present methodology provides only an indirect measure of the phenomenon, since it only deals with cross-border holdings of assets, without any reference to their price.§ Nevertheless, we claim that this approach can add to our understanding of international financial integration. In fact, not only can one look at the total amount of foreign assets and liabilities maintained by each country, but it is possible to study their geographical distribution. This is far from trivial since two countries with the same stock of foreign assets are in a different position depending on whether these assets are concentrated within a few partners or rather distributed across a wide range of issuing countries. Moreover, knowing the structure of the IFN provides interesting and useful information on the way a possible financial crisis may spread.

4. Data

The source of bilateral asset trade data is the Coordinated Portfolio Investment Survey (CPIS) performed by the IMF. The CPIS gives information on the quantity of assets issued by all partner countries held by each country participating to the survey. This source suffers from two main limitations: data are available on only a few years and it covers a limited number of countries.¶ Trade data are taken from the UN Comtrade database with the target of building a sample covering the same period and the same countries present in the CPIS.⊥ The sample size varies by year and ranges between 61 and 65 countries: it nevertheless accounts for roughly 80% of world trade in each of the years under consideration.

Network analysis treats countries as nodes and goods or asset trade between them as links. Hence, in the context

†Among the weighted clustering coefficients reviewed in Saramaki *et al.* (2007), the one used here is the only one that takes into account the weights of all three edges in any triangle (while disregarding weights not participating in any triangle), and that is invariant to permutations of edge weights (which allows one not to discriminate single nodes but rather to consider cliques or triads as one single entity).

‡Then, while we expect the IFN to be on average less clustered for the reasons seen above, it is likely that the WCC attains its maximum values in correspondence of financial hubs.

§It is worth noting that the very notion of international financial integration is still debated. For instance Bekaert and Harvey (2003) suggest that integration occurs only when '*assets of identical risk command the same expected return irrespective of their domicile*' (p. 4). This implies that an expected return model is required to pursue a direct measure of financial integration.

¶At the time when this paper was written, only data for 2001–2004 were available. The list of countries used in the analysis is reported in Appendix A; note that a few important players such as China did not participate to the survey.

⊥A perfect match was impossible to achieve, since the CPIS includes a number of small financial centres for which no trade data are available.

of the binary analysis a link a_{ij}^t exists if at time t country i holds a positive amount of asset type k issued by country j.† In the case of goods trade, the relationship is established if country i exports to country j at time t. When we turn to weighted analysis, a generic link w_{ij}^t represents the average between the assets issued by country j and held by country i, and those issued by i and held in j (at time t). Analogously in the case of the ITN, w_{ij}^t is the average trade (import and export) flow between country i and country j in year t.

We treat our networks as undirected, thus disregarding the directions of flows: this reduces the complexity of the analysis and appears appropriate in the present context since we aim at providing the reader with a broad picture of real and financial integration. Nevertheless, we have tested the symmetry of our data in order to assess how much information we loose by disregarding the directions of exchanges. In the context of binary relationships, this is done by simply counting the proportion of bilateral links in the network: we have found that 96% of links are bilateral in the case of goods trade, while around 75% of financial connections are reciprocated. Moving to weighted networks, we have exploited an index based on the difference between the matrix of network links and its transpose (see Fagiolo 2006). Here as well, results support our choice, suggesting that the degree of symmetry is high enough to make a directed analysis unnecessary.‡

5. Results

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 means 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 62% and 69% for the IFN. In this latter case the density of the network has increased between 2001 and 2004. In economic terms this hints to the fact that, as one would expect, real markets are more integrated than financial ones, and that the international movement of financial assets tends to be mediated by a small number of financial centres.

CPIS data break down total financial asset holding into equities and debt, further discriminating between short- and long-term bonds. From table 1 we can see that the degree of financial integration depends on asset types. Cross-border holding of long-term debt contracts is substantially more widespread than in the case of equities and short-term debt. The latter in particular forms a rather sparse network with a density of 25–30% only.§

Table 1. Network density.

