INNOVATION-FUELLED, SUSTAINABLE, INCLUSIVE GROWTH

Working Paper

Spatio-Temporal Patterns of the International Merger and Acquisition Network

Marco Dueñas
Universidad de Bogotá

Rossana Mastrandrea
IMT School for Advanced Studies, Lucca

Matteo Barigozzi
London School of Economics and Political Science

Giorgio Fagiolo
Scuola Superiore Sant'Anna, Pisa

19/2017 July

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 649186

Spatio-Temporal Patterns of the International Merger and Acquisition Network

Marco Dueñas[1,*], Rossana Mastrandrea[2], Matteo Barigozzi[3], and Giorgio Fagiolo[4]

[1]Department of Economics, International Trade and Social Policy, Universidad de Bogotá Jorge Tadeo Lozano, Bogotá
[2]IMT School for Advanced Studies, Lucca
[3]Department of Statistics, London School of Economics and Political Science, London
[4]Istituto di Economia, Scuola Superiore Sant'Anna, Pisa
[*]E-mail: marcoa.duenase@utadeo.edu.co (corresponding author)

ABSTRACT

This paper analyzes the world web of mergers and acquisitions (M&As) using a complex network approach. We use data of M&As to build a temporal sequence of binary and weighted-directed networks for the period 1995-2010 and 224 countries (nodes) connected according to their M&As flows (links). We study different geographical and temporal aspects of the international M&As network (IMAN), building sequences of filtered sub-networks whose links belong to specific intervals of distance or time. Given that M&As and trade are complementary ways of reaching foreign markets, we perform our analysis using statistics employed for the study of the international trade network (ITN), highlighting the similarities and differences between the ITN and the IMAN. In contrast to the ITN, the IMAN is a low density network characterized by a persistent giant component with many external nodes and low reciprocity. Clustering patterns are very heterogeneous and dynamic. High-income economies are the main acquirers and are characterized by high connectivity, implying that most countries are targets of a few acquirers. Like in the ITN, geographical distance strongly impacts the structure of the IMAN: link-weights and node degrees are strongly non-linear, and an assortative pattern is present at short distances.

Introduction

In the past two decades foreign direct investments (FDI) have become a major source of capital inflows for both developed and developing countries[1], with mergers and acquisitions (M&As) as the dominant mode of FDI, regardless of their higher volatility and sensitivity to financial conditions with respect to greenfield projects. In fact, M&As cover, on average, more than 80% of total national FDI[2].

In recent years, within the framework of a complex-network perspective, an increasing body of literature has been studying international trade[3–12], financial flows between countries, mostly considering transactions in equity securities, such as common stock and debt securities[13,14], and, more recently, both financial and trade flows[10,15,16]. Compared to traditional international trade and investment indicators, the topological web architecture is expected to explain to a greater extent country growth and development patterns.

Although the study of the determinants of M&As has been of great interest to economists, only recently the attention has been focused on the topological properties of cross-border M&As as a network of complex interactions (in terms of M&As flows) between countries (nodes). Two recent contributions analyze cross-border investments for specific regions. Sánchez Díez et al.[17] study the role of Spanish investments in Latin America. They show that Spain had played a central role in Latin American investments that recently decreased with the arrival of new investors. Using data from the OECD, Garas et al.[18] explore the properties and the link between the international migration network and the international FDI network (IFDIN), employing undirected network statistics and stocks of FDI. Using a gravity model, they found a strong relation among FDI and migration for those countries that are more central in the international migration network.

In this context, we introduce a pioneering study on the international M&As network (IMAN) in space and time for a relatively long time period (1995-2010).

Investment interactions between countries in the form of cross-border M&As imply active management or control of the issuing companies, in contrast to passive financial investments. Thus, geographical distance might have a different effect on this kind of cross-border investments because higher transaction costs could be expected. Also, the temporal analysis for the IMAN is a novelty that might shed light on the international investment network. But since M&As and trade can be understood as complementary ways of reaching foreign markets, it is imperative to carry out our analysis by referring to the international trade network (ITN).

In addition, the effects of geography have been often neglected in complex network analysis (for a review of different networks in which space has relevant implications see Barthélemy[19]). We consider that in the context of international networks, distance certainly plays an important role at shaping the topological properties of the interactions among countries.

Our analysis is guided by two underlying motivations. In the first place, cross-border M&As have experienced periods of impressive growth in the number of involved countries, the number of links, the number of acquisitions, and volumes. Their over-time dynamics has been characterized by a wave-like behaviour, specifically, with two waves in the period analyzed here. Nevertheless, we argue that the properties of the IMAN are relatively stable over time.

Secondly, geographical distance is expected to affect investment links. Several authors have stressed that information asymmetries increase with distance creating a barrier to cross-border movements of capitals[20–22]. These authors argue that, from a theoretical point of view, there is no clear net effect of the geographical distance on cross-border M&As. As trade costs increase with distance, the simplest premise is that the decision to set up affiliates in foreign countries is positively affected by distance. In contrast, several empirical analysis show that the effect is negative. This evidence suggests that, in addition to trade costs, there might exist other sort of costs related to the distance that should be considered in the case of M&As. However, we postulate that these mixed findings might also be related with the existence of a non-linear effect of distance on M&As.

This study represents a first step towards a deeper exploration of global M&As-activity from a spatial and temporal network perspective. We study the architecture of the IMAN observed in a narrow time window (a few months) in order to capture its prevailing or evolving patterns. In addition, we perform a statistical analysis for binary and weighted networks to provide evidence on the topological properties in different cross-sections. Then, we use the distance between countries to study how geography affects the architecture of the network.

We observe that the IMAN appears very concentrated in a few countries and strongly target oriented. We found that the IMAN is a low density network characterized by a persistent giant component with a few number of reciprocated links and with many weakly connected external nodes. The giant component is mainly composed by developed economies, which have more reciprocal investment relationships, high connectivity, and clustering.

We observe a high heterogeneity in the countries clustering of the IMAN. There are neither well established nor persistent hubs in the network. Interestingly, binary clustering coefficients are higher for countries known to have favorable legal and fiscal frameworks to attract FDIs and, particularly, for tax havens. On the other hand, mainly high-income and emerging market economies show high weighted clustering coefficients.

Despite the erratic dynamic evolution of M&As, several network features appear quite stable over time and can be considered as stylized facts: i) the density is very low and reacts very little to changes in the number of links, ii) the size of the giant component is around a half of the whole network, iii) correlations between node degree and node strength are very high and significant, and iv) clustering patterns are persistently unstable.

Finally, in order to understand the role of geographical distance in shaping the topology of the IMAN architecture, we analyze the network statistics restricting the interactions between country pairs to specific ranges of distances. We show that there are strong non-linearities related to the geographical distance, with link-weight and node degree very high in the limit cases of short and long geographical distances. Also, despite the absence of an assortative pattern in the IMAN, for short distances there exists a positive assortative pattern, i.e. at a regional level, countries tend to be connected to countries with similar node degrees and strengths. Interestingly enough, following a similar methodology, Abbate et al.[23] showed that these non-linear patterns with distance are also present in the ITN.

Our results might be contrasted with those presented by Garas et al.[18] in their description of the IFDIN. There are important differences in their approach and the one presented in this paper. First, they use a symmetrized representation, which leads to important implications for the connectivity. And second, they use data from stocks of FDI, which consider other forms of cross-border investments rather than M&As. Due to the nature of cross-border investments we found that acquires and targets behave very differently. The direction of the investments certainly play an important role in order to understand the architecture of cross-border investments. On the other side, the fact that we use flows instead of stocks might be an issue because of the volatility of M&As. However, in the temporal analysis we found that the main features of the architecture of the IMAN are observed at very short and long time spans. As in the IMAN, the IFDIN has a low density and low clustering. The main difference between these networks is the way in which assortativity patterns emerges. The IFDIN has a negative assortative pattern, while the IMAN has a positive assortativity for links restricted to relative short distances, and no significant pattern for unrestricted distances.

Results

Network topology

Capital investment worldwide has had remarkable changes since the mid 1990s. Figure 1a shows the total amount of investments abroad cumulated over all countries, developed countries (DCs), and least developed countries (LDCs). Historically, most of the outflows of M&As have been done by DCs, however, the proportion of M&As outflows done by LDCs has been increasing over time. The time series of M&As clearly depicts the so-called ‘wave-like’ behavior of cross-border M&As, characterized by substantial variation over time, with some periods of rapid growth and other periods of rapid decline[24]. In the period under study, we observe two waves: the first one between 1995 and 2003, and the second one from 2003 to 2010.

