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INTERLOCKING DIRECTORATES IN ITALY: SOCIAL NETWORK ANALYSIS OF THE FTSE-MIB COMPANIES

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1. INTRODUCTION

Despite Social Network Analysis being a promising field of research highly considered by both academics and practitioners, it is surprising to find a lot of room for related corporate-wise empirical research.

Interlocking directorates and the composition of the network developed around them have been, and are currently being, widely discussed in the business literature: Elouaer (2009) addresses the topic in the case of the French firms included in the CAC 40 and SBF 250 Market Indexes, while an analogous work is done by Milaković, Alfarano, and Lux (2010) with all the Germany traded companies that crossed a certain size threshold or were listed in one of the four prime standard indices[1]. A European-scale analogous example is offered by Heemskerk (2011); despite going beyond the scope of this research, similar analyses for cases outside the Old Continent are present as well (e.g. the publications of Burris, 2005 for United States and Asokanb, Satheesh Kumar, Prem Sankar, 2015 for India).

The topic was not overlooked in Italy, either: Farina (2009) highlights Financial Companies' Centrality in the network, while Drago, Ricciuti and Santella (2015) evidence the effects of the 2011 'Save Italy' law on the density of the Italian network, and furthermore Bellenzier and Grassi (2013) highlight the network recurring dynamics and the existence of a persistent core over time in the network.

Despite these works present huge differences from one to another due to the metrics, the definition of the sample and the aim of the research itself, there is a clear *fil rouge* that connects them, namely the Social network analysis among boards through their directors and/or executives and the central role of the interlocking directorates. The work within this dissertation aims therefore at giving a contribution to the existing research, by providing a portrait of the interlocking phenomenon in Italy in the recent years, through the network analysis of the companies included in the FTSE-MIB (which alone represents the 80% of the Italian market capitalization), and their directorates, considering the data from 2014 to 2016, and summarizing the main characteristics of the directors that have an important role in the network.

[1] The four prime standard indices in Germany are the DAX, the MDAX, the TecDAX, and the SDAX. The DAX is comprised of the top thirty companies ranked by market capitalization. The SDAX and MDAX refer to small cap and mid-cap companies, while the TecDAX consists of the thirty largest companies in the technology sector.

The analysis starts from a description of the network through the observation of the connections within it and the use of some numerical indicators; the purpose is to get a portrait of the network, as well as the magnitude of links within it and its evolution in the three-years lapse from 2014 to 2016; with regard to this goal, some interesting features that are explored and measured are the presence and persistence of cohesive groups of companies and directors, the way they cluster together, and the roles that they play within the set of linkages under analysis; particular attention is also provided to the presence of a certain *nucleus* over time, its persistence and variability in composition, and what is the contribution of banks in its cohesiveness as well as the connectivity of the entire network.

The different measures that are accounted for mainly aim at describing two characteristics of the network: its cohesiveness, in order to get an idea of 'how compact' the network as a whole is and the distance between the elements that form it, and the relevance and centrality of its components, in order to highlight the possible special role of some companies in holding the network together or strengthening the connections within it.

Concerning the first of these aspects, i.e. the analysis of the network as a whole, besides relying on the observation of the graphs themselves, the analysis is benchmarked on a wider spectrum of indicators that give different perspective and a complete overview of the network, including its density, degree sequence and diameter.

An equal importance is given to the detection and the identification of the individuals holding an interlocking directorate, and therefore driving the ties in the graph, and the degree of connections among themselves in a wider framework, i.e. the full scheme including both the directors and the companies; the main tools used are therefore be bigraphs and their subsets, as well as centrality indicators.

As necessary complement to this analysis, and therefore parallel goal of this paperwork, a descriptive analysis clarifies the role of the most relevant directors in the network and assesses the determinants of their presence in the board. The framework that led the past century corporate research, which kept a focus on agency theory and resource dependence theory as determinants of their presence in the board, was frequently penalized by the commonly accepted insider vs. outsider categorization. With the intent of creating a follow-up study, this analysis borrows the taxonomy from Hillman, Cannella and Paetzold (2000), whose study further breaks down outside directors into three main categories: Business Experts, Support Specialists, Community Influentials. The aim of this analysis will be identifying the role that these managers hold in the boards, understanding if they have the same role in all the boards they sit on, and trying to depict the most likely profile of interlocking directors in Italy.

Both the topics will be developed within two parallel perspectives: the analysis of the overall network of companies, including the ones completely isolated, to have the widest summary possible, and the analysis of the main components that form up in each network, removing the marginal components and the isolated companies, in order to understand what the state of the art is in the core of the network, i.e. where the relevant directors are more likely to be found.

The analysis benefits of comparisons of the state of the links over time as well, in the sense that, given the measures and a comprehensive idea of the network in each year, comparisons are possible and are hence made.

2. The interlocking literature

2.1. Theory behind the interlocking directorates

With the purpose of explaining the reasons of the existence of interlocking board memberships and the role of interlocking directors, several theories and models have been developed over time, especially from the seventies onwards.

The Resource Dependence Model proposed by Selznick (1949) sees interlocking directors as a way to face the uncertainty in the business life of companies that comes from the relationships with the other stakeholders (namely customers, suppliers, competitors) and environmental conditions (macroeconomic situation, regulation). In this sense, interlocking directorships bring integration between the company and institutions or business partners; furthermore, the presence of interlocks can also add some intangible asset to the company, such as information or reputation. In more recent literature, the Resource Dependence Theory highlights similar concepts, stressing the importance of corporate boards as a mechanism to reduce the environmental uncertainty (Pfeffer, 1972), manage external dependencies (Pfeffer, Salancik and Stern, 1979) and reduce the transaction costs related to environmental interdependency (Williamson, 1984).

The Financial Control Model sees interlocking directorships as a means to provide an easier access to debt or equity capital from banks or funds, reducing the information gap and adding a guarantee for the capital suppliers on the company business; such a model is supported empirically by a wide literature that found interlocking directorships to be more present in the companies with an increasing demand of capital, including Dooley (1969), Mizruchi (1998) and Mizruchi and Stearns (1988). Coherently with the Resource Dependency Theory conclusions about the reduction of the costs associated with uncertainty and interdependence (Pfeffer, Salancik and Stern, 1979; Williamson, 1984), as well as the statements in Hillman, Cannella and Paetzold's (2000) work, having a member of financial institutions serving as a director may send outside two important messages: that the firm is in need of capital on the one hand, and that it is ready to commit and disclose to the capital suppliers any relevant information. In fact, the bank may benefit of a better monitoring of the debt, while the company may benefit from rising more debt capital. The Financial Control Model seems also coherent with Elouaer's (2009) findings, i.e. that companies in financial difficulty tend to form a close association with financial houses, while banks find it advantageous to attract large deposits and reliable customers through the election of company officers to the bank's board of directors. This theory has indeed solid theoretical fundamentals and empirical evidence but does not explain other types of interlocks that are not company-bank wise.

Collusion Theory observes that interlocking directors ease the creation of communication channels between corporations at the expense of consumers, because they can guarantee (and easily check if some of the companies undermines) a cartel agreement. Pennings and Thurman (1980), for instance, highlight a positive association between industry concentration and horizontal ties.

Some other models use a different perspective, considering the issue from the viewpoint of directors themselves more than the need of the company. The Management Control Model, for instance, stresses the importance of interlocks as a way for managers to follow strategies detrimental to the shareholders' interest, highlighting a clear conflict. Managers tend to appoint busy directors with executive roles in other firms, with the attempt to weaken the control system in the company. Palmer (1983) finds out that, once an interlocking director retires or dies, the link is hardly created again, unless they are functional to connect two institutions. Moreover, Hallock (1997) finds that cross-interlocks have a positive effect on the CEO's salary.

According to the Class Hegemony Model, interlocking directors reflect a strong social cohesion, as (Nobles and Useem, 1985) directors get in touch with their peers because they share the same hobbies, beliefs, values or political opinion.

Finally, the Career Advancement Model (Stockman, Van der Knoop, Wasseur, 1988; Perry and Peyer, 2005) regards more in detail the interest of each interlocking director, which may be related to compensation, prestige and future job and networking opportunities.

The paperwork of Hillman, Cannella and Paetzold (2000) provides a classification that is mainly based on the Resource Dependency Theory and the Financial Control Model, albeit with consideration for the Agency theory. They find room for improvement with respect to the traditional approach, in the sense that they further tailor the insider/outsider classification used in the literature, dividing the Outsiders between Business Experts, who have prior experience as directors or managers and good decision-making and problem-solving skills, Support Specialists, who have knowledge in specialized fields not directly related to the business, such as financial or legal areas, and may provide ties for an easier access to financial capital, in perfect accordance with the Financial Control model, and Community Influentials, usually retired politicians or university faculty who have influence on communities and associations different from for-profit organizations. Despite this classification was not supposed to be used for the analysis of interlocking relationships, it is deemed to be more comprehensive and complete, and therefore is used as benchmark in the analysis of the role of the directors in the companies.

2.2. Relevant cases and findings in SNA Literature

Despite the literature of Network Analysis having its roots in the 20th century, interlocking directorates have been more deeply discussed by the literature in recent years; different studies have then started to be conducted on the most important economies of the world, including United States and the main European countries, on which this section focuses.

With respect to France, Elouaer’s (2009) work is the first one that provides a full description of the network of the most important listed companies within the country, benchmarking her studies on the CAC 40 and SBF 250 French Market Indexes; according to her findings, in 1996 about 16.60% of the directors sitting on the boards of the top 40 French Companies, and 18.04% among the top 250, were actually sitting on more than one board, with a slow decaying trend that led this number to 15.21% for the top 40 companies and 12.46% for the top 250. This drop highlighted a slow declining of interlocking directorships over time, as well as a concentration of the latter among the biggest companies. Such a trend is further confirmed by the density level, which drops over time for both graphs, and the trend in the closeness centrality (whose meaning further described in the taxonomy) for the ‘most central’ companies in the chart, which again increases in both cases; this is also coherent with one of the main findings, which is, that the big companies are central actors in the network, and the higher their market capitalization, the higher their number of ties with other firms. A great portion of the interlocks, finally, is due to financial institutions, which alone form up the 30% of the most connected firms in the network; this is mainly because the interlock is seen as a mechanism to create an association between the firm and the financial house, secure a reliable customer for the banks and attract large deposits from the ‘linked’ companies.

A similar work for Germany is done by Milaković, Alfarano, and Lux (2010) with all the Germany traded companies which either had a market capitalization of more than one hundred million euros, or were included within one of the four main German Indices: the DAX, the MDAX, the TecDAX, and the SDAX, with a lower average board seat per director (1.12 compared to the 1.19 and 1.22 in the two above mentioned Indices France in 2005); this may highlight a less sparse network on the one hand, or a tendency towards the reduction of the density in the networks over time on the other, if we assume France and Germany to be homogeneous from this point of view and consider that the data related to the present analysis concerns a vary ranging period ranging from 2014 to 2016.

The same declining trend is also observed in the United States from 1962 to 1995 by Barnes and Ritter (2001), despite they partially impute this effect to the increase in the frequency of the M&A activity among big companies in the considered time period, suggesting that in the globalized age interlocks still remain an indicator of corporate power, but maybe expanding the field of vision is necessary.

On a European perspective, an analogous study is conducted by Heemskerk (2011); among the other findings, one of the most interesting is the existence of a core of companies that, even on a European scale, 'hold the reins' of the entire network. Although the presence of a stable core is a constant, anyway, the companies composing it change continuously due to the activity of Mergers and Acquisitions; nonetheless, the firms that persist in both the networks of 2005 and 2010, thereby called 'dominant firms', form up the 69% of the European network by 2010, with an increasing number of national and European ties and interlocks – and, therefore, network denseness – between the two analysed years. Despite this, it seems that the contribution of the 'hard core' to the cohesion of the European network, related to 16 to 17 directors depending on the year, drops from 46.4% in 2005 to barely 25.2% in 2010. The obvious conclusion is that the network is strengthened more from the outside, with a slow decline in the importance of the European corporate elite. Nonetheless, this study highlights that the recent developments in the European network make it less centred around banks, which seems to make the past century theories that considered interlocks as means of bank control or signs of the power of finance capital (Mizruchi, 1996) at least partially obsolete, despite them being still a solid benchmark.

A model comparison is also offered by Drago, Polo, Santella, Gagliardi (2009), who consider the interlocking directorships on Italy, France, UK, Germany and United States using data between 2007 and 2008 on the first forty Blue Chips of each country, and highlight the presence of two main standing national models: a first one, more peculiar of the Continental European countries, where companies seem to be linked to each other through directors who serve on several boards, and an opposite second model present in UK, with fewer company being connected by directors who hold usually not more than 2 board memberships, with the United States being somewhere in the middle, since they present a high number of companies connected by directors having only two different board positions at a time. In particular, this study shows an average board membership in Italy in December 2017 equal to 1.17 (i.e. the average directors sits on 1.17 boards) and several directors having multiple memberships, ranging from 2 to 5 (12.83% of the directors in the sample or, in absolute terms, 63 individuals); the density of the network graph is equal to 0.1039 (the significance of such a metric is defined below in the taxonomy; as a first approximation, it measures the level of cohesiveness of the network), which indicates a network more clustered than UK and United States (which are thereby defined 'collusive' markets) and sparser than France and Germany (which, on the opposite, are regarded as 'competitive' markets).

A recent and full-scale study in Italy made by Drago, Ricciuti, Santella (2015) puts the focus on the Save Italy reform (2011), comparing the network before (2009) and after (2012) the change in the regulatory framework. This time, however, the sample is not restricted to Blue Chips, but considers all the dataset available in the Consob public data collection. It concludes that the reform affected the network, even if slightly, and pushed companies in the centre towards a different behaviour than the one highlighted by Heemskerk's European-scale research, in the sense that they reduced their connections with the periphery while keeping their strategic links; if we match this conclusion with Heemskerk's research, it seems that the 'area' where the drop in interlocks takes place depends on some country-related determinants.

With reference to this study, one of the goals of the research hereby carried is to create a follow-up and assess whether the declining trend was entirely attributable to the Save Italy reform or there actually *is* a declining trend that is independent from the regulation, especially considering the overall declining trend observed in the other papers; moreover, the study has also the purpose assess the presence of a stable core and its stability over time.

Finally, a deep attention will be given to Farina's (2009) work, which highlights the centrality of banks in 2006 network graph, who seem to hold the greater power of influencing in the network of interlocking directorates formed with other firms, to assess whether such a 'status quo' persists in the period (2014 to 2016) considered in the present study as well.

3. Methodological Section

3.1. Social network Analysis

According to Mitchell's (1969) definition, we may describe Social Networks as 'a specific set of linkages among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behaviour of the persons involved'.

The structural analysis of network graphs traditionally covered a wider variety of topics than social relationships, ranging from Technological to Information to Biological Networks, and has traditionally been, on the first place, more a descriptive task than inferential, borrowing tools that belong more to pure mathematics or computer science than 'pure' statistics, with contributions from Social Network Analysis and physics as well.

Within this framework, Social Network Analysis (SNA) may be defined (Monaghan, Lavelle, Gunnigle, 2017) as 'the research into the patterning of relationships among social actors or among actors (…) at different levels of analysis' (such as persons and groups). The social actors are represented through *points* (also named *vertices*), while the connection between two vertices is defined as the *link* (or *edge*) that connects them.

In building the network graph from an underlying system of interest, the choice of what is deemed to be the 'elements' of the network, as well as the 'interactions' between them, may be a nontrivial exercise, especially when putting into account the measurements to take for each of them; a clear definition of both is necessary, as this could in fact alter the analyses of such graphs and the conclusions that may be drawn thereof. Using 'friendship' as interaction criterion, for instance, may present multiple issues and threaten the clarity of the analysis, or even present a misleading one, not only because such a definition may be difficult to identify or may not be mutual, but also because, even if one assumes that one could ask directly for the personal relationship between all the people in the network (e.g. through a survey), the value that the different people give to such a word, and the way they 'feel' friends, may be different from one subject to another, and therefore lead to misleading conclusions.

Because of the nature and the complexity of the system under study, the natural challenge following the network graph building is its visual representation; this process is often referred to as *network mapping*. Given a set of edges and vertices and the additional information concerning further characterizations of the network, the goal pursued in network mapping is the representation of the network itself through a clear visual image that effectively communicates the information that the graph carries within. Such representation may not necessarily be unique, as there are multiple ways to draw a network, depending on the presence of weights in the links, labels, annotations and, in case of bigraphs, the type of relationship that one wants to highlight (this particular case is discussed below).

It should be highlighted that the data one usually considers in network analysis (from now on also referred to as ‘network data’) does not necessarily include the entire population, and it is important to distinguish between enumerated, partial and sampled data. *Enumerated data* are collected in an exhaustive fashion from the entire population and is the most desirable kind of information for any SNA. A *Partial* dataset, on the other hand, is a full enumeration of a subset of the population; it is often the case that an Enumerated dataset can be seen as a Partial dataset of a bigger population under some constraint. Finally, *Sampled data* are data on units randomly selected; unlike partial data, there is no *a priori* discriminant rationale behind their sampling from the population.

Since data collection is more nuanced and may combine different aspects of more than one of these, it is worth mentioning a different framework from past literature on statistical data collection (Gibson, Little and Rubin, 1989), which distinguishes between *observed* and *missing* data, and is often more convenient to use to copy with reality. This paradigm has evolved over time into an organized approach, with categorizing mechanisms for missingness of data, assessment methods for their impact on a given analysis, and possible adjustments for such effects. Despite empowering the current state of the art in the research, it is beyond the scope of our study and will not be further explored.

3.2. BASIC GRAPHS TAXONOMY

Descriptive analysis in a network is a task that entails some discretionary choice of the most suitable measures and of the numbers that one decides to emphasize; a deep understanding of the metrics used below is crucial, and therefore a well-defined taxonomy plays a fundamental role in giving a clear overview of such metrics and their meaning from both a theoretical and practical point of view, as well as a clever understanding of the information that each of the indicators used in this dissertation delivers.

Unless differently specified, all the considerations below refer to a Network Graph $G = (V, E)$, with V indicating the set of N_V vertices $v_1, v_2, \dots, v_{N_V}$, and E analogously indicates the set of Edges connecting the vertices $e_1, e_2, \dots, e_{N_E}$; the number of vertices (N_V or $|N|$) is referred to as *order* of the graph, while the number of edges is called (N_E or $|E|$) also *size*; lastly, a *subgraph* of G is a graph $H = (V_H, E_H)$ where $V_H \subseteq V$ and $E_H \subseteq E$.

A chart with *loops*, i.e. vertices connecting to themselves, or *multi-edges*, i.e. edges connecting the same pair of vertices, is called *multi-graph* and it is not considered an ordinary (or, technically speaking, *single*) graph; since all the graphs we are considering are single graphs, this category is of no interest for our purposes and is not further investigated. Another type of graph that is not going to be of any relevance in this study is the *directed graph* or *digraph*, which differ from normal graphs because there is an ordering in the vertices at the extreme of the edges (i.e. the edge points from one vertex to another).

Concerning the connectivity of the graph, two vertices are said to be *adjacent* if joined by an edge in E; vice versa, two edges are said to be adjacent if they connect to the same vertex. Finally, a vertex is said to be *incident* on an edge if it is an endpoint of the latter.

Some important concepts concerning the movements within a graph are to be known as well: a *walk* is an alternating sequence of vertices and edges $\{v_0, e_1, v_1, e_2, \dots, v_{l-1}, e_{l-1}, v_l\}$ which connects v_1 and v_l passing by incident vertices; a *trail* is a walk with no repeated edges, and a *path* is a walk without repeated vertices.

As regards the distance between vertices, the most commonly used measure is the *geodesic distance*, which is the length of the shortest path between vertices; interestingly, this allows to identify the *diameter* of the graph as well, that is, the longest geodesic distance that can be found in the graph.

A vertex is said to be *reachable* from another vertex if a walk between the two exists, and a graph can be defined *connected* if every vertex is reachable from every other in the graph; finally, a *component* is a maximally connected subgraph of G where adding any other vertex in V would ruin the property of connectivity of the graph.

A *complete* graph is a graph where every vertex is connected to every other via an edge; namely, where every vertex is adjacent to every other in the graph; a *clique* is a complete subgraph, i.e. a subgraph with the same property of a complete graph.

One of the most important concepts, and key driver of the entire analysis that is going to be shown in the chapters below, is the *bipartite graph*. A bipartite graph is a graph $G = (V, E)$ where the vertex V is actually partitioned in two sets, say V_1 and V_2, and each of the edges in E has an endpoint in V_1 and the other in V_2. Usually, these two 'families' of vertices belong to two different real-life categories: for instance, V_1 could be a list of clubs, and V_2 a list of people who are club members; an example more consistent with this paperwork would see V_1 as the list of board directors sitting on at least one board in the FTSE-MIB companies, and V_2 the list of such companies.