	2001	2002	2003	2004
Trade	0.986	0.984	0.986	0.991
Total assets	0.615	0.631	0.660	0.692
Equities	0.485	0.489	0.515	0.556
Total debt	0.557	0.572	0.595	0.626
Long-term debt	0.549	0.564	0.590	0.614
Short-term debt	0.252	0.274	0.294	0.308

The presence of a very high density suggests that binary analysis is not so informative in the case of the ITN, since there are not that many differences in node behaviour. On the other hand, the weighted analysis still provides a clear picture of network connectivity even when density is high. Having said this, it is important to note that for the IFN the characterization of the network from both a binary and a weighted perspective provides a much clearer picture of the network features than if one only considers one of the two.¶

5.1. *Connectivity*

The fact that international integration is stronger in goods than in financial markets is confirmed by results on the number of links maintained by each country, which is very high for the ITN and lower but increasing for the IFN. The upper panels of figure 1 display the distributions of node degree for the two networks by means of a kernel density plot.⊥

In the case of trade, the vast majority of countries have a very large number of partners: as the upper-left panel of figure 1 shows, the distribution has most of the mass on the right tail, as nearly all countries trade with everybody else. As far as the IFN is concerned, the distribution of node degree displays some bimodality: this suggests the existence of an *elite* of countries connected with everybody else, a second group of nodes characterized by average connectivity, and a peripheral group. The picture changes significantly when we analyse the distributions of node strength, which are depicted on the lower panels of figure 1. These are heavily skewed to the right: a vast majority of very weak relationships coexists with a small number of strong links, and this feature is common to both the ITN and the IFN.

†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.
‡The full set of results on symmetry is available upon request.
§In the rest of the paper we will only discuss the network of total financial assets. Results for specific asset types do not change much from a structural point of view. A brief discussion is nevertheless presented in section 5.6 below.
¶One alternative possibility to deal with very dense graphs is to define thresholds for the interactions among links (see Kali and Reyes 2007), which allows one to eliminate 'weak' ties. We will see in what follows that a threshold approach does not allow us to recover the results of weighted analysis.
⊥The support of the distributions is standardized to offset the impact of different sample sizes.

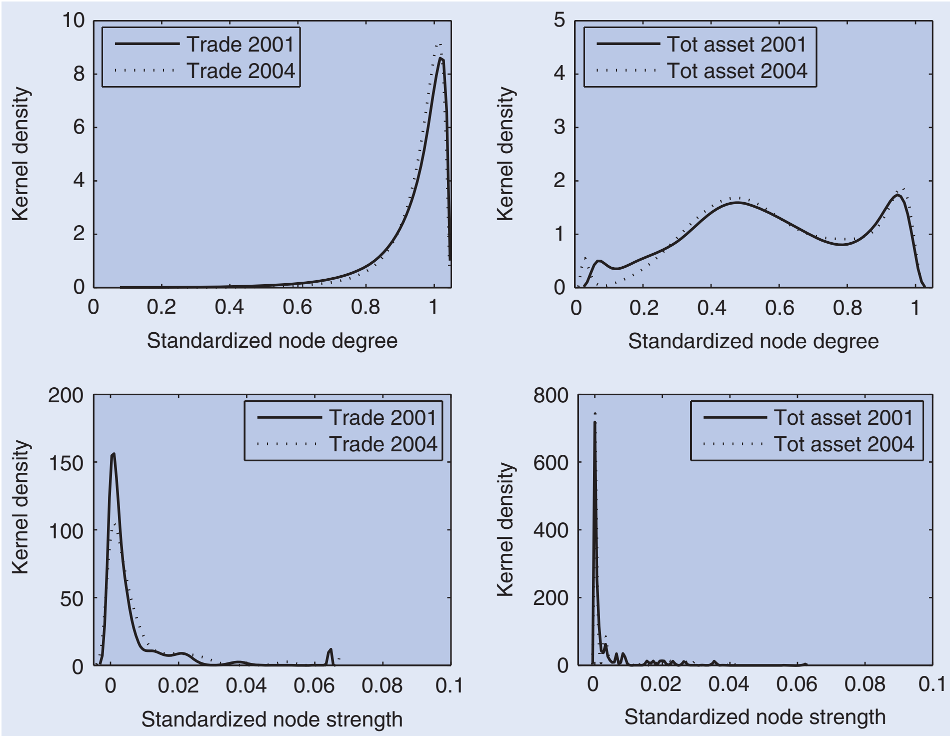

Figure 1. Node degree and strength density distributions.