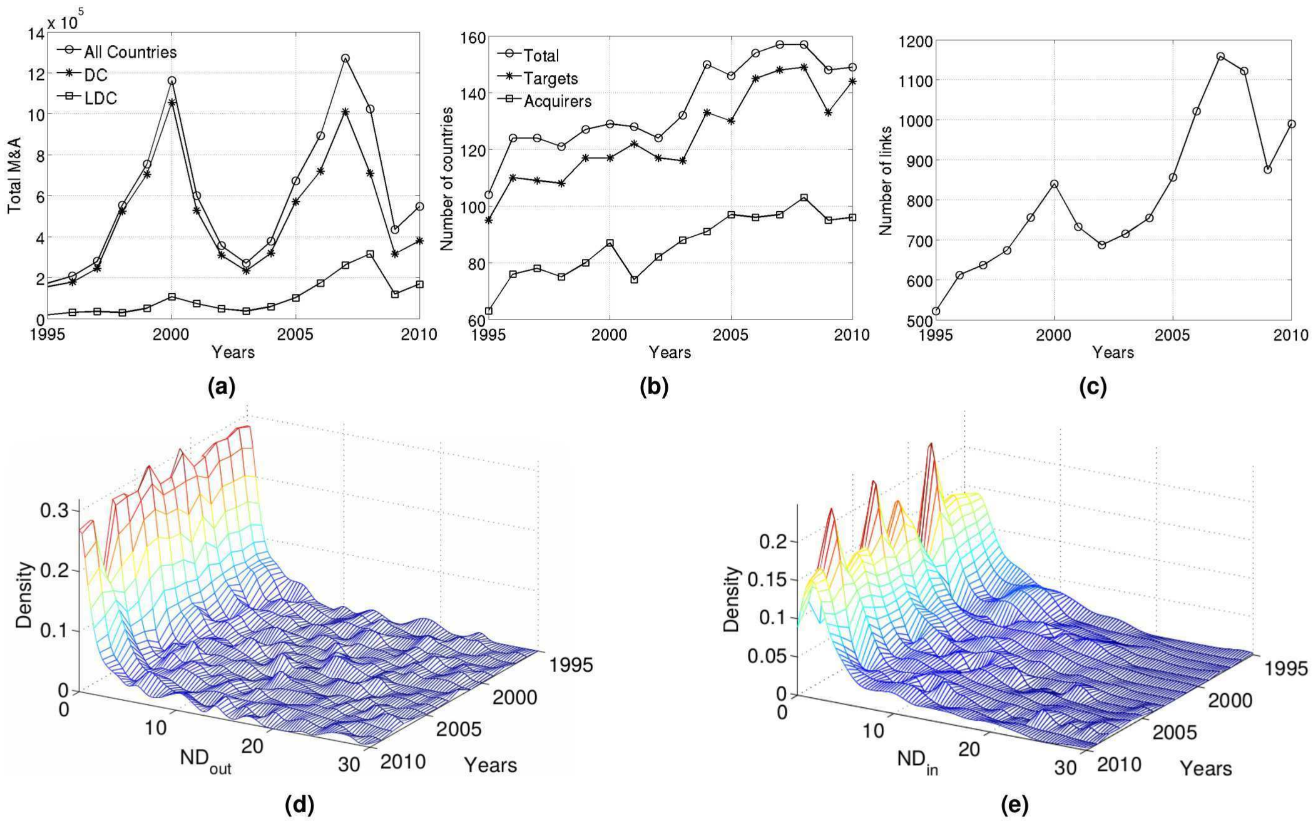

Figure 1. Network statistics. **(a)** Evolution of total outflow of M&As for countries of different development levels. **(b)** Evolution of the number of countries, targets, and acquirers. **(c)** Evolution of the number of links. **(d)** Out-degree and **(e)** in-degree kernel density estimation.

Figure 1b shows that the number of countries participating in the IMAN increases over time, countries receiving foreign capitals exceed the quantity of countries investing abroad, i.e. there are relatively few acquirers and several target markets. Similarly, Figure 1c shows that the number of links has increased over time.

Table 1 presents some additional descriptive statistics for different years of the data. We include statistics for: 1995, the first year of the time series, 2000, the peak of the first wave, 2003, the turning point of the waves, 2007, the peak of the second wave, and 2010, the last year of the time series. Even thought the number of links tends to grow over time, the density is very low and it ranges between 4 and 5%. Density reacts very little to changes in the number of links: in 2007, the year with the highest amount of links, the density is not the highest. This means that during boom periods links grow faster than the squared of the number of participating countries and, therefore, the binary network might be better characterized for having a stable density. In other words, new nodes contribute with very few links with respect to the possible ones.

The proportion of reciprocated links is around 20%. This suggests that investments tend to be strongly target-oriented. Also, the number of acquirers/targets making up a high percentage (50% or 90%, respectively) to/from targets/acquires is very concentrated in a few countries, although it slightly increases over time, which may indicate a spread of acquirers to new markets. Finally, the number of flows making up to 50% and 90% of M&As is also very concentrated.

The IMAN is characterized by a giant component and many weakly connected components. The size of the giant component is about a half of the complete network, and around a 95% of total M&As belongs to it. These statistics differ greatly from the corresponding statistics derived for the ITN. Probably, the most relevant difference between the ITN and the IMAN is the level of link reciprocity. In contrast to M&As relations, which are mainly unilateral, trade relations are typically reciprocal, leading to a higher density and full connectivity[8,25]. However, once we consider reciprocity using bilateral trade

Table 1. Summary statistics of the IMAN and its giant component.

	1995	2000	2003	2007	2010
International M&As Network					
Countries (No.)	104	129	132	157	149
Mergers (No.)	95	117	116	148	144
Acquirers (No.)	63	87	88	97	96
Links (No.)	522	840	715	1159	990
Density (%)	4.9	5.1	4.1	4.7	4.5
Share of reciprocated links (%)	18.8	20.1	19.4	21.1	21.2
Targets making up to 50% of M&As	3	2	5	5	6
Targets making up to 90% of M&As	19	16	29	28	31
Acquirers making up to 50% of M&As	2	2	2	5	6
Acquirers making up to 90% of M&As	12	13	18	24	24
Flows making up to 50% of M&As	12	9	20	31	34
Flows making up to 90% of M&As	109	103	161	243	214
Giant Component					
Countries (No.)	53	70	68	86	84
Size Giant Comp. (%)	51.0	54.3	51.5	54.8	56.4
Share of Total M&As (%)	95.1	99.2	94.6	98.0	94.7
Density (%)	15.1	14.7	12.7	13.3	12.4
Share of reciprocated links (%)	23.6	23.8	24.0	25.2	24.3

imbalances, it turns out that the ITN has very heterogeneous imbalances, typically developed countries have more balanced trade relationships than developing countries[26].

Figure 1d and 1e show the probability density distributions of ND_{out} and ND_{in} for every year in our data set. These statistics measure the number of targets and acquirers per country, respectively. There are relevant differences between the two distributions given the different role of acquirer and target nodes in the IMAN, but they also present some over-time variations. First, there is a high concentration of zero out-degrees, with the range falling faster until approximately 5 nodes, while for the in-degree distribution most of the probability mass is concentrated in a range between zero and around 20 nodes. This confirms that cross-border M&As are performed by a limited group of countries. Only a few countries invest in a high number of targets, which also implies that most countries attract capitals from a limited number of countries. Second, both distributions seem to be multimodal. In particular, the density of ND_{out} shows many maximums at high degree levels, which implies that a few countries invest in many targets. Comparing within statistics, the densities mainly differ in their tails.

The analysis of the degrees reveals the heterogeneity of countries patterns for abroad investments. A few countries have many inflows and outflows driving an important extent of the investments worldwide, and the rest of the countries have much higher inflows than outflows. In contrast to the ITN, it is difficult to postulate stability in the in- and out-degree profiles of the IMAN.

Now, we want to see whether the total country's M&As (i.e, node strength) is positively correlated with the country's number of partners (e.g., node degree). Indeed, the top rankings of countries according to node degree and strength are very similar and composed in a great extent by high-income economies (e.g., USA, UK, Germany, Canada, etc.) and the presence of a few emergent countries (e.g., China, Brazil, India). This suggests the existence of an over time positive correlation between the two distributions. Figure 2a plots the correlation between node degree and node strength for all years. The evidence confirms that countries with more target and acquirer partners have more outflow and inflow investment volumes, correspondingly. Additionally, the within in- and out-statistic correlations are also positive and significant, which indicates a positive relation among the number of targets and acquirers, and also among the amount of outflows and inflows investment volumes.

