Economic network dynamics: a structural analysis of the international connectivity of Chinese manufacturing firms

Michele Lo Re
GRIF "Fabio Gobbo", Department of Economics, LUISS Guido Carli University, Rome, Italy
Eleonora Veglianti
Lille Catholic University, Lille, France
Fabrizio Parente
Functional Neuroimaging Laboratory IRCCS Santa Lucia Foundation, Rome, Italy
Umberto Monarca
Department of Law, University of Foggia, Foggia, Italy, and
Cosimo Magazzino
Department of Political Science, Roma Tre University, Rome, Italy

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Abstract

Purpose – This paper explores international trade of the Chinese manufacturing industries through the lenses of network analysis (NA) to visualise the world trade network of the Chinese economy, describe its topology and better explain the international organisation of Chinese manufacturing industries.

Design/methodology/approach – The authors built a dataset of 40,550 Chinese companies and their 107,026 subsidiaries in 118 countries from Orbis-BVD and used a NA to investigate the connection between China and other countries. In particular, the authors studied the connections between Chinese companies and their subsidiaries in order to build a network of Chinese industries.

Findings – The authors found that the network of Chinese companies is ramified but not wide and it can be divided into two clusters. Moreover, the relations between China and other peripheral countries are strongly mediated by a few leading locations (e.g. Hong Kong and the USA).

Originality/value – This paper contributes to the literature in several ways. First, the authors provide empirical evidence on the magnitude and ramifications of Chinese enterprises in the world. The existing studies generally focus on applying NA to sectoral insights (Mao and Yang, 2012; Shaikh *et al.*, 2016; Zheng *et al.*, 2016; Wanzenbö ck, 2018; Krichene *et al.*, 2019), whereas in this work the authors take a comprehensive view of the entire Chinese manufacturing system. Second, this paper complements the existing literature identifying the difference between cluster levels in Chinese manufacturing (Wu and Jiang, 2011) by proposing a cluster centralisation method to analyse the international network of Chinese firms rather than just the national network. Finally, the results also shed light on the international trade relationship between China, Hong Kong and the USA.

Keywords China, Network analysis, Globalization, Manufacturing industries, Network clustering

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1. Introduction

The extraordinary performance of the Chinese economy has attracted the attention of scholars and policymakers (Grossman and Helpman, 1991; Gereffi, 1999; McCombie *et al.*, 2002; Pieper, 2003; Antràs and Helpman, 2004; Magazzino and Mele, 2021).

Many academic scholars have enquired about the main key factors that have characterised the worldwide expansion and diversification of Chinese exports in the global markets. From the analysis of the literature, these factors can be summarised in five different points (Xing, 2016): (1) the abundant labour endowment and corresponding comparative advantage in labour-intensive products (Adams *et al.*, 2006); (2) reforms of domestic institutions, such as the transition to a market-oriented economy, the adoption of export-led growth strategy and unilateral trade liberalisation (Chang and MacMillan, 1991; Hu and Khan, 1997; Li and Matlay, 2006); (3) the improved market access for China's exports through institutional arrangements, namely the World Trade Organisation (WTO) membership, bilateral and multilateral free trade agreements and the abolishment of multi-fibre arrangement (Prasad, 2009); (4) the exchange rate regime adopted by the Chinese government and an undervalued currency (Marquez and Schindler, 2007; Thorbecke and Smith, 2010); (5) massive inflows of export-oriented foreign direct investments (FDIs) (Zhang and Song, 2001; Whalley and Xin, 2010; Udemba *et al.*, 2020).

From a more microeconomic perspective, other scholars have explored the role of enterprises in China's expansion in the global markets using traditional approaches of international economics (Xu *et al.*, 2015; Jones and Zeng, 2019). However, these studies underestimate the role played by firms that are part of a corporate network, such as a business or multinational group (Pan, 2018).

In order to fill this gap, this paper explores international trade of the Chinese manufacturing industries through the lenses of network analysis (NA) to visualise the world trade network of the Chinese economy, describe its topology and better explain the international organisation of Chinese manufacturing industries. NA is, thus, particularly suited for studying and graphically representing several socio-economic structures, illustrating different kinds of dyadic links between the interacting participants in a specific context (Wasserman and Faust, 1994). The main advantage of using NA to explore the international links of Chinese firms relies on the information that networks provide. To capture the global properties of such a system, it is important to model them as a graph whose nodes represent the dynamic units and whose links stand for interaction between them.

We built a dataset of 40,550 Chinese companies and their 107,026 subsidiaries in 118 countries from Orbis-BVD and used a NA to investigate the connection between China and other countries. In particular, we studied the connections between Chinese companies and their subsidiaries in order to build a network of Chinese industries.

This paper contributes to the literature in several ways. First, we provide empirical evidence on the magnitude and ramifications of Chinese enterprises in the world. The existing studies generally focus on applying NA to sectoral insights (Krichene *et al.*, 2019; Mao and Yang, 2012; Shaikh *et al.*, 2016; Zheng *et al.*, 2016; Wanzenböck, 2018), whereas in this work we take a comprehensive view of the entire Chinese manufacturing system. Second, this paper complements research identifying the difference between cluster levels in Chinese manufacturing (Wu and Jiang, 2011) by proposing a cluster centralisation method to analyse the international network of Chinese firms and not just the national network. Finally, the results of this study shed light on the international trade relationship between China, Hong Kong and the USA.

The study is organised as follows: Section 2 explores the literature review on NA in economic issues; Section 3 describes the methodology, data; and measures; Section 4 is followed by the analysis and discussion of the empirical results; finally, Section 5 concludes by providing a set of specific managerial and policy implications and avenues for future research.

2. Literature review

Compared to traditional methodological approaches that use firms as the focus of their analysis, NA takes the relationships between agents as the object of investigation and states that agents' behaviour is influenced by the relationships that surround them (Borgatti *et al.*, 2009). Wasserman and Faust (1994) identified four distinctive elements of NA compared to traditional statistical methods: (1) actors and their actions are viewed as interdependent rather than independent; (2) relational ties between actors are channels for transfer or flow of resources (either material or nonmaterial); (3) network model focussing on individual view the network structural environment as providing opportunities for or constraints on individual action; (4) network models conceptualise structure as lasting patterns of the relation amongst actors.

Social NA is thus particularly suited for studying and graphically representing several socio-economic structures, illustrating different kinds of dyadic links between the interacting participants in a specific context. NA is also a well-known and widely used methodology in the field of economic analysis (Aviv *et al.*, 2003; Borgatti *et al.*, 2009; Carrington *et al.*, 2005; Wasserman and Faust, 1994). From the initial studies carried out by Freeman (1977, 1978), scholars have focussed on analysing how different patterns of relationships amongst a network's members may directly or indirectly generate and affect the structural characteristics of the network and observed performances.