Figure 2 presents the same information by means of size-rank plots†. The left panel confirms that the two networks differ substantially from a binary perspective: while the ITN is almost fully connected, the IFN is characterized by more heterogeneity in the number of links. More interestingly, the right panel of figure 2 allows us to see that even in terms of node strength, the IFN displays more dispersion, something that was not possible to appreciate looking at kernel densities in figure 1.

Table 2 reports the mean values of node disparity for both networks. This measure tells us whether trade and financial links are homogeneous or rather countries display few strong links together with a large number of weak ones. Disparity is low and stable in the case of the ITN, and somewhat larger for the IFN. Results thus confirm the idea that the intensity of financial links is less homogeneous. Once again, this is consistent with the fact that trade in financial assets is channelled through a few large financial centres, whereas goods trade occur more directly. It should be noted that the observed disparity is lower than the expected values obtained in a random network with the same binary structure but re-shuffled weights. Thus, when compared with the behaviour of nodes in a random graph, node strength is less concentrated than expected. This may simply imply that the economic forces driving international trade in goods and financial assets (economies of scale, comparative advantages, portfolio diversification) lead countries to exploit a wider set of relationships than they would if the identity of partners were completely irrelevant.

Additional information on the overall structure of the trade and financial networks is provided by the correlation between node degree and node strength. As pointed out by Goyal and Van der Leij (2006), networks characterized by a skewed degree distribution and by a positive correlation between degree and strength present a core–periphery structure, with strong ties being located in the core. In this context strong connections (rather than weak ones as postulated by Granovetter 1974) are crucial for bridging different parts of the graph.

Since NS is always increasing in ND (as NS is defined as the sum of all link weights for a given node), to investigate whether links between countries with many partners tend to be stronger, we look at the correlation between the average weight of links connected to a node and its degree. The fact that the ITN is almost fully connected results in the correlation being small (around 0.16), as ND displays very little variation.‡ On the contrary, the correlation is positive and significant in the case of the IFN, ranging between 0.62 and 0.71 depending on the year. This means that on average countries with many trading partners also tend to maintain more intense relationships.

Figure 3 gives a pictorial representation of the phenomenon, showing how the average weight of links connected to a node behaves as a function of node degree.

†Size-rank plots display the fraction of nodes with a degree (strength) higher than a given value; in other words they plot ND (NS) against their complementary cumulative distribution in log–log scale, thus magnifying the upper-tail behaviour of the distribution.
‡A further consequence is that the correlation between ND and NS in the trade network is only significant at 11%.

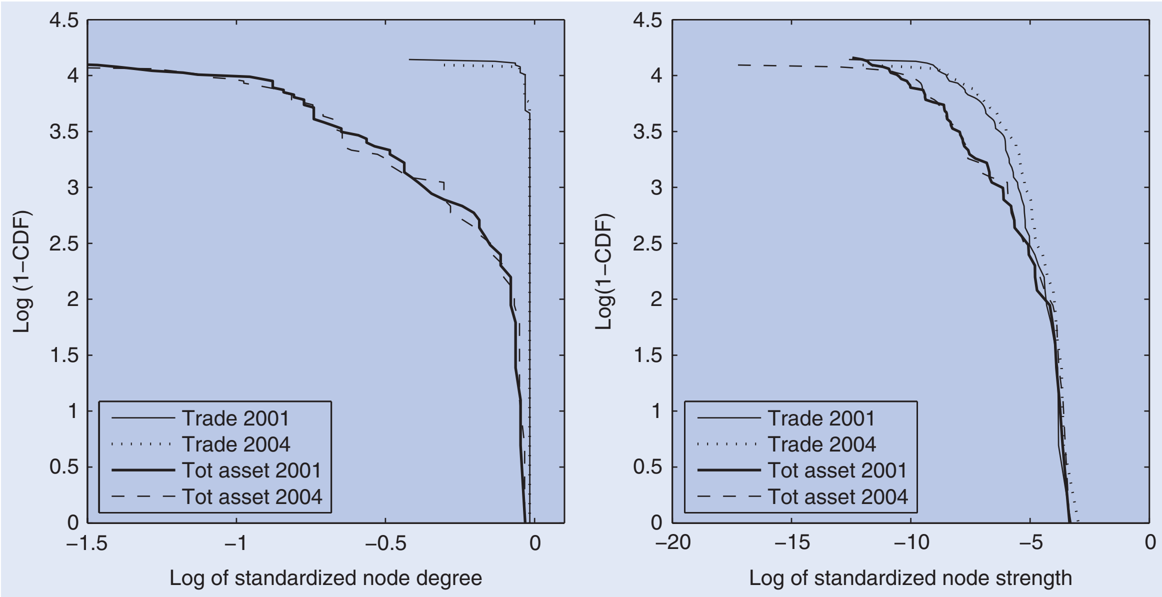

Figure 2. Node degree and strength size–rank plots.