In Figure 2b and 2c, we show the correlations between node degree/strength with countries' GDP and GDP per capita (GDPpc) to further investigate how node degree and strength relate with the level of size and income of countries. We use GDP as a measure of size and GDPpc as an indicator of income –these variables are frequently used as determinants of M&As. We observe that these correlations are generally positive and significant, even if they vary much over time. The correlation is especially higher in the case of GDP, which might imply that variations of M&As across countries could be closer related to their size rather than to their income. For the case of the ITN and the international financial network (IFN),[27] shows, that

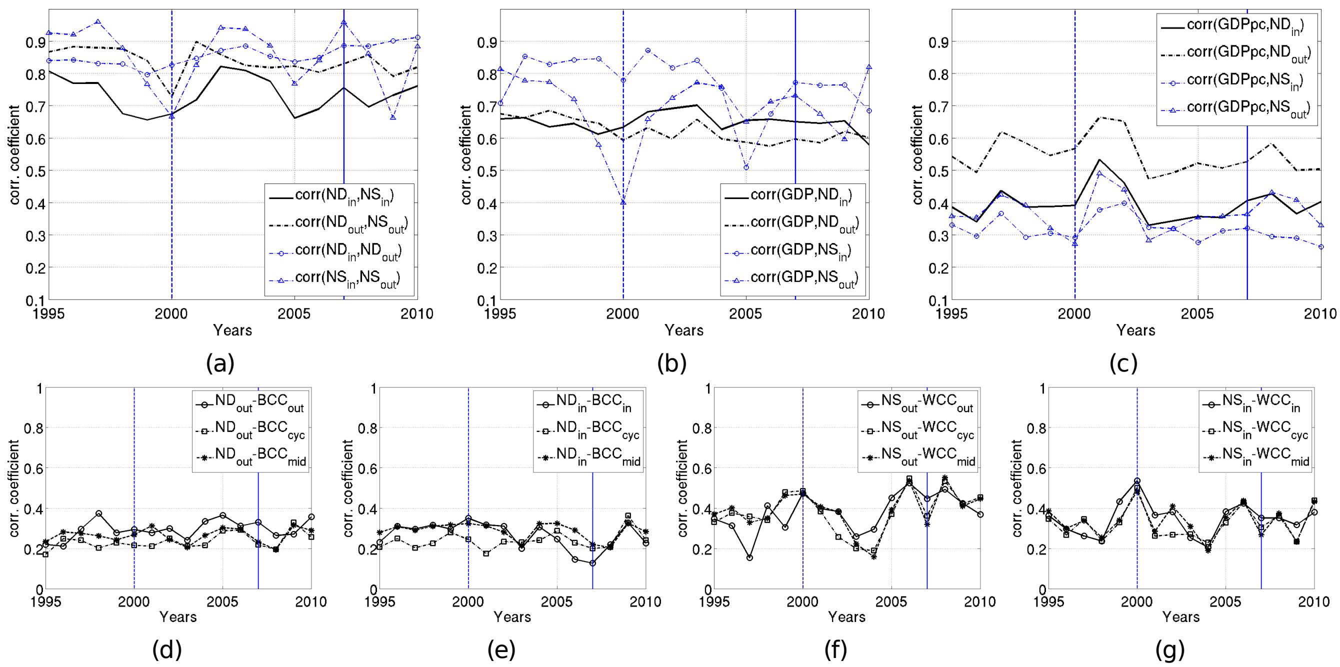

Figure 2. Correlation patterns. Vertical lines indicate the peaks of the two waves. **(a)** Node degree and node strength. **(b)** Node degree/strength with country size. **(c)** Node degree/strength with country income. **(d)** Node out-degree with node binary clustering. **(e)** Node in-degree with node binary clustering. **(f)** Node out-strength with node weighted clustering. **(g)** Node in-strength with node weighted clustering.

countries belonging to the core are those with higher GDP per capita.

Finally, we want to test to what extent the IMAN exhibits a structure where countries that are more evolved in M&As are more intensively clustered. We study the correlations between pairs of node degree/strength and binary/weighted clustering coefficients (Figure 2d to 2g). We find weak but significant correlations. It is interesting that even if the correlations fluctuate around a certain level they do not seem to react in a particular way to M&As booms, and those correlations related to the binary representation change less across time than their weighted counterparts. In fact, the correlations for the same weighted quantities are stronger in some years.

The reason behind these weak and fluctuating correlations is related to the fact that the binary and weighted clustering patterns of the IMAN reveals a markedly heterogeneity along time. Table 2 shows the top-5 positions for all directed clustering types[28]. The evidence suggests that there are neither well established nor persistent hubs in the network. For the binary clustering coefficients, the lists of rankings contain countries that are known for having favorable legal and fiscal frameworks to attract FDIs –this is the case of Puerto Rico, which has an established policy to offer huge tax brakes to US-investors– and tax havens. In the case of weighted clustering, tax havens are less common, while there are mainly high-income economies and emerging market economies. These results shed light on an important aspect of M&As. Indeed, it is well known that a relevant number of M&As moves through tax havens and that also other countries get involved either because they are emerging economies or because their main industries are related to commodities of great value in international markets, such as mining and oil.

It is worth noticing that as the top acquirers and targets are very stable and although the evidence suggests that the more clustered countries are not necessarily the most connected ones, the fact that correlations between the pairs: $(ND_{in/out}, BCC_{cyc})$, $(ND_{in/out}, BCC_{mid})$, $(NS_{in/out}, WCC_{cyc})$, and $(NS_{in/out}, WCC_{mid})$ are significant, might reveal a sort of reinforcing mechanism in the motifs of the IMAN. These types of clustering patterns are characterized by triads in which the node sends and receives foreign investments. Therefore, an important extent of the volumes go and return to their places of origin, or end up in one of the biggest acquirers. Thus, a third country gets involved in the looping mechanism, increasing its clustering levels.

The international M&A network in time

We have observed that investment decisions are very limited and selective. In this section, we study the stability of the architecture of the IMAN by analyzing how the network properties change when we consider time windows of different length. We focus on network properties of the monthly-cumulated IMAN and look for the smallest reasonable time window

Table 2. Binary and weighted clustering coefficient rankings.

1995	2000	2003	2007	2010
		BCC_{out}		
Cuba	Puerto Rico	Costa Rica	Dominican Rep.	Puerto Rico
Barbados	Dominican Rep.	Guernsey	Costa Rica	Barbados
British Virgin	Guatemala	Luxembourg	Guyana	Costa Rica
Ireland Rep.	Bolivia	Greece	Bolivia	Jersey
Luxembourg	Isle of Man	Estonia	Isle of Man	Isle of Man
		BCC_{in}		
Kuwait	Isle of Man	Bahamas	Liechtenstein	Macao
Indonesia	Iceland	Guernsey	Oman	Philippines
Luxembourg	Bahrain	Jersey	Vietnam	Indonesia
Denmark	Papua New Guinea	Netherlands Antilles	Western Samoa	Qatar
Israel	China	Monaco	Jersey	New Zealand
		BCC_{cyc}		
Cuba	Puerto Rico	Trinidad & Tobago	Bahamas	US Virgin Is.
Uruguay	Antigua and Barbuda	Costa Rica	Barbados	Uruguay
British Virgin	Panama	Peru	Costa Rica	Liechtenstein
Netherlands Antilles	Venezuela	Guernsey	Gibraltar	Kazakhstan
Luxembourg	Guernsey	Monaco	Botswana	Macao
		BCC_{mid}		
Bahamas	Puerto Rico	Trinidad & Tobago	Bahamas	Liechtenstein
Netherlands Antilles	Antigua and Barbuda	Costa Rica	El Salvador	Seychelles
Ghana	Panama	Uruguay	Costa Rica	Kazakhstan
Luxembourg	Guernsey	Guernsey	Montenegro	Macao
Denmark	Isle of Man	Jersey	Botswana	Bangladesh
		WCC_{out}		
Czechoslovakia**	Germany	Luxembourg	Belarus	Papua New Guinea
Ireland Rep.	Luxembourg	Italy	Qatar	Puerto Rico
Sweden	Spain	Greece	El Salvador	Mexico
Australia	Belgium	Israel	Puerto Rico	Brazil
Brazil	Netherlands	Portugal	Hungary	Bermuda
		WCC_{in}		
South Africa	Papua New Guinea	Ireland-Rep	Argentina	Qatar
Italy	France	Israel	Germany	New Zealand
Saudi Arabia	Iceland	Netherlands Antilles	Iceland	Bermuda
France	Bermuda	Monaco	Norway	Ireland Rep.
Sweden	Switzerland	Guernsey	New Zealand	Israel
		WCC_{cyc}		
Netherlands Antilles	Germany	Trinidad & Tobago	Bahamas	Bermuda
Argentina	France	Israel	Iceland	Kazakhstan
Sweden	Luxembourg	Monaco	Germany	Brazil
Switzerland	Switzerland	Luxembourg	Italy	Ireland Rep.
Italy	Bermuda	Italy	France	Mexico
		WCC_{mid}		
Netherlands Antilles	Germany	Trinidad & Tobago	Iceland	Kazakhstan
Sweden	France	Luxembourg	Bahamas	Bermuda
Switzerland	Guernsey	Israel	Germany	Mexico
France	Spain	Italy	El Salvador	Brazil
Italy	Luxembourg	Ireland Rep.	France	United States

** Although in 1993 Czechoslovakia split into two sovereign states, still in 1995 several firms appear in the database as based in Czechoslovakia.

in which the network exhibits all its properties (more details in the section of Methods).