In parallel, we define an *induced* graph $G_1 = (V_1, E_1)$ – or, in an analogous way, $G_2 = (V_2, E_2)$ – as the graph connecting all the vertexes in V_1 (or V_2) using as connection criterion their adjacency with a common vertex in V_2 (V_1), i.e. a common member in the club (or, analogously, a membership of some individuals in the same club).

The linear algebra behind the calculations made and the R algorithms designed for the purpose of the analysis is not going to be fully explored for the sake of keeping the explanation of this introductory section as much straightforward as possible (although proper references will be made when necessary). That said, the underlying apparatus behind the network analysis (i.e. the adjacency matrix) and its functioning are at least worth mentioning: the *adjacency matrix* of the graph G is a binary, symmetric, $N_V \times N_V$ matrix with entries

$$A_{ij} = \begin{cases} 1, if\ \{i, j\}\ \in E \\ 0, otherwise \end{cases}$$

This matrix aims at catching the adjacent vertices in a Graph; in fact, the entries correspond to 1 only when the vertices i and j are connected (analytically speaking, when the edge that could connect these two points exists in E).

Such a matrix has a certain set of specific algebraic properties that, for the scope of this work, are not to be considered and are therefore not treated; for our purposes, the relevant element is that it is the basic input that any algorithm for graph modelling requires in order to depict a network and calculate metrics on it.

3.3. VERTEX DEGREE AND RELATED METRICS

Borrowing the approach from Kolaczyk (2009), the most important metrics may be separated in two families: a set of measures aimed at describing the characteristics of individual vertices and edges, and a second set related to the cohesion of the network as a whole, or subsets of the latter. Within the first group of measures, a second distinction is made between characterizations based upon vertex degrees (explored in this section) and the so-called centrality measures, whose main purpose is assessing the 'importance' of a vertex within the network.

Concerning the characterization of the single elements of the network, the first and most trivial measure related to a vertex is indeed its *Degree*; it is defined as the number of edges in E incident upon the vertex itself.

Given that every vertex v carries has a degree d_v , the degree sequence $\{d_1, \dots, d_{N_V}\}$ considers the set of the degrees corresponding to each vertex and is therefore a trivial aggregate measure; in the case of *directed graphs*, there are two different degree sequences for in- ($\{d_V^{in}\}$) and out-degrees ($\{d_V^{out}\}$). Through the analysis of the degree sequence, various measures of the nature of the overall connectivity in the graph can be defined.

The first one is the *degree distribution* $\{f_d\}_{d\geq 0}$, i.e. the collection of every f_d corresponding to the fraction of vertices $v \in V$ with degree $d_v = d$. For instance, a degree sequence {2,1,3,5,2,3,1} will have a degree distribution of $\left\{f_1 = \frac{2}{7}, f_2 = \frac{2}{7}, f_3 = \frac{1}{7}, f_5 = \frac{1}{7}\right\}$; obviously, in this example f_4 is absent since there is no vertex with degree 4 in the sequence, and all the values within the distribution sum up to 1.

The *degree correlation* is one more advanced measure and any use of this metric goes beyond the scope of the work; nonetheless, it is treated for completeness. It is a two-dimension analogue of the degree distribution, and it is based on an edge-wise perspective: it corresponds to a (symmetric) matrix where each value f_{d_j,d_i} (or, analogously, f_{d_j,d_i}) is the relative frequency of edges connecting vertices with exact degrees d_i and d_j. All the values within the matrix sum up to 1 as well.

3.4. CENTRALITY MEASURES

While the degree of a vertex is the most intuitive measure of its connectivity with the chart, it does not necessarily deliver any meaningful information about how close it is to holding the 'reins of power' within the network. To assess the importance of a vertex in the graph, centrality measures may look more appropriate.

In this sense, one may want to look at the Centrality of some vertices in the network; as observed by Freeman (1978), 'there is certainly no unanimity on exactly what centrality is or on its conceptual foundations, and there is little agreement on the proper procedure for its measurement'. While vertex degree is the most intuitive and commonly used measure of centrality, it completely disregards the position of a vertex in the network. Three more proper measures of centrality are Closeness, Betweenness and Eigenvector centrality which, for the sake of simplicity, we are considering under the assumption that G is an undirected graph.

Closeness Centrality

Closeness centrality follows from the definition of 'central' as 'as close as possible' to many other peers. Sabidussi (1966) considers a measure that varies inversely with the total distance of a certain vertex v from all others.

The corresponding formula is

$$c_{Cl}(v) = \frac{1}{\sum_{u \in V} dist(v,u)}$$

where $dist(v,u)$ is the geodesic distance between the vertices $u, v \in V$. Normally, this measure is further standardized to lie in the interval [0,1], multiplying it by a factor $N_V - 1$.

The main limit for such a metric is the strong underlying assumption that the graph G is connected, otherwise at least one of the distances between any vertex u and the every vertex of interest v is going to be equal to infinite and, therefore, this will have a positive impact in the denominator and result in every $c_{Cl}(v) = 0$.

Despite this fix being theoretically tempting, as it proxies very well the real state of the vertex in the network (a vertex at infinite distance is impossible to reach), it still leaves unsolved the problem of the computational infeasibility of such an important metric in all the graphs under investigation, as one could safely assume that in every (or almost every) SNA some portion of the sample will always be completely unconnected to the largest component, or even not connected at all to the rest of the network.

To overcome this problem, one could implement via R a simple workaround:

- Separate the graph into all the isolated but connected subgraphs that compose it;
- Calculate the centrality value for each of the vertices in the subgraphs;
- Take note of, and report, any relevant value within the relevant component(s).

But even then, the choice of 'relevant' would be arbitrary; as a thumb rule, one could consider a graph 'relevant' if it entails at least 4 companies (i.e. more than 10% of the companies in the sample), or consider only the main one, which is something that this research will do anyway.

More importantly, this would still give measures that are somewhat 'local' with respect to the overall graph, despite 'global' in the single components separately considered.

The fix proposed by Douglas (2018) in his manual seems the best compromise available: it sets the geodesic distance from any unreachable point to N_V (i.e. equal to the number of all the other vertices present in the network), compared to the 'traditional' approach that considers it equal to infinite. This allows to maintain a global perspective on the network while still imposing a strong enough penalty for unconnected vertices, since N_V is still higher than the value of the 'longest shortest path' that one could generally find in a network; furthermore, it allows to compare points in the network that, despite being unconnected from some other entities, may still have deep differences in their centrality that is at least worth distinguishing. In the 2015 companies' network later explored, for instance, this could be the case for UnipolSai, FinecoBank and Azimut, which according to the traditional definition would carry a closeness centrality measure of $c_{Cl}(v) = 0$, but play clearly different roles (respectively the most central unit of the network and of the main component, the most central vertex of a smaller component and an isolated company), while considering unreachable vertices as being reachable within N_V steps provides different values for the three companies, which can be at least compared.

Betweenness Centrality

That said, one could be interested in centrality upon the perspective of a vertex position with respect to the paths in the network graph; this is precisely the purpose of the definition of Betweenness Centrality introduced by Freeman (1977), which is more related to the criticality of a vertex in the communication process, and summarizes the extent to which a vertex is located 'between' other pairs of vertices.

The formula is

$$c_B(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)},$$

with $\sigma(s,t|v)$ being the total number of shortest paths between s and t that pass through v, and $\sigma(s,t)$ being the sum of each of the shortest paths between s and t passing by v for *each* vertex v. Note that, in case the shortest paths are unique, $c_B(v)$ is simple the number of shortest paths that pass through v (as the numerator and the denominator in the fraction will be always equal, making the fraction always equal to 0 or 1, and the summation itself will turn into a 'counter' of shortest paths that pass through v). To standardize this measure limiting it within the unit interval, it is hereby divided by a factor $(N_v - 1)(N_v - 2)/2$.

The main disadvantage of this approach is that some companies connected to the largest components, albeit in very marginal position, will score $c_B(v) = 0$, which is the 'lower boundary' for this indicator and is the same value that isolated companies score; this problem is nonetheless of little relevance, as such a measure is aimed at capturing the most (and not the *least*) 'in-between' companies; a further issue is that, in the case of presence of multiple 'big' components, comparing the values of vertices belonging to different components may give misleading indication.

Eigenvector Centrality

A third class of centrality measure is based on the notion of 'prestige' of the elements. Eigenvector centrality, which takes its moves from this concept, is calculated on the assumption that the higher the importance of the elements surrounding some vertex v is, the higher the importance of v itself. In analytical terms, it is calculated as (Bonacich, 1972):

$$c_{E_i}(v) = \alpha \sum_{\{u,v\} \in E} c_{E_i}(u),$$

where $\boldsymbol{c}_{E_i} = \left(c_{E_i}(1), c_{E_i}(2), \dots, c_{E_i}(N_V)\right)^T$ is the solution to the eigenvalue problem $\boldsymbol{A}\boldsymbol{c}_{E_i} = \alpha^{-1}\boldsymbol{c}_{E_i}$ with A being the Adjacency matrix of the network graph G; an optimal solution, as suggested by Bonacich, would be picking the largest eigenvalue of α and obviously choosing the corresponding eigenvector to be $\boldsymbol{c}_{E_i}$.

Despite this measure being fascinating because of its mathematical representation of a concept that is usually difficult to quantify using less analytical approaches, it is our arbitrary choice to prefer the other two centrality measures: the limited number of companies in the sample, despite being detrimental to some aspects in the analysis, presents the great advantage of intuitive interpretation of the results. A value such as $c_{E_i}(v)$ may be useful for relative comparison with respect to its own definition of centrality (more edge- than vertex-wise), which is a feature common to all the centrality measures so far considered anyway, but the price is a more complicated interpretation of the values that emerge. Therefore, the other two measures of centrality are hereby preferred.

3.5. NETWORK COHESION MEASURES

Measuring the relative importance of vertices, and the distribution of the corresponding indicators, only gives a description of very local aspects of the chart. To consider the graph as a whole or, in some cases, a set of subgraphs, an analysis of the cohesion of the network is more appropriate, which considers three aspects in parallel: the density of the network, its connectivity, and the chances to partition it.

Local Density

The first and most important element to take into account when analysing a network as a whole is its cohesiveness, and the chance that a coherent subset of nodes in the network structure are locally 'denser' in the graph. The maximally 'dense' graph that one can think of is, obviously, a *clique*, since all its vertices are connected by edges. In real-word networks, cliques are more a theoretical benchmark than empirical evidence, as they are very rare to observe; the restrictiveness of such a definition of density is the reason why cliques are rarely used as cohesion measure. The use of other alternative measures, such as *plexes* or *cores*, require a wider computational effort and are therefore of little efficiency. Also, for the purpose of this work, the term *core* is used in a non-technical fashion, to indicate high concentration of connected vertices in the middle of the network that drives most of its connections.

The best alternative available, according to Kolaczyk (2009), is the use of a measure of local density, with the purpose of defining, through a ratio, the extent to which subsets of vertices are dense. The *density* of a graph G according to this logic can be therefore defined as:

$$den(G) = \frac{N_E}{N_V * (N_V - 1)/2}$$

As the value in the denominator is the maximum theoretical possible number of edges between N_V vertices, this value is a standardized measure of cohesion.

Another possible measure (according to Watts and Strogatz, 1998) with similar purposes, is the average of all the $den(H_v)$ that can be deducted from each vertex, where H_v is the subgraph of the 'immediate neighbourhood' of each vertex v and is therefore a measure of the extent to which there is effectively some 'clustering' around a specific vertex. Not only this is more time consuming in terms of calculations, but it is hereby deemed to deliver little additional content when matched to the density and centrality measures. Furthermore, Bollobás and Riordan (2006) have pointed that, being such a clustering coefficient (that is thereby re-expressed in terms of *triangles* and *connected triples*, which are not treated in this context) an 'average of averages', it could even be more inefficient than the appropriate weighted average of the clustering coefficient of each vertex (using the number of connected triples around every vertex v as weights). Therefore, it is our choice to disregard the analytical implications of such a measure in this work.

Connectivity

For what concerns connectivity, a good (albeit redundant) proxy is the *average distance* between distinct vertices, expressed as

$$\bar{l} = \frac{1}{N_V(N_V + 1)/2} \sum_{u \neq v \in V} dist(u, v)$$

When one has already considered figures related to the density and the degree sequence, it does not add any relevant information, especially because Watts and Strogatz (1998) empirically observe that a small value of $\bar{l}$ is accompanied by a high value for the clustering coefficient.

A more tailored measure of connectivity is the notion of *k-vertex (k-edge) connectivity*, which question the possibility that, once an arbitrary subset of k vertices (edges) have been removed, the remaining chart remains connected.

More in detail, a graph is called k-vertex connected if

(i) $N_V > k$

(ii) The removal of any subset of vertices X ‘belongs to’ V of cardinality $|X| < k$ leaves a subgraph $G - X$ that is connected

Analogously, it is k-edge connected if

(i) $N_V \geq 2$

(ii) The removal of any subset of edges $Y \subseteq$ E of cardinality $|Y| < k$ leaves a subgraph $G - Y$ that is connected

Lastly, we define *vertex (or edge) connectivity* of G as the largest integer such that G is k-vertex-connected (or k-edge connected).

Needless to say, given the shape of the network under analysis in our case, the main components of each bigraph or the related induced graphs are always 1-edge and 1-vertex connected. Therefore, such a measure is a poor contribution to our study, but this finding alone indicates that the relevant contribution that connectivity analysis can provide comes from the cut-off points that constraint the vertex and edge connectivity to 1.

One notion of higher interest is maybe the one of *vertex-cut* and *edge-cut* graphs, which are graphs that are disconnected when a particular set of respectively vertices or edges is removed; in a 1-vertex (1-edge) graph context, it means that the removal of a certain vertex or edge alone is sufficient to completely disconnect that graph, and identifying which these key elements are could provide some interesting food for thought, as discussed later.

Graph partitioning

Partitioning refers to the activity to ‘split’ the graph G into ‘natural’ subsets. More formally, Kolaczyk (2009) defines: ‘a *partition* $\mathcal{C} = \{C_1, \dots, C_k\}$ of a finite set S is a decomposition of S into K disjoint, non-empty subsets C_k such that $\cup_{k=1}^{K} C_k = S$.’ It is used in literature to find in an unsupervised learning environment, subsets of vertices that demonstrate a certain ‘cohesiveness’ with respect to the underlying relational patterns.

As first approximation, we could define a subgraph ‘cohesive’ if the vertices inside it are

(i) ‘highly interconnected’ among each other

(ii) relatively ‘well separated' from the remaining vertices.

From this point of view, components (as defined in the taxonomy) may be seen as the most intuitive and extreme partition that one can find, being them groups of vertices totally isolated and with no connection to the rest of the graph. Partitions will be mostly referred to as 'clusters' in this work.

Partitioning is usually carried through an algorithm, whose choice is partly discretionary and may depend on the specific features that one may desire (for instance, some functions support directed networks, weighted networks or are able to partition networks with more than a component); many methods for partitioning are affine to Hierarchical Clustering algorithms, which greedily search all the space for the possible partitions $\mathcal{C}$; another common approach exploits spectral graph theory and associates the connectivity of a graph G with the eigen-analysis of certain matrices, such as the adjacency matrix that we mentioned before.

With reference to this work, it was our choice to rely mainly to the *walktrap*[2] algorithm, which is based on the intuition that random walks on a graph tend to get 'trapped' into densely connected parts. This algorithm proceeds as follows. It first starts from a single partition $P_1 = \{\{v\}, v \in V\}$ and calculates all the distances among vertices; then, it iterates the following steps (for each k):

(1) choose two communities C_1 and C_2 in P_k according to a distance-based criterion
(2) merge these two communities into a new community $C_3 = C_1 \cup C_2$ and create the new partition: $P_k + 1 = (P_k \setminus \{C1, C2\}) \cup \{C3\}$
(3) update the distances between communities

After n – 1 steps, the algorithm finishes and we obtain $P_n = \{V\}$.

[2]For a more complete overview of the walktrap algorithm, please refer to Pons P., Latapy M. 2006. 'Computing communities in large networks using random walks'.

4. THE DATA

4.1. SAMPLE USED AND CHOICES OF DATA STRUCTURING

The data analysed is a parallel set of three networks, one for each year between 2014 and 2016; the members of the network are a list of 35 companies listed in the Milan Stock Exchange and part of the FTSE-MIB index, and the directors sitting on the corresponding boards.

The database has been manually built on a csv file after gathering the data from the Corporate Governance reports, subsequently treated with the statistical software R and some of its additional packages, including ‘statnet’, ‘igraph’ and ‘network’.

As the list of directors in a company continuously changes, either because of their election in the shareholder meeting or because of extraordinary events (such as legal issues or death), the network includes the directors that have been sitting in the related boards within the year.

In order to be considered part of the dataset, and therefore give a contribution to the shaping of the network, the companies must be listed as part of the FTSE-MIB index at the date of 31st December 2017.

Despite this, five companies are absent from the dataset, namely: Unipol, Ferrari, Banca Mediolanum, STMicroelectronics, Tenaris.

The reasons behind their absence is the impossibility to gather information about the composition of the boards, which is due to different reasons depending on the company.

As long as the companies are listed in the stock exchange prior to their adding to the FTSE-MIB and therefore data concerning their board composition exists, the full collection available is considered. This means that, even if some companies that entered the index *during* the period considered (e.g. Recordati, which entered in the Index in 2016), they are still considered in the sample in the years *prior* their inclusion in the FTSE-MIB Index, provided that data is available.

Two exceptions to this rule are PosteItaliane and Italgas, since they were listed respectively only from 2015 and 2016, and therefore data prior to these dates is missing. This causes a small change in the size of the networks analysed over time; the sample will consist of 33 companies in 2014, 34 in 2015, 35 in 2016; this difference anyway is deemed to be of little relevance for the purpose of catching the big picture of the network, even if might have some distortive effects during the breakdown of its edges, clusters and components.

Moreover, Banca Mediolanum (whose data is missing) and Banca Popolare di Milano merged into Banco BPM in end 2016; therefore, the data available for Banca Mediolanum is limited to years 2014-15, replaced by the directors of Banco BPM in 2016, even if the company was officially listed the 2nd January 2017.

Finally, the companies in the sample present three different possible governance Models, two of which were introduced in January 2004:

- The traditional structure, peculiar of the Italian system and adopted by the majority of the companies in the sample, with the company run by a single board (consiglio di amministrazione) and a second company organ (collegio sindacale) serving as an internal auditing device;
- The dualistic model, which follows the German two-tier board, with a management board (consiglio di gestione) and a supervisory board (consiglio di supervisione);
- The monistic model, that ties in with the Anglo-Saxon Model, with a board (consiglio di amministrazione) composed by one third of independent directors which also includes a control committee (comitato per il controllo sulla gestione).

Most of the companies in the sample, mirroring the choice of most of the Italian companies, adopted the traditional model; in this case, only the directors sitting on the consiglio di amministrazione were considered, since the collegio sindacale is of different nature, more related to auditing; as regards the dualistic model, directors of belonging to both organs were included, while the third model obviously includes all the directors in the only present board .

The analysis and comparison of the three different networks for each year is based on a set of three bipartite graphs showing all the connections between the executives and the companies. Because of the peculiar structure of bipartite graphs, the corresponding vertices have a different ‘dignity’ as they represent two different categories, and in some cases, for the purpose of focusing on some relationships or simply having a clearer overview, it has been deemed necessary to observe some subgraphs or induced graphs corresponding to either of them, using the main charts as the underlying networks.

4.2. ANALYSIS APPROACH

Depending on the scope of our research in every topic developed, the same links are analysed using different perspectives, i.e. with the simultaneous analysis of different graphs.

In the overall work, we are considering five main charts, and some key statistics about a fictious sixth one. The first step is the analysis of the affiliation networks, as a whole system of directors and companies, using a full bipartite graph without distinction in the different meaning and importance of the vertices (Figure 4.1); this is below referred to as the 'full graph', 'bipartite graph' or 'overall graph' from now onwards. At a first glance, the three graphs highlight a modest connectivity, and apparently none of the companies in the network appears to have a proper 'central' role; besides this, any analysis of indicators concerning two joint sets of vertices that we know having different roles and dignity could be misleading, and this is the reason why, despite being the chart carrying the biggest amount of information, we also use different representations that are derived from the same data.

The second chart that we are considering is the induced graph (Figure 4.2) consisting of only the companies vertices (from now onwards, 'companies network'), as it allows to gain insight into the connections of companies *through* the directors that the formers share; graphically speaking, this basically means that two companies are connected through an edge if there is at least a manager sitting on the boards of both. This chart plays a relevant role in the of the connections among companies as well as the clusters that form up, which are highlighted in the corresponding image as well. The same chart is also presented in a heatmap-like variant, for the purpose of analysing specifically the centrality of some of its elements and the behaviour of the core of the graph.

