Relational Economics and Organization Governance

Lucio Biggiero
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Inter-firm Networks

Coordination Through Board and Department Interlocks

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Relational Economics and Organization Governance

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Contents

Abbreviations

General

AKE	Asymmetric Knowledge Exchange
ACT	Agency Cost Theory
BINT	Board Interlocks
CONEU	Continental EU
CPAH	Centrality/Performance Advantage Hypothesis
DINT	Department Interlocks
HINT	Hybrid Interlocks
HTSF	Heavy-Tail Scale-Free
LPH	Low-Performance Hypothesis
MOS	Management and Organization Sciences
MPH	Medium Proximity Hypothesis
OPH	Optimal Proximity Hypothesis
PCR	People Coordination Relationship
PFH	Pivotal Finance Hypothesis
PPH	Proportional Proximity Hypothesis
RDT	Resource Dependence Theory
SPCH	Size Proportional Connectivity Hypothesis
TCT	Transaction Cost Theory

Economic-Financial

CF	Cash flow
EC	Equity capital
EM	Number of employees
PM	Profit margin
ROCE	Return on capital employed
ROE	Return on equity

TASS	Total assets
TURN	Turnover

Network

ALL	All types of links together in a single network
D2D	Director-to-Director
MC	Main Component
EASIN	European Aerospace Industry Network
E+N/EASIN + NEIGH	EASIN + Neighbors
EASINT	EASIN Integrated
M2D	Manager-to-Director
M2M	Manager-to-Manager

Network Indexes (Where Applicable Weighted Versions Substitute the First "B" with "W")

BBc	Binary Betweenness centrality
BICc	Binary In-Closeness centrality
BIDc	Binary In-Degree centrality
BIEc	Binary In-Eigenvector centrality
BIKc	Binary In-Katz centrality
BOCc	Binary Out-Closeness centrality
BODc	Binary Out-Degree centrality
BOEc	Binary Out-Eigenvector centrality
BOKc	Binary Out-Katz centrality
BRc	Bridging centrality (only binary)
BTDc	Binary Total Degree centrality
LORC	Local Out-Reaching Centrality
LIRC	Local In-Reaching Centrality
RWBc	Random Walk/Random Walk Betweenness centrality

ADc	Average Degree Centrality
Apl	Average path length
Bc_CE	Betweenness CEntralization
BOKc	Binary Out-Katz centrality
Eig_CE	Eigenvector CEntralization (which can be binary or weighted)
GCL	Global Clustering Coefficient
GORC	Centralization degree of hierarchical degree according to the Out-Reaching Centrality

GIRC	Centralization degree of hierarchical degree according to the In-Reaching Centrality
Hk	Hierarchical degree according to Krackhardt's approach
Katz_CE	Katz CEntralization (which can be binary or weighted)
Out_Dc_CE	Out-Degree CEntralization: (Fre) is according to Freeman, while (Sni) is according to Snijders
Out_Eig_CE	Out-Eigenvector CEntralization (which can be binary or weighted)
Out_Katz_CE	Out-Katz CEntralization (which can be binary or weighted)
SW	Small-World index
WOKc	Weighted Out-Katz centrality
EIDB	External In-Degree centrality Binary
EIDW	External In-Degree centrality Weighted
EODB	External Out-Degree centrality Binary
EODW	External Out-Degree centrality Weighted
IDB	Internal Degree centrality Binary
IDW	Internal Degree centrality Weighted
ShITB	Share of Internal Total Binary links
ShITW	Share of Internal Total Weighted links
ShTB	Share of Total Binary links
ShTW	Share of Total Weighted links
TDB	Total Degree centrality Binary
TDW	Total Degree centrality Weighted

Sectors' Symbols

A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air-conditioning supply
E	Water supply; sewerage; waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transporting and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities

R Arts, entertainment and recreation
S Other services activities
T Activities of households as employers; undifferentiated goods—and services—producing activities of households for own use
U Activities of extraterritorial organisations and bodies