Figure 3a shows the size of the giant component for the monthly-cumulated representation for different periods. We observe that already in the first month, the size of the giant component is very high (more than 35%), compared with the maximum size observed for yearly data (just above 50%). The 50% level is reached quickly, between 3 and 4 months, and for longer time-windows, the giant component grows very little and very irregularly with some fluctuations. Moreover, if we allow to accumulate up to 24 months (and even more), the size increases, but never gets close to the 100%. In other words, the network never gets fully connected.

The fact that the giant component grows modestly with the aggregation of upcoming links indicates that an intensive margin of investments governs over the extension to new partners. In other words, it means that existing relationships benefit from higher investments and that there is little expansion to new markets. Moreover, as time goes by, the isolated and weakly connected nodes hardly get strongly connected.

Figure 3b and 3c show the correlations between pairs of node degree and node strength for the monthly-cumulated representation of the IMAN in 2007, selected as a benchmark given the highest cross-border volumes of M&As in this year. These

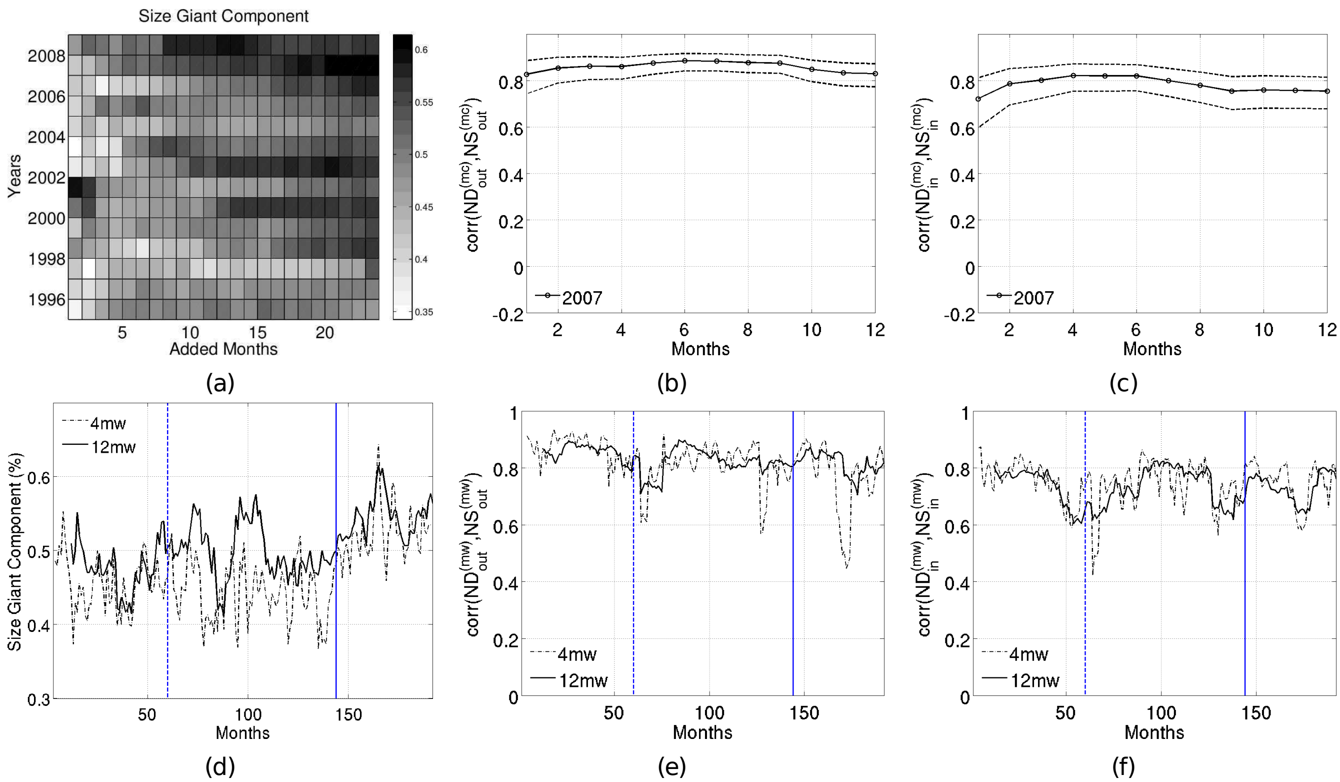

Figure 3. Network properties of the monthly-cumulated IMAN representation for fixed (top) and moving windows (bottom). Vertical lines indicate the peaks of the two waves. **(a)** Size of the giant component. **(b)** Correlations between outward statistics. **(c)** Correlation between inward statistics. Correlations with 95% confidence intervals in 2007. **(d)** Size of the giant component. **(e)** Correlation between node out-degree and out-strength. **(f)** Correlation between node in-degree and in-strength.

correlations are quite stable and get very strong in the smallest time window (one month). The evidence suggests that the network structure is very stable and it reacts very little to the increase in the number of links. Since the giant component is present in every month, and it is the only component with more than one member, we can say that it fully characterizes the patterns of the IMAN. Therefore, weakly connected countries play a marginal role and do not contribute to the structure of the network.

We could expect the architecture of the network to react differently to the worldwide booms of M&As. In order to explore this, we use a moving-window network approach. Thus, given an initial month, t_0 and a fixed δt, we consider moving windows of one step: $[t_0+1, t_0+\delta t+1]$. Figure 3d shows the evolution of the size of the giant component. We use two different time window sizes, $\delta t = 4$ and $\delta t = 12$, in order to observe possible differences in the short- and medium-term. Also, we have included two vertical lines indicting the peaks of the two waves: 2000 and 2007. We observe that the size of the giant component fluctuates around a certain average level. In accordance with Table 1, after the 2007 boom, the giant component seems to be enlarged.

Figure 3e and 3f show the correlations between pairs of node degree and node strength. While these correlations fluctuate, on average, there are no major differences between the trends at different time-windows. In the case of a time-window of 4-months, one can observe that for very short periods the correlations get weaker, so the relationship between the number of peers and exchanged volumes is less significant. However, the trend is quickly recovered.

We can conclude that it is difficult to recognize a specific evolving pattern in the topology of the network, nor even during the boom phases of M&As. This evidence allows us to state that the characteristics of the network are quite robust over time. Similarly, Fagiolo et al.[9] show that the structural properties of the ITN display a remarkable stationarity and claimed that recent trade integration has not had a significant impact on the structure of the ITN.

The international M&A network in space

In this section, we study how the geographical space affects the topology of the IMAN. Geographical distances might be able to capture bilateral characteristics of countries and to shed light on the barriers conditioning countries interactions.

The idea consists in using the geographical distances between countries that report a transaction to build a sequence of sub-networks. Links in each sub-network are expected to share similar distances and, for this reason, expected to be related to similar barriers to invest. Then, we analyze how the topological properties of the sub-networks change as distance increases.

We compute the deciles of the distribution of geographical distances and use them to split the IMAN in two different families of sub-networks. The *restricted representation*, consists of sub-graphs derived by keeping the links associated to geographical distances between the limits of a given decile in a given year. The *cumulated representation*, consists of sub-graphs derived by keeping the links with geographical distances below the upper limit of a given decile. These network families are complementary. The cumulated framework gives us a picture of the IMAN for links constrained between zero and a given threshold, while the restricted framework gives us a picture of the IMAN constrained to a certain range (more details in the section of Methods).

We find that cross-border investments distribute mostly in relatively short and intermediate distances, as the higher shares are observed for the first and sixth deciles (see Table 3). The average of weights is comparatively higher for links with very short and medium geographical distances. On the contrary, the average of node degrees for long distance is comparatively as higher as the one observed for very short distances. This means that countries tend to have many relationships in their own geographical neighborhood and, on average, to receive/make investment flows from/to many partners located far from them. Long distance interactions do not play an important role for the binary clustering coefficients. Indeed, they are equal to zero for most decile intervals, except the firsts ones. Hence, the probability that any pair of partners of a node are themselves partners, subject to that all countries are separated by long geographical distances, is practically null. It is worth mentioning that these topological features for the restricted sub-networks agree with the shape of the distribution of distances, which is left-skewed, bi-modal with a higher peak at farther distances, and very stable.