A third graph that deserves a special distinction in the analysis, especially in the identification of the most relevant key-players in the network, and is therefore sometimes mentioned, is a subgraph of the full bipartite graph including only the vertices of degree higher than 1 (Figure 4.3). The intent of this variation is to remove all the 'noise' of 1-degree directors that don't create or shorten any connection between companies or people, being therefore of poor relevance for our purposes. Therefore, the graph includes all and only the 'key directors' whose removal from the network (i.e. they are fired) would imply the loss of a connection or, even worse, the complete detaching of a company from a cluster or a component. This helps detecting the parts of the charts that are most likely to be isolated and the key directors that keep them in the network. This representation may be referred to as 'key-directors', 'key-players' or 'key-individuals' graph.

As we are interested also in the dynamics inside the main component and less concerned about the companies that bring no connections or gather in isolated triples, two more interesting charts are a couple of subgraphs of the latter two (one for the companies chart, and one for the key-players chart) consisting only of the biggest component that is visible each year, i.e. the main components of the graphs present in Figure 4.1, 4.2 and 4.3.

Finally, some space in the analysis is dedicated to some features of a sixth chart, the induced graph of the directors alone, even if it is not graphically depicted because it would be hard to interpret.

4.3. LIMITS

Before proceeding through, one should be aware of the limits of this work, that may to a certain extent weaken or slightly bias the conclusions in this chapter, as well as in the followings.

Since the chart only includes 33 to 35 companies (the exact number depends on the year of observation), any consideration concerning its shape, density, centrality, connectivity, etc. could still be made without taking into account some important connections that are present outside of this framing and are beyond the scope of this study; the reasons of this issue emerging are mainly three: on the one hand, the fact that the subject of research is limited to listed Italian companies somewhat representative of the economy, further restricted because of the lack of availability of a minority of them; on the other hand, as non-listed companies are less subject to compliance and disclosure, it has been somewhat difficult to gather the data concerning their board composition on a regular yearly basis. For instance, the density values of the chart could be deemed surprisingly low (at least in absolute terms), albeit worth consideration; moreover, besides regulation issues, part of this evidence could be resulting from the restricted sample and the absence of extra-MIB connections, not mapped in the chart.

Furthermore, while still being valid and interesting for the analysis *within* the network, its representation may be part of a bigger framework that is not properly depicted in this context, meaning this could only be – and, very likely, is – the cohesive subset of vertices (or a subset of a cohesive partition) of a larger network, which is impossible to analyse both because of practical issues (the most important being gathering the data, especially concerning non-listed companies and other non-industrial entities such as clubs and institutions) and problems on a theoretical level (even if we *could* gather the whole universe, its analysis would be messy and unclear as the set of data could be too big to draw a satisfying synthesis).

5. ANALYSIS OF THE FTSE-MIB NETWORK AND INTERLOCKING DIRECTORATES

5.1. PRELIMINARY DESCRIPTIVE STATISTICS

Some initial analysis of the sample, disregarding the network and considering only the list of the companies, could provide some interesting insights concerning the composition of the sample, which is fully listed in the Table 5.1.

Some main features of this dataset can be highlighted on the spot, and they are all related to the peculiar structure of the Italian Economy: first, 33% of the companies in the sample offer some kind of banking, insurance or financial services, which is something that one would expect from a list of companies taken from an Italian market index; directly related to this point comes the second one: as per the art. 36 of the 'Save Italy' Law in 2011), most of the possible interlocking directorships within companies or groups operating in Banking, Insurance and Financial markets are forbidden; the implementation of this law, according to past literature, had an impact on the connectedness of the chart (Drago, Ricciuti, Santella, 2015); therefore, one could intuitively expect this to limit the connectivity within the network that is going to be analysed as well. Third, even when looking among the remaining companies, most of them (31%) operate within the same sectors: Fashion, Energy, Utilities. This could further lower the connectivity within the network, as there are very poor chances that a director, especially an insider or someone with an executive role, is found out 'serving two masters'.

This preliminary analysis suggests a general lack of linkages between the companies, which should not be regarded with surprise, as it may have several other reasons, including the existence of connections outside FTSE-MIB companies, including non-listed firms or political institutions.

The widest representation of the network is the bipartite graph (Figure 4.1) consisting of the companies (33 to 35 from 2014 to 2016, respectively) present in the MIB in 2017 – net of the ones whose data is missing – and the corresponding directors (ranging from 487 to 494, depending on the year), for a total set of 543 elements (i.e., vertices) in 2014, 521 in 2015 and 529 in 2016, linked by a roughly equal amount of edges (respectively 549, 519, 534); all the relevant data are summarized in Table 5.2.

Despite the two sets of vertices are very different in the information they carry, a first glance analysis at the degree sequence (Table 5.3) is still feasible knowing that, given the nature of the dataset, all the vertices with degree ≤ 4 correspond to a director and the remaining ones are the boards[3]. The degree of each of the vertices in these bigraphs has a notable meaning as it defines, depending on the nature of the vertex, either the number of the boards that a certain director sits on or the number of directors sitting on the boards of a certain company.

Concerning the directors (Table 5.3a), a vast majority of them (93.33% in 2014, 94.25% in 2015 and 92.91% in 2016) is only part of 1 board; this means that roughly, on average during the three years, all the connections among the companies – around 30 edges in the companies chart – are barely driven by the 6.5% of the directors.

Company-wise (Table 5.3b), the number of directors sitting on the boards ranges from 7 to 43 depending on the year and on the Company. Anyway, it is possible to notice a trend towards reduction of the directors in the boards (Table 5.4), with a median level dropping by 1 point per year and an average number of directors slowly diminishing as well[4]. This tendency towards a slight reduction in the number of board seats seems to be confirmed by the ratio between companies and number of directors (Table 5.5), i.e. the average number of directors per boards, which is 15.45 in 2014, 14.32 and 14.11 in 2016. The lower value of the simple ratio between directors and number of companies compared to the average grade of the companies themselves is imputable to their definition: by counting the degrees of each board, every director is technically counted multiple times, corresponding to the number of board seats they have, which is something that does not happen when one considers the overall number of directors, regardless of the number of boards they sit on. On the other hand, the relative closeness of these two set of numbers highlights a substantial lack of connections between directors.

The ratio related to the average board seats per director deserves a special mention; the value is 1.076 in 2014, 1.066 in 2015, 1.081 in 2016. The latter result can be seen as consistent with Elouaer's (2009) analogous studies that show an average board membership per director in France[5] equal to 1.19 / 1.22 in 2005 if one accepts the same conclusion as the author, who in particular highlights a decaying trend of the ratio, far higher in 1996 (1.33/1.30); assuming that the average board membership in Italy in the corresponding periods was roughly at least around the same scale, the decaying trend could explain the consequent drop to values that range from 1.066 to 1.081. To further strengthen both these two findings, the same indicator assumes a value of 1.12 in Germany in 2008 (Milaković, Alfarano, Lux, 2010). For the sake of completeness, one should also consider that at least

[3] A manual check has been carried as well.
[4] Please notice that the 15.25 in 2016 is mainly due to the company with 43 degrees, which alone drives the average from 13.73 to 15.25 and the volatility from 4.13 to 7.49, while the highest degree observed in the companies of the other two subsets is 35
[5] Elouaer considers both the CAC40 index and the SBF250, conducting two separate analyses

part of the cause of the slightly lower values for the Italian case may also be related to the lower number of companies considered compared to the German one, which leads to a higher likelihood of ignoring existing parallel board memberships of the directors in the sample, or to the peculiar structure of the Italian economy, where companies are most likely family-run with little participation of external share/stakeholders in the governance or in the property of the company.

5.2. NETWORK SHAPE, CLUSTERS AND EVOLUTION OVER TIME

A closer look at the set of linkages in the network, abstracting from metrics, could provide a more complete reference point in its description and in the analysis of its structure, in the sense that it can help to detect and explicitly mention the central companies and key directors that lead the connections, the tendency of the elements within the network to aggregate into clusters, and the evolution of such relationships over time.

As a reminder, we are considering two companies as 'connected' when they share at least one common director in their boards.

On the one hand, this analysis will focus on the clustered companies' chart (Figure 4.2) and the 'best partitions' that it is possible to identify within it, albeit sometimes these may be very connected to each other. The exercise of shaping different subgraphs may prove particularly challenging as the graph becomes sparser and more decentralized or, at the extreme opposite, very compact. This is because, as mentioned above, a high level of flexibility is required when outlining the partitions and, in addition, sometimes using qualitative criterions could even be more complex than following some quantitative 'decision boundary'. Therefore, while pursuing the goal of partitioning the entire chart, one has to accept that few partitions may be highly connected with some others or may include a huge number of vertices, giving unclear indications to interpret.

On the other hand, following the exactly opposite philosophy, a useful approach consists of simply isolating a subgraph of the formers, namely the largest component that shows up every time. Some of the considerations made can be, as a matter of fact, more trustworthy and effective once applied to this subset alone, because they focus more on the relationships, and sometimes give interesting explanations for counterintuitive evidence.

This two-level partitioning and analysis is the best compromise available to detect separate entities somewhat similar to clusters and keeping track of the most 'critical' links (we could say, the ones most 'at risk' in case a particular vertex is removed) and the corresponding vertices, while at the same time getting the main idea of what happens inside the *heart* of the map.

The first chart we have in Figure 4.2a (33 elements), concerning the first of the three periods considered, highlights eight companies with no connection at all; the remaining 25 vertices compose the largest and only non-atomic component, that can be easily partitioned into a main 'core' (with non-technical use of the term) and two tails: a longer one (5 companies), connected to Eni, and a shorter one (2 companies), connected to Moncler.

The remaining 18 companies in the core are highly interconnected and therefore less likely to be distinguished, and despite the walktrap algorithm can clearly partition them, the exercise of interpreting the results is in any case discretionary. A first, intuitive interpretation is fostered by the intuition of distinguishing the 'Agnelli universe' in a compact partition (4 vertices) as this compacts in the same cluster the triangle composed of CNH Industrial, FCA and Exor, which connects UniCredit to the rest of the network as well; concerning the rest of the graph, we can distinguish two 4-vertices partitions and a main 7-vertices cohesive group where Telecom Italia plays a central role in connecting the cluster with the outside, having 5 extra-partition edges out of a total of 7. Other relevant vertices that connect the groups together are Exor (6 connections, of which 4 outside the cluster it belongs to), UnipolSai and Eni (both with 5 connections, of which 3 outside).

In 2015 (Figure 4.2b), for the reasons explained above, Poste Italiane joins the network, bringing the number of total vertices to 34. The chart apparently becomes less compact (the density this year drops to its minimum in the three-years history), resulting in the least dense picture of the overall time framing. Despite this, within the main component the density trend (discussed below) seems to be the opposite.

We still have eight companies isolated, but the news is in the remaining 26, which now are split into three separate components; two of them are 'linear' and very weak in terms of connectivity, with 5 and 3 companies respectively; naming them after the central (and most connected) company within each group, they are the FinecoBank and the Brembo components.

A2A and Prysman, already connected in 2014 as very peripheric part of the component in the longest tail, gain now a more direct access to the core thanks to their connection to Saipem as Ms. Cappello (already present in the boards of the former two) joins it, and Mr. Cao from A2A joins Saipem's board as well (Figure 4.3b).

We clearly see that these newly formed triangles and the Agnelli partition (this time joined by Enel as well) are now both connected to the biggest component of the network by a single company each (respectively Saipem and Exor).

While the overall picture gives more the idea of ‘sparse’ since the smaller partitions are very weakly connected within them, the big component presents stronger linkages, as it is impossible and of no use separating it into different groups, even if one could see that Atlantia, Telecom Italia and Mediobanca alone can keep together almost the whole subgraph.

In the 2016 chart (Figure 4.2c) Italgas enters the network as well, and we now have all the 35 companies of the dataset, while Banca Popolare di Milano is contextually replaced with Banco BPM.

The corresponding year highlights a slightly different trend: the isolated partitions now ‘join’ the network to some extent, albeit weakly in some cases, and instead of having a big core with some disconnected components around (despite still having a partition that looks more important than the others), we now have a smaller core connected to a set of more internally compacted triples and triangles.

Two evidences immediately stand out: first, the biggest partition is the only one to keep the network together, if we exclude the links within the upper part from the Prysmian-SNAM and Italgas-Brembo edges; second, the Agnelli triangle, while joint to Enel, is now completely isolated.

In the biggest partition, which has five total connections with the other ones, the triple Atlantia-Mediobanca-Telecom Italia still does most of the job in keeping the group together.

Another interesting triangle is the Moncler-Luxottica-Banco BPM one, connected to UBI Banca as well, which is the mostly connected to the central partition.

5.3. SIZE AND DISTANCES

This section and the following three further explore the network, relying explicitly on the contribution that the quantitative metrics and measures in the framework of the Social Network Analysis bring to this study compared to the mere observation of the network or ‘simple’ descriptive statistics related to directors, companies and board seats.

As stated earlier, the overall charts from 2014 to 2016 include 33, 34 and 35 vertices respectively corresponding to the companies and roughly between 500 and 550 vertices corresponding to the executives, while the company charts include the same number of company vertices and the edges connecting them, which are between 30 and 36.

It is of little or no surprise, and in perfect accordance with the conclusions drawn so far, that the number of vertices in the bigraph is roughly the same as the edges: all the edges have an extreme in the subset of company vertices, and the other in the subset of the executives, and most of the executives – from 93% to 95% of the sample, depending on the year – have only one connection (i.e., sit on a single board) and therefore one single edge.

A more interesting issue comes from the observation the same empirical evidence within the companies chart, that gives the idea of a very sparse network, which it is, as it could be intuitively observed from the affiliation network described in Section 5.2 and is better described in Section 5.4 with the analysis of the network density. The situation seems to be slightly heterogeneous, as the degree sequence of the overall chart observed previously in Table 5.3 correctly signalled: as a matter of fact, according to Table 5.6, between 2014 and 2016 we always have a relevant number of companies with more than a degree (63.6%, 52.9% and 65.7% respectively) and a relevant number (7 to 8 out of 33 to 35, between 20% and 24%) of completely isolated companies.

From the former of these two results, there seems to be a decreasing trend of the connections between 2014 and 2015, and an increasing one in the opposite direction from 2015 to 2016. This seems to be confirmed by the reduction in the degrees associated with the companies in their induced graph, whose average (Table 5.7) drops from 2.18 to 1.76 and then rises to 2.06; the standard deviation of the degree sequence, on the other hand, keeps dropping from 1.83 (2014) to 1.38 (2016), implying that the situation is becoming less and less polarized, as one could intuitively infer from the degree sequence in Table 5.6.

Nonetheless, we hereby have the first apparently curious evidence: as the number of connections within the companies scales down (as well as the density, shown in Table 5.8 and more appropriately discussed in Section 5.4), one would intuitively expect both the average distance in 2015 and the diameter to increase, and vice versa for the change between 2015 and 2016, while these two measures seem to be *positively* correlated with the density: for the three years, the average distance is 3.47, 2.65, 3.52, while the three diameter lengths are respectively 9, 6, 8 (Table 5.9); similarly, the corresponding values in the bigraph follows an analogous pattern.

The reason of this phenomenon lies within the clustering of the graph: the 2015 affiliation network graph is the only chart where part of the connected points of the graph (8 out of a sample of exactly 24 connected points) are disconnected from the main component, which *ceteris paribus* makes the density and the average vertex degree drop but *reduces* the diameter and the average distance at the same time, making the remainder part in the largest component more compact.

To make sure that this intuition is right, a more detailed density analysis of the network is necessary. This will also provide the 'big picture' of the network as a whole and its evolution.

5.4. NETWORK DENSITY

The density metric in the bipartite graphs corresponding to each of the three years is (Table 5.8), as one could expect, always far below 0.01, while the companies' and the directors' charts present a far higher value in magnitude, despite still low in absolute terms. This is because, since the graph derives from a mere list of the connections between individuals and companies, and since most of the executives in the sample only have 1 connection with the company on whose board they sit, the number of actors in the bigraph is roughly on the same size order of the number of ties in the network, making it look far less compact (and with a far lower density) compared to the companies or the directors network or the directors.

To consider the same phenomenon from an analytical perspective, we should look at the formula of the local density, which we report here for simplicity:

$$den(G) = \frac{N_E}{N_V * (N_V - 1)/2}$$

Since the number of actors has a quadratic-like impact on the denominator, while the number of ties has a linear impact on the numerator, we expect the density to become lower for a higher number of 1-degree vertices (which imply a +1 both in the number of actors and ties), since they make N_E and N_V scale proportionally, and therefore the denominator scale quasi-quadratically compared to the numerator.

The density values to highlight are the ones corresponding to the companies' charts (Figure 4.2), which remain below 0.1 (0.0682 in 2014, 0.0535 in 2015, 0.0605 in 2016); this tells us that the companies network, where, as a reminder, we claim two companies to be *connected* when they have at least a director in common, is still a very poorly dense network, while confirming all the trends identified earlier, i.e. the drop in density in 2015 (which indicates that the graph becomes sparser) and its partial recovery in 2016 (which on the other hand signals that the graph compacts again). This poor cohesiveness is not surprising if one considers the most recent past literature; for instance, Drago, Ricciuti and Santella (2015), in their social network analysis of the 40 companies in the corresponding market indices in 2008, return density values of 0.1039 in Italy, 0.1551 in France, 0.0410 in UK, 0.1984 in Germany, 0.0564 in United States; despite the results in Table 5.8 are closer to competitive than collusive systems', one must take into account the difference in the sample size (which in our case ranges from 33 to 35 instead of 40) and the difference in the period over which the analysis is conducted (this study considers years from 2014 to 2015, while the paper uses 2007/2008 data), given the decaying trend of density described in the literature previously considered and the (slight but nonetheless present) effects of the Save Italy law.

Aside comparisons with other authors, there may be multiple intuitive reasons behind the low densities in all the charts that are very peculiar of the Italian case: first, the companies are picked from a stock that reflect the overall Italian economy, and more than one third of them are banks or financial institutions which, as stated before, are forbidden by law to have ties through interlocking directorates; second, part of the interlocking directors are chosen according to their expertise in the business or their support in very segment-specific areas (this can be the case of a Business Expert in the automotive industry or a Support Specialist such as a lawyer very specialised on media and communication legal issues), and may be therefore be of little help in companies working in different industries, as seems confirmed by the small number of interlocking Support Specialists (discussed in Section 5.8); third, even taking out the companies that do financial activity of any sort, half of the remaining companies work on very similar business, being in Fashion, Energy or industries within the Manufacturing sector, and having directors sitting on the boards of two companies within the same business may create tensions in the board that companies would like to avoid.

A useful second density-related benchmark, as anticipated, would be the density of the companies' graph calculated when considering only the biggest partition of the network every year. The values shown (Table 5.10) are now two-digits and far higher than their counterparts for the overall graph illustrated in Table 5.8. Of course, a comparison with the two sets of values would be pointless and misleading, but this new data can be used to pursue other comparison over time of a slightly different phenomenon.

Given that considerations and explanations concerning the low absolute values of densities are analogous to the ones for the 'global' charts (segment specialization of directors, conflicts of interest, regulation, limited representation of the true full network), the local densities of their corresponding main components are obviously higher since they consider only the biggest component, cutting off all the smaller ones, most of which are either isolated companies or groups of 1- or 2-degree vertices.

The most important effect to notice is that the change in the 'cohesion' trend: density is roughly the same in the 2014 and 2016 charts (0.120 and 0.116), but is higher (0.157) in 2015, as the density for the 'global' company chart in that period suffered more the presence of small components.

Despite it might look contradictory with the evidence found so far, this gives instead a possible explanation, and proves what one could deduct as an 'intuition' in the first-glance look at the network: while 2015 presents on average less connected companies, the ones in the main component are far more connected than the ones in 2014 and 2016, highlighting that in that years the companies tended either to be in the most aggregated subnetwork of the three year or completely outside.

In conclusion, the partitions of the network that were outside in 2015 were weakly connected to the main network in the other years, resulting of course in a higher density of the 2014 and 2016 charts, but also a larger diameter and higher average distance, causing the corresponding charts to be more inclusive but less dense compared to 2015, which by contrast highlighted a much more concentrated component.

5.5. CENTRALITY OF FIRMS IN THE NETWORK

A premise concerning one of the centrality indicators, i.e. closeness centrality, is necessary. Because we consider the distance between two non-reachable points equal to the number of vertices in the graph (e.g. the maximum theoretical distance possible for two connected vertices in such a graph), the measures we adopted for betweenness and closeness centrality can be provided with respect to the entire graph with no need to consider the components separately, but on the other hand the high number of isolated points deflates the value of the closeness centrality, while this problem is not present in betweenness counterpart, which focuses only on the shortest paths detected. This 'bias' downwards anyway will obviously have a higher impact on the closeness centrality of the smaller components, therefore having the benefit to give a higher value to very central companies in very small isolated groups; in this aspect, closeness and betweenness centrality act in an opposite way: the former provides a value which makes a comparison between vertices on different components more feasible, although it gives very similar values for vertices in the same one, therefore somewhat biasing the 'ranking' according to the component that each vertex belongs to, while the latter is more a relative measure for vertices between the same component, but may return misleading results when comparing vertices belonging to different ones. For instance,[6] in 2015, FinecoBank has a betweenness centrality value of 0.0076, while Generali Assicurazioni scores less than half (0.0033), but if one looks at the chart, obviously Generali Assicurazioni is more connected with a far greater portion of the network compared to FinecoBank. This does not necessarily need to be looked as a problem, anyway, but can be regarded as a feature of the betweenness measure, which does a good job in the identification of central units in smaller components, giving them more relevance than its closeness-related counterpart.