The socioeconomic issues to which the tools of NA are applied can be summarised as follows: the study of global value chains (GVC), where NA contributes to determining the structure and complexity of the relationships created in the supply chain (Zheng *et al.*, 2016; Zhou *et al.*, 2016; Amador and Cabral, 2017); the study of environmental impacts through the analysis of the structure distribution and functional relationships within the ecosystem (ecological NA, Hannon, 1973; Shaikh *et al.*, 2016); the analysis of trade and economic relations between different countries analysed from different perspectives, e.g. connections between manufacturing sectors (Monarca *et al.*, 2019), linkages of different national R&D networks (Krichene *et al.*, 2019), the study of trade flows (Bhattacharya *et al.*, 2008).

3. Methodology

3.1 Data and network settings

A database containing 40,550 Chinese companies and their 107,026 subsidiaries in 118 countries has been extracted from ORBIS-BVD database. All Chinese manufacturing firms that owned at least one subsidiary abroad have been selected. Table 1 shows the distribution of extracted firms by firms' annual operating revenue.

Annual operating revenue (K EUR)	Number of firms	%
Min-1,000	865	2.1
1,001–5,000	3,725	9.2
5,001–10,000	13,202	32.6
10,001–25,000	8,723	21.5
25,001–50,000	6,163	15.2
50,001–100,000	4,386	10.8
100,001–500,000	1,710	4.2
500,001–1,000,000	889	2.2
1,000,000–10,000,000	837	2.1
10,000,001-Max	50	0.1
Total	40,550	100.0

Source(s): Authors' elaborations on ORBIS-BVD database

Table 1. Distribution by firms' annual operating revenue (2017)

Using such data, we made a weighted network defining the countries as nodes and the weights as the number of different Chinese companies having branches in both the given countries; i.e. a link between two countries existed if at least one Chinese firm had a branch in both countries. We obtained a bi-directed, weighted network (link without a direction). Then, we obtained an adjacency matrix with the following characteristic: $N = 118$ nodes, $K = 1,980$ links and $W = 9,788$ total weights. The network developed does not take into account companies originating in other countries than China.

3.2 Network and statistical analysis

NA is particularly suited for studying and graphically representing several socio-economic structures, illustrating different kinds of dyadic links between the interacting participants in a specific context (Wasserman and Faust, 1994). The results of NA might be used to: identify the countries that play central roles; discern information breakdowns, bottlenecks and structural holes, as well as isolated countries; strengthen the efficiency and effectiveness of existing relationships; refine strategies (Serrat, 2017).

To study different properties of the network, we split the analysis into three steps: (1) General analysis of degree distribution and strength distribution; (2) analysis of weighted network; (3) analysis of the binary network.

In order to perform the weighted and binary NA, we normalised our network: (1) rescaling all weight magnitudes to the range [0,1] for the former case; i.e. dividing the whole set of weights to the maximum one; and (2) setting all weights of network to 1 (then we have only two possible values 1 and 0) for the latter case. In the following analysis, we compare the weighted network with its binary version. In such a way, possible relations between the quantitative properties of weighted links and the minimal network structure (topology of the network) can be obtained.

In the first step, we calculated the strength and degree distribution amongst the nodes. The strength (s_i) is calculated as the sum of the nodes' weights. In the same way, the node degree (k_i) is calculated as the sum of the weights of the binary matrix; i.e. as the possible values are only 0/1, this corresponds to the number of links of a given node. Then, we calculated the distribution function using the node strength and the node degree. This analysis measures the distribution probability that a node has a given strength/degree value, providing general information about the structure of a network. Because of the peculiar characteristics of the scale-free network (Choromański *et al.*, 2013), we fit the obtained distribution with the power-law distribution using the method of Clauset *et al.* (2009).

In the second step, we used a classical analysis of weighted networks (Barrat *et al.*, 2004), analysing five different indicators.

(1) The dependences between the strength and node degree if the strength as a function of degree (k) has the empirical form of $s(k) = k^{\beta}$ with $\beta = 1$, there is a linear relationship between strength and node degree, and thus they provide the same information on the system (Barrat *et al.*, 2004).

(2) The disparity index (Y) explores the setting of weights around nodes; if all edges of nodes tend to have the same weight values, then $Y(k) = 1/k$. Otherwise, if the weight of a single link dominates, then Y(k) is independent of k (Derrida and Flyvbjerg, 1987). Note that, from an economic point of view, the disparity index indicates whether the weight of each nation is given by the strong presence of a bilateral relationship with another nation (dependence; therefore, indicating relative weakness in economic keys, such as exposure to external shocks) or if the weight is due to multiple relationships between the country/node examined and the others (relative independence; therefore strength index in the economic sense).

(3) The clustering coefficient (C) measures the global density of interconnected node triplets (i.e. three fully connected nodes; the binary form considers only the topological features of the network) and then studies the cohesiveness of each node in the network. Further, for the weight network (C^w), the local cohesiveness takes into account the importance of the clustered structure based on the weight's intensity actually found on the local triplets. These indices provide global information on the correlation between weights and topology: if $C^w > C$, the triplets are formed by the edges having high weight values; if $C^w < C$ the clusterised nodes are formed by edges with low weight values. More information can be carried out by exploring the clustering coefficient (both binary and weight version) as a function of node degree C(k). Thus, if this analysis shows an exponential decaying behaviour (power-law decay), low-degree nodes have interconnected communities (with a high clustering coefficient), while more connected nodes tend to have a small clustering coefficient value. Such architecture is called hierarchical network model (HNM) (Ravasz and Barabási, 2003).

(4) The weighted average nearest-neighbours degree (k_{nn}^{w}) is a measure capable to characterise the assortative/disassortative behaviour in a weighted network (Newman, 2002). Such an index describes the preference of nodes to have connections with others having similar (assortative network) or dissimilar (disassortative network) strength. As for the clustering coefficient, we compare the binary (k_{nn}) and the weighted form (k_{nn}^{w}). Then, if $k_{nn}^{w} > k_{nn,}$ the edges with larger weights are pointing to the neighbours with a larger degree; if $k_{nn}^{w} < k_{nn,}$ then the opposite behaviour. In economic terms, the index measures the propensity of a nation/node to connect with the weakest/peripheral nations or with the most central and strong ones.