Chapter 1
Introduction

Firms do not interact only through prices, quantity or quality: rather they employ many other ways to coordinate their behavior. However, it is still rather unclear under which circumstances the mix of different ways is built, neither the relative relevance of each of them. What is sure is that one of such ways is through sharing a director between boards of related companies: this is the phenomenon named interlocking directorates or, more recently, board interlock (BINT), known since long, but still deserving a lot of attention. Actually, this is a form of coordination which occurs at a company's highest level, because boards decide—or at least address to—the strategic behavior. There are indeed many reasons to share a director, reasons that do neither always nor intentionally deal with strategic issues. However, whatever they are, the effects of board interlock always impact, to a more or less extent, the sphere of strategies. Further, and more noteworthy, more or less intentionally and extensively, they imply some form of knowledge creation and sharing, especially under its tacit form. In fact, what should actually be done when one sits in a board and how to perform this is not a task so precisely defined: its concrete execution depends primarily and essentially on the personal characteristics of each involved director and on various organization-specific circumstances. Hence, this is the conceptual perspective applied into this book: Board interlocks are inter-firm coordination forms that channel strategic knowledge, which is a resource particularly precious in innovation-based industries, and one becoming progressively more important also in all other industries. Due to these characteristics, the main research streams employed in this work are the four following: board interlocks, knowledge networks, inter-firm networks and Social Network Analysis (hereafter, SNA) as the main methodological approach.

Our work innovates the literature on board interlocks in a number of ways. First, it takes a macro (or, to better say, meso) perspective, because it investigates a network

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formed by dyadic board interlocks at the level of the whole EU28 Aerospace Industry as of 2019, and of its neighbor companies coming from a whole range of sectors, but primarily from Manufacturing, Financial, Wholesale, Professional Activities, and ICT. Actually, approaches rooted in the Management and Organization Sciences (hereafter, MOS) focused traditionally on a very micro-level by investigating the reasons for building board interlocks, while we leave them in the background and point only at its knowledge flow implication. Organizational Sociology as well ran studies at macro level, but they focused only on largest companies—usually listed or public ones—across all sectors and sometimes across different countries. Conversely, we take a single industry view, which allows to associate our findings to its main features, primarily its high-tech characteristic and its "glocal" structure: global in sales, local in production. Hence, this industry-specific approach is a second element of novelty of our work. Finally, studies on Industrial Economics and Policy Issues focus usually on the same samples of those in Organizational Sociology, though from the perspective of measuring market inefficiency generated by the collusive behavior that is supposed to be at the grounds of board interlocks. Moreover, they do not deal with the topological aspects, neither at company level nor at geographical level.

The third element of novelty of this book is that of considering *all* limited liability companies, thus not only the listed or public companies, which usually are less than 0.1% of all limited liability companies. This choice is due to our conviction that, though statistically not prevalent, 99% of companies are topologically very important, as they facilitate ways in which the 1% is connected, disclosing additional, potentially hidden structures. Therefore, they determine how and how much strategic knowledge flows within the industry and between it and its neighbors. Because the identification of our object of study is based on the two criteria of being Aerospace Industry and being in the EU28, the neighbors can be Aerospace companies out of the EU28 or any non-Aerospace companies, within or outside the EU28.

The fourth element of novelty concerns the "discovery" of other two, still person-based, forms of inter-firm coordination, namely department interlocks and department-board interlocks. The former (hereafter named DINT) is built by sharing a manager between two (or more) companies' departments and the latter by sharing a person who covers a manager's position in one company and a director's position in another. We have called them, respectively, as department interlocks and hybrid interlocks. Scientific literature has overlooked so far both phenomena, likely because there was a lack of big data about them, a lack recently filled in, among few, by the Orbis database provided by Bureau van Dijk.

While board interlocks convey strategic knowledge, department interlocks convey the operative one, that is, knowledge mostly dealing with the know-how about technological, managerial or market operations a firm should employ and develop. In this case, the share of tacit knowledge is supposed to be smaller than in the case of board interlock, though still rather important. In the case of hybrid manager-director coordination form (hereafter named HINT), we argue that an unequal knowledge exchange is at stake, because operative (manager-related) knowledge is "exchanged" (indeed, shared) for strategic (director-related) knowledge. Likely, even many BINTs or DINTs hide some sort of asymmetric relationship in favor of the company that appoints the shared person into the board or the department of the other company, respectively. However, our research is not about the composition of boards and departments, but rather about the amount of conveid knowledge and the network of connections through which that knowledge is distributed among companies in the EU28 Aerospace Industry and with their neighbors. Therefore, we will consider only HINTs as asymmetric relationships, because in this case the "unfair" exchange is evident.