Table 2. Node disparity.

	2001	2002	2003	2004
Trade	0.130†	0.125†	0.122†	0.117†
Assets	0.207†	0.215†	0.196†	0.191†

†Disparity is significantly (5%) smaller than in a random network with the same topology but re-shuffled weights.

Average weight is displayed in logs to grant a clearer picture, and the figure only refers to the years 2001 and 2004. In the trade network the limited range of values taken by ND makes the graph not very illuminating; yet one can see that all the points are located near to the north-eastern corner of the graph. A strong positive correlation between degree and average link weight is more evident in the case of financial assets: links between countries with many partners tend to be stronger.

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 binary perspective only, one runs the risk of getting a misleading picture of the underlying phenomena. Looking only at the presence or absence of links, we find a high degree of integration in both networks. Yet the weighted approach points in the direction of a few nodes controlling the majority of trade and financial flows. In other words, countries establish trade and financial relationships with many partners, but only a few of these connections are intense.

5.2. *Assortativity*

Node degree and node strength only take into account links to one-step-away partners and do not convey any information on the finer structure of the network. Indeed, as explained in section 2 above, we wish to know whether countries having many partners are likely to be linked with poorly-connected countries (this is the case of a disassortative network), or, conversely, with other well-connected countries. By reporting the values of the correlation between ANND and ND (for the binary network), and between ANNS and NS (in the weighted case), table 3 provides precisely this kind of information.

The correlation is negative in both cases, suggesting that nodes with a small number of links tend to connect to hubs, i.e. to nodes with many partners. This pattern is consistent with findings by Serrano and Boguñá (2003) and suggests that the ITN and the IFN are organized as star-shaped networks. Moreover, this structure is also maintained in terms of intensities of interactions, with low-trade-volume countries connecting to nodes characterized by stronger activity in world markets.†

The behaviour of financial links, in particular the strong negative correlation in the binary case, can be rationalized in terms of financial centres intermediating a large fraction of trades in financial assets, or with the existence of benchmark securities entering almost every portfolio. Moreover, the fact that the correlation is much lower when we weight links depends on the fact that the bulk of capital flows occur between the small subgroup of financial centres. In fact, our previous finding that node

†To compare our results with existing studies of the ITN, we have also set a minimum threshold value for each (trade) link weight (along the lines of Kali and Reyes 2007), which implies dropping around 20% of all (trade) links. The resulting binary statistics imply a strongly disassortative network: the correlation between ND and ANND ranges between −0.96 and −0.93, suggesting the existence of many low-weight links connecting peripheral nodes among themselves, so that imposing a threshold artificially inflates the relevance of hub-spokes connections. This however is not a correct representation of the ITN according to the weighted approach discussed above. Similar conclusions hold for a smaller threshold that eliminates only 10% of links.

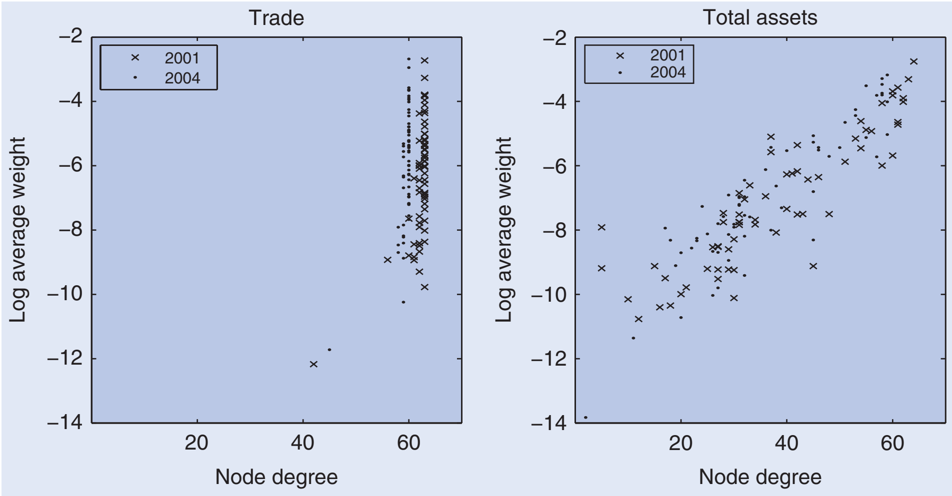

Figure 3. Relation between node degree and node strength.