(5) Global and local efficiency are measures of exchanges of information efficiency (Latora and Marchiori, 2001). In particular, global efficiency indicates the information exchange across the whole network; while, local efficiency indicates information exchanged by a node to its neighbours. As a general remark, a *path* is a particular trajectory between two nodes not passing more than one time on each node, and then the efficiency is the reciprocal value of the *shortest path length* between each network node, indicating the minimum set of nodes in the path between two nodes. Note that, in the case of a weighted network, the *shortest path length* is calculated by the lower set of link weights between two nodes, and then the same index can feature different results in binary and weighted networks. In particular, the global efficiency takes into account the whole set of network nodes, while the local efficiency takes into account the node neighbours of a given node. For example, if in a binary network going from node A to node B, the minimum path must pass through C, D and E, the indicator is evaluated as 1/3, because three nodes have to be passed through to make the connection between A and B. The network is more efficient if there are a few intermediate nodes between two randomly taken nodes. To characterise the non-random structure of the network, we compared the efficiency indices calculated in the real network to the same values calculated in 100 random models. Note that the distances are calculated only on the network properties and do not take into account the real geographical distance between countries.

In the last step, we explore the topological features of the networks. We can further subdivide the analysis into three other phases.

(1) In the first phase, we study the possible small-world architecture of the network. This model is characterised by a high level of segregation and a high level of integration. We calculated these quantities using local efficiency as a measure of segregation and

global efficiency as a measure of integration (Latora and Marchiori, 2001). To prove the statistical property of such measures, we carried out these analyses in 100 randomised matrices, and then we compared the real network values to the random one. In the presence of small-world topology, the local efficiency has a value greater than the random model, while the global efficiency has the same value as the random model. In order to confirm the previous analysis, we used an alternative method to define the small-world architecture (Humphries and Gurney, 2008). In such a way, we calculated the clustering coefficient (the same index as the previous section) and the average path length (APL). This last index measures the average of the path (i.e. sequence of links connecting a sequence of nodes, which does not pass through the same node two times) amongst all the network nodes; the greater this value is, the more distant (and less integrated) are nodes themselves. Then, we calculated these indices for the real network and in 100 randomised models. Consequently, a normalised form of clustering coefficient (gamma) and APL (lambda) were performed, and the small-worldness index (sigma) was calculated (a ratio between gamma and lambda). In fact, it is easy to see that a segregated network has a gamma value higher than one, while the lambda value is equal to one. Thus, in a small-world architecture, the sigma index has value higher than one.

(2) Furthermore, since different companies' strategies are possible depending on geographical factors, we explore the modularity of the network. We used the modularity algorithm (Newman, 2006), searching for an optimal network subdivision into non-overlapping groups of nodes. We performed 100 repetitions of calculation, taking the best result that maximise the number of within-group links and minimise the number of between-group links (high values of Q index). Finally, to prove the non-randomness of our result, we compared these results to 100 times randomised models.

(3) In the last phase, we pointed to the local properties of the network. In such a way, we performed the centrality analysis and the functional cartography analysis. Regarding the centrality analysis, we characterised nodes with three different centrality measures: strength, betweenness (Freeman, 1977) and eigenvector centrality (Ruhnau, 2000; Bonacich and Lloyd, 2001). Finally, to improve the description of local features within the whole network characteristic, we use the functional cartography analysis (Guimerà and Amaral, 2005). In this analysis, we used the information from the previous modularity analysis to characterise the specific role of each node in the network. In particular, the within-degree z-score (z) and the participant coefficient (P) are calculated: the first index measures the node degree of nodes within their own module, describing the intra-module connectivity (since it is a standard deviation transformation, the range of such an index is theoretically from – infinite to + infinite, nodes having values upper than 2.5 are defined as a hub); the second index studies how the node connections are distributed amongst all modules (this index ranges from 0, if all the node connections are within own module, to 1, if node connections are distributed in all modules equally).

Consequently, on these assumptions, we set the following node classes (Guimerà and Amaral, 2005):

(1) R1-*Ultra-peripheral nodes* (with connections only within its module, $z < 2.5$ and $P \approx 0$);

(2) R2-*Peripheral nodes* (having most of the connections within its module, $z < 2.5$ and $P < 0.62$);

(3) R3-*Non-hub connectors* (with circa half of the connections within its module, $z < 2.5$ and $0.62 < P < 0.80$);

(4) R4-*Non-hub kinless nodes* (with most of the connections outside its module and not clearly associated with a single module, $z < 2.5$ and $P > 0.80$);

(5) R5-*Provincial hubs* (central nodes having most of the connections within its module, $z > 2.5$ and $P < 0.30$);

(6) R6-*Connector hubs* (central nodes with half connections outside it module, $z > 2.5$ and $0.30 < P < 0.75$);

(7) R7-*Kinless hubs* (central nodes with few connections within its module and not clearly associated with a single module, $z > 2.5$ and $P > 0.75$).

The random model of the network was performed preserving the degree and strength distributions for the weighted network (Rubinov and Sporns, 2011) and preserving the degree distribution for the binary network (Maslov and Sneppen, 2002). A set of homemade scripts and the brain connectivity toolbox (BCT) in Matlab (Rubinov and Sporns, 2010) were used to perform the whole analysis.

4. Results

4.1 General information on the network

The connectivity density is equal to 0.29 (total number of possible links: 6,903). The mean degree is $<k>$: 33.6, with a maximum value of 118 node degree and a minimum of 1 node degree. The sum of all weights is $W = 9{,}788$, while the mean strength is $<s \geq 82.9$, with a maximum of 1,033 and a minimum of 1 (see Figure 1).

The degree and strength distribution shows a long-tail curve. In particular, the degree distribution (Figure 2, left panel) has a trend for a power-law distribution (*p*-value: 0.057) with a cut-off at 40 node degree S.D. 5.3 and a beta value of 3.5 S.D. 0.27; the strength distribution (Figure 2, right panel) does not fit with the power-law distribution (*p*-value: 0.92). From the 40 node degree (cut-off), it is possible to note a trend for the power-law distribution (Figure 2, left panel).