As a reminder, one could highlight the difference between the two concepts of centrality as follows: closeness centrality highlights ‘how fast you are’ at reaching the point you are considering, while betweenness considers ‘how many times do you *need* that point to reach the others through in the fastest way possible’.

In both cases, the values returned from the calculations are very low even for the most central companies (whatever the meaning we give to ‘centrality’ is), giving therefore the idea of a very sparse network, and likely confirming the idea that there is not a true ‘leader’ company with a central role, despite some elements having a certain importance in keeping the network cohesive.

Calculating the centrality indicators of the vertices in Table 5.11 and Table 5.12 considering only the biggest components for each year does not affect the ‘main’ outcome except that from the numerical perspective, as no company vertex in the tables lies outside of them; this basically cancels one of the main problems in the use of the betweenness centrality.

Averaging the centrality is not deemed necessary and can be overlooked, as giving an ‘overall’ idea of the chart is not an aim of this Section and other metrics, such as the density or distance-related measures, do this job more properly.

The most central companies, in both the ‘betweenness-wise’ and ‘closeness-wise’ ideas of centrality, are all connected to the main component to some extent, therefore there is no fear for illegit comparisons.

If one trusts the betweenness indicators (Table 5.11), three companies out of ten remain steadily in the centre of the network: UnipolSai, Mediobanca and Telecom Italia, while three to four companies per year among Brembo, Atlantia and Exor, Saipem and Prysmian are shown twice. There is therefore a relative stability of such a role, as one would expect, as directors are usually appointed

[6] Values not reported in the Tables

on a three-year basis (as per the art. 2385 of the Italian Civil Code), despite some variability may be added by M&A activity or directors that resign or die over time.

On the other hand, the closeness centrality values (Table 5.12) produce more ‘clustered’ results, where significant drops can be observed only when we shift from one isolated group to another; the values are more similar, but the relative ranking among companies is nonetheless more steady: from this perspective, in fact, six companies – Atlantia, Generali Assicurazioni, Mediobanca, Saipem, Telecom Italia and UnipolSai – are steadily within the network, and the rest of the companies, with the exception of two companies in 2015, show up twice in the lists.

This highlights a very high stability in the network, in the sense that (according to the definition of closeness centrality) the companies from which, *on average*, it is more feasible reaching the rest of the peers in the network are more or less the same over time, analogously to Heemskerk’s (2011) ‘dominant’ companies. To give a graphical perspective of the concept, a variant of the induced graph is provided in Figure 5.1, where the companies are ranked according to their closeness centrality value (as per the values provided Table 5.12).

On the one hand, this implies the presence of a stable reference point, while on the other hand the list of the companies within this reference point slightly changes, leaving some room to access this a durable backbone.

The distinction element in this network, compared to some of their European peers, is the very limited presence of financial services providers is the absence of steadiness of multiple banks in the central core: only Mediobanca persists in all the years in Table 5.11. Table 5.12 tells an identical story, except that FinecoBank is present twice as well and Intesa Sanpaolo is listed once.

Concerning the evolution of the centrality over time, we notice that during 2014 some companies had a certain central role (betweenness ranges from 0.089 to 0.194 and closeness from 0.092 to 0.098), at least relatively more relevant than in other years (except seven companies in 2016 showing higher centrality values); in 2015 there is a significant drop of the centrality values, which is recovered in 2016. The trend, from this point of view, mirrors the one followed by the density, as the two values are somewhat linked.

The change of scenario from 2014 to 2015 is astonishing if we consider that the three most in-between companies, i.e. Moncler, Eni and Brembo, disappear from the ranking the following year; this is due to their temporary importance in connecting the main partition to the two ‘tails’ (visible in Figure 4.1) that disappear the next year, and a similar thing happens from 2015 to 2016 to Exor and

Atlantia, two out of five of the highest ranked companies. On the other hand, the closeness metrics do not deliver such notable examples, as they are far steadier and more similar, depending on a different definition of centrality.

Such examples, as well as the higher heterogeneity of the betweenness values obtained, enforce the conclusion that the main core of the network remains the same, in the sense that the boards one would be to be in touch with to reach the biggest possible portion of the network in the lowest amount of time are approximately always the same 6 to 10, and being connected to them is good enough to have a good closeness with the rest of the network (where by ‘good’ we mean ‘the best that can be achieved in that period’), but on the other hand the companies that are necessarily in-between many shortest paths that connect the rest of the network change drastically over time.

Despite these values, as evidenced earlier, are to be considered ‘low’, at least part of the reason is that they are ‘deflated’ by the presence of micro components or isolated companies, which makes any vertex look less central; and as the analysis carried in this Section concerns more single individuals or companies than the overall network, a natural complement of the indicators we considered so far is replicating the same calculation only in the biggest component of each companies’ chart – the one that matters when a director wants to be central in some set of connections, at the end of the day.

Observing *both* these sets of values (the three ‘overall’ or ‘global’ chart and the three corresponding largest isolated groups) gives also the advantage of considering the phenomenon highlighted in 2015, i.e. the presence of a more sparse network but a more compact main component, and removes the impact of the presence of other micro-components or isolated companies in the centrality indicators, since they are *not* present in the subgraph (the biggest component) that we build each year, which we are taking the second set of metrics from. In other words, this second set of values is more likely to check the situation of ‘central’ companies ‘in their neighbourhood’, with no concern of what is happening in the other small components.

Once again, there is a dichotomy in the trends of the global company graphs and the main components alone that is highlighted by the joint observation of the results obtained in this Section and a second set of numbers (Table 5.13 and Table 5.14) related to the largest component alone.

The numbers related to the main component, in fact, partially tell a different story, at least betweenness-wise; putting aside the obvious consideration that within the largest connected subgraph the companies have a far more central role as the corresponding metrics scale to higher values, the news is in the overall trend. Surprisingly, while the centrality still drops from 2014 onwards, the values of the main components between 2015 and 2016 are very similar, and even slightly higher in 2015 if we consider the two companies with highest betweenness level.

This result may be in part derived by the phenomenon that we explained above: since the 2015 network is split into three components plus the isolated companies, this leads to low density for the overall network; but when considering the main component alone (Table 5.10), the density is perfectly comparable to, and even higher than, the numbers related to the previous and the following years. Therefore, vertices with similar or even slightly higher centrality values in 2015 compared to 2016 can be a normal feature of such a graph.

The degree sequence of the main components alone (Table 5.7) leads to a very similar conclusion when read as a centrality measure, with an average degree slightly higher in 2014 (2.88) and two identical values for the remaining years (2.67).

The closeness indicator pushes these conclusions even further: in 2015, reaching every other company in the subgraph was particularly easier than 2014 and 2016, as denoted by the higher closeness values; this result is clearly somewhat expected, since the subgraph in 2015 is composed by only 18 companies.

Regardless of the centrality measure used, there is a strong empirical evidence against the centrality of banks in the network; in fact, despite banking and financial services providers being more than one third of the sample, they do not have a particularly relevant role in building the ties of the network maybe because of the tighter regulation they are subject to. Closeness-wise, in fact, only Mediobanca, FinecoBank and Intesa Sanpaolo seem to score in the top 10 central companies, and usually only two of them show up in the list. This is in contrast with some of the most relevant examples in the past literature (Dooley, 1969; Mizruchi, 1996), while providing evidence analogous to more recent studies, namely Heemskerk's (2011) European-scale network analysis, maybe indicating that, in force of the recent regulation constraints on interlocking directorates on the one hand, and the higher disclosure requirements on the other, the mutual need and possibility to keep ties between banks financial companies has reduced in the recent years.

5.6. CENTRAL INTERLOCKING DIRECTORS

The centrality metrics of the directors' graph provide some deeper understanding of the centrality level of the strategic people in the net of relationships. This Section is mainly focused on the 'global' chart, with less attention to the corresponding possible components and clusters, because the conclusions would be analogous and pretty much redundant.

The goal of this Section is, instead, to check whether the directors who lead the relationships are always the same or they change over time and measure the relative differences in the related graph numbers; besides completing the analysis, this also provides an additional perspective to assess the decline in the importance of the (still persisting) 'Corporate Elite' highlighted by Heemskerk (2011).

The reason for using a separate chart is simple: compared to the affiliation graphs, which gives a higher consideration to the linkages of directors to boards keeping even the closest directors as second-degree ties, the induced graph of directors weights more equally the centrality *and* the size of the board where the directors sit on, and is therefore deemed more appropriate for the analysis of the relationships among peers. Therefore, the only linkage analysed is the 'pure' connection between a director and his/her peers, regardless of its vehicle, instead of giving a relatively higher importance to the number of boards a director sits on than their size. For instance, a director sitting on 4 boards with 10 other different peers each would be seen, everything else being equal, as slightly 'more important' than another director sitting on one single board with 40 peers.

The closeness centrality set (Table 5.15) pretty much mirrors the time trend of its company-related counterpart, and shows once again very similar values from one director to another, indicating that being in the 'right' component is sufficient to be 'close' enough to the rest of the directors, independently from the number of ties with different boards; the difference in centrality between the vertices is very limited and therefore does not describe any 'hierarchy' among them; this evidence is of little support in the research of the *existence* of a core and its eventual stability, as the only very relevant drops in centrality are found when moving from one component to another (not shown in the tables).

Considering the whole chart's betweennesses (Table 5.16), it seems that there is not a director with a 'central' role: all the corresponding numbers are below or around (±0.03) the value of 0.1, except five observations in 2014 (namely Faia, Moriani, Recchi, Rocca, Saviotti), which are between 0.19 and 0.24 and owe part of this result to their position to the longest tail.

Nonetheless, as per the ones above, some considerations are feasible, coherently with the picture that we already got from the density of the network and the centrality of some companies within it: it seems that 2014 was characterised by a ‘higher’ level of centrality, in the sense that the network as a whole benefited of the presence of stronger ‘key individuals’ that could keep it together or shorten the distances (the ‘degrees of separation’ within it, or at least in some of its parts) compared to the following year, where apparently there is no executive with a higher betweenness centrality than about 0.08, if we exclude Mr. Recchi (0.12); despite with a peak that is not much higher (Mr. Magistretti, 0.13), 2016 highlights a different trend with several many more executives becoming slightly more central than the main ones in 2015.

Given the differences in betweenness centrality, a focus on the inner largest groups (Table 5.17), for this metric only, may still deliver some interesting information. Despite the order of the most central directors being exactly the same, the time pattern of the numbers is different, as one would be used to expect at this point of the paperwork, with the most in-between directors in 2015 looking now much more similar to 2014 and in most cases higher than their 2016 counterparts; the members inside the largest components are isolated from the rest, but stronger in the connection within them, and many of them present a betweenness value higher than 0.5, with Saviotti (0.748 in 2014) and Recchi (0.739 in 2014 and 0.720 in 2015) having a value very close than 0.75, therefore indicating that the ‘penalty’ in betweenness was once again very high.

From the joint observation of both charts, in other words, it seems evident that Mr. Recchi, Mr. Saviotti and Mr. Magistretti are the directors that one wanted to know to be able to reach a good portion of the network as quickly as possible.

As usual, the ‘tail-wise’ bias that we already detected for companies is still present: Mr. Saviotti in 2014, for instance, with the highest centrality value overall, does not look that ‘central’, but connects an important tail of 5 companies otherwise disconnected from the main network.

Coherently with the setting that we had already depicted in the previous analysis of the main component, we can safely conclude that there was a drop in the centrality of the most ‘relevant’ individuals in the network from 2014 to 2016, which is in particular due to a huge decrease in 2015 and, for most of the cases, only a partial recovery in 2016.

Another important fact to notice is that, as expected, some of the directors who have a 3- or 4-degree connection (Table 5.18) in the overall chart (which means, that portion lower than 1% of the directors that every year sit on a high number of boards) are not in the list; from Marchionne and

Elkann this is expected to some extent, as they are always part of the Agnelli universe, which is either a component or a cluster poorly connected with the rest of the network, but the chart corresponding to year 2016 is more peculiar.

For instance, Mr. He during 2016 sits on three different boards (Terna, Italgas, SNAM) but located in a very periferic position, and Mr. Moriani during 2016 connects the triple Moncler-Eni-Generali Assicurazioni. This means that Mr. He and Mr. Moriani play a very important role in strengthening two triples in the chart and significantly contributing to the level of density of the chart and the connection between two clusters in the main component, but on the other hand their *very important* role is held in a very peripheric area of the chart, which doesn't give them much centrality (except for Mr. Moriani's scoring fifth in terms of closeness). Analogously, Mr. Cattaneo has 3 degrees in 2014 in the 'right component', but in a very peripheric area, and therefore despite being connected to Telecom it is just the ninth director in that year's betweenness centrality ranking.

In conclusion, having a relationship with more than a company is a necessary condition to have a role in this social network, but indeed not sufficient; analogously, a higher degree makes one prone to have a higher centrality (and, in this case, a degree higher than 2 is necessary) but there is no mathematical 'law' that guarantees it.

5.7. CUTPOINTS

One last aspect of the social network to be analysed is the presence of ties that would 'isolate' some portions of the charts if suppressed. They cannot be completely caught with an algorithm and will therefore require a joint closer look at the clustered version of the companies' charts (Figure 4.2) and the key-players' charts (Figure 4.3). The former allows to pick the companies' edges whose detaching would imply the total separation of a partition (or a single company) from the main component, while the latter helps in detecting all the possible vertices (i.e. the managers that generate the edges in the companies' charts) that, if removed, would isolate a company or a cluster in a similar way.

Please notice that the two concepts, despite leading to very similar behaviours of the chart, are somewhat different: a single edge between companies could be driven by simultaneously two executives, and therefore the connection could be more difficult to catch in the joint chart, even when reduced by all the 1-degree directors (even though it still *is* detectable paying enough attention); at the same time, a single vertex could drive multiple edges, and therefore the companies' chart could give the false idea of a solid connection of a triangle that would completely break into three separate vertices if the executive that holds it together disappears.

This lack of the perfect 1:1 correspondence between vertices in the overall chart and edges in the companies' chart is the first reason of the joint observation. The second one is that, despite the key directors chart helps doing most of the job, it is not that good when it comes to detecting the relationships that, if broken, would break or weaken significantly the direct connection between *entire cohesive groups* in the chart.

Of course, for this kind of analysis, we are only considering the largest component for each year, since the size of the smaller ones, when present, is of little relevance for this work and usually very weakly connected.

Table 5.19 shows the 'key players' who, as per the given definition, would cause a company or a partition to be completely disconnected in case they disappear. For each of the three years represented, the first column reports the name of the director who would cause such a detachment, the second and third column indicate respectively the company that would leave the main partition and the one it would be detached from in case of the director disappearance, while the last column indicates the size of the component that would subsequently be created.

Observing Table 5.19a jointly with Figure 4.3a, two notable 'tails' emerge:

- Moncler-Brembo-Buzzi Unicem-UBI Banca-A2A-Prysmian
- Eni-FinecoBank-Banca Popolare di Milano

Should any of the directors between these companies disappear – namely Ms. Cappello, Ms. Brogi, Ms. Faia, Mr. Rocca, Mr. Saviotti for the first tail, Mr. Foti and Mr. Guindani for the second tail – the remaining part of the chain would become an isolated component, starting from the element on the right of the one disconnected, in the order they have just been mentioned (i.e. if Mr. Rocca resigns, breaking the link between Brembo and Buzzi Unicem, a new isolated cluster would be formed by Buzzi Unicem, UBI Banca, A2A and Prysmian).

Concerning the other notable directors in this sense, should Mr. Cattaneo disappear, Terna would be completely detached from both the SNAM-Atlantia-Generali Assicurazioni newly created triple and Telecom Italia, while the Atlantia-Generali Assicurazioni edge would remain the only thing to connect Generali Assicurazioni (and the above mentioned triple) to the rest of the chart. Even without weakening any other connection, Mr. Cordero di Montezemolo and Mr. Clò play an analogous role in keeping UniCredit connected to FCA and SNAM to Atlantia, respectively.

Despite not isolating any firm in particular, Mr. Recchi deserves a special mention: should he disappear from the chart, some of the most important vertices of the graph (UnipolSai, Eni, Exor, Telecom Italia) would lose their linkages with each other (except Eni and Telecom Italia which would be directly connected by Mr. Zingales); they would therefore evidence a far lower level of connectivity and centrality, and the overall graph would look less dense, as five company-wise edges within this core would disappear at once (with the sixth one holding only thanks to Mr. Zingales).

In 2015 three components form up. Concerning the main one (Table 5.19b), the most notable individual is indeed Mr. Recchi (who is also highlighted as critical in 2014, despite not potentially being responsible for the total detachment of any company from the component in that year) whose disappearance would cause the complete isolation of the Agnelli cluster (FCA-Exor-CNH Industrials), jointly with Enel, while also weakening the connection between Telecom and UnipolSai.

With a lower impact, the removal of Ms. Cappello would be analogous, as it would just remove Prysmian from the component and leave to Mr. Cao the role of connecting Saipem and A2A (and, therefore, A2A and the main component as well).

Other notable names, crucial to connect some firms to the main component are Mr. Lapucci (which links Banca Generali to the network), Mr. Clò (SNAM), Ms. Brogi (UBI Banca), Grieco (Enel).

Finally, there are two separate components – Moncler-Eni-FinecoBank-Yoox Net-à-Porter Group-Campari and Buzzi Unicem-Brembo-Poste Italiane – which are completely isolated and linear-shaped, where the removal of any of the interlocking directors would cause a further fragmentation of these already small chains.

The 2016 network presents a very peculiar circle, composed by the sequence of Saipem, Prysmian, SNAM, Italgas, Brembo, Campari, Yoox Net-à-Porter-Group, FinecoBank, Mediobanca, Telecom Italia and UnipolSai; such entity has many possible 'weakest links in the chain', and one could create two big, separate components just by removing two among the following directors: Ms. Picchi (Saipem-UnipolSai), Ms. De Virgiliis (Prysmian-SNAM), Ms. Borra (Italgas-Brembo), Mr. Cavallini (Brembo-Campari), Mr. Foti (Yoox Net-à-Porter Group-FinecoBank).

In the same circle, the removal of Ms. Cappello would be (once again) highly significant as not only would isolate A2A, but would also weaken the connection between Saipem and Prysmian and therefore the whole partition that the triple belongs to: in fact, it would break down the triple A2A-Prysmian-Saipem and leave Prysmian, as well as the triangle SNAM-Terna-Italgas, connected to the network only via to Brembo.

A similar situation could be caused by the removal of Mr. He (sitting on the boads of Terna, SNAM and Italgas), except that Mr. Bini Smaghi would keep Italgas and SNAM connected, with only Terna being cut off and no damage to the above mentioned ‘circle’.

Other notable elements, who keep some companies in the network are Ms. Brogi (who keeps UBI Banca in the component thanks to its board membership in Luxottica), Mr. Rocca (Buzzi Unicem, thanks to Brembo) and Mr. Nicodano (Poste Italiane, thanks again to Brembo).

Two other notable cases (not shown in the table) are the linkage, in the smaller component, between Enel and CNH Industrial thanks to Mr. Grieco, and the link to Intesa Sanpaolo and Telecom Italia, which is deemed to be critical but indeed not at risk, as it is held by three common directors.

5.8. THE MOST RELEVANT DIRECTORS

Since, as anticipated, one of the purposes of this research is to identify the interlocking directors and give a portrait of their characteristics, it is beneficial to draw a list of the directors that appear at least once in the affiliation graph as a 2-degrees vertex, automatically having some role in the linkages within the network and therefore the highest centrality levels for their corresponding years.

To describe their role in the company, we refer to the taxonomy of Hillman, Cannella and Paetzold (2000), which uses the traditional division between Insiders and Outsiders, further framing the latter category in three possible roles: Business Experts, Support Specialists, Community Influentials.

Insiders are the directors who work in the company as managers, employees or owners of the firm; despite them potentially providing some valuable resource to the firm, the main reason behind their presence in the board is their knowledge of the firm itself.

Business Experts have a business background because of their past as current or former senior officers/directors in other firms, therefore bringing their expertise in problem-solving, decision-making and competition, as well as different business-related viewpoints, and providing some channels of communication with other firms.

Support Specialists sit on the board mainly for their specialized expertise in banking, legal, financial, insurance and/or public relations, who provide access to channels of communication with suppliers or government agencies as well as vital resources such as legal or financial support; their activity is usually essential for the company but is not related directly to the business.

Community Influentials are current or former faculty, politicians, clergy members, or leader of social organizations; they provide non-business expertise and perspectives on issues, they sometimes represent outside markets and are in the board mainly for their ‘political’ influence on other stakeholders and government institutions, and they are mainly included because they serve the board of directors ‘as a means of averting threats to its stability or existence’ (Selznick, 1949) .