Table 3. Summary network statistics for the restricted representation (by deciles).

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
					Share of total M&As (%)					
1995	25	10	2	3	2	27	8	3	5	15
2000	37	5	6	5	2	22	12	4	4	3
2003	17	6	9	5	6	31	8	4	7	8
2007	25	9	7	5	3	23	8	4	8	8
2010	16	5	4	6	14	18	10	9	8	10
					Link Weight Averages					
1995	861	315	79	90	67	887	262	115	166	507
2000	5,147	639	913	676	246	3,023	1,733	613	605	379
2003	655	237	334	194	227	1,226	316	146	272	313
2007	2,848	1,002	825	562	290	2,698	921	485	888	948
2010	899	251	252	344	775	1,024	549	491	468	575
					Node Degree Averages					
1995	3.4	2.8	2.7	1.9	2.1	3.3	2.5	2.3	3.3	3.0
2000	3.9	3.2	3.6	3.4	2.7	3.0	3.2	3.2	3.5	3.5
2003	3.5	3.1	3.0	2.1	2.6	3.2	2.8	2.9	3.1	3.4
2007	3.8	4.0	3.1	3.0	2.9	3.8	2.9	3.4	3.8	4.0
2010	3.2	3.1	2.9	2.9	2.8	4.0	2.8	3.6	3.5	3.9
					Binary Clustering Averages					
1995	0.17	0.03	0.02	0.00	0.01	0.00	0.00	0.00	0.01	0.00
2000	0.25	0.04	0.04	0.00	0.01	0.01	0.00	0.00	0.01	0.00
2003	0.21	0.05	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.01
2007	0.15	0.01	0.02	0.02	0.03	0.01	0.00	0.00	0.02	0.00
2010	0.14	0.01	0.02	0.02	0.00	0.00	0.01	0.00	0.00	0.00

Figure 4a displays the number of components and the size of the giant component for the cumulated IMAN, $A^{(c)}$. The connectivity changes as the links with longer geographical distances join the network. Although the number of connected components decreases with distance, when we only consider link separated short geographical distances, there are many isolated countries. This is confirmed by Figure 4b showing the number of components with size bigger than one.

Therefore, only the giant component grows as more distant links join the network. Indeed, the giant component gets fully connected at medium distances, around the sixth decile. The rest of the isolated components are weakly connected as targets of a few acquirers belonging to the giant component. Figure 4c shows the growing pattern of the giant component as

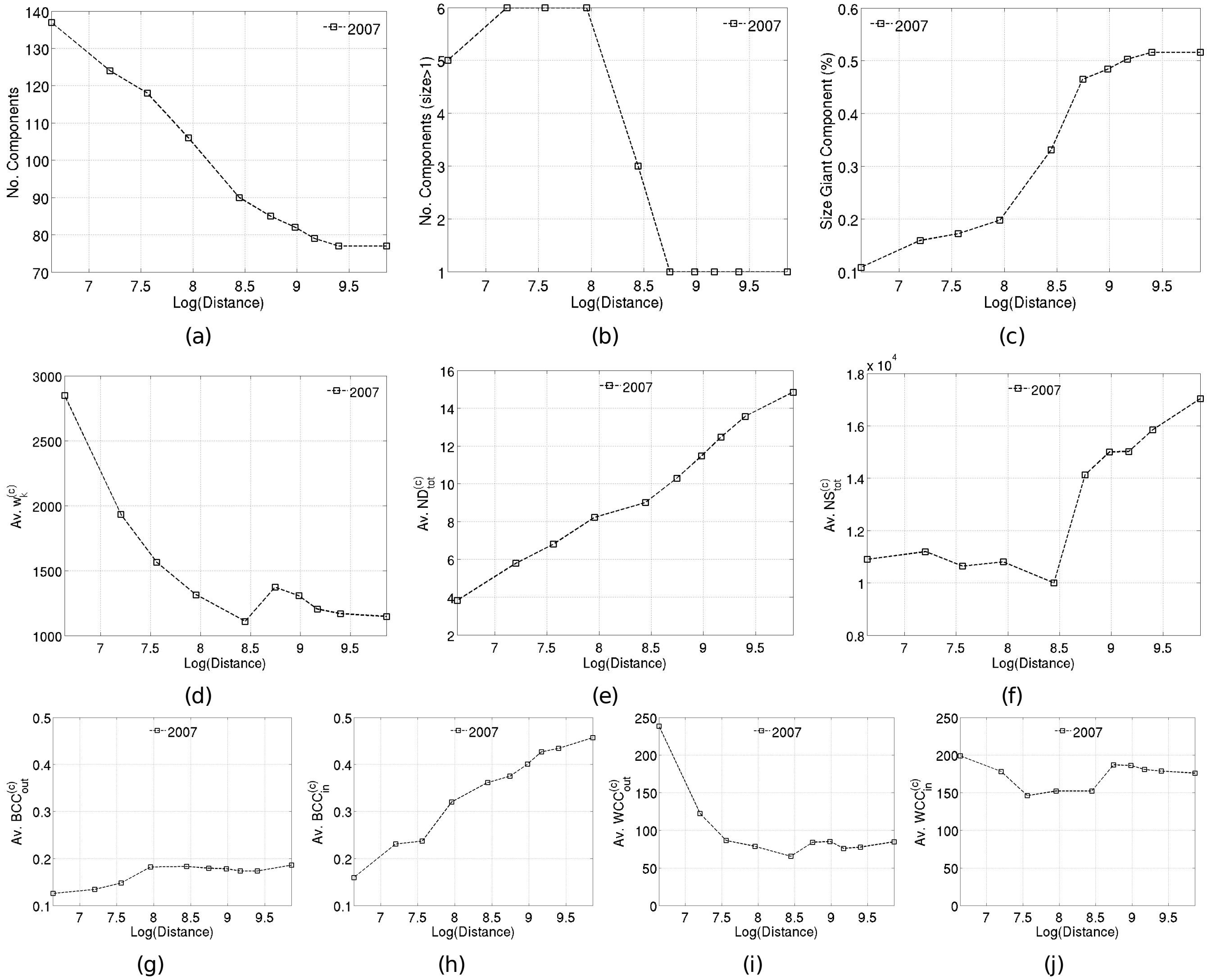

Figure 4. Network statistics of the cumulated representation in 2007. **(a)** Number of components. **(b)** Number of components of size greater than one. **(c)** Size of the giant components. **(d)** Average link weights. **(e)** Average node degree. **(f)** Average node strength. **(g)** Average binary out-clustering. **(h)** Average binary in-clustering. **(i)** Average weighted out-clustering. **(j)** Average weighted in-clustering.

a percentage of the total number of countries. The giant component grows approximately 5 times until the most distant links are added to the cumulated representation, covering almost 50%.

Figure 4d, 4e and 4f show, for the cumulated network representation, how the average of link-weights, node degree and strength vary with distance. It exists a decreasing and non-linear relationship between the average of link-weights and the distance. The decrease in distance is rather moderate, in contrast with the dramatic decrease observed in the case of the ITN[23]. Instead, node degree on average increases smoothly as more distant links are attached to the network. This implies that countries tend to have many M&As relationships with a number of countries around the world regardless the distance to them. The average node strength increases sharply as more distant links are attached, only when the giant component gets fully connected. This highlights that even if huge investment flows travel long distances, they are very concentrated among members of the giant component. Although it is important to say that a significant part of the investments go to those weakly connected countries.

Figure 4g and 4h show the binary clustering coefficients for the cumulated representation. The average of $BCC_{out}^{(c)}$ increases very slowly with distance. This implies that, on average, the probability that two target partners are linked is low (less than 20%) regardless the geographical distance between all of them. Instead, the average of $BCC_{in}^{(c)}$ increases with distance, implying that the probability that two acquirer partners are linked increases as more distant links are attached to the network. It is worth noticing that the population of target countries is greater than the population of acquirer countries, which agrees with the fact that the average $BCC_{out}^{(c)}$ is lower than the average of $BCC_{in}^{(c)}$, in most decile intervals.

Figure 4i and 4j show the weighted clustering patterns of the network statistics for the cumulated representation. On average, the $WCC_{out}^{(c)}$ is comparatively high for the first distance decile. Hence, triplets of M&As, in which two target partners interact with each other, are more intense for links related to shorter geographical distances. On average, the $WCC_{in}^{(c)}$ is rather stable, fluctuating around a given level. This outcome compared with the binary counterpart suggests that the intensity of triplets of M&As, in which two acquirer partners interact with each other, distributes uniformly with respect to the geographical distances between connected partners.

Spatial correlation patterns

In this section we focus on correlation patterns between networks statistics and country properties (size and income) for the cumulated representation to shed light on the role, if any, of geographical distance in shaping the IMAN structure. We aim to understand to what extent spatial connectivity might affect local and higher order network properties, including clustering and assortativity.