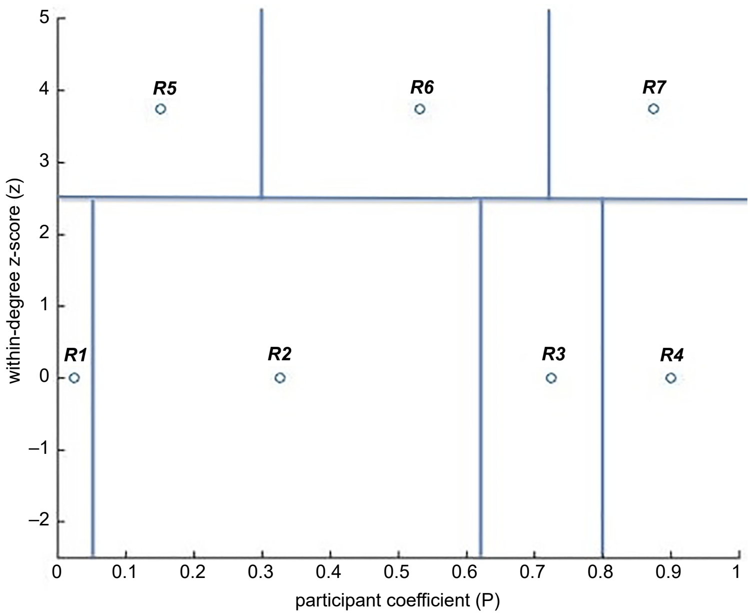
4.2 Network Analysis

(1) Weighted network

The study of strength/degree dependences shows a relative linear function between them (Figure 3, left panel). The beta coefficient is equal to: 1.28 (95% confidence bounds, 1.22–1.34), meaning that strength tends to grow faster than the degree; thus, the more connected countries host more companies than other countries.

Moreover, the disparity analysis gives a beta coefficient of −0.77 (−0.82, −0.72) (Figure 3, right panel). Thus, there is a trend to have an equal number of weights within each node. Note that for the most connected nodes, this trend is less clear due to a more weight variability amongst their links, as it is possible to note in the right panel of Figure 2; more connected nodes tend to be more distributed around the fitted line.

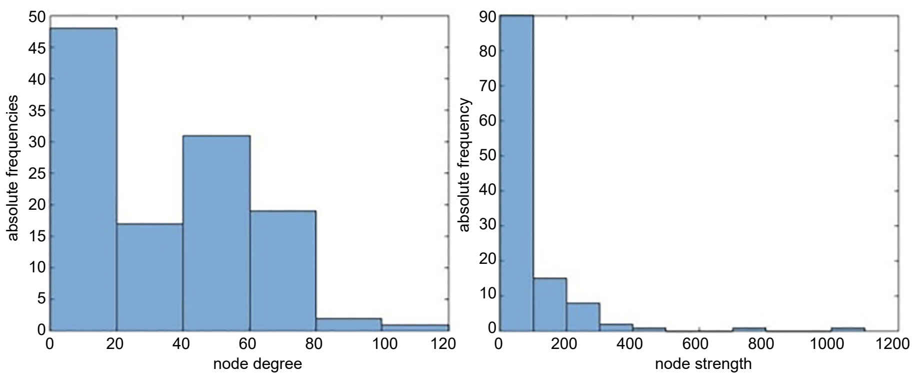
In order to better understand the hierarchical structure of the network, we compare the weighted network with a simplified binary version of the same network. As analysed above, in the weighted network a link exists between two countries if at least one Chinese firm has a branch in both countries, and we measure the weights of this link as the number of different Chinese firms having branches in both the given countries. In the simplified binary version, the link between the different countries exists under the same conditions as in the weighted network, but the weights of this link are always one, if it exists at all, regardless of the number of Chinese firms involved. In these two network versions, we compare the clustering coefficient and k_{nn} indicators (Figure 4).



Note(s): As a function of the within-degree z-scores (z) and the participation coefficient values seven classes of nodes can be defined. Depending on the degree within the module, we classify nodes with z ≥ 2.5 as module hubs and nodes with z < 2.5 as non-hubs. Both hub and non-hub nodes are then characterised more finely using the values of the participation coefficient described in par. 3.2

Source(s): Authors' elaborations in Matlab and Gephi

Figure 1.
Distribution of the node roles across the z/P scatter plot



Source(s): Authors' elaborations in Matlab and Gephi

Figure 2.
Left panel: degree distribution; right panel: strength distribution

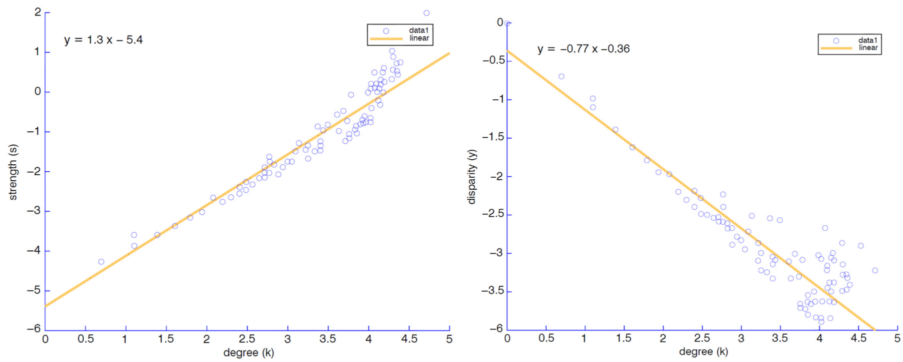
The weighted clustering coefficient (C^w) is equal to 0.42 (s.d. 0.09), while the C in the binarised network is: 0.79 (s.d. 0.23). While the high value of the topological index shows a high-clusterised network, the lower value of the weighted index is related to a structure having low link weights amongst network triangles. Figure 4 (right panel) shows dependence between the binarised clustering coefficient and node degree, indicating a hierarchical structure of the network.

Both networks show a negative value of slope (weighted: −0.16; binary: −0.25). Figure 4 (left panel) shows the k_{nn} values as a function of the node degree: it is clear that only for the binary network there is a negative dependence, then while central nodes tend to link less connected nodes, the corresponding weights are not distributed in the same manner. As a result, the central countries, i.e. those with the most connections, are evenly connected to all the other countries in their portion of the network, thus not showing stronger connections to the peripheral countries.

Finally, we studied the organisation of weights by comparing the local and global efficiency of the real network and the same indices of the randomised network. Figure 5 shows non-significant differences between the real and the random network for the local efficiency index; thus, the combination of weights around the network does not give information about their clusterisation. Moreover, the global efficiency of the real network has a lower value than the related index in the random model, confirming a random distribution of weights around the network.

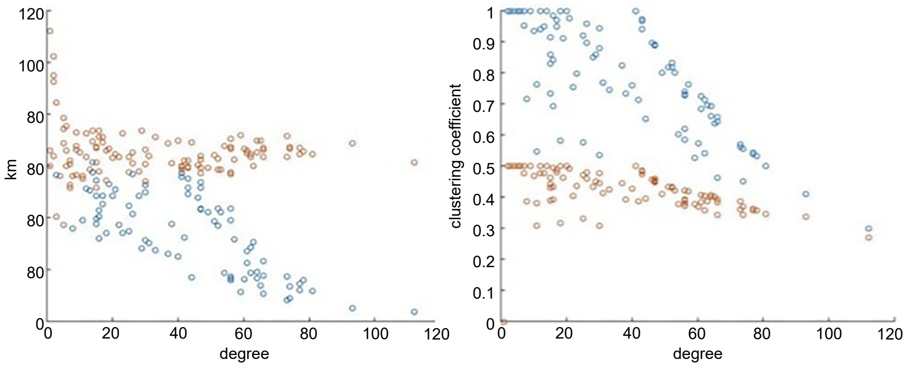
(2) Binary networks

The previous analysis shows a particular architecture of binary networks. Thus, we explore in-depth the topological characteristics of the network, removing the weight information.