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

	2001	2002	2003	2004
		Degree – ANND		
Trade	−0.705†	−0.661†	−0.572†	−0.659†
Assets	−0.959‡	−0.937‡	−0.934‡	−0.903‡
		Strength – ANNS		
Trade	−0.607	−0.513	−0.494	−0.679
Assets	−0.421	−0.392	−0.531	−0.555‡

†The correlation is significantly (5%) *weaker* than in a random network.
‡The correlation is significantly (5%) *stronger* than in a random network.

strength is more concentrated in the case of the IFN implies that connections between hubs and spokes are not very strong and therefore explains the fall in the correlation between NS and ANNS relative to the very high values observed in the binary network.

When we compare our results with the expected values computed for comparable random graphs, we find that the ITN displays a weaker correlation between ND (NS) and ANND (ANNS), whereas the opposite holds for the IFN†. Once again this is in line with previous results on disparity and signals a strong tendency of peripheral nodes in the IFN to attach to a hub. This can be rationalized in terms of economies of scale and scope in the processing of relevant information that lead to the emergence of leading financial centres. Such a feature is much less relevant in the case of trade in goods, since the mutual benefit from bilateral trade is quite independent of the number (and strength) of links maintained by each partner.

5.3. Clustering

Clustering measures the shares of the partners of country *i* that are themselves connected to each other. The binary clustering coefficient (CC) is almost 1 in the case of the ITN, consistent with the fact that the graph is almost fully connected, but values are quite high for the IFN as well. Therefore, countries tend to establish trade and financial relationships with partners that are also linked with each other. This sort of 'cliquishness' suggests that local ties still play a very relevant role, and is consistent with empirical results showing that greater distance reduces the amount of goods and asset trade.‡

When we incorporate weights into the analysis we find that weighted clustering (WCC) is low. The index used here (Onnela *et al.* 2005) measures the intensity of interactions in each triangle compared to the maximum intensity present in the network. This means that for a node to display a high WCC we need all the three ties to be strong. Hence, given the heterogeneity among nodes that we have documented so far, with a star-shaped structure characterizing both the ITN and the IFN, it is not surprising to find, on average, a low WCC.

In table 4 we look at the correlation between clustering (CC and WCC) and node degree or strength. We find that while the CC is negatively related to node degree, the correlation between their weighted counterparts (WCC and NS) is positive and very high. Similar results are reported in Saramaki *et al.* (2007) in the context of the world trade network. Hence, we observe that high-trade-volume countries establish strong links with each other so that nodes characterized by high strength (hubs) are clustered. Strong interactions thus occur within a small

†In the binary case, the random network amounts to a graph with same density but re-shuffled links. In the weighted case, we keep the binary structure constant and we re-shuffle link weights. The comparison between the observed correlations and those computed for the random networks is similar for both the binary and the weighted networks. In the latter case, however, differences are significant only at a level of 7–15%.

‡In the international trade literature, a large body of evidence have investigated the role of distance in the context of so-called gravity models (see for instance Brun *et al.* 2005). Recently, this methodology has been applied to financial data as well: Portes and Rey (2005) suggest that distance proxies some information costs. Furthermore, Hau (2001) postulates that informational asymmetries in financial markets may depend on investor location.

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

	2001	2002	2003	2004
		Degree – Clustering		
Trade	−0.520	−0.496	−0.369	−0.482
Assets	−0.959	−0.940	−0.962	−0.964
		Strength – Weighted clustering		
Trade	0.946*	0.947*	0.954*	0.957*
Assets	0.934*	0.948*	0.963*	0.971*

*The correlation is significantly (5%) *stronger* than in a random network.

'rich club'. Moreover the correlation between NS and WCC is higher than the one observed in a comparable random network with the same bilateral structure but re-shuffled weights.