Finally, another category has been considered, which consists of directors whose reason to be in the board is unclear; when they are not insiders, they might have been considered for a seat in the board because of their expertise in decision-making, their political/social ties, or their particular knowledge of some peculiar area that is not directly involved in the core business. Such category is therefore for directors that may hold ‘multiple roles’ memberships.

This part of the analysis is carried on the sample of all the 50 directors that hold more than a board membership at least in one of the three years, therefore being interlocking in some period in the timespan considered.

The total number of memberships (Table 5.20) over time of the individuals that had a role as interlocking directors at least in one of the three years considered equals 87 in 2014, 83 in 2015, 91 in 2016; with these data at hand, the average number of ties for interlocking directors is easy to calculate, and is equal to 2.56, 2.86 and 2.46 for each of the three years. Once again, this data is consistent with the previous analysis, indicating that in 2015 the number of interlocking directors drops, but the ones that are present in the graph hold a slightly higher number of ties on average.

While analysed on a year-by-year basis, the results look very similar for the entire timespan. Under the taxonomy chosen, on average 25.25% (Table 5.21) of the directors has an Insider role, while the remainder board memberships are held by outsiders. A huge majority of the outsider memberships considered consists of Business Experts, with a limited number of Community Influentials-related board seats and very poor relevance, in number terms, of Support Specialists;

there is a minority of board seats assigned to directors whose role is unclear, as they could cover all the three roles and there are multiple potential (or actual) reasons for them to sit on the boards.

In number terms (Table 5.20), out of 65 outsider board memberships in 2014, 46 were related to Business Experts, 3 to Support Specialists, 11 to Community Influentials and 5 to people who held or might hold all the former roles. The data concerning 2015 is very similar, with 43 Business Experts out of 63, with a slightly more important relative minority of Support Specialists (4), Community Influentials (9) and 'multiple-roles' board memberships. Finally, in 2016 we have 48 Business Experts' memberships out of 67, 4 Support Specialist-related board seats, 8 Community Influentials and 7 'multiple roles' memberships.

The numbers in percentage in the Table 5.21 help to catch the in relative frequency of these categories and their change over time. Business Experts consist of slightly more than half of the interlocking directors' memberships; this information is not surprising, since it is coherent with the results of previous literature (Hillman, Cannella and Paetzold, 2000) albeit it did not consider interlocks.

One quarter of the board seats in this tailored sample, as anticipated, seems to be allocated to Insiders, i.e. firms' executives or owners; the fact that they have in the very best case half of the numerical consistence of Business Experts may be have different interpretations. On the one hand, this could lead the conclusion that executives are less likely to be sitting on more boards, as they are more involved in the firm's life and/or may be looked suspiciously by their peers because of their particular interest in the company they manage; furthermore, their position as directors in the board may be related to management control issues. This hypothesis can also be apparently backed up from the numbers in the Table 5.22, which highlights the presence of relevant percentage of insider directors that hold no outsider role elsewhere, even when sitting on multiple boards, and calculates the ratio between the executives in the sample that hold either an insider or outsider role a given year and the ones who hold both simultaneously, which in fact ranges from 4.11 to 9. Since this calculation includes also the board memberships of the interlocking directors in the years where they were not sitting on more than a single board, such numbers could be considered misleading. It has been deemed necessary to include them as they might have precluded some interlocking board membership because of their insider role in other boards; nonetheless, for completeness Table 5.23 repeats the same calculation taking out of the sample all the memberships related to the periods where the directors were actually not interlocking with a ratio that ranges from 2.78 to 4.8, and the number of insider directors is still relevant (albeit lower) when compared to the number of directors holding both roles in different companies. In both cases, such numbers indicate that interlocking directors holding both executives and non-executive roles are less frequent than their counterparts covering either of the two roles, but interlocking 'pure' insider directors are definitely a minority.

On the other hand, another possible reason of the numerical superiority of Business Experts may simply be the existence of an efficient – or close to efficient – mix of expertise of outsider Business Experts and Insiders with knowledge of the peculiar company business that can provide more help than a full-insiders or full-outsiders board.

Support Specialists seem to be far less frequent, maybe because the expertise they provide mainly covers accounting, financial or legal support[7], that may be very tailored to the firm they work for, and the deep knowledge of these data jointly with the board membership gives them access to very firm-specific, sensitive or private information that are reluctantly shared outside; the financial or legal advisor of a firm is very unlikely to be the advisor of one of the stakeholders around it, including competitors or capital providers. Another possible assumption is that such a role may be more time demanding and, therefore, the number of boards where one could sit is more limited than a Business Expert, an Executive or a Community Influential. If one considers that Support Specialists are also the individuals who provide particular easiness of access to capital from banks, their low relative frequency may also imply a reduced use of the interlocks as a mean to reduce transaction costs in relationship lending, in contrast with the Financial Control Model supported by the previous century literature. This may be also regarded as an empirical evidence in favour of Heemskerk's (2011) conclusion, which may highlight a development of the European network towards a less bank-centred structure over time and is further supported by the results summarized in Figure 5.1, which do not show any particular relevance of banks as drivers of centrality (albeit, as already discussed, few notable exceptions *are* present).

Finally, Community Influentials seem to be more frequent than Support Specialists (two to almost four times), but far rarer than Business Experts or Insiders. This result, if we take into account the presence of multi-role directorships and assume that some portion of them could effectively have a Community Influential role, is roughly in line with the fraction of Community Influentials in the overall sample (including non-interlocking directors) and Hillman, Amy and Paetzold's results for USA which didn't consider interlocking directorships; therefore, the number consistency of Community Influentials should not be attributed to any interlocking-specific feature; for a possible explanation, one could consider that the benefits obtained from having multiple connections with

[7] Manually checked

non-business organizations or authorities, as well as a non-business perspective, may be seen as less relevant than the benefit coming from having in the board multiple directors holding different management, decision-making or problem-solving expertise.

6. CONCLUSIONS

Compared to previous studies, there seems to be a trend towards dissembling in the Italian Network, which becomes less dense over time; this seems confirmed as well from the trend from 2014 to 2016. Concerning the three years analysed in detail, there is some variability, smaller in magnitude, associated with a short-term trend: 2014 seems by all aspects the most compact network, while 2015 is a very special case, as it sees a sudden drop in density, mainly due to some components that are completely disconnected from the largest one; on the contrary, the main partition within that component is 'highly' interconnected and by far the most compact over the timespan considered. In 2016, finally, we assist to a return to a more inclusive network, despite it being still more sparse than 2014 and less compact than the main cluster of 2015. Roughly one third of the companies are not connected at all. And among the connected ones, outside of the most compact groups the connections are very weak and easy to break in the following year, as proven by the presence of a relevant number of cutpoints and smaller, non-atomic components.

Some ties between industrial firms and companies that provide financial or insurance services (funds, banks, insurance companies) are definitely present and may be related to the necessity of having a closer monitoring or insider perspectives, in order to control the environmental uncertainty and facilitate relationships; moreover, some banks or financial institutions persist for more than a year, with the most notable case being Mediobanca, which seems to steadily hold a central position in the network in all the three years. Despite this, there is no indicator that highlights a particular central role of banks in the network, as Mediobanca is the only one with such a feature and the rest of the persistent companies do not belong to the banking industry or do not see it as their core business. This is in contrast with the data related to the past literature, which anyway in some cases highlighted that all the networks all over Europe were assuming a less bank-centric shape. This phenomenon may have been the main driver of the drop in the density of the network.

A reason for both the lack of centrality of banks and the low density of the network may be the relevant presence of banks in the Italian economy, since they compose a great portion of the FTSE-MIB and can no longer be connected via interlocking directors due to the recent regulation, as well as the reduced use of interlocks as a mean to reduce transaction costs in relationship lending or control uncertainty probably due to more developed financial markets and higher disclosure than in the past.

In general, while on the one hand we see some companies that maintain a central role over time that may be regarded as analogous to Heemskerk's (2011) 'dominant' companies – the most evident cases being UnipolSai, Telecom Italia, Mediobanca, Atlantia, Saipem, Generali Assicurazioni – on the other hand no complete steadiness in the roles, in the sense that many companies are highlighted as very central – or completely isolated – only for one or two years. In all the graphs, there is either a very compact cluster or some highly interconnected ones which may be seen as a core, with poorly connected peripheric partitions or completely disconnected components. Access to this core seems to be difficult, but not unlikely, as proven by several companies that are able to join it for one or a couple of years; therefore, there always is a group that ensures the network cohesiveness and stability, even if some of the key players within it change over 'short' timespans, retracing the same trend observed by Drago, Ricciuti, Santella (2015) in the European case.

Concerning the interlocking directors, who act as links between these companies, the corresponding network is less stable than its firms-related counterpart; excluding two notable exceptions (both from a closeness and betweenness concept of centrality), there is no director that remains 'central' for more than two out of three years in the network. Despite the existence of a core that keeps a relevant portion of the network at least moderately connected, there is no stability in its composition. Interlocking directorates are indeed rare, with only a small percentage of them (ranging from 5.75% to 7.09% according to the year) having more than 1 board seat and therefore creating an interlock. Most of these (except for 4 to 5 individuals per year) have degree 2 and they do not maintain the status of 'central' interlocking director for more than two years in a row, which further strengthens the idea of a poorly connected network.

Considering the set of the board memberships related to this minority of individuals (including the years where they sit only on a board or even none at all), we have in total 87 board memberships within the entire period considered, associated with 50 directors.

Considering the role of the board memberships for each director (on average 87 board memberships per year out of a sample of 50 directors), Business Experts seem to be dominant, covering more than half of the memberships, coherently with the past results; Support Specialists are on the opposite very rare in number (less than 5%), even when compared with the past literature results (Hillman, Amy, Paetzold, 2000); part of the reason may be the decrease in the use of interlocks as instruments to reduce the uncertainty on the firms' activities and therefore easiness of access to capital, or the above mentioned reduction in the transaction cost of relationship lending; Community Influentials-related memberships, coherently with the past findings, compose 10.7% of the sample list, despite a decrease in the trend over time may be noticed. Insiders memberships, on average, are roughly slightly more than a quarter of the overall sample, and it may be noticed that they rarely are roughly slightly more a quarter of the overall sample; many directors holding an insider role, anyway, hold no memberships as outsiders the same year, highlighting the possibility that the board seats may be used as a tool to achieve a stronger control in the companies where they are executives, or that holding an executive role and a director seat is complicated due to regulatory and market competition issues.