Source(s): Authors' elaborations in Matlab and Gephi

Figure 3.
Right panel: log-log scatter plot between degree and strength; left panel: log-log scatter plot of degree as a function of disparity



Note(s): In red the node degree in weighted network, in blue the node degree in binary network
Source(s): Authors' elaborations in Matlab and Gephi

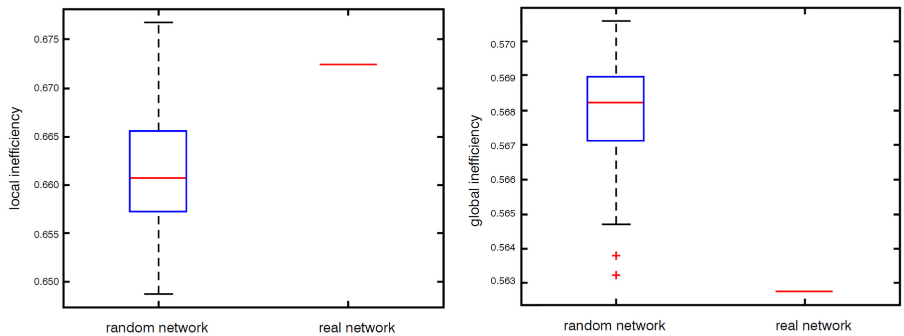
Figure 4.
Left panel: scatter plot of node degree and knn; right panel: scatter plot of node degree and clustering coefficient

In Table 2, we can see the local and global efficiency of a binary network; in contrast to the weighted values, these indices describe a well-clusterised network (local efficiency of real network upper than corresponding randomised value) and a good level of sharing information amongst nodes (global efficiency of real network equal to the corresponding randomised values). These characteristics together describe a small-world network; the small-worldness index (sigma) confirms this trend (sigma: 1.090 s.d. 0.007). For a complete description of index values, see Table 2.

Both local and global values of efficiency show an efficient exchange of information across the whole network, as well as on local scales. The sigma value shows a good balance between the segregation and integration level, confirming the small-world architecture of the network (Table 1).

We identify modules by maximising the modularity of the network as in Guimerà and Amaral (2005). This technique minimises the problem of finding suboptimal partitions, but more importantly does not require specifying *a priori* the number of modules, which will be a result of the algorithm. Our algorithm can reliably identify modules in a network whose nodes have up to 50% of the connections outside their module (Guimerà and Amaral, 2005). The link between two countries is detected if a Chinese company has a branch in both countries. For example, if the Chinese firm Alfa has a branch in US and IT, the algorithm detects a link between US and IT. The more a country is linked to others, in the way just described, the more its centrality in the network increases, and vice versa, i.e. the fewer links a country has with others, the more peripheral it is in the network. The modularity analysis investigates the absence of connections and identified two modules (Table 3). The modularity analysis shows two main clusters with a Q score of 0.17.

The centrality analysis shows two main central nodes for all the centrality measures used. These nodes have a z-score value higher than two for the node degree and the betweenness, while eigenvector centrality has lower z-score values (higher than 1.7). In Table 4 the related nodes and centrality values are inserted.



Source(s): Authors' elaborations in Matlab and Gephi

Figure 5. Box-plot of weighted efficiency measures; left panel: local efficiency; right panel: global efficiency

Network index	Values
Local efficiency	0.875 s.d. 0.187
Global efficiency	0.639
Sigma	1.090 s.d. 0.007
Gamma	1.095 s.d. 0.006
Lambda	1.005 s.d. 0.003
Assortativity	−0.254

Source(s): Authors' calculations in Matlab

Table 2. Indices values of binary network

The two modules can be considered two independent sub-networks. This means that countries placed in one module are connected to each other but have no direct connections to countries in the other module. Countries placed in two different modules could only communicate with each other through the presence of a possible connector node, which we try to identify using centrality analysis.

Finally, in order to study the role of each node in its modules, we study the functional cartography of the network. From this analysis, the ultra-peripheral nodes are: AG, AZ, BF, EC, ET, FM, GA, GN, IR, JO, KG, LA, MH, MR, TD, TJ, VE, ZM; the connector hub is HK, while the USA has a limit values for this category; all the remaining nodes are peripheral nodes. Note that the ultra-peripheral nodes and the connector hubs belong to the same module.

Most nodes belong to the R2 square (peripheral nodes), indicating a well-clusterised structure inside their module, but having a small amount of extra-module connection. A small part of the nodes falls in the R1 square (ultra-peripheral), indicating no extra-module connections. Only one node (HK) belongs to the R6 square (connector hubs) appearing as the main connector between modules; the USA has a trend to be a connector hub.

A general issue about the network: we found a quasi-linear correspondence between node degree and strengths with an equal distribution of weights amongst the node links. Moreover, analysis of the weighted network shows an independent distribution of weights amongst the network nodes. Then, it seems that weights are randomly distributed and do not represent the structural characteristic of this network. Conversely, the binary network has very peculiar features different from a random network.

In particular, it has a small-world topology, with a well-clusterised structure and well-shared information amongst nodes at the same time. This means clustering features as a regular network and efficient communication amongst nodes as a random network. These characteristics together describe a complex network in which the integration–segregation features are balanced. However, the dependence of clustering coefficient as a function of node degree indicates a hierarchical structure in which central nodes are not well clustered, but at the same time tend to connect nodes with a small number of links. Thus, the network studied has a hierarchical architecture with a small-world topology.