Figure 5 shows the Pearson's correlation between node degree and strength, for the cumulated distance networks in 2007. We observe positive correlations for all geographical distances. Hence, countries with many acquirer partners are also receiving high levels of investment, and similarly, countries with many target partners are making high levels of investments. This evidence might be against the hypothesis that geographical distances represent barriers to invest. We observe that the geographical extension of markets and the intensity of the transactions are positively correlated, with the correlation getting stronger when long-distant pairs are considered.

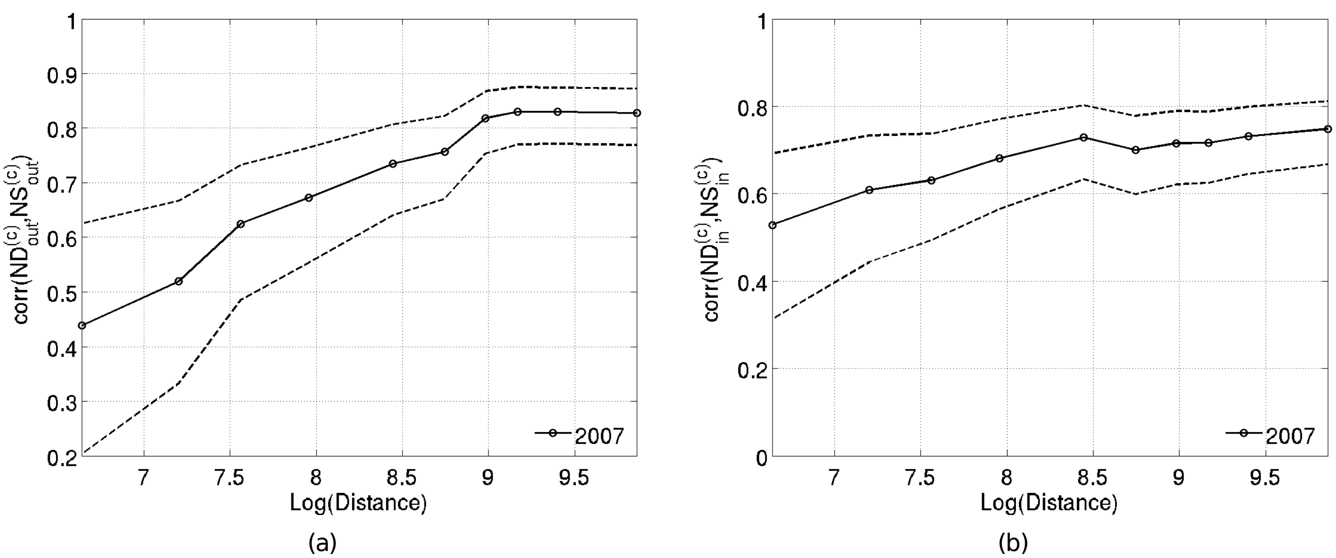

Figure 5. Node degree and strength correlations of the cumulated representation. Correlations with 95% confidence intervals in 2007.

Figure 6a shows the correlation coefficients between (in/out) node degree/strength and average nearest-neighbor degree/strength. We find that both binary and weighted cumulated representations exhibit a very assortative pattern at short distance deciles with the correlation becoming quickly non-significant as the limit of the geographical distance increases (except for the binary outflow case). The assortative pattern survives until the third and fifth deciles. This result could be explained in part by the existence of international investment agreements (IIAs) and bilateral investment treaties (BITs) that are quite diffused at the regional level. On the other hand, assortativity might be broken by the wealth distribution in the world: high capitals are concentrated in a few countries, giving them the possibility to invest in others who do not necessarily have many cross-border relationships. These results can be compared with those obtained for the ITN, which is disassortative but it also exhibits an assortative pattern when links are restricted to short distances[23].

The correlation coefficients between node degree/strength and clustering coefficients are positive and significant for most distance deciles (Figure 6b). In the binary representation this means that if one considers only links below a certain geographical distance threshold, it turns out that countries that hold more target/acquirer partners are more clustered than those with a

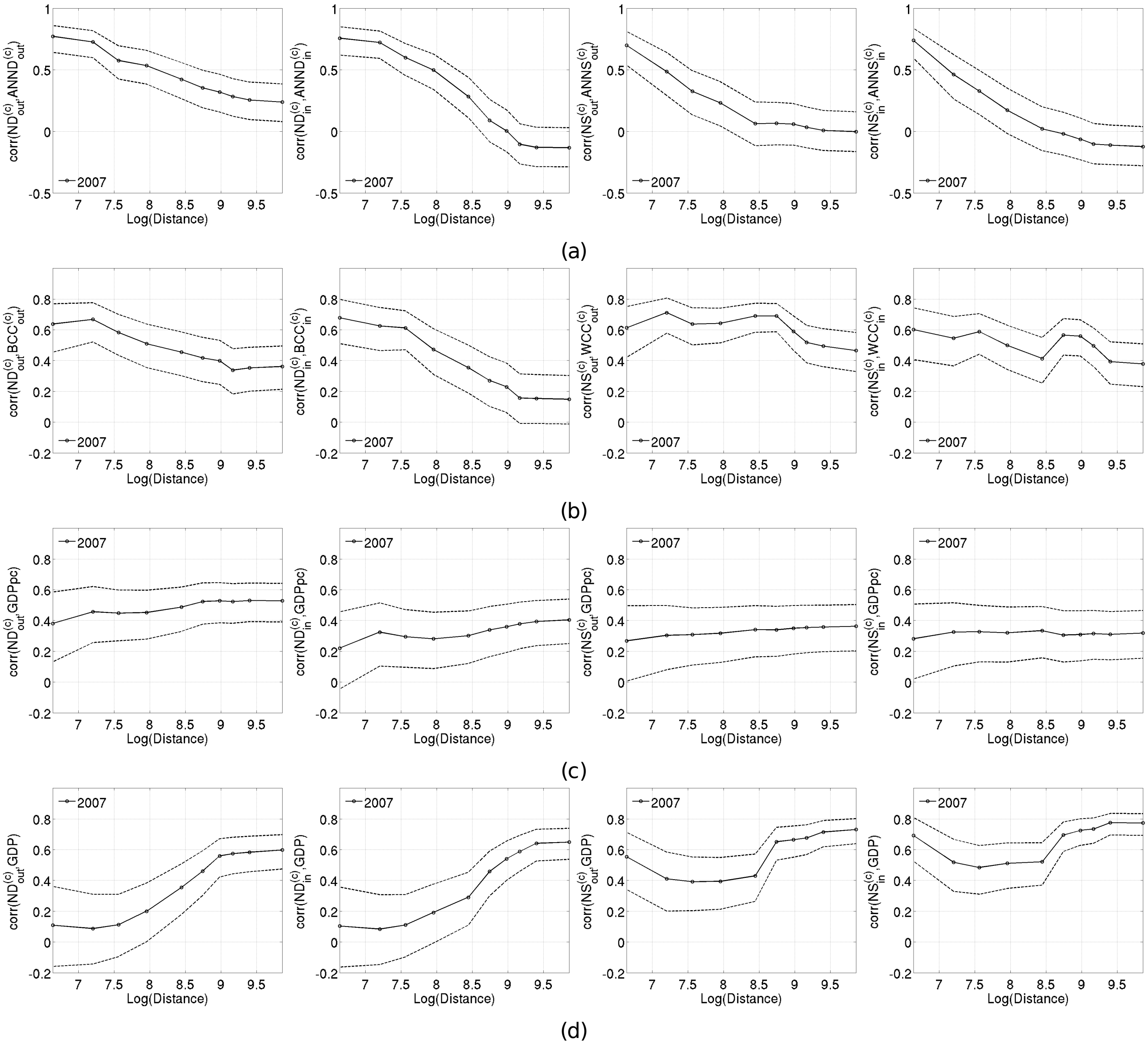

Figure 6. Spatial correlation patterns of the cumulated representation. Correlations with 95% confidence intervals in 2007. **(a)** Assortative patterns. **(b)** Node degree/strength correlations with clustering coefficients. **(c)** Size correlations with node degree/strength. **(d)** Income correlations with node degree/strength.

few target/acquirer partners. However, this patterns fade away when the threshold gets higher, since the computed correlations decrease as more distant links join the network. In the weighted representation, if links are constrained to a certain distance threshold, countries with high intensity of M&As relationships are typically involved in intense interconnected triples. In contrast to the binary counterpart, the computed correlations in the weighted network remain roughly constant across different distance deciles.