APPENDIX – CHARTS AND TABLES

Figure 4.1a – Affiliation Network in 2014

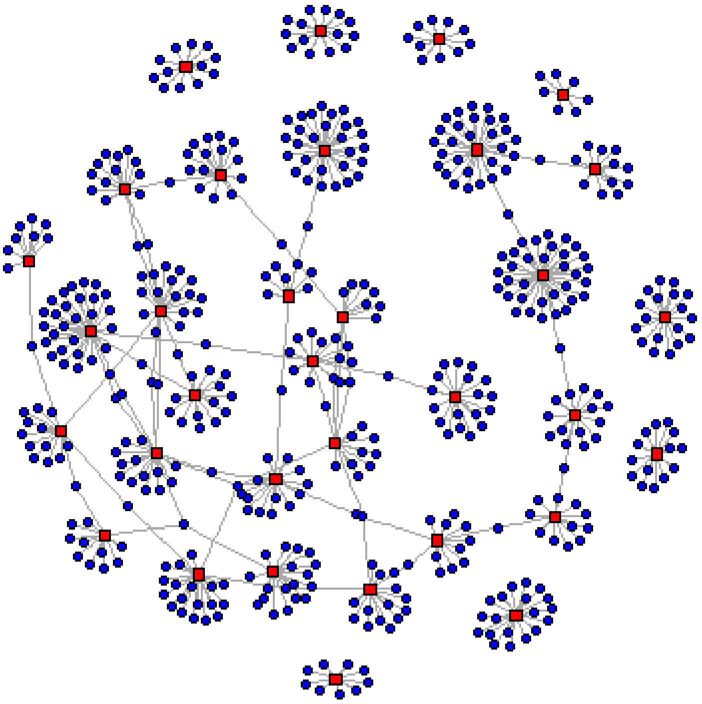

Figure 4.1b – Affiliation Network in 2015

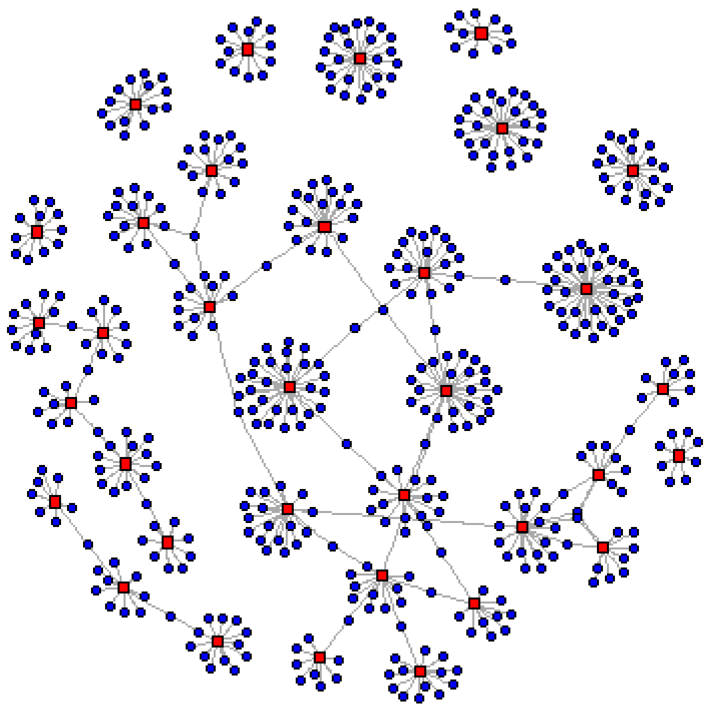

Figure 4.1c – Affiliation Network in 2016

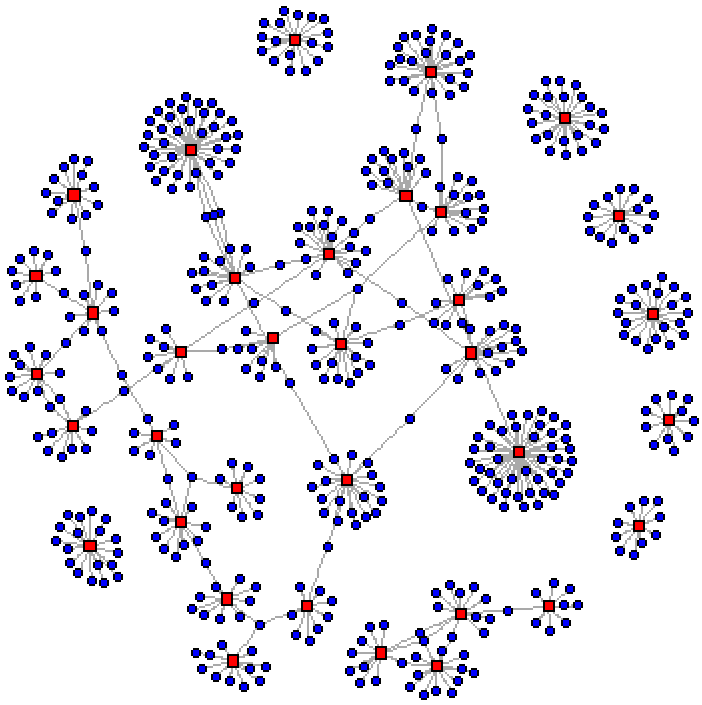

Figure 4.2a – Induced graph of the Companies Network in 2014, clustered

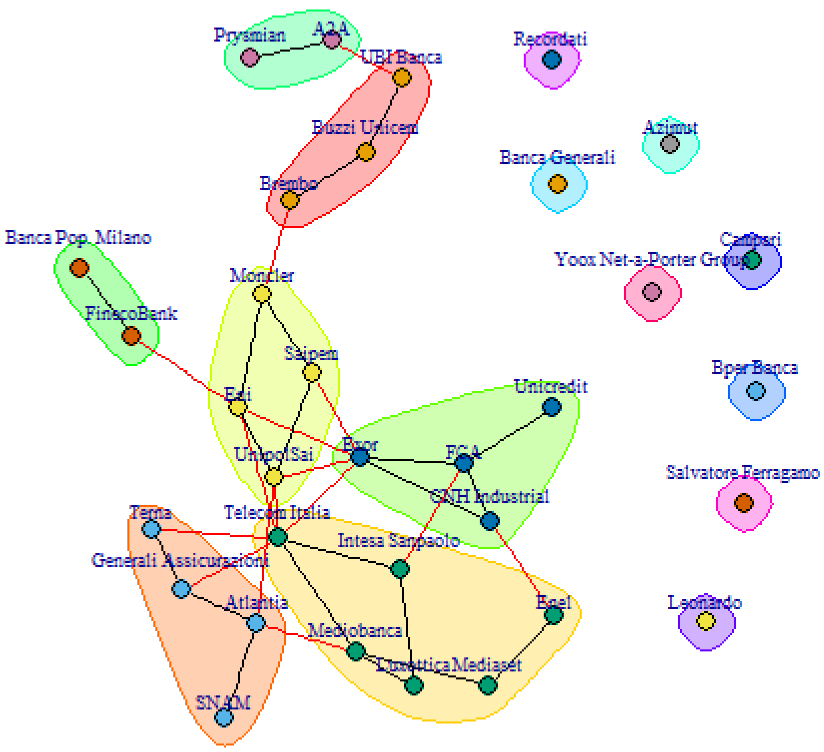

Figure 4.2b – Induced graph of the Companies Network in 2015, clustered

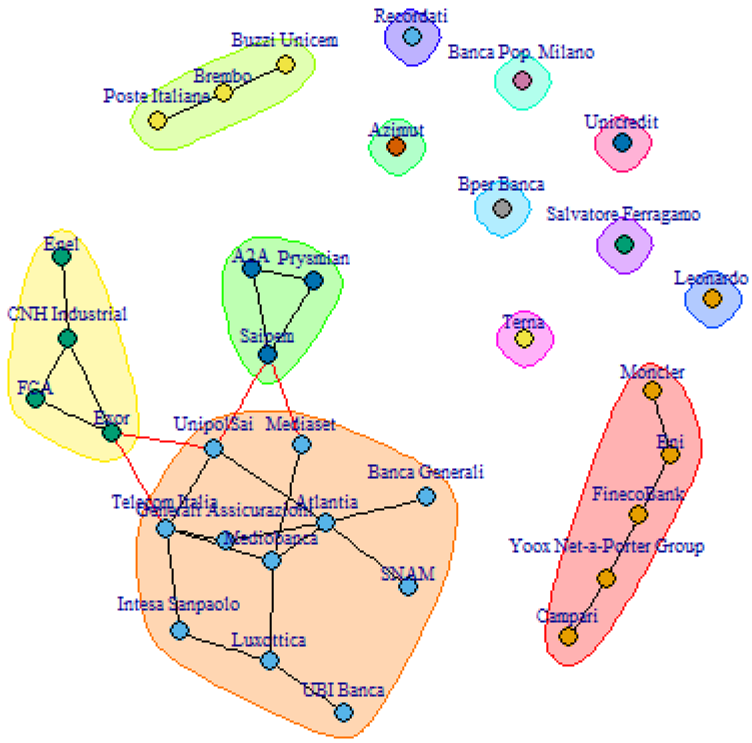

Figure 4.2c – Induced graph of the Companies Network in 2016, clustered

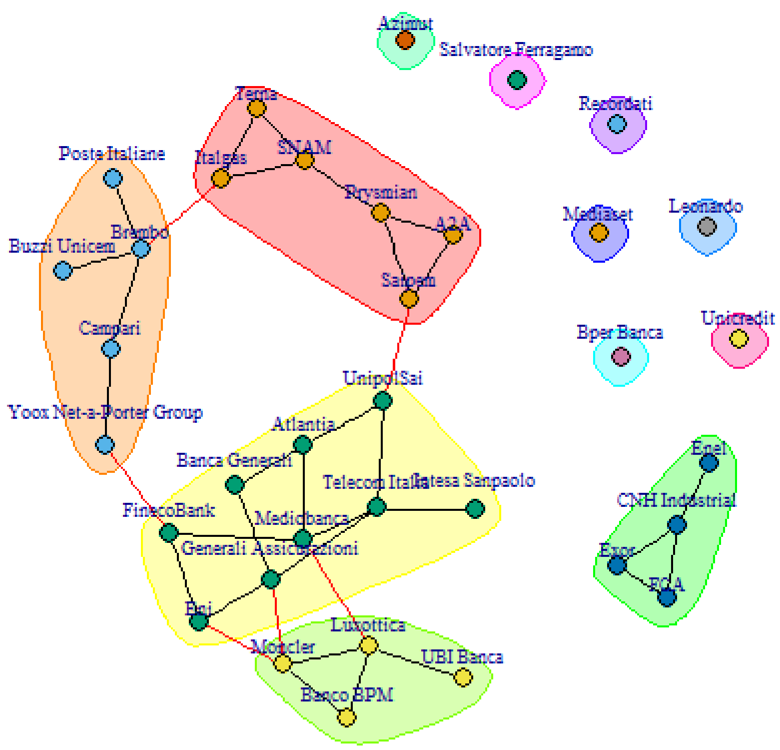

Figure 4.3a – Affiliation Network in 2014 only with directors of degree >1

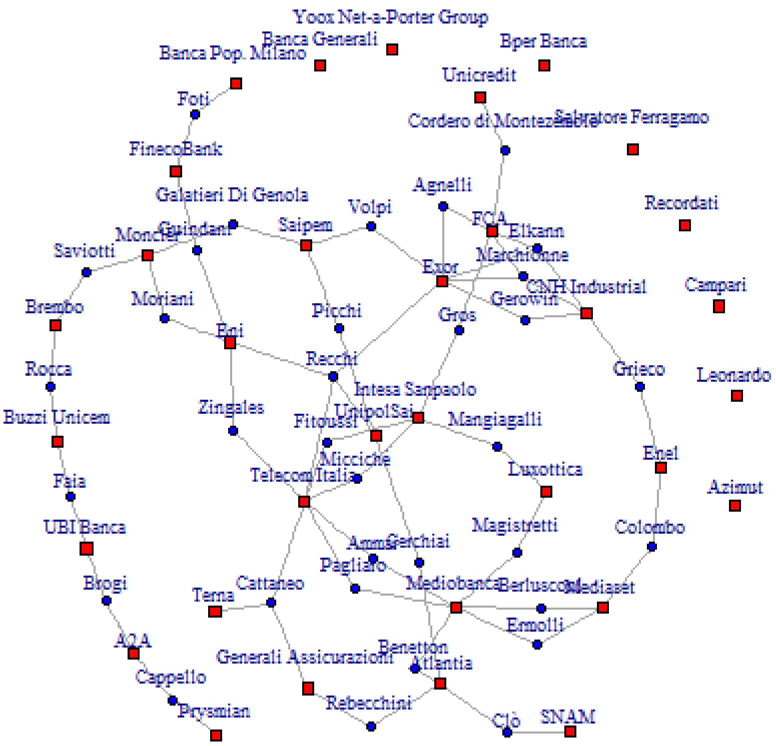

Figure 4.3b – Affiliation Network in 2015 only with directors of degree >1

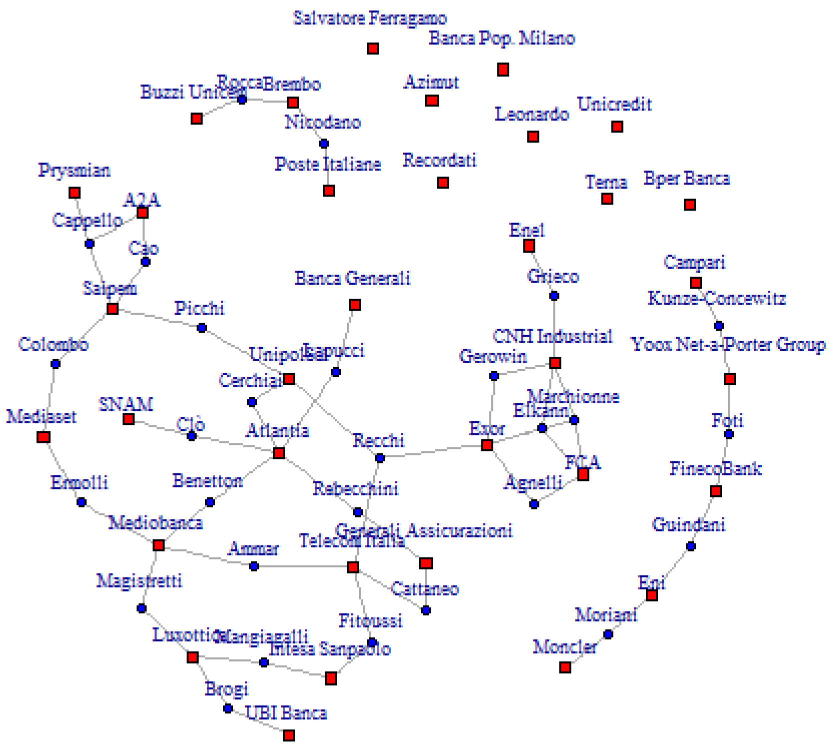

Figure 4.3c – Affiliation Network in 2016 only with directors of degree >1

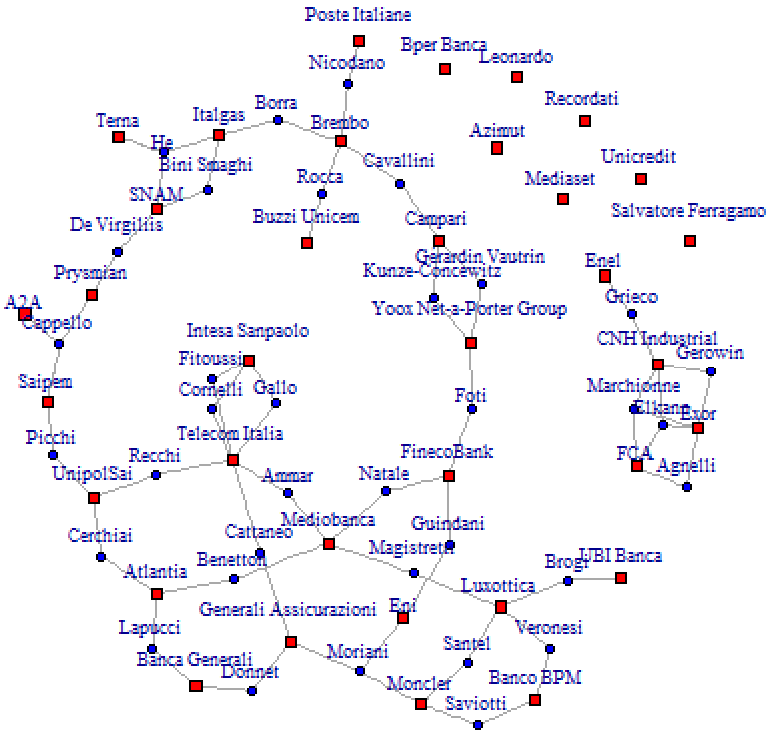

Figure 5.1a – Induced Graph of the Companies Network in 2014 with 'heatmap' of centrality values

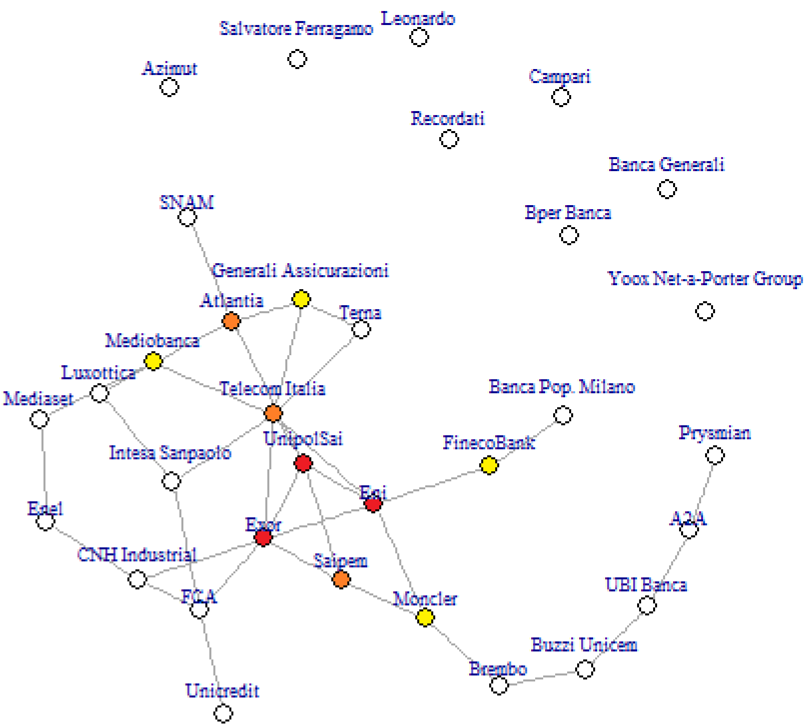

Figure 5.1b – Induced Graph of the Companies Network in 2015 with 'heatmap' of centrality values

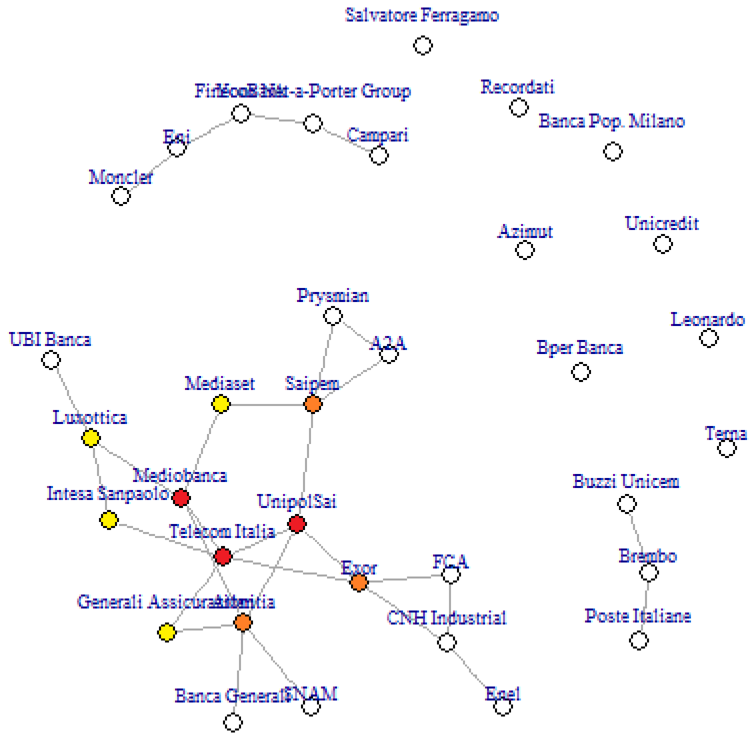

Figure 5.1c – Induced Graph of the Companies Network in 2016 with 'heatmap' of centrality values

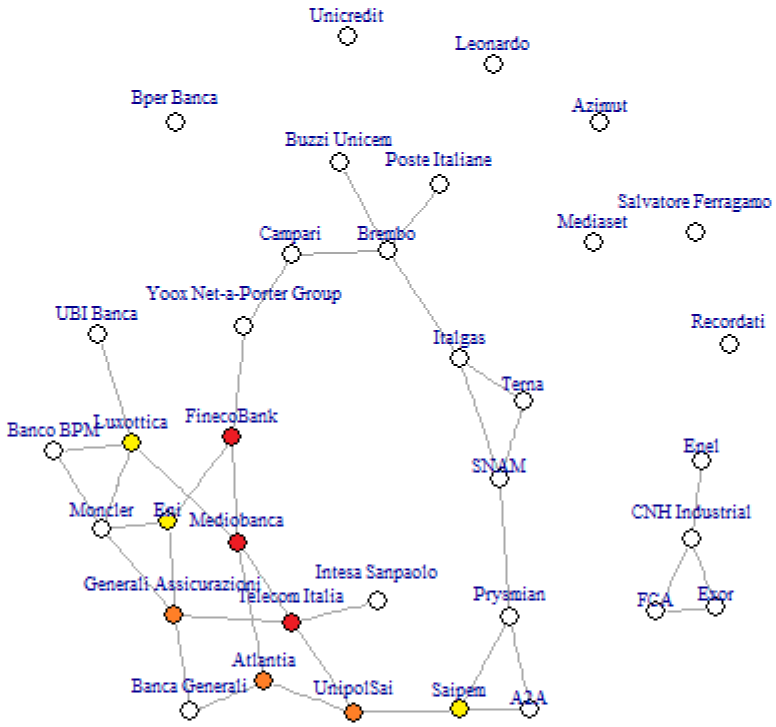

Table 5.1 – Companies in the sample

Banco BPM / Banca Pop. Milano	Bank
BPER Banca	Bank
FinecoBank	Bank
Mediobanca	Bank
Intesa Sanpaolo	Bank
UBI Banca	Bank
UniCredit	Bank
Azimut	Financial Services
Banca Generali	Financial Services
Generali Assicurazioni	Insurance
UnipolSai	Insurance
Poste Italiane	Public Services - Insurance - Financial services
A2A	Public Services - Energy, Environment
Enel	Public Services - Energy – Utilities
Eni	Public Services - Energy
SNAM	Public Services – Utilities
Terna	Public Services - Utilities – Energy
Italgas	Public Services – Energy
Saipem	Energy
Telecom Italia	Telecommunications
Mediaset	Media
Atlantia	Transports
FCA	Automotive
Exor	Holding Company
CNH Industrial	Metalworking
Brembo	Metalworking
Prysmian	Manufacturing
Leonardo	Heavy Industry
Buzzi Unicem	Constructions
Yoox Net-à-Porter Group	Fashion - eCommerce
Moncler	Fashion
Salvatore Ferragamo	Fashion
Luxottica	Fashion
Recordati	Health
Campari	Beverage

Table 5.2 – Structure of the Network

(a) Affiliation Network			
	2014	**2015**	**2016**
Edges	549	519	534
Directors	510	487	494
Companies	33	34	35
(b) Companies Network			
	2014	**2015**	**2016**
Edges	36	30	36
Companies	33	34	35

Table 5.3 – Degree sequence of the FTSE-MIB network bigraph, 2014-2016

(a) Companies			
Degree	**2014**	**2015**	**2016**
1	476	459	459
2	30	24	30
3	3	4	5
4	1		
(b) Directors			
Degree	**2014**	**2015**	**2016**
7	1		
8		2	
9	3	4	5
10	1	2	3
11	1	6	5
12	3	1	3
13	2	1	3
14	2	5	1
15	4	2	4
16	3		1
17	2	1	2
18	2		1
19	2	2	1
20	1	2	1
21	1	1	1
22	1		1
24		1	1
25		1	
27		1	
29	1	1	
30	1		
31	1		
35	1	1	
38			1
43			1

Table 5.4 – Key statistics about the degree sequence of companies in the affiliation network in the different years

	2014	2015	2016
Mean	16.64	15.26	15.26
StDev	6.64	6.62	7.49
Median	15	14	13

Table 5.5 – Board seats and Directors in the Network between 2014 and 2016

	2014	2015	2016
Seats	549	519	534
Directors	510	487	494
Seats/Directors	15.45	14.32	14.11

Table 5.6 – Degree sequence of the companies in the induced graph

Degree	2014	2015	2016
0	8	8	7
1	4	8	5
2	9	10	8
3	5	2	9
4	3	4	6
5	2	2	
6	1		
7	1		

Table 5.7 – Degree Sequence key statistics in the Companies induced graph

Induced graph of companies			
	2014	**2015**	**2016**
Average Degree	2.1818	1.7647	2.0571
StDev	1.8333	1.5342	1.3777
Largest component only			
	2014	**2015**	**2016**
Average Degree	2.8800	2.6667	2.6667
StDev	1.5574	1.3333	1.0274

Table 5.8 – Density for the affiliation network bigraph and the induced graphs

	2014	2015	2016
Overall	0.0037	0.0038	0.0038
Companies	0.0682	0.0535	0.0605
Directors	0.0384	0.0373	0.0390

Table 5.9 – Distance measures in the affiliation network bigraph and in the companies induced graph.

Affiliation Network			
	2014	**2015**	**2016**
Avg. Distance	9.0871	6.8236	8.6878
Diameter	20	14	18
Companies Network			
	2014	**2015**	**2016**
Avg. Distance	3.4688	2.6481	3.5174
Diameter	9	6	8

Table 5.10 – Density in the main components for each year's induced Companies' Network

	2014	2015	2016
Main component	0.1200	0.1569	0.1159

Table 5.11 – Top 10 companies by standardized Betweenness centrality in the related induced graph

2014		2015		2016	
Moncler	0.1935	<u>**UnipolSai**</u>	0.0866	<u>**Mediobanca**</u>	0.1346
Eni	0.1839	***Exor***	*0.0795*	FinecoBank	0.1218
Brembo	*0.1613*	<u>**Telecom Italia**</u>	0.0689	<u>**UnipolSai**</u>	0.1197
<u>**UnipolSai**</u>	0.1481	**Atlantia**	0.0679	***Saipem***	*0.1090*
Atlantia	0.1343	***Saipem***	*0.0625*	***Brembo***	*0.1084*
Buzzi Unicem	*0.1270*	<u>**Mediobanca**</u>	0.0609	<u>**Telecom Italia**</u>	0.1055
Exor	0.1267	Luxottica	0.0336	*Yoox N.a.P. G*	*0.1031*
<u>**Mediobanca**</u>	0.0951	*CNH Industr.*	*0.0303*	*Campari*	*0.0906*
<u>**Telecom Italia**</u>	0.0918	Mediaset	0.0170	***Prysmian***	*0.0841*
UBI Banca	*0.0887*	***Prysmian***	*0.0152*	*SNAM*	*0.0680*

Bold: the company is present twice in the table
<u>**Bold and underlined**</u>: the company is present every year in the table

Table 5.12 – Top 10 companies by standardized Closeness centrality in the related induced graph

2014		2015		2016	
<u>**UnipolSai**</u>	0.0979	<u>**UnipolSai**</u>	0.0581	<u>**Mediobanca**</u>	0.0764
Exor	0.0977	<u>**Telecom Italia**</u>	0.0580	<u>**Telecom Italia**</u>	0.0761
Eni	0.0973	<u>**Mediobanca**</u>	0.0579	**FinecoBank**	0.0756
<u>**Saipem**</u>	0.0962	<u>**Atlantia**</u>	0.0578	<u>**Atlantia**</u>	0.0754
<u>**Atlantia**</u>	0.0959	**Exor**	0.0577	<u>**UnipolSai**</u>	0.0754
<u>**Telecom Italia**</u>	0.0959	<u>**Saipem**</u>	0.0574	<u>**Generali Ass.**</u>	0.0753
Moncler	0.0943	<u>**Generali Ass.**</u>	0.0570	**Eni**	0.0748
<u>**Mediobanca**</u>	0.0938	Mediaset	0.0570	<u>**Saipem**</u>	0.0746
<u>**Generali Ass.**</u>	0.0922	Intesa Sanpaolo	0.0569	**Luxottica**	0.0742
FinecoBank	0.0917	**Luxottica**	0.0568	**Moncler**	0.0742

Bold: the company is present twice in the table
<u>**Bold and underlined**</u>: the company is present every year in the table

Table 5.13 – Top 10 companies by standardized Betweenness centrality in the largest component of the related induced graph

2014		2015		2016	
Eni	0.7652	UnipolSai	0.6354	Mediobanca	0.5538
Moncler	0.6678	Exor	0.5833	FinecoBank	0.5308
Telecom Italia	0.5959	Telecom Italia	0.5058	Brembo	0.5018
Brembo	0.5565	Atlantia	0.4977	Yoox N.à.P.	0.4689
Buzzi Unicem	0.4382	Saipem	0.4583	UnipolSai	0.4679
Exor	0.4371	Mediobanca	0.4468	Campari	0.4260
UBI Banca	0.3061	Luxottica	0.2465	Saipem	0.4225
Mediobanca	0.2383	CNH Industr.	0.2222	Telecom Italia	0.4210
UnipolSai	0.2354	Mediaset	0.1250	Prysmian	0.3290
Atlantia	0.1919	Intesa Sanpaolo	0.0880	SNAM	0.2798

Bold: the company is present twice in the table
Bold and underlined: the company is present every year in the table

Table 5.14 – Top 10 companies by standardized Closeness centrality in the largest component of the related induced graph

2014		2015		2016	
Eni	0.4138	UnipolSai	0.5000	Mediobanca	0.3485
Telecom italia	0.4000	Telecom Italia	0.4857	Telecom Italia	0.3382
Exor	0.3934	Mediobanca	0.4722	FinecoBank	0.3333
UnipolSai	0.3810	Atlantia	0.4595	Atlantia	0.3194
Moncler	0.3478	Exor	0.4474	UnipolSai	0.3194
Saipem	0.3478	Saipem	0.4146	Generali Ass.	0.3151
Mediobanca	0.3288	Generali Ass.	0.3778	Eni	0.3067
Atlantia	0.3243	Mediaset	0.3778	Yoox N.à.P.	0.3026
FCA	0.3200	Intesa Sanpaolo	0.3617	Saipem	0.2987
Intesa Sanpaolo	0.3200	Luxottica	0.3542	Luxottica	0.2875

Bold: the company is present twice in the table
Bold and underlined: the company is present every year in the table

Table 5.15 – Top 10 directors by standardized Closeness centrality in the related induced graph