Module 1	Module 2
AT – BD – BG – BH – BW – CH – CI – CO – DE – DK – DZ – EG – FR – GB – GH – HU – IE – IT – JP – KR – LV – MA – MD – MG – MT – MX – NA – NO – PE – PL – PT – RO – RS – SC – SE – SK – TH – TN – UZ – VN	AE – AG – AL – AR – AU – AZ – BB – BE – BF – BM – BN – BR – BY – CA – CD – CG – CL – CM – CY – CZ – EC – ES – ET – FI – FM – GA – GN – HK – ID – IL – IN – IR – JO – KE – KG – KH – KW – KY – KZ – LA – LK – LT – LU – MH – ML – MM – MN – MO – MR – MY – MZ – NG – NL – NZ – PA – PG – PH – PK – QA – RU – SA – SG – SI – SR – TD – TJ – TR – TW – TZ – UG – US – UY – VE – VG – WS – ZA – ZM – ZW

Note(s): To identify each country the "ISO standard – Codes for the representation of names of countries and their subdivisions" has been used (see Appendix)
Source(s): Authors' calculations in Matlab

Table 3. Countries belonging to module 1 and 2, respectively

Country	Node degree	Betweenness	Eigenvector
HK	112	2,803	0.17
US	93	815	0.17

Source(s): Authors' calculations in Matlab

Table 4. Centrality values of central nodes

In addition, clusters of the network form two defined modules. The functional cartography shows that the first module is formed only by peripheral nodes, sharing most of the links within their module. Few ultra-peripheral nodes and connector hubs form the second module, besides the peripheral nodes.

As a last comment, it is probable that the central nodes (HK and US) tend to have connections to the ultra-peripheral nodes only, and then other peripheral nodes share their information in an efficient way independently. Thus, a possible phenomenon between the hubs connector and the ultra-peripheral nodes independently from the two found modules cannot be excluded.

5. Conclusions

From a descriptive point of view, the network of Chinese firms that we have reconstructed has two characteristics. First, the international network of Chinese firms is highly ramified, but not very wide. The network has characteristics of a non-random network in the binary analysis. In particular, the international network of Chinese firms has a pronounced cluster structure, but at a lower level of node degree, as described by the hierarchical model (Ravasz and Barabasi, 2003). At the same time, communication efficiency between nodes in maintained indicating a good balance between integration-segregation features, in according to the small-world model (Latora and Marchiori, 2001). Moreover, the peripheral countries tend to be connected between them in an independent manner, while the countries located in the ultra-peripheral nodes need the mediation of the central nodes to relate to each other and to the rest of the network.

Second, it is possible to divide the network into two clusters. The first cluster (module 1) contains the main European and African countries, while the second and larger cluster contains a few European countries (mainly from the East) and countries from the remaining continents, in particular North and South America. The division into clusters indicates that the network of Chinese enterprises operates in the two areas almost independently.

From an economic perspective, these characteristics of the Chinese firm network lead to important considerations. Our analysis is not dynamic but represents a snapshot of the network that Chinese firms have built to date. We have identified the structural characteristics of this network, which has been described as wide but not deep. These characteristics imply that the different subsidiaries of Chinese firms scattered in different countries have not yet created strong mutual connections. From a relational point of view, all this means that the foreign network of Chinese firms is qualitatively poor, i.e. not able to foster and strengthen itself through synergetic processes between the subsidiaries located in the target countries. Without the mediation of the parent company, the subsidiaries are not able to profitably interact with each other or open new markets.

This particular network structure could be the result of an initial phase of expansion of Chinese enterprises abroad, a phase that focussed more on quantity, i.e. the extension of the network to an increasingly larger number of countries, than on quality, i.e. the strengthening of autonomous links between subsidiaries located in foreign countries. Policy measures such as the Belt and Road Initiative can be contextualised in this analysis as instruments aimed at closing the season of quantitative expansionism of Chinese companies and opening a new course aimed at strengthening ties with certain foreign countries in order to generate those network synergies that, at the moment, Chinese expansionism abroad does not seem to have fully achieved (Mele and Magazzino, 2020). Compared to these analyses, two countries emerge as exceptions, HK and US, which stand out as the only strong and branching nodes in the network of Chinese enterprises abroad. These countries are in fact, in addition to China itself of course, connectors, i.e. Chinese subsidiaries located in HK and US facilitate the connection of other subsidiaries in the network, especially those located in countries with fewer connections within the network (ultra-peripheral countries). The role of these two countries is important at the moment, but their impact on the future development of the network may be marginal. In fact, the real policy challenge will be to strengthen the quantitative and qualitative linkages also with other countries in order to have a more efficient network with several countries playing the role of connectors.

There are several possibilities for future research, in particular as regards the deepening of the model by extending the research with backward-looking data. The use of data from at least the last five years, for example, would make it possible to understand not only the current conformation of the international network of Chinese companies (as in this article), but also the path that has projected them so far. It is important to carry out an increasingly detailed monitoring process, which enables a thorough assessment of Chinese industrial dynamics as a potential threat or opportunity posed to target countries.

References

Adams, F.G., Gangnes, B. and Shachmurove, Y. (2006), "Why is China so competitive? Measuring and explaining China's competitiveness", *World Economy*, Vol. 29 No. 2, pp. 95-122, doi: 10.1111/J.1467-9701.2006.00773.X.

Amador, J. and Cabral, S. (2017), "Networks of value-added trade", *The World Economy*, Vol. 40 No. 7, pp. 1291-1313, doi: 10.1111/TWEC.12469.

Antràs, P. and Helpman, E. (2004), "Global sourcing", *Journal of Political Economy*, Vol. 112 No. 3, pp. 552-580, doi: 10.1086/383099.

Aviv, R., Erlich, Z., Ravid, G. and Geva, A. (2003), "Network analysis of knowledge construction in asynchronous learning networks", *Journal of Asynchronous Learning Networks*, Vol. 7 No. 3, pp. 1-23.

Barrat, A., Barthélemy, M., Pastor-Satorras, R. and Vespignani, A. (2004), "The architecture of complex weighted networks", *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 101 No. 11, pp. 3747-3752, doi: 10.1073/pnas.0400087101.

Bhattacharya, K., Mukherjee, G., Saramäki, J., Kaski, K. and Manna, S.S. (2008), "The International Trade Network: weighted network analysis and modelling", *Journal of Statistical Mechanics: Theory and Experiment*, Vol. 2008 No. 02, P02002, doi: 10.1088/1742-5468/2008/02/P02002.

Bonacich, P. and Lloyd, P. (2001), "Eigenvector-like measures of centrality for asymmetric relations", *Social Networks*, Vol. 23 No. 3, pp. 191-201, doi: 10.1016/S0378-8733(01)00038-7.

Borgatti, S.P., Mehra, A., Brass, D.J. and Labianca, G. (2009), "Network analysis in the social sciences", *Science*, Vol. 323 No. 5916, pp. 892-895, doi: 10.1126/science.1165821.

Carrington, P.J., Scott, J. and Wasserman, S. (2005), *Models and Methods in Social Network Analysis*, Cambridge University Press, Cambridge.

Chang, W. and MacMillan, I. (1991), "A review of entrepreneurial development in the People's Republic of China", *Journal of Business Venturing*, Vol. 6 No. 6, pp. 375-379.