Therefore, applied to the case of the EU28 Aerospace Industry and its neighbors, we analyze three types of inter-firm coordination forms based on interlocks: Director-to-Director (D2D), Manager-to-Manager (M2M) and Manager-to-Director (M2D). Each type generates a specific topology (structure, distribution of connections) and involves a specific mix of countries and, when concerning neighbors, also a specific mix of sectors. Hence, we deal with a huge multi-layer network, whose layers are the three coordination forms. The fact that the same director or manager can be involved in more than one interlock of the same or different types—for example, a manager can be shared in one or more departments and in one or more hybrid interlocks—makes the analysis rather complicated but, at the same time, very interesting. When we wish to stress more the phenomenon of interlock in its whole, we will use the label of Board Interlock (BINT) or Department Interlock (DINT) or Hybrid Interlock (HINT), while when we are more interested to underline the topological and connectivity aspect, we refer to D2D, M2M and M2D.

This multi-layer aspect adds to this work a fifth element of originality, because it is still seldomly employed in current SNA studies. Indeed, we run both statistical and network methods, some of which are also not popular, like the Snijders' and the Katz centralization indexes, the geodesic reciprocity, the reach centrality and other centralization indexes. Moreover, we introduce also a variant of the measure of structural equivalence according to the Jaccard Matching. The inclusion of those less-popular methods is yet another novelty of our work.

Let us give a hint at some basic features of our object of study, as it came out to be after the preliminary analyses, like the number of companies, persons and connections involved. Out of the 3143 companies forming the European Aerospace Industry (hereafter, EASIN) in 2019, 1402 resulted to have at least one of the three types of interlock coordination. They were connected to more than 6600 neighbors, mostly operating in the Manufacturing sector and geographically in the US. Hence, it immediately comes clear that *the EU and the US companies, despite being harsh competitors especially in this industry, do exchange a lot of strategic and operative knowledge, and coordinate their behaviors.* The EASIN network is coordinated through the significant number of 1151 connections, most of which (61%) are made by managerial (M2M), 35% by directorial (D2D), and the remaining 4% by hybrid (M2D) positions.

When including also the neighbors, the number of connections raises up to more than 357,000 ties, with a larger predominance of DINT (88%), followed by BINT (11%), and the remaining 1% by HINT. Hence, it appears clear that *EASIN coordinates its strategic and operative behaviors more with neighbors than within itself* and that, either within or with neighbors, operative knowledge counts quantitatively much more than strategic knowledge, and the hybrid forms are residual. However, in qualitative terms, these latter are as well important, because they are employed by companies that play a relatively more bridging role than others and more related to the Financial sector. Further, still in *the juxtaposition of the EU28 and the US, the American companies are mostly on the side of the "exploiters" of strategic knowledge rather than on the side of the "exploited".*

In terms of people who are the carriers of knowledge sharing and who concretely make interlocks happen, in the extended network, *7344 individuals (6272 managers and 1710 directors) are employed directly into the coordination forms, mostly (83%) among neighbors.* Noteworthy, the distribution of the positions covered by these coordinators is a clear example of an uneven distribution generally occurring in economic networks and for other parameters of inter-firm coordination: 90 managers coordinate more than 110 operative positions each. Inter-board positions are less polarized, because only 10 people seat in at least 110 boards, but anyway one director is member of 256 boards and another one of 153.

Besides investigating the structure of the networks generated by each type of interlock coordination, in chapter eight we have also tested seven hypotheses, which basically correspond to the main topics discussed in the debates related to BINTs and recalled in chapter one. Such tests - listed here below - have been applied also to the other two types of coordination:

1. Interlock coordination enhances a better economic performance;
2. The relation between interlock coordination and economic performance can be nonlinear;
3. Proximity influences the propensity to employ interlock coordination;
4. The interlock connectivity of EASIN with the Financial sector is higher than with other sectors;
5. The interlock connectivity of EASIN with the Financial sector is higher for continental Europe than for Anglo-American companies;.
6. There is a positive association between company size and interlock coordination;
7. If any, that association is country-specific.

This book deals with a number of topics crossing different disciplinary fields, like Management and Organization Sciences, Sociology of Organizations, Organizational