2014		2015		2016	
Recchi	0.0095	**Recchi**	0.0049	**Ammar**	0.0064
Moriani	0.0095	**Ammar**	0.0049	**Benetton**	0.0064
Zingales	0.0095	**Magistretti**	0.0049	**Magistretti**	0.0064
Volpi	0.0095	Cerchiai	0.0049	Natale	0.0064
Ammar	0.0095	**Fitoussi**	0.0049	**Moriani**	0.0064
Pagliaro	0.0095	**Benetton**	0.0049	**Recchi**	0.0064
Guindani	0.0095	Ermolli	0.0049	**Cattaneo**	0.0064
Fitoussi	0.0095	**Cattaneo**	0.0049	Bini	0.0064
Micciché	0.0095	**Picchi**	0.0049	Bolloré	0.0064
Picchi	0.0095	Bertazzoni	0.0049	Carfagna	0.0064

Bold: the director is present twice in the table
Bold and underlined: the director is present every year in the table

Table 5.16 – Top 10 directors by standardized Betweenness centrality in the related induced graph

2014		2015		2016	
Saviotti	0.2383	**Recchi**	0.1231	**Magistretti**	0.1281
Recchi	0.2352	**Magistretti**	0.0802	**Foti**	0.1058
Rocca	0.2182	**Brogi**	0.0721	**Brogi**	0.1032
Moriani	0.1968	Fitoussi	0.0576	**Picchi**	0.0998
Faia	0.1900	**Picchi**	0.0549	**Cappello**	0.0959
Brogi	0.1132	Ermolli	0.0532	**Ammar**	0.0903
Guindani	0.1030	**Ammar**	0.0470	Natale	0.0901
Foti	0.0819	**Cappello**	0.0430	**Recchi**	0.0837
Cattaneo	0.0792	Benetton	0.0411	Cavallini	0.0796
Zingales	0.0754	Cerchiai	0.0394	**Moriani**	0.0761

Bold: the director is present twice in the table
Bold and underlined: the director is present every year in the table

Table 5.17 – Top 10 directors by standardized Betweenness centrality in the largest component of the related induced graph

2014		**2015**		**2016**	
Saviotti	0.7475	**<u>Recchi</u>**	0.7180	**Magistretti**	0.5376
<u>Recchi</u>	0.7386	**Magistretti**	0.4688	**Foti**	0.4442
Rocca	0.6846	**<u>Brogi</u>**	0.4215	**<u>Brogi</u>**	0.4331
Moriani	0.6172	Fitoussi	0.3366	**Picchi**	0.4190
Faia	0.5962	**Picchi**	0.3208	**Cappello**	0.4024
<u>Brogi</u>	0.3553	Ermolli	0.3110	**Ammar**	0.3790
Guindani	0.3232	**Ammar**	0.2748	Natale	0.3790
Foti	0.2568	**Cappello**	0.2515	**<u>Recchi</u>**	0.3514
Cattaneo	0.2483	Benetton	0.2400	Cavallini	0.3342
Zingales	0.2366	Cerchiai	0.2303	**Moriani**	0.3194

Bold: the director is present twice in the table
<u>Bold and underlined</u>: the director is present every year in the table

Table 5.18 – Directors holding at least 3 board memberships in the corresponding years

2014		**2015**		**2016**	
Cattaneo	3	Cappello	3	Cappello	3
Elkann	3	Elkann	3	Elkann	3
Marchionne	3	Marchionne	3	He	3
Recchi	4	Recchi	3	Marchionne	3
				Moriani	3

Table 5.19a – Directors acting as cutpoints in the affiliation graph in 2014

Name of director	Company isolated	Detachment from …	N° co. in the new partition
Cappello	Prysmian	A2A	1
Brogi	A2A	Ubi Banca	2
Faia	UBI Banca	Buzzi Unicem	3
Rocca	Buzzi Unicem	Brembo	4
Saviotti	Brembo	Moncler	5
Cattaneo	Terna	Generali Ass. / Telecom Italia	1
Clò	SNAM	Atlantia	1
Cordero di Montezemolo	UniCredit	FCA	1
Foti	Banca Pop. Milano	FinecoBank	1
Guindani	FinecoBank	Eni	2

Table 5.19b – Directors acting as cutpoints in the affiliation graph in 2015

Name of director	Company isolated	Detachment from …	N° co. in the new partition
Brogi	Luxottica	UBI Banca	1
Cappello	Prysmian	Saipem/A2A	1
Clò	SNAM	Atlantia	1
Grieco	Enel	CNH industrial	1
Lapucci	Banca Generali	Atlantia	1
Recchi	Exor	Telecom Italia / UnipolSai	4

Table 5.19c – Directors acting as cutpoints in the affiliation graph in 2016

Name of director	Company isolated	Detachment from …	N° co. in the new partition
Rocca	Buzzi Unicem	Brembo	1
Nicodano	Poste Italiane	Brembo	1
He	Terna	Italgas/SNAM	1
Cappello	A2A	Saipem/Prysmian	1
Brogi	Ubi Banca	Luxottica	1

Table 5.20 – Board memberships of Interlocking Directors (sitting on multiple boards at least in one of the years considered) divided by type

	B.E.	**S.S.**	**C.I.**	**All**	**Outsiders**	**Insiders**	**Total**
2014	46	3	11	5	65	22	87
2015	43	4	9	7	63	20	83
2016	48	4	8	7	67	24	91

B.E.: Business Expert
S.S.: Support Specialist
C.I.: Community Influentials
All: Outsiders which may hold all the three roles above

Table 5.21 – Board memberships of Interlocking Directors (sitting on multiple boards at least in one of the years considered) divided by type, row percentage numbers

	B.E.	**S.S.**	**C.I.**	**All**	**Outsiders**	**Insiders**	**Total**
2014	52.9%	3.4%	12.6%	5.7%	74.7%	25.3%	100.0%
2015	51.8%	4.8%	10.8%	8.4%	75.9%	24.1%	100.0%
2016	52.7%	4.4%	8.8%	7.7%	73.6%	26.4%	100.0%

B.E.: Business Expert
S.S.: Support Specialist
C.I.: Community Influentials
All: Outsiders which may hold all the three roles above

Table 5.22 – Role of Interlocking Directors (Insiders/Outsiders/Both) and ratio between directors holding both roles vs. directors holding only one; all the membership considered for directors who are interlocking in at least one year.

	Insiders only	**Outsiders**	**Both roles**	**Both/Single ratio**
2014	7	30	9	4.111
2015	9	36	5	9
2016	9	32	8	5.125

Table 5.23 – Role of interlocking directors (Insiders/Outsiders/Both) and ratio between directors holding both roles vs. directors holding only one; only interlocking memberships considered

	Insiders only	**Outsiders**	**Both roles**	**Both/Single ratio**
2014	4	21	9	2.778
2015	4	20	5	4.8
2016	5	24	8	3.625

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ABSTRACT

The dissertation considers and analyses the Social Network composed by the directors and the companies of the FTSE-MIB Market Index to investigate some relevant features of the Italian network, including its shape, compactness and connectivity, the presence and the importance of the central elements within it, both among the companies and the directors, and obviously the tendency of the companies within it to group into clusters; relevant literature is taken as benchmark in evaluating the quantitative metrics related to these characteristic, as well as for the purpose of assessing the importance of the banking system within the Italian companies, the presence of relevant directors and their reason-to-be on the boards, and the presence of a stable 'core' and its composition. A descriptive analysis of the board memberships is also carried, in order to clarify the role of the most relevant directors and assess the determinants of their presence in multiple boards.

1. INTERLOCKING DIRECTORATES, SNA AND RELATED LITERATURE

The literature in Social Network Analysis (SNA) pays a great attention to interlocking directorates and Corporate Networks; two notable examples for the European case are Elouaer's (2006) work based on the French firms and to the analogous study of Milaković, Alfarano, and Lux (2008) for Germany. On a larger scale, Heemskerk (2011) repeats the same work with a particular focus on the changes in importance of the European Corporate Elite. Examples in the Old Continent are present as well (e.g. the publications of Burris, 2005, for United States). Finally, Drago, Polo, Santella, Gagliardi (2009) propose a study which compares networks in Italy, France, UK, Germany and United States using 2007 and 2008 data.

All the past studies give similar results: continental Europe economies (i.e. France and Germany) show in absolute terms higher density and a relevant number of interlocking directors within the sample (between 10% and 20% depending on the State and the year considered), with a decaying tendency in the cohesiveness of the networks; there seems to be a concentration of interlocking directorships among the biggest companies and a dominant role of financial institutions, which form up a relevant portion of the most connected firms in the network; nonetheless, there is a trend towards reduction in the importance of financial institutions. On the other hand, networks in a competitive system such as the U.K. market are far less connected and show very poor density coefficients. Both in the case of European and US networks, however, there is a clear reduction in the importance of the 'corporate élite', whose role becomes less and less central, despite still important.

The Italian case is given attention as well; Farina (2009) highlights financial Companies' centrality in the network, while Drago, Ricciuti and Santella (2015) evidence a slight decrease in the network density after the ‘Save Italy’ law and state that companies reduced their connections with the periphery while only keeping their strategic ties; Bellenzer and Grassi (2013), finally, illustrate the network recurring dynamics and the existence of a persistent core over time.

On a different note, there is countless attempts in literature to model the reasons for the presence of interlocking directorships; to name few, the Resource Dependence Model (and the related Resource Dependence Theory), the Financial Control Model, the Collusion Theory, the Management Control Model, the Class Hegemony Model and the Career Advanced Model.

With the intent to create a follow-up study specifically for interlocking directorates, this analysis borrows the taxonomy from Hillman, Cannella and Paetzold (2000), who split directors between insiders (e.g. executives) and outsiders, and, improving the classification used in the previous literature, further tailor the Outsider category into Business Experts, Support Specialists, Community Influentials. This classification is mainly based on the Resource Dependency Theory and the Financial Control Model, albeit with consideration for the Agency theory. While the word ‘Insider’ keeps its usual meaning, indicating a director who is either owner of a firm or works there as manager or employee and therefore has some firm-specific knowledge, the ‘Outsider’ category (in the past regarded as a residual category for all the directors who did not fit in the previous description) is now separated into three groups: Business Experts, who have prior experience as directors or managers and good decision-making and problem-solving skills and may as well have some alternative communication channels with other firms, Support Specialists, who have knowledge in specialized fields not directly related to the business, such as financial or legal areas, and may provide ties for an easier access to financial capital, and Community Influentials, usually retired politicians or university faculty who have influence on communities, institutions, associations and, more broadly, associations different from for-profit organizations. Despite this classification was not supposed to be used for the analysis of interlocking directors or, in general, in a SNA context, it is deemed to be more comprehensive and complete, and therefore is used as benchmark.

2. METHODOLOGICAL SECTION: DATA AND TOOLS FOR SOCIAL NETWORK ANALYSIS

According to Mitchell’s (1969) definition, we may describe Social Networks as ‘a specific set of linkages among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behaviour of the persons involved’.

With the purpose to describe the FTSE-MIB network with the highest possible level of detail, highlighting its links and its evolution over time, a descriptive analysis is carried on its composition between the three-years lapse that ranges from 2014 to 2016, using a sample of 36 companies[8]. The database has been manually built on a csv file after gathering the data from the Corporate Governance reports, subsequently treated using the statistical software R.

While the bipartite graph (also called *bigraph*), i.e. the network graph that includes both companies and directors distinguishing them by their nature, is the most complete portrait of the linkages within the Italian companies analysed, for the sake of seeking relevant information there is a recurring use of *induced graphs* of the former (which are, graphs that only consider the ties among companies through directors, or vice versa), and subgraphs representing only the largest *components* (i.e. the largest connected group) within them.

Statistically speaking, two different sets of metrics are used to provide a complete overview of the network. When the network is considered as a whole, in order to get an idea of its size and the distances within it and to understand the extent to which all the companies cluster together, the features analysed are its density, the diameter, the degree sequence and obviously some metrics directly related to the vertices (corresponding to individuals and companies) and the edges (i.e. the links) of the graph. On the other hand, some vertex-specific centrality measures (degree, closeness and betweenness centrality) consider the single points of the network and assess the 'importance' of the central individuals and firms, and the extent to which they are 'in the middle' of the network.

The most basic metric related to a vertex in the graph is the *Vertex degree*, i.e. the number of edges incident on it. Given that a vertex v has a degree d_v, the *degree sequence* $\{d_1, \dots, d_{N_V}\}$ considers the set of the degrees corresponding to each vertex and is therefore a trivial aggregate measure. Another notable element for the analysis of the network as a whole is its *degree distribution* $\{f_d\}_{d \geq 0}$, i.e. the collection of every f_d corresponding to the fraction of vertices $v \in V$ with degree $d_v = d$.

As regards the distance between vertices, the most commonly used measure is the *geodesic distance*, which is the length of the shortest path that connects them; this allows to identify the *diameter* of the graph as well, that is, the longest geodesic distance in the graph between two reachable vertices. A vertex is said to be *reachable* from another vertex if a walk between the two exists, and a graph can be defined *connected* if every vertex is reachable from every other in the graph; finally, a *component* is a maximally connected subgraph of G where adding any other vertex in V would ruin the property of connectivity of the graph.

[8] The data related to four of the companies is missing, while for some companies only partial data is available, namely Poste Italiane (2015-16), Italgas (2016), Banca Popolare di Milano (2014-15) and Banco BPM (2016; created from the merger between Banca Popolare di Milano and Banco Popolare)

To assess the cohesiveness of a network, the most widely used measure is the *local density*:

$$den(G) = \frac{N_E}{N_V * (N_V - 1)/2}$$

As the value in the denominator is the maximum theoretical possible number of edges between N_V vertices, this value lies in the interval (0,1] and is a standardized measure of cohesion.

Concerning the role of the single vertices, instead, their degree may not deliver enough meaningful information about their position in the network; centrality measures are therefore more appropriate. According to Freeman (1979), there is ‘no unanimity on exactly what centrality is or on its conceptual foundations, and there is little agreement on the proper procedure for its measurement’. In this context, the concepts of closeness and betweenness centrality are used.

Closeness centrality defines being ‘central’ as ‘as close as possible’ to the other peers. Sabidussi’s (1966) measure varies inversely with the total distance of a certain vertex v from all others:

$$c_{Cl}(v) = \frac{1}{\sum_{u \in V} dist(v,u)}$$

where $dist(v,u)$ is the geodesic distance between the vertices $u, v \in V$. Normally, this measure is further standardized to lie in the interval [0,1], multiplying it by a factor $N_V - 1$.

This formula, anyway, is computationally infeasible if the graph is not connected; to overcome the problem, following the approach proposed by Douglas (2015), the geodesic distance from/to any unreachable point is set to N_V (i.e. equal to the number of all the other vertices present in the network). This allows to maintain a global perspective on the network while still imposing a strong enough penalty for unconnected vertices, since N_V is still higher than the value of the ‘longest shortest path’ that one could generally find in a network, and it allows to compare points in the network that, despite being not connected to the main component, may still have centrality values that is worth considering.

Concerning the betweenness centrality, it assesses the importance of a vertex according to how crucial it is in accelerating the communication process in the rest of the network. Freeman (1977) proposes the following formula to assess the extent to which a vertex stands ‘in-between’ other pairs:

$$c_B(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)},$$

with $\sigma(s,t|v)$ being the total number of shortest paths between s and t that pass through v, and $\sigma(s,t)$ being the sum of each of the shortest paths between s and t passing by v for *each* vertex v. To standardize this measure limiting it within the unit interval, this value is usually divided by a factor $(N_v - 1)(N_v - 2)/2$. Note that this measure may disregard the size of component that the vertex is part of; it is therefore good to highlight connected vertices inside smaller components, but it leads to misleading conclusions when comparisons are made between vertices belonging to different ones.

The last methodological issue concerns the graph *partitioning*, that is, the activity to 'split' the graph G into 'cohesive' subsets (*partitions*, sometimes hereby referred to as clusters) that are highly interconnected among themselves and relatively 'well separated' from the remaining vertices. More formally, Kolaczyk (2009) defines: 'a *partition* $\mathcal{C} = \{C_1, \dots, C_k\}$ of a finite set S is a decomposition of S into K disjoint, non-empty subsets C_k such that $\cup_{k=1}^{K} C_k = S$.' With reference to this work, it was our choice to rely mainly to the *walktrap* algorithm.

3. Main findings

Network composition, structure and cohesiveness

The bipartite graph that represents the entire network (Figure 3.1) consists of most of the companies (33 to 35 from 2014 to 2016) present in the MIB in 2017[9]; the corresponding directors range from 487 to 494, depending on the year, for a total set of 543 vertices in 2014, 521 in 2015 and 529 in 2016, linked by a roughly equal amount of edges, respectively 549, 519, 534.

At a first glance, the network does not look dense (Table 3.1). A vast majority of the directors (93.33% in 2014, 94.25% in 2015 and 92.91% in 2016) is only part of 1 board; this means that roughly, on average during the three years, all the connections among the companies – around 30 edges in the companies chart – are barely driven by the 6.5% of the directors. The density of the graph is therefore very low and always far below 0.01. The induced graph of companies is poorly connected as well, with density of 0.0682 in 2014, 0.0535 in 2015 and 0.0605 in 2016.

There is a trend towards reduction of the directors in the boards, with a median level dropping by 1 point per year and an average number of directors slowly diminishing as well[10]. The average number of directors per boards drops over time, moving from 15.45 in 2014 to 14.32 in 2015 and, finally, 14.11 in 2016. Conversely, the average board seats per director in the network ranges from 1.066 to 1.081, consistently (if one assumes homogeneity on the interlocks dynamics and trends within continental Europe) with Elouaer's (2006) analogous studies that show an average board membership

[9] The full list of the companies is: Banco BPM / Banca Popolare di Milano, Bper Banca, FinecoBank, Mediobanca, Intesa Sanpaolo, UBI Banca, Unicredit, Azimut, Banca Generali, Exor, Generali Assicurazioni, UnipolSai, Poste Italiane, A2A, Enel, Eni, SNAM, Terna, Italgas, Saipem, Telecom Italia, Mediaset, Atlantia, FCA, CNH Industrial, Brembo, Prysmian, Leonardo, Buzzi Unicem, Yoox Net-a-Porter Group, Moncler, Salvatore Ferragamo, Luxottica, Recordati, Campari

[10] Please notice that the 15.25 in 2016 is mainly due to the company with 43 degrees, which alone drives the average from 13.73 to 15.25 and increases the volatility, while in the other two subsets the highest degree observed is 35.

per director in France[11] equal to 1.33/1.30 in 1996 and 1.19 / 1.22 in 2005, highlighting a decreasing trend of such a ratio; analogously, the same indicator assumes a value of 1.12 in Germany in 2008 (Milaković, Alfarano, Lux, 2008), which is a more recent period.

To provide some more literature benchmark the SNA of Drago, Polo, Santella, Gagliardi (2009), concerning a sample of 40 companies per Market Index, returns density values of 0.1039 (Italy), 0.1551 (France), 0.0410 (UK), 0.1984 (Germany), 0.0564 (U.S.).

Compared to this study, our low density values are closer to a 'competitive' than a 'collusive' system, but are acceptable in light of the decaying trend in density (considering that this study covers years from 2014 to 2016) and of the numbers shown in the comparable study for 'the neighbourhood'.

Multiple reasons may also be found within some peculiar features of the Italian Economy. First, Italian firms are most likely most likely family-run with less participation of external share/stakeholders in the governance or in the property of the company than in other countries. Second, 37% of the companies in the sample offer some kind of banking, insurance or financial services; as per the art. 36 of the 'Save Italy' Law in 2011, most of the possible interlocking directorships within companies or groups operating in Banking, Insurance and Financial markets are forbidden, which may limit the connectivity within the network, which is also highlighted in the past literature (Drago, Ricciuti, Santella, 2015). Third, most of the remaining companies (31%) operate within the same sectors: Fashion, Energy, Utilities; this could further lower the connectivity within the network, as there are very poor chances that a director, especially an insider or someone with an executive role, is found out 'serving two masters', and having directors sitting on the boards of two companies within the same business may create tensions in the board that firms may want to avoid. Moreover, part of the interlocking directors are chosen according to their expertise in the business or their support in very segment-specific areas (this can be the case of a business expert in the automotive industry or a support specialist such as a lawyer very specialised on media and communication legal issues), and may be therefore be of little help in companies working in different industries, as seems confirmed by the small number of interlocking Support Specialists (discussed below). Finally, lack of linkages may also be partially attributed to the existence of connections outside FTSE-MIB companies, including non-listed firms or political institutions, that are not hereby mapped.

These results may anyway be a consequence of the slightly smaller number of firms (33 to 35) considered, which may cause parallel board memberships of the directors in the sample to be ignored.

[11] Elouaer considers both the CAC40 index and the SBF250, conducting two separate analyses

Changes in the network shape

Despite different in many aspects, the graphs related to the three years indeed show some analogies. In all the three cases, seven to eight companies in the sample have no connections at all, while the shape of the rest of the network is highly volatile, with the only constants being a stronger core every year and a weak connectivity due to a reduced number of interlocking directors, consistently with the low densities discussed above.