To explore this evidence further, we computed a rich club coefficient (RCC) along the lines of Bhattacharya *et al.* (2008). Similar to what was reported in Fagiolo *et al.* (2009), the binary version of our networks do not exhibit any significant rich club behaviour, due to the very high density of the graphs. On the contrary, the weighted version of RCC shows that a small group of countries command a very large share of international flows in goods and financial assets. The rich club index – the share of total flows in the network that can be imputed to exchanges occurring only among the first k nodes of the NS ranking in each year – increases steeply in the size of the club (k), as shown in figure 4 for the year 2004 (the behaviour in other years is qualitatively the same). As a result, the top 10 countries in terms of NS account for more than 40% of world trade in goods (figure 4, left panel), and this share grows to above 60% when considering trade in financial assets (figure 4, right panel). The concentration of flows in the hands of a restricted number of key players in confirmed by the comparison of the empirical observations with their expected values for a random network with the same binary structure but re-shuffled weights. This is represented by the solid line in figure 4, along with the 95% confidence intervals, and is much lower than observed data, already for a small 'club' of five countries. The rich club behaviour appears to be more relevant for the IFN, consistent with the existence of leading financial centres intermediating a large share of asset trade.

To summarize, the binary structure of both networks is made of a core and a periphery, linked in a star-like structure: countries holding only a few links are connected through hubs rather than being directly in contact. This hierarchy is less pervasive in the ITN, since the very nature of trade in financial assets assigns a more relevant role to hubs in the financial world. From a methodological point of view, we see the benefit of combining binary and weighted analysis, as they both convey important pieces of information and allow us better to describe the economic phenomena that underlie network statistics.†

5.4. Centrality

So far we have treated nodes as anonymous, not considering which countries display higher or lower network properties. Now we use a measure of centrality (*random walk betweenness centrality*, or RWBC) to identify the core of the international trade and financial networks, i.e. those countries that belong to the 'rich club' mentioned above.

Figure 5 depicts the distribution of RWBC by means of a rank-size plot. First and foremost, the graph shows evidence that centrality is distributed according to a power-law. This implies the existence of a strong heterogeneity, with extreme values much more likely than under a normal distribution, and is therefore consistent with a core–periphery structure.

To identify the countries belonging to the core we (arbitrarily) impose a threshold at the 90th percentile of RWBC: hence, only countries with a value of RWBC within the top 10% are considered part of the core.‡ The composition of the core is quite stable (see table 5), and we find all the 'usual suspects' with only a few exceptions. The presence of Russia in the core of the ITN in 2001 seems occasional as the country drops out in following years and never comes close to rejoining the 'club'. In both the ITN and the IFN, the Netherlands switches in and out, 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 is a key player in financial markets while has a very minor role in goods trade.

5.5. Network properties and per capita GDP

Centrality analysis suggests that the core of the network is made up of high-income countries. In this section we address the issue more directly by studying the correlations between the network properties of each country and its per capita GDP (pcGDP). Our main findings on the subject are summarized in table 6.

High density in the ITN results in a non-significant (from a statistical point of view) relation between ND and pcGDP, while the correlation is positive and significant in the case of financial assets. The correlation is strong and positive when we consider weights, and this pattern is common to both the trade and the financial networks.

†This point is confirmed by a comparison of the binary results with a 'threshold analysis'. As before, we have set a minimum value for each link weight, so as to retain only 80% of all trade links and then computed binary indicators (as proposed in Kali and Reyes 2007). In the case of the correlation between node degree and clustering, results from this 'threshold-based' analysis not only confirm the negative sign, but the coefficient is much more negative, ranging between −0.88 and −0.86, thus conveying a picture substantially different from the one obtained through the weighted approach.

‡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.

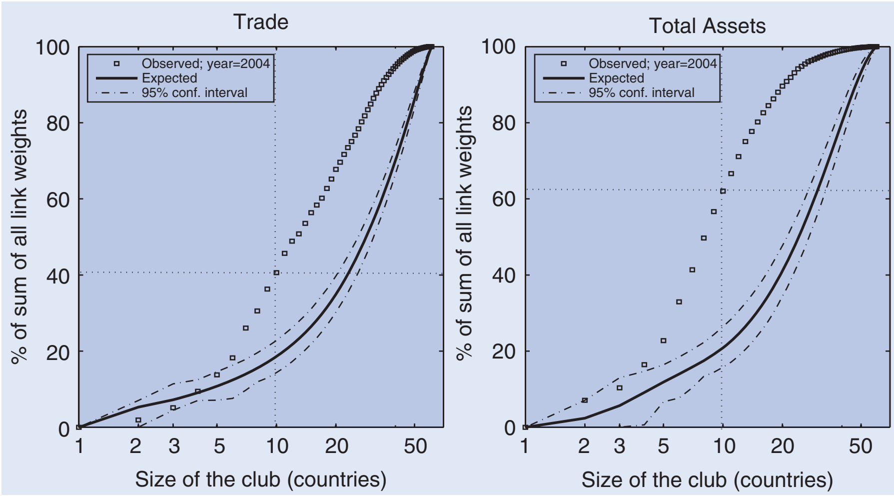

Figure 4. Rich club behaviour in the ITN and IFN.

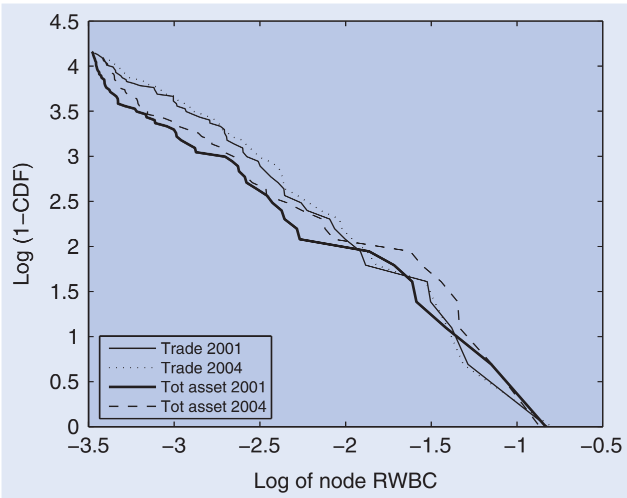

Figure 5. Random Walk Betweenness Centrality size-rank plot.

Table 5. Composition of the core.

2001	2002	2003	2004
	Trade Network		
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	
	Financial Assets Network		
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	

Hence, high-income countries tend to have more partners and to maintain stronger links: in short they are better connected. Of course, causality can (and most probably does) run both ways. Economic integration is likely to spur growth, at least in the medium-to-long run, and in the presence of economies of scale there is a rather strong incentive to connect to high-income countries since they represent richer markets. Also, if part of the gains from (goods) trade comes from technology spillovers as suggested by endogenous growth theory, then more advanced countries become naturally the preferred partners of every economic system. Thus, it is not surprising that these correlations tend to be statistically greater than those observed in a random network, as countries have rather strong incentives to select their own partners on the basis of economic considerations.

The correlations between node clustering and per capita income mimic those obtained above: partners of high-income countries are not very connected (in terms of number of links) among themselves, meaning that

Table 6. Correlation between network indexes and per capita GDP.

	2001	2002	2003	2004
		Degree – pcGDP		
Trade	0.173	0.178	0.178	0.182
Assets	0.720*	0.685*	0.757*	0.772*
		Strength – pcGDP		
Trade	0.477*	0.472*	0.469*	0.411*
Assets	0.577*	0.579*	0.569*	0.576*
		Clustering – pcGDP		
Trade	−0.341*	−0.395*	−0.366*	−0.216
Assets	−0.747*	−0.735*	−0.779*	−0.785*
		Weighted clustering – pcGDP		
Trade	0.518*	0.513*	0.521*	0.464*
Assets	0.695*	0.689*	0.676*	0.691*
		Centrality – pcGDP		
Trade	0.412*	0.401*	0.398*	0.366*
Assets	0.490	0.486	0.472	0.476

*The correlation is significantly (5%) *stronger* than in a random network.

high-income countries tend to act like hubs. On the contrary, strong ties exist among advanced economies, which thus form intensely connected triads.

Finally, the analysis of the correlation between per capita GDP and RWBC reveals a pattern that is similar to that observed for the relationship between node strength and pcGDP. Results presented in the bottom part of table 6 show that, although the correlation is positive for both networks, it is higher in the IFN: this further corroborates the idea that international trade integration is more widespread, so that also lower-income economies can have relatively high centrality. In other words, a higher degree of international financial integration (as measured by network centrality) is more likely related to a high income than strong integration in real markets. Most probably this reflects the fact that, especially after the wave of financial crises of the late 1990s (East Asia, Russia, Argentina), developing countries have become more cautious in their pursuit of capital markets liberalization, so that financial integration has turned into a 'luxury good'. On the contrary, participation in the international trade network has become very widespread also among middle-income countries: the slicing-up of the production chain has resulted in the rapid inclusion of peripheral countries into the trade network.

5.6. *Different asset types*

As mentioned above, CPIS provides information on cross-border holding of financial assets broken down into different classes: equities, total debt, long-term debt and short-term debt. No significant difference emerges in the structural properties of the networks made up by various types of assets. We have already seen (table 1 above) that the density of the graphs corresponding to equities and short-term debt is lower. Similarly, the strength of ties is more concentrated for these two types of assets, as the disparity associated with their graph is higher.

All financial networks display a disassortative nature, so that the star-shaped structure appears to be a common feature of financial relationships. The correlation between ND and CC (and between NS and WCC) has the same sign as the one reported above; its magnitude is also similar to the values observed for total assets, except in the case of short-term debt where the figures are sensibly smaller and the 'rich club' phenomenon is less pervasive.†

6. Discussion and possible extensions

This paper investigates the properties of the international trade and financial networks using both binary and weighted network analyses. The combination of the two approaches yields more precise and thorough insights into the topological structure and properties of the ITN and the IFN.

Our results are consistent with the findings of a number of papers that have applied network analysis to international trade flows. On the contrary, this is the first time that this kind of analysis has been used to investigate patterns of integration in international financial markets. Besides finding that goods markets are more densely connected than financial ones, our results suggest that both types of network display a disassortative, star-shaped structure dominated by a handful of hubs. These hubs form a *rich club*, which is characterized by strong links and can be thought of as the core of the network. This hierarchical structure is more marked in financial than in real markets: we rationalize this in terms of the existence of economies of scale and scope in the processing of information inherent to financial intermediation. Such scale economies lead to the emergence of large financial centres that offer a more efficient intermediation and therefore attract many partners. Moreover, we find that high-income countries tend to be more integrated and more clustered. Hence, they act as hubs for poorer economies, so that a hierarchy exists also in terms of economic development.

Goyal and Van der Leij (2006) point out that in networks characterized by both a star-like structure and a positive correlation between node degree and node strength, strong ties are more important than weak links for bridging different parts of the system. This *strength of strong ties* feature, as they call it, can be seen as another way to express the idea that networks are robust but fragile. In fact, removing one of the peripheral nodes generates no particular problem for the stability of the system. On the contrary, a shock hitting the core will be quickly transmitted to the whole network and can therefore trigger a systemic crisis. Hence, the structure of the trade and financial networks can explain why economic upturns and downturns have often a regional dimension, while shocks hitting key players tend to have a global impact. Also, it is easy to identify the pattern of contagion of the recent financial crisis that originated at the very centre of the financial system. The strong ties existing within the core have implied a quick spreading among high-income countries. Diffusion to developing countries has been slower, due to the peripheral position maintained by those economies in the network. Our results only hint at this issue, and more work is needed to investigate the role played by the topological structure of financial networks in determining contagion when a crisis occurs.

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†The full set of results on different asset classes is available from the authors upon request.

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Appendix A

Table A1. Countries in the sample.

Argentina	Greece	Pakistan
Aruba (only in 2001–02)	Hong Kong SAR	Panama
Australia	Hungary	Philippines
Austria	Iceland	Poland
Bahamas (only in 2001–03)	Indonesia	Portugal
Bahrain	Ireland	Romania
Barbados	Isle of Man (only for CPIS 2001–03)	Russian Fed
Belgium	Israel	Singapore
Brazil	Italy	Slovak Republic
Bulgaria	Japan	South Africa
Canada	Kazakhstan	Spain
Chile	Korea, Republic	Sweden
Colombia	Lebanon	Switzerland
Costa Rica	Luxembourg	Thailand
Cyprus	Macao SAR (only in 2001–02)	Turkey
Czech Republic	Malaysia	Ukraine
Denmark	Malta	United Kingdom
Egypt	Mauritius	United States
Estonia	Mexico	Uruguay
Finland	Netherlands	Vanuatu
France	New Zealand	Venezuela
Germany	Norway	