Figure 6c and 6d show the correlation values between node degree/strength and GDPpc and GDP for the cumulated representation. We observe that the correlations between GDPpc and total degree and strength are low but positive and significant, and they vary very little across distance deciles. Therefore, countries with high GDP per capita are expected to have many partners and more intense M&As. The correlations of node degree with GDP are also positive but they are especially high for pairs of countries that lie very far apart, and not significant for pair of countries that lie nearby. The correlations of node strength with GDP are also positive and significant, and although they are not particularly stable, they decrease when countries at short distances are included and increase when long-distance ones are considered.

Overall, the spatial analysis shows that the architecture of the restricted IMAN at different geographical distance deciles exhibit different topologies, which in turn may be different from those observed in the whole network. On the other side, the structure of the cumulated subnetworks display properties that move towards the one observed for the whole network.

Discussion

In this paper we have developed a comprehensive study of the international M&As network using a complex network approach. In the first place, we have studied the topological architecture of the network. Secondly, we have focused on the dynamics of these properties over time. Finally, we have analyzed how the geographical distance affects the structure of the network.

Given that trade and M&As are two common strategies of firms to reach a foreign market, we employed network statistics commonly used in the analysis of the ITN. This allowed us to highlight the differences and similarities between the IMAN and the ITN.

The analysis of the topology of the network, has uncovered several interesting features. Firstly, cross-border M&As are performed only by a limited group of countries, which invest in a high number of targets, implying also that most countries attract capitals from a limited number of countries. This makes the IMAN strongly target-oriented with a very low proportion of reciprocated links and creates a strong correlation between node degree and node strength. Secondly, the configuration of the IMAN in the very short and the long term consists of many weakly connected low-income target countries in a periphery and high-income strongly connected economies concentrated in a core. Therefore, the IMAN is well characterized by a giant component and many standing alone nodes that only have a unilateral link with the remaining network. Thirdly, in the IMAN, clustering patterns are very heterogeneous. There are neither well established nor persistent hubs in the network, and more clustered countries are not necessarily the most connected ones.

Some of these properties contrast with those of the ITN. The latter is a high dense network, with a majority of reciprocated links, a stable giant component corresponding to the whole network, and robust clustering patterns. However, both investment and trade networks are characterized by a very dominant core of rich countries, which have more reciprocal interactions and shape, in a great extent, the topological structure of the international networks.

The temporal analysis showed that, despite M&As have had periods of impressive growth and decline, the topological architecture of the network remains quite invariant over time. The spatial analysis revealed the existence of a non-linear relationship between M&As and geographical distance. Cross-border investments distribute mostly in relatively short and intermediate distances. This has two important implications for the architecture of the network: i) long distance interactions allow the giant component to get fully connected at medium distances; and, ii) short distance interactions generate a very assortative pattern, meaning that well-connected countries tend to interact with other well-connected countries.

Moreover, we showed that link-weights are higher at short and medium geographical distances and countries tend to direct their investments not only to the immediate geographical neighborhood, but also, they tend to have several partners located far from them. The geographical extension of M&As markets and the intensity of the transactions are positively correlated and get stronger when long-distant investment partners are considered. Therefore, a possible barrier to invest, as the geographical distance, does not seem to represent a real obstacle to long-distance transactions. This finding contributes to the open debate regarding the effect of the geographical distance on cross-border M&As.

These non-linear effects of the geographical distance on the IMAN are also present in the ITN and international financial networks. Our results complement recent studies on the geographical properties of international complex networks[16,23]. In these networks, a relevant part of the interactions take place in geographical neighborhoods, but several network patterns need longer distances to emerge.

Borrowing from the broad literature related to the ITN, a possible extension of this research would be exploring the determinants of the architecture of the network following traditional economic modeling[29] and null network models[30]. In addition, given the interplay and complementary of trade, migration, financial investment, and M&As flows, it would be interesting to develop a multilayer network analysis[10,18,26]. This could provide new insights on the international relations and the movement of factors of production that shape globalization.

Methods

The data for the analysis are extracted from Worldwide Mergers, Acquisitions, and Alliances Databases SDC Platinum (Thomson Reuters), a collection of financial databases that provide extensive large-scale information on global transactions since 1985 to present. Our study covers the period 1995-2010 because the number of takeovers registered in the first 10 years is rather limited.

Most of the recorded transactions (in volume) refer to domestic M&As-activity (74%, on average). The domestic links represent around 10%, indicating that, on average, M&As tend to be more oriented towards abroad, but the average volume of foreign operations is much lower.

The nominal monthly M&As inflows and outflows (millions of current USD) are deflated using the Industrial Production Index provided by the US Bureau of Labor Statistics[31] to build a set of directed adjacency matrices from the real M&As data with rows indicating acquirer countries (i.e. investors) and columns standing for M&As targets. Our choice to focus on a directed network is driven by the need to keep a clear distinction between who invests and who receives the foreign capital inflows and also because the network is strongly asymmetric.

Using these data, we can define the IMAN in its weighted and binary representation where nodes are countries linked by capital flows. We distinguish between *acquirer*, countries investing abroad, and *targets*, countries hosting capitals from a foreign country.

The ***Weighted International M&A Network*** in a given point of time t is represented by a weighted-directed graph, where the nodes are the $N(t)$ countries and link weights are fully characterized by the $N(t) \times N(t)$ asymmetric matrix $W(t)$, with entries $w_{ij}(t)$, i.e. a flow of M&As from country i to country j.

The ***Binary International M&A Network*** in a given point of time t is represented by a binary-directed graph, where the nodes are the $N(t)$ countries and binary links are fully characterized by the $N(t) \times N(t)$ asymmetric adjacency matrix $A(t)$, with entries $a_{ij}(t) = 1$ if and only if $w_{ij}(t) > 0$, i.e. M&As flows from country i to country j are strictly positive.

The IMAN in time

Cross-border M&As have periods of impressive growth and decline that might affect the architecture of the IMAN. In order to recognize the evolving patterns of the network's topology, we propose to study sequences of filtered sub-networks, restricted to specific time periods. More precisely, let $Z(\tau) \equiv (z_{ij}(\tau))_{1 \leq i,j \leq N(\tau)}$ be a temporal network for a specific month τ. Thus, the monthly-cumulated network at time t is defined as:

$$Z^{(mc)}(t;\delta t) = \sum_{\tau=t}^{t+\delta t} Z(\tau); \tag{1}$$

where, δt is the length of the time-window, and $Z(\tau)$ can be either $A(\tau)$ or $W(\tau)$. In this way, we aim to analyze the cumulated properties of the IMAN for any time-window $[t, t+\delta t]$.

The IMAN in space

Geography matters for the interaction between countries. In gravity models, the geographical distance is commonly employed as a proxy of transaction costs, for example it is frequently included for the estimation of international trade, migration, and foreign direct investment. In order to understand how the architecture of the IMAN relies on the distance, we propose to analyze two different families of sub-networks capturing links with similar distance ranges. These families are: the *restricted matrices* and the *cumulated matrices*,

Thus, we define the geographical-distance matrix D as;

$$D = \begin{cases} d_{ij}, & \text{if } a_{ij} = 1, \\ 0, & \text{otherwise}; \end{cases} \tag{2}$$

whose generic element d_{ij} is equal to the geographical distance between countries i and j, computed using the great-circle formula. This matrix is asymmetric as the IMAN has very low levels of reciprocity.

Let $Z(t) \equiv (z_{ij}(t))_{1 \leq i,j \leq N}$ be a generic adjacency matrix (binary or weighted) at time t; let introduce δ_k, with $k = 1, 2, ..., 10$, the deciles of the distribution of geographical distances ($\delta_0 = 0$). In each year, the *restricted matrices* are defined as:

$$Z_k^{(r)} = \begin{cases} z_{ij,k}^{(r)} = z_{ij}, & \text{if } \delta_{k-1} < d_{ij} \leq \delta_k, \\ z_{ij,k}^{(r)} = 0, & \text{otherwise}; \end{cases} \tag{3}$$

and the *cumulated matrices* are defined as:

$$Z_k^{(c)} = \begin{cases} z_{ij,k}^{(c)} = z_{ij}, & \text{if } d_{ij} \leq \delta_k, \\ z_{ij,k}^{(c)} = 0, & \text{otherwise}. \end{cases} \tag{4}$$

Network Statistics

We use node statistics that are commonly employed in the international networks of countries[3,8,32,33]. These statistics allow studying node characteristics in terms of connectivity and clustering. The binary statistics are: node degree (*ND*), average nearest-neighbor degree (*ANND*), and the clustering coefficient (*BCC*). These statistics can be generalized to the weighted network: node strength (*NS*), average nearest-neighbor strength (*ANNS*), and the weighted clustering coefficient (*WCC*). Both sets of statistics are used in their corresponding directed versions. Table 4 defines the network statistics employed.

Table 4. Binary and weighted topological statistics.