Several differences may be evidenced: 2014, for instance, is by far the most dense network among the three, with 25 vertices connecting into one single component, where two 'tails' form up (respectively of 2 and 5 firms), while the remaining 18 that form the core are highly interconnected.

In 2015 the chart is apparently less compact, with the density dropping to 0.0535 (the minimum in the three-years history). The 26 companies that are not isolated now split into three separate components, with two of them being very simple, 'linear-shaped' groups and very weak in terms of connectivity. Despite this, the largest component is the most compact of the entire dataset, with a density value of 0.1569 (Table 3.1); in fact, it presents stronger linkages, as it is impossible and of no use separating it into different groups, and one could see that Atlantia, Telecom Italia and Mediobanca alone can keep together almost the whole subgraph.

The 2016 chart compacts again and highlights a slightly different trend: the isolated partitions now 'join' the network to some extent, and instead of having a big core with some disconnected components around (despite still having a partition that looks more important than the others), we now have a smaller core connected to a set of more internally compacted triples and triangles. Two evidences immediately stand out: first, the biggest partition is close to be the only one to keep the network together; second, the Agnelli triangle, connected to Enel, is now completely isolated. The triple Atlantia-Mediobanca-Telecom Italia still does most of the job in keeping the group together.

Time trends and differences within the largest components

Despite the data seems consistent with the long-run trend highlighted in the literature, there seems to be some short-term effects as well. The key statistics indicated so far, including the density of both the affiliation bigraph of the network and the induced graph of the companies, the median level of the degree sequence, the average members per board, have a very similar trend: they rise from 2014 to 2015 (which indicates that the graph becomes sparser) and they drop again by 2016 (which signals that the graph compacts again).

Analogously, the proportion of directors with degree higher than 1 in the charts is shown to be slightly higher in 2015, while, according to Table 3.1, the fraction of companies in their own induced Graph with more than a degree decreases in 2015 and is restored to roughly the original value in 2016 (the exact percentage for the three years are 63.6%, 52.9% and 65.7% respectively). This trend seems to be also confirmed by the reduction in the degrees associated with the companies in their induced graph, whose average drops from 2.18 to 1.76 and then rises to 2.06.

Nonetheless, as the number of ties within the companies scales down and the density of the network both scale down, one would intuitively expect the both the average distance in 2015 and the diameter to increase, and vice versa for the change between 2015 and 2016, while these two measures seem to be *positively* correlated with the density: for the three years, the average distance is 3.47, 2.65, 3.52, while the three diameter lengths are respectively 9, 6, 8 (the corresponding values in the bigraph follows an analogous pattern).

The reason of this phenomenon lies in the clustering of the graph: the 2015 affiliation network graph is the only chart having three components disconnected from each other, which *ceteris paribus* makes the density and the average vertex degree drop but *reduces* the diameter and the average distance at the same time, making the remainder part in the largest component more compact.

In fact, the density of the three subgraphs corresponding to the largest components of every chart (which, obviously, are two-digits and higher than their counterparts for the entire graphs) highlights a change in the 'cohesion' trend: it is roughly equal in the 2014 and 2016 cases (0.120 and 0.116), but higher (0.157) in 2015, as the density for the 'global' company chart in that period suffered more the presence of small components.

Centrality analysis of Companies and Directors

The low centrality values confirm that idea of a very sparse network, with 'leader' companies – all belonging to the largest component in that period – still being weakly connected.

In terms of betweenness indicators (Table 3.2), three companies out of ten remain steadily in the centre of the network, namely UnipolSai, Mediobanca and Telecom Italia, while three to four companies per year among Brembo, Atlantia and Exor, Saipem and Prysmian are shown twice. There is therefore a relative stability of the most in-between companies, despite change is still present and there is room for access within this durable backbone.

The closeness centrality values (Table 3.3) produce more 'clustered' results, where significant drops can be mainly observed when we shift from one isolated group to another; the relative ranking among companies is nonetheless more stable: six companies – Atlantia, Generali Assicurazioni, Mediobanca, Saipem, Telecom Italia and UnipolSai – are steadily within the network, and almost every other firm shows up twice in the lists. This highlights that the companies from which, *on average*, reaching the rest of the peers in the network is more feasible, are the same over time, analogously to Heemskerk's (2011) 'dominant' companies.

In conclusion, while the main core of the network is subject to minimal changes, in the sense that the boards one would be to be in touch with to reach the biggest possible portion of the network in the lowest amount of time are approximately always the same, and being connected to them is the best way to good enough to have a good closeness with the rest of the network (where by 'good' we mean 'the best that can be achieved in that period'), the companies that are necessarily in-between many shortest paths that connect the rest of the network change more frequently over time.

Compared to some of their European peers, this network shows a very limited presence of banks in the central core, maybe because of the tighter regulation they are subject to; in terms of betweenness, only Mediobanca persists in all the three yearly lists of the 10 most central banks (Table 3.2). The closeness centrality values (Table 3.3) tell an identical story, except that FinecoBank and Intesa Sanpaolo are sometimes present as well. This is in contrast with some of the most relevant examples in the past literature (Dooley, 1969; Mizruchi, 1996), and provides evidence analogous to more recent studies, namely Heemskerk's (2011) European-scale SNA, maybe indicating that, in force of the recent regulation constraints on interlocking directorates on the one hand, and the higher disclosure requirements on the other, the mutual need and possibility to keep ties between banks financial companies has reduced in the recent years.

The trend of the centrality values in absolute terms, finally, mirrors the other previous indicators: during 2014 the top 10 companies had a relatively 'high' central role (betweenness from 0.089 to 0.194 and closeness from 0.092 to 0.098), with a significant drop in 2015 (betweenness from 0.015 to 0.087, closeness from 0.057 to 0.058) and a partial recovery in 2016 (betweenness from 0.068 to 0.135, closeness from 0.074 to 0.076).

As regards a similar analysis on the largest components alone, the only surprising evidence is that while the centrality still drops from 2014 onwards, the values of the main components between 2015 and 2016 are very similar, and even slightly higher in the case of a couple of companies in 2015, highlight that the dynamic in the inner core of the network is not really different between these two years. The key statistics related to the degree sequence of the main components alone (Table 3.1) lead to a very similar conclusion when read as a centrality measure, with an average degree slightly higher in 2014 (2.88) and two almost identical values for the remaining years (2.67).

A parallel analysis can be carried on the directors may help to assess the decline in the importance of the 'Corporate Elite' highlighted by Heemskerk (2011). Mirroring its company-related counterpart, the closeness centrality set (Table 3.4) shows that the most important directors have very similar values, indicating that being in the 'right' component is sufficient to be 'close' enough to the rest of the peers, independently from the number of ties with different boards; the difference in centrality between the vertices is very limited and does not describe any 'hierarchy' among them, making even the *existence* itself of a corporate elite questionable, as the only very relevant drops in centrality are found when moving from one component to another. The betweenness values (Table 3.5) do not show any 'central' director either: all the corresponding numbers are below or around (±0.03) the value of 0.1, except five observations in 2014 having values between 0.19 and 0.24 (owing part of this result to their position inside or close by the longest tail). Nonetheless, it seems that 2014 was characterised by a 'higher' level of centrality, in the sense that the network benefits of the presence of more important 'key individuals' than the following years' charts.

Note that some of the directors who have a 3- or 4- degree connection are not even in the centrality lists. This is mainly due to their position in the network: almost of them are in very peripheric area of the chart or even completely disconnected[12]; this is, for instance, the case of Mr. Marchionne and Mr. Elkann, which steadily belong to the Agnelli universe.

Interlocking Directorates

To complete the portrait of the network, an analysis of the role of the interlocking directors, using the taxonomy of Hillman, Cannella and Paetzold (2000); a special category has been created for the directors who could have multiple reasons to be sitting on their boards.

This part of the analysis is carried on the 50 directors that hold more than a board membership at least in one of the three years, therefore being interlocking in some period in the timespan considered. The total number of memberships (Table 3.6) over time of the subset so obtained equals 87 in 2014, 83 in 2015, 91 in 2016; the average number of ties per interlocking directors corresponds, for each year, to 2.56, 2.86 and 2.46 respectively. Once again, this data is consistent with the previous analysis,

[12] Excluding Elkann and Marchionne (Degree 3 in all the three years), other notable directors are (degree in brackets): Cattaneo (3) and Recchi (4) in 2014, Cappello (3) and Recchi (3) in 2015, Cappello (3), He (3) and Moriani (3) in 2016.

indicating that in 2015 the number of interlocking directors drops, but the ones that are present in the graph hold a slightly higher number of ties on average.

While analysed on a year-by-year basis, the results look very similar for the entire timespan. For completeness, the absolute values have been reported as well, but obviously the numbers in percentage are discussed. On average 25.25% of the directors has an Insider role, while the remainder board memberships are held by outsiders. A huge majority of the outsider memberships considered consists of business experts, with a limited number of Community Influentials-related board seats and very poor relevance, in number terms, of Support Specialists; there is a minority of board seats assigned to directors whose role is unclear, as they could cover all the three roles and there are multiple potential (or actual) reasons for them to sit on the boards.

Business Experts alone consist of roughly slightly more than half of the interlocking directors' memberships; this information is not surprising, since it is coherent with the results of previous literature (Hillman, Cannella and Paetzold, 2000) albeit they did not consider interlocks.

One quarter of the board seats in this tailored sample, as anticipated, seems to be allocated to Insiders, i.e. firms' executives or owners, who in the very best case have half of the numerical consistence of business experts, maybe because executives are less likely to sit on more boards, as they are more involved in the firm's life and/or may be looked suspiciously by their peers because of their particular interest in the company they manage. Another possible reason may be related to regulation and best practices, according to which a certain number of directors in the board should be independent and, therefore, hold no executive role.

Support Specialists seem far less frequent (3.3 to 4.8%), maybe because the expertise they provide mainly covers accounting, financial or legal support, that may be very tailored to the firm they work for, and the deep knowledge of these data jointly with the board membership gives them access to firm-specific, sensitive information that is reluctantly shared outside; the financial or legal advisor of a firm is very unlikely to be the advisor of one of the stakeholders around it, including competitors or capital providers. Also, such a role may be more time demanding and, therefore, the number of boards where a Support Specialist could sit may be more limited. If one considers that Support Specialists are also the individuals who provide particular easiness of access to capital from banks, their low relative frequency may also imply a reduced use of the interlocks as a mean to reduce transaction costs in relationship lending and the trend towards a less bank-centred European network.

Finally, Community Influentials (8.8 to 12.6%) seem to be more frequent than support specialists but rarer than Business Experts or Insiders. This result, assuming that part of the multi-role directorships may correspond to a Community Influential role, is roughly in line with the numbers in the non-interlocking directors sample and Hillman, Amy and Paetzold's results for USA which didn't consider interlocking directorships; therefore, the possibility that this low number may be attributed to any interlocking-specific feature can be disregarded. Instead, one could consider that the benefits obtained from having multiple connections with non-business organizations or authorities, as well as a non-business perspective, may be seen as less relevant than the benefit added by multiple directors holding different management-related expertise, or that they may simply be rarer.

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APPENDIX – CHARTS AND TABLES

Table 3.1 – Structure of the Network

(a) Affiliation Network			
	2014	**2015**	**2016**
Edges (n° seats)	549	519	534
Vertices (Directors)	510	487	494
Vertices (Companies)	33	34	35
Density	0.0037	0.0038	0.0038
Avg. Degree of companies (StDev)	16.64 (6.64)	15.26 (6.62)	15.26 (7.49)
Median Degree of companies	15	14	13
Avg. Distance	9.0871	6.8236	8.6878
Diameter	20	14	18
Fraction of directors with degree > 1	6.67%	5.75%	7.09%
(b) Companies Network			
	2014	**2015**	**2016**
Edges	36	30	36
Companies	33	34	35
Density	0.0682	0.0535	0.0605
Density in the largest component	0.1200	0.1569	0.1159
Average Vertex Degree (StDev)	2.182 (1.833)	1.765 (1.534)	2.0571 (1.378)
Avg. Degree largest component (StDev)	2.880 (1.557)	2.667 (1.333)	2.667 (1.027)
Avg. Distance	3.4688	2.6481	3.5174
Diameter	9	6	8
Fraction of companies with degree > 1	63.6%	52.9%	65.7%

Table 3.2 – Top 10 companies by standardized Betweenness centrality in the related induced graph

2014		**2015**		**2016**	
Moncler	0.1935	**<u>UnipolSai</u>**	0.0866	**<u>Mediobanca</u>**	0.1346
Eni	0.1839	***Exor***	*0.0795*	FinecoBank	0.1218
Brembo	*0.1613*	**<u>Telecom Italia</u>**	0.0689	**<u>UnipolSai</u>**	0.1197
<u>UnipolSai</u>	0.1481	**Atlantia**	0.0679	***Saipem***	*0.1090*
Atlantia	0.1343	***Saipem***	*0.0625*	***Brembo***	*0.1084*
Buzzi Unicem	*0.1270*	**<u>Mediobanca</u>**	0.0609	**<u>Telecom Italia</u>**	0.1055
Exor	0.1267	Luxottica	0.0336	*Yoox N.a.P. G*	*0.1031*
<u>Mediobanca</u>	0.0951	*CNH Industr.*	*0.0303*	*Campari*	*0.0906*
<u>Telecom Italia</u>	0.0918	Mediaset	0.0170	***Prysmian***	*0.0841*
UBI Banca	*0.0887*	***Prysmian***	*0.0152*	*SNAM*	*0.0680*

Bold: the company is present twice in the table

<u>Bold underlined</u>: the company is present every year in the table

Table 3.3 – Top 10 companies by standardized Closeness centrality in the related induced graph

2014		2015		2016	
UnipolSai	0.0979	**UnipolSai**	0.0581	**Mediobanca**	0.0764
Exor	0.0977	**Telecom Italia**	0.0580	**Telecom Italia**	0.0761
Eni	0.0973	**Mediobanca**	0.0579	**FinecoBank**	0.0756
Saipem	0.0962	**Atlantia**	0.0578	**Atlantia**	0.0754
Atlantia	0.0959	**Exor**	0.0577	**UnipolSai**	0.0754
Telecom Italia	0.0959	**Saipem**	0.0574	**Generali Ass.**	0.0753
Moncler	0.0943	**Generali Ass.**	0.0570	**Eni**	0.0748
Mediobanca	0.0938	Mediaset	0.0570	**Saipem**	0.0746
Generali Ass.	0.0922	Intesa Sanpaolo	0.0569	**Luxottica**	0.0742
FinecoBank	0.0917	**Luxottica**	0.0568	**Moncler**	0.0742

Bold: the company is present twice in the table

Bold underlined: the company is present every year in the table

Table 3.4 – Top 10 directors by standardized Closeness centrality in the related induced graph

2014		2015		2016	
Recchi	0.0095	**Recchi**	0.0049	**Ammar**	0.0064
Moriani	0.0095	**Ammar**	0.0049	**Benetton**	0.0064
Zingales	0.0095	**Magistretti**	0.0049	**Magistretti**	0.0064
Volpi	0.0095	Cerchiai	0.0049	Natale	0.0064
Ammar	0.0095	**Fitoussi**	0.0049	**Moriani**	0.0064
Pagliaro	0.0095	**Benetton**	0.0049	**Recchi**	0.0064
Guindani	0.0095	Ermolli	0.0049	**Cattaneo**	0.0064
Fitoussi	0.0095	**Cattaneo**	0.0049	Bini	0.0064
Micciché	0.0095	**Picchi**	0.0049	Bolloré	0.0064
Picchi	0.0095	Bertazzoni	0.0049	Carfagna	0.0064

Bold: the company is present twice in the table

Bold underlined: the company is present every year in the table

Table 3.5 – Top 10 directors by standardized Betweenness centrality in the related induced graph

2014		2015		2016	
Saviotti	0.2383	**Recchi**	0.1231	**Magistretti**	0.1281
Recchi	0.2352	**Magistretti**	0.0802	**Foti**	0.1058
Rocca	0.2182	**Brogi**	0.0721	**Brogi**	0.1032
Moriani	0.1968	Fitoussi	0.0576	**Picchi**	0.0998
Faia	0.1900	**Picchi**	0.0549	**Cappello**	0.0959
Brogi	0.1132	Ermolli	0.0532	**Ammar**	0.0903
Guindani	0.1030	**Ammar**	0.0470	Natale	0.0901
Foti	0.0819	**Cappello**	0.0430	**Recchi**	0.0837
Cattaneo	0.0792	Benetton	0.0411	Cavallini	0.0796
Zingales	0.0754	Cerchiai	0.0394	**Moriani**	0.0761

Bold: the company is present twice in the table

Bold underlined: the company is present every year in the table

Table 3.6 – Board memberships of Interlocking Directors (sitting on multiple boards at least in one of the years considered) divided by type, with row percentage numbers

	Business Experts	Support Specialists	Community Influentials	Multiple roles	Outsiders	Insiders	Total
2014	46	3	11	5	65	22	87
2015	43	4	9	7	63	20	83
2016	48	4	8	7	67	24	91
2014 (%)	52.9%	3.4%	12.6%	5.7%	74.7%	25.3%	100.0%
2015 (%)	51.8%	4.8%	10.8%	8.4%	75.9%	24.1%	100.0%
2016 (%)	52.7%	4.4%	8.8%	7.7%	73.6%	26.4%	100.0%

Figure 3.1 – Affiliation Network from 2014 to 2016

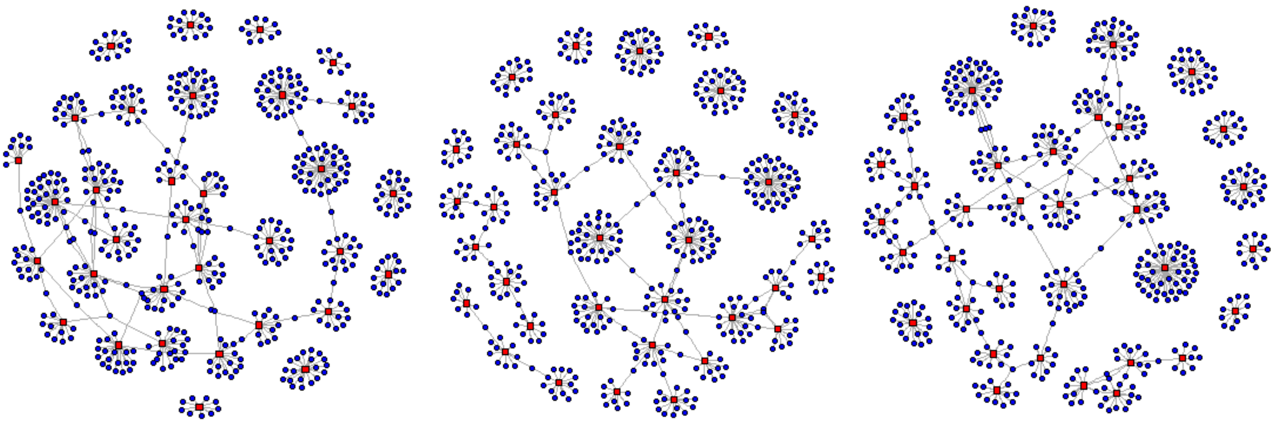

Figure 3.2 – Induced graph of the Companies Network from 2014 to 2016, clustered

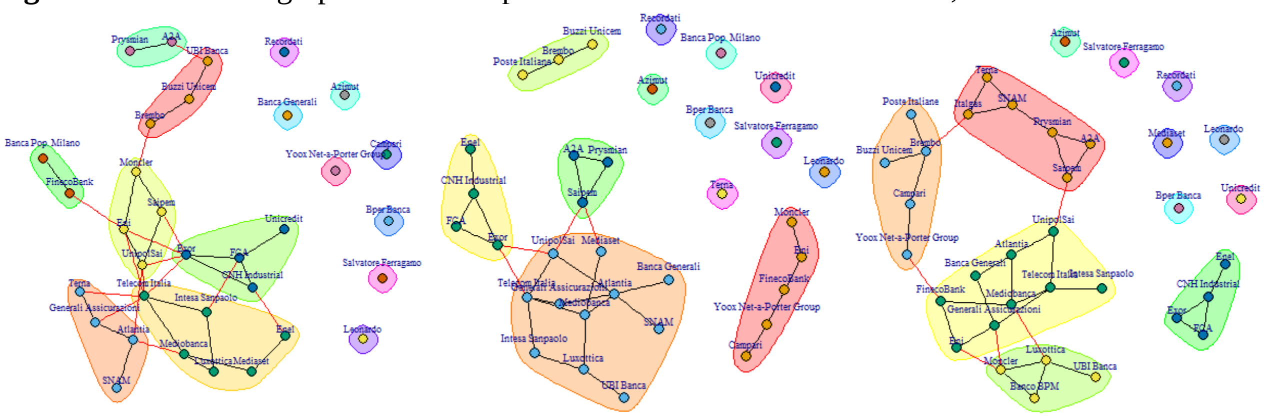

Figure 3.3 – Affiliation Network from 2014 to 2016 only with directors of degree >1