Choromański, K., Matuszak, M. and Miękisz, J. (2013), "Scale-free graph with preferential attachment and evolving internal vertex structure", *Journal of Statistical Physics*, Vol. 151 No. 6, pp. 1175-1183, doi: 10.1007/s10955-013-0749-1.

Clauset, A., Shalizi, C.R. and Newman, M.E.J. (2009), "Power-law distributions in empirical data", *SIAM Review*, Vol. 51 No. 4, doi: 10.1137/070710111.

Derrida, B. and Flyvbjerg, H. (1987), "Distribution of local magnetisations in random networks of automata", *Journal of Physics A: Mathematical and General*, Vol. 20 No. 16, pp. L1107-L1112, doi: 10.1088/0305-4470/20/16/013.

Freeman, L.C. (1977), "A set of measures of centrality based on betweenness", *Sociometry*, Vol. 40 No. 1, pp. 35-41.

Freeman, L.C. (1978), "Centrality in social networks", *Social Networks*, Vol. 1 No. 1968, pp. 215-239, doi: 10.1016/0378-8733(78)90021-7.

Gereffi, G. (1999), "International trade and industrial upgrading in the apparel commodity chain", *Journal of International Economics*, Vol. 48 No. 1, pp. 37-70, doi: 10.1016/S0022-1996(98)00075-0.

Grossman, G.M. and Helpman, E. (1991), *Innovation and Growth in the Global Economy*, MIT Press, Cambridge, MA.

Guimerà, R. and Amaral, L.A.N. (2005), "Cartography of complex networks: modules and universal roles", *Journal of Statistical Mechanics: Theory and Experiment*, Vol. 2005 No. 02, P02001, doi: 10.1088/1742-5468/2005/02/P02001.

Hannon, B. (1973), "The structure of ecosystems", *Journal of Theoretical Biology*, Vol. 41 No. 3, pp. 535-546, doi: 10.1016/0022-5193(73)90060-X.

Hu, Z.F. and Khan, M.S. (1997), "Why is China growing so fast?", *IMF Staff Papers*, Vol. 44 No. 1, pp. 103-129, doi: 10.2307/3867499.

Humphries, M.D. and Gurney, K. (2008), "Network 'small-world-ness': a quantitative method for determining canonical network equivalence", *PLoS ONE*, Vol. 3 No. 4, e0002051, doi: 10.1371/journal.pone.0002051.

Jones, L. and Zeng, J. (2019), "Understanding China's 'Belt and Road Initiative': beyond 'grand strategy' to a state transformation analysis", *Third World Quarterly*, Vol. 40 No. 8, pp. 1415-1439, doi: 10.1080/01436597.2018.1559046.

Krichene, H., Fujiwara, Y., Chakraborty, A., Arata, Y., Inoue, H. and Terai, M. (2019), "The emergence of properties of the Japanese production network: how do listed firms choose their partners?", *Social Networks*, Vol. 59, pp. 1-9, doi: 10.1016/J.SOCNET.2019.05.002.

Latora, V. and Marchiori, M. (2001), "Efficient behavior of small-world networks", *Physical Review Letters*, Vol. 87 No. 19, 198701, PMID: 11690461, doi: 10.1103/PhysRevLett.87.198701.

Li, J. and Matlay, H. (2006), "Chinese entrepreneurship and small business development: an overview and research agenda", *Journal of Small Business and Enterprise Development*, Vol. 13 No. 2, pp. 248-262, doi: 10.1108/14626000610665953.

Magazzino, C. and Mele, M. (2021), "On the relationship between transportation infrastructure and economic development in China", *Research in Transportation Economics*, Vol. 88, 100947, doi: 10.1016/j.retrec.2020.100947.

Mao, X. and Yang, Z. (2012), "Ecological network analysis for virtual water trade system: a case study for the Baiyangdian Basin in Northern China", *Ecological Informatics*, Vol. 10, pp. 17-24, doi: 10.1016/J.ECOINF.2011.05.006.

Marquez, J. and Schindler, J. (2007), "Exchange-rate effects on China's trade", *Review of International Economics*, Vol. 15 No. 5, pp. 837-853, doi: 10.1111/J.1467-9396.2007.00700.X.

Maslov, S. and Sneppen, K. (2002), "Specificity and stability in topology of protein networks", *Science*, Vol. 296 No. 5569, pp. 910-913, doi: 10.1126/science.1065103.

McCombie, J.S.L., Pugno, M. and Soro, B. (2002), *Productivity Growth and Economic Performance: Essays on Verdoorn's Law*, Palgrave Macmillan, New York.

Mele, M. and Magazzino, C. (2020), "A machine learning analysis of the relationship among iron and steel industries, air pollution, and economic growth in China", *Journal of Cleaner Production*, Vol. 277, doi: 10.1016/j.jclepro.2020.123293.

Monarca, U., Cassetta, E., Lo Re, M. and Meleo, L. (2019), "A network analysis of the intersectoral linkages between manufacturing and other industries in China and Italy", *Global Journal of Emerging Market Economies*, Vol. 11 Nos 1-2, doi: 10.1177/0974910119871367.

Newman, M.E.J. (2002), "Assortative mixing in networks", *Physical Review Letters*, Vol. 89 No. 20, 208701, doi: 10.1103/PhysRevLett.89.208701.

Newman, M.E.J. (2006), "Finding community structure in networks using the eigenvectors of matrices", *Physical Review E*, Vol. 74 No. 3, 036104, doi: 10.1103/PhysRevE.74.036104.

Pan, Z. (2018), "Varieties of intergovernmental organization memberships and structural effects in the world trade network", *Advances in Complex Systems*, Vol. 21 No. 02, 1850001, doi: 10.1142/S0219525918500017.

Pieper, U. (2003), "Sectoral regularities of productivity growth in developing countries - a Kaldorian interpretation", *Cambridge Journal of Economics*, Vol. 27 No. 6, pp. 831-850, doi: 10.1093/cje/27.6.831.

Prasad, E.S. (2009), "Is the Chinese growth miracle built to last?", *China Economic Review*, Vol. 20 No. 1, pp. 103-123, doi: 10.1016/J.CHIECO.2008.05.007.

Ravasz, E. and Barabási, A.-L. (2003), "Hierarchical organization in complex networks", *Physical Review E*, Vol. 67 No. 2, 026112, doi: 10.1103/PhysRevE.67.026112.

Rubinov, M. and Sporns, O. (2010), "Complex network measures of brain connectivity: uses and interpretations", *NeuroImage*, Vol. 52 No. 3, pp. 1059-1069, doi: 10.1016/j.neuroimage.2009.10.003.