Topological Properties	Binary	Weighted
Degrees/Strengths	$ND_i^{out} = A_{(i)}\mathbf{1}$	$NS_i^{out} = W_{(i)}\mathbf{1}$
	$ND_i^{in} = A'_{(i)}\mathbf{1}$	$NS_i^{in} = W'_{(i)}\mathbf{1}$
	$ND_i^{tot} = ND_i^{in} + ND_i^{out}$	$NS_i^{tot} = NS_i^{in} + NS_i^{out}$
ANND/ANNS	$ANND_i^{out} = \frac{(A+A')_{(i)}(A+A')\mathbf{1}}{ND_i^{out}}$	$ANNS_i^{out} = \frac{(W+W')_{(i)}(A+A')\mathbf{1}}{ND_i^{in}}$
	$ANND_i^{in} = \frac{(A+A')_{(i)}(A+A')\mathbf{1}}{ND_i^{in}}$	$ANNS_i^{in} = \frac{(W+W')_{(i)}(A+A')\mathbf{1}}{ND_i^{in}}$
Clustering	$BCC_i^{out} = \frac{(A^2A')_{ii}}{ND_i^{out}(ND_i^{out}-1)}$	$WCC_i^{out} = \frac{(Z^2Z')_{ii}}{ND_i^{out}(ND_i^{out}-1)}$
	$BCC_i^{in} = \frac{(A'A^2)_{ii}}{ND_i^{in}(ND_i^{in}-1)}$	$WCC_i^{in} = \frac{(Z'Z^2)_{ii}}{ND_i^{in}(ND_i^{in}-1)}$
	$BCC_i^{cyc} = \frac{(A^3)_{ii}}{ND_i^{in}ND_i^{out}-NB_i}$	$WCC_i^{cyc} = \frac{(Z^3)_{ii}}{ND_i^{in}ND_i^{out}-NB_i}$
	$BCC_i^{mid} = \frac{(AA'A)_{ii}}{ND_i^{in}ND_i^{out}-NB_i}$	$WCC_i^{mid} = \frac{(ZZ'Z)_{ii}}{ND_i^{in}ND_i^{out}-NB_i}$

Note: $A_{(i)}$ is the ith row of A; $Z = [W]^{[1/3]}$ stands for the matrix obtained from W after raising each entry to $1/3$; $(Z)^3_{ii}$ is the ith entry on the main diagonal of $Z \cdot Z \cdot Z$; and, NB_i is the number of reciprocal partners of node i.

Acknowledgments

Giorgio Fagiolo gratefully acknowledges support by the European Union's Horizon 2020 research and innovation program under grant agreement No. 649186 - ISIGrowth. The authors thank useful comments and suggestions from Mercedes Campi and Pablo Galaso. We also thank participants in WEHIA (Universitat Jaume I Castelló de la Plana, June 2016) and in the Workshop Dinámica Económica: Teoría y Aplicaciones (Universidad de la República, Montevideo, November 2016).

Contributions

MD, RM, MB, and GF conceived and designed the study. MB collected the data. MD and RM analyzed the data, performed the statistical analysis, created the tables and figures, and wrote the final version of the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing financial, professional or personal interests that might have influenced the performance or presentation of this contribution.

References

1. Qiu, L. & Wang, S. FDI policy, greenfield investment and cross-border mergers. *Rev. Int. Econ.* **19**, 836–851 (2011).
2. UNCTAD (ed.) *World Investment Report 2010. Investing in a Low-Carbon Economy* (United Nations, New York and Geneva, 2010).
3. Serrano, M. Á. & Boguñá, M. Topology of the world trade web. *Phys. Rev. E* **68**, 015101(R) (2003).
4. Garlaschelli, D. & Loffredo, M. I. Structure and evolution of the world trade network. *Phys. A: Stat. Mech. its Appl.* **355**, 138–144 (2005).

5. Serrano, M. Á., Boguñá, M. & Pastor-Satorras, R. Correlations in weighted networks. *Phys. Rev. E* **74**, 055101 (2006).
6. Serrano, M. Á., Boguñá, M. & Vespignani, A. Patterns of dominant flows in the world trade web. *J. Econ. Interact. Coord.* **2**, 111–124 (2007).
7. Fagiolo, G., Reyes, J. & Schiavo, S. On the topological properties of the world trade web: A weighted network analysis. *Phys. A: Stat. Mech. its Appl.* **387**, 3868–3873 (2008).
8. Fagiolo, G., Schiavo, S. & Reyes, J. World-trade web: Topological properties, dynamics, and evolution. *Phys. Rev. E* **79**, 036115 (2009).
9. Fagiolo, G., Reyes, J. & Schiavo, S. The evolution of the world trade web: a weighted-network analysis. *J. Evol. Econ.* **20**, 479–514 (2010).
10. Schiavo, S., Reyes, J. & Fagiolo, G. International trade and financial integration: a weighted network analysis. *Quant. Finance* **10**, 389–399 (2010).
11. De Benedictis, L. & Tajoli, L. The world trade network. *The World Econ.* **34**, 1417–1454 (2011).
12. Fagiolo, G. The international trade network: Empirics and modeling. In Victor, J. N., Montgomery, A. H. & Lubell, M. (eds.) *The Oxford Handbook of Political Networks*, 173–193 (Oxford Handbooks Online, 2016).
13. Song, D.-M., Jiang, Z.-Q. & Zhou, W.-X. Statistical properties of world investment networks. *Phys. A: Stat. Mech. its Appl.* **388**, 2450–2460 (2009).
14. Joseph, A., Joseph, S. & Chen, G. Cross-border portfolio investment networks and indicators for financial crises. *arXiv preprint arXiv:1306.0215* (2013).
15. Sgrignoli, P. The world trade web: a multiple-network perspective. *arXiv preprint arXiv:1409.3799* (2014).
16. Zhang, S., Wang, L., Liu, Z. & Wang, X. Evolution of international trade and investment networks. *Phys. A: Stat. Mech. its Appl.* **462**, 752–763 (2016).
17. Sánchez Díez, A., Galaso Reca, P. & García de la Cruz, J. M. Las fusiones y adquisiciones realizadas por empresas españolas en américa latina: un estudio desde la perspectiva del análisis de redes. *Revista CEPAL* **120**, 55–74 (2016).
18. Garas, A., Lapatinas, A. & Poulios, K. The relation between migration and FDI in the OECD from a complex network perspective. *Adv. Complex Syst.* **19**, 1–20 (2016).
19. Barthélemy, M. Spatial networks. *Phys. Reports* **499**, 1–101 (2011).
20. de Ménil, G. Real capital market integration in the EU: How far has it gone? What will the effect of the euro be? *Econ. Policy* **14**, 165–201 (1999).
21. di Giovanni, J. What drives capital flows? The case of cross-border M&A activity and financial deepening. *J. Int. Econ.* **65**, 127–149 (2005).
22. Portes, R. & Rey, H. The determinants of cross-border equity flows. *J. Int. Econ.* **65**, 269–296 (2005).
23. Abbate, A., Benedictis, L. D., Fagiolo, G. & Tajoli, L. The International Trade Network in Space and Time. LEM Papers Series 2012/17, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy (2012).
24. Brakman, S., Garita, G., Garretsen, H. & van Marrewijk, C. Unlocking the value of cross-border mergers and acquisitions. Working Paper Series 2294, CESifo (2008).
25. Garlaschelli, D. & Loffredo, M. I. Patterns of link reciprocity in directed networks. *Phys. review letters* **93**, 268701 (2004).
26. Dueñas, M. & Fagiolo, G. Global trade imbalances: A network approach. *Adv. Complex Syst.* **17**, 1450014 (2014).
27. Fagiolo, G. The empirics of macroeconomic networks: A critical review. In *Complex Networks and Dynamics*, 173–193 (Springer, 2016).
28. Fagiolo, G. Clustering in complex directed networks. *Phys. Rev. E* **76**, 026107 (2007).
29. Dueñas, M. & Fagiolo, G. Modeling the international-trade network: a gravity approach. *J. Econ. Interact. Coord.* **8**, 155–178 (2013).
30. Fagiolo, G., Squartini, T. & Garlaschelli, D. Null models of economic networks: the case of the world trade web. *J. Econ. Interact. Coord.* **8**, 75–107 (2013).

31. US Bureau of Labor Statistics. Import/Export Price Indexes, www.bls.gov/web/ximpim/beaexp.htm, accessed on March 2016 (2016).

32. Li, X., Jin, Y. Y. & Chen, G. Complexity and synchronization of the world trade web. *Phys. A: Stat. Mech. its Appl.* **328**, 287–96 (2003).

33. Garlaschelli, D. & Loffredo, M. Fitness-dependent topological properties of the world trade web. *Phys. Rev. Lett.* **93**, 188701 (2004).