Rubinov, M. and Sporns, O. (2011), "Weight-conserving characterization of complex functional brain networks", *NeuroImage*, Vol. 56 No. 4, pp. 2068-2079, doi: 10.1016/j.neuroimage.2011.03.069.

Ruhnau, B. (2000), "Eigenvector-centrality — a node-centrality?", *Social Networks*, Vol. 22 No. 4, pp. 357-365, doi: 10.1016/S0378-8733(00)00031-9.

Serrat, O. (2017), "Social network analysis", *Knowledge Solutions*, Springer, Singapore, pp. 39-43, doi: 10.1007/978-981-10-0983-9_9.

Shaikh, F., Ji, Q. and Fan, Y. (2016), "Evaluating China's natural gas supply security based on ecological network analysis", *Journal of Cleaner Production*, Vol. 139, pp. 1196-1206, doi: 10.1016/J.JCLEPRO.2016.09.002.

Thorbecke, W. and Smith, G. (2010), "How would an appreciation of the renminbi and other East Asian currencies affect China's exports?", *Review of International Economics*, Vol. 18 No. 1, pp. 95-108, doi: 10.1111/J.1467-9396.2008.00799.X.

Udemba, E., Magazzino, C. and Bekun, F.V. (2020), "Modeling the nexus between pollutant emission, energy consumption, foreign direct investment and economic growth: new insights from China", *Environmental Science and Pollution Research*, Vol. 27, pp. 17831-17842, doi: 10.1007/s11356-020-08180-x.

Wanzenböck, I. (2018), "A concept for measuring network proximity of regions in R& D networks", *Social Networks*, Vol. 54, pp. 314-325, doi: 10.1016/J.SOCNET.2017.10.003.

Wasserman, S. and Faust, K. (1994), *Social Network Analysis*, Cambridge University Press, Cambridge, doi: 10.1017/CBO9780511815478.

Whalley, J. and Xin, X. (2010), "China's FDI and non-FDI economies and the sustainability of future high Chinese growth", *China Economic Review*, Vol. 21 No. 1, pp. 123-135, doi: 10.1016/J.CHIECO.2009.11.004.

Wu, X. and Jiang, Y. (2011), "Sectoral role change in transition China: a network analysis from 1990 to 2005", *Applied Economics*, Vol. 44 No. 21, pp. 2699-2715, doi: 10.1080/00036846.2011.566196.

Xing, Y. (2016), "Global value chains and China's exports to high-income countries", *International Economic Journal*, Vol. 30 No. 2, pp. 191-203, doi: 10.1080/10168737.2016.1148403.

Xu, X., Wu, S. and Wu, Y. (2015), "The relationship between Renminbi's exchange rate and East Asia currencies before and after the "financial crisis", *China Finance Review International*, Vol. 5 No. 1, pp. 34-52, doi: 10.1108/CFRI-05-2014-0026/FULL/PDF.

Zhang, K.H. and Song, S. (2001), "Promoting exports: the role of inward FDI in China", *China Economic Review*, Vol. 11 No. 4, pp. 385-396, doi: 10.1016/S1043-951X(01)00033-5.

Zheng, L., Liu, Y. and Liu, W. (2016), "Globalization and regionalization of complete auto's and auto parts' trade", *Scientia Geographica Sinica*, Vol. 36 No. 5, pp. 662-670, doi: 10.13249/J.CNKI.SGS.2016.05.003.

Zhou, M., Wu, G. and Xu, H. (2016), "Structure and formation of top networks in international trade, 2001-2010", *Social Networks*, Vol. 44, pp. 9-21, doi: 10.1016/J.SOCNET.2015.07.006.

Appendix

Country	Code	Country	Code	Country	Code
United Arab Emirates	AE	France	FR	New Zealand	NZ
Antigua and Barbuda	AG	Gabon	GA	Panama	PA
Albania	AL	United Kingdom	GB	Peru	PE
Argentina	AR	Ghana	GH	Papua New Guinea	PG
Austria	AT	Guinea	GN	Philippines	PH
Australia	AU	Hong Kong	HK	Pakistan	PK
Azerbaijan	AZ	Hungary	HU	Poland	PL
Barbados	BB	Indonesia	ID	Portugal	PT
Bangladesh	BD	Ireland	IE	Qatar	QA
Belgium	BE	Israel	IL	Romania	RO
Burkina Faso	BF	India	IN	Serbia	RS
Bulgaria	BG	Iran	IR	Russian Federation	RU
Bahrain	BH	Italia	IT	Saudi Arabia	SA
Bermuda	BM	Jordan	JO	Seychelles	SC
Brunei Darussalam	BN	Japan	JP	Sweden	SE
Brazil	BR	Kenya	KE	Singapore	SG
Botswana	BW	Kirghizstan	KG	Slovenia	SI
Belarus	BY	Cambodia	KH	Slovakia	SK
Canada	CA	South Korea	KR	Suriname	SR
Congo (Kinshasa)	CD	Kuwait	KW	Chad	TD
Congo (Brazzaville)	CG	Cayman Island	KY	Thailand	TH
Switzerland	CH	Kazakhstan	KZ	Tajikistan	TJ
Cote d'Ivoire	CI	Lao PDR	LA	Tunisia	TN
Chile	CL	Sri Lanka	LK	Turkey	TR
Cameroon	CM	Latvia	LT	Taiwan	TW
Colombia	CO	Luxembourg	LU	Tanzania	TZ
Cyprus	CY	Morocco	MA	Uganda	UG
Czech Republic	CZ	Moldova	MD	United States of America	US
Germany	DE	Madagascar	MG	Uruguay	UY
Denmark	DK	Marshall Island	MH	Uzbekistan	UZ
Algeria	DZ	MAli	ML	Venezuela	VE
Ecuador	EC	Malta	MT	British Virgin Island	VG
Egypt	EG	Mexico	MX	Viet Nam	VN
Spain	ES	Namibia	NA	Samoa	WS
Ethiopia	ET	Niger	NG	South Africa	ZA
Finland	FI	Netherlands	NL	Zambia	ZM
Micronesia	FM	Norway	NO	Zimbabwe	ZW

Table A1.
Modularity analysis: country codes ISO 3166-1-Aplha 2

Subsidiaries	Number of countries
Min-100	59
101–250	26
251–500	10
501–1,000	9
1,001-Max	14
Total	118

Source(s): Authors' elaborations on ORBIS-BVD database

Table A2.
Distribution of extracted subsidiaries by countries (2017)

Corresponding author
Cosimo Magazzino can be contacted at: cosimo.magazzino@uniroma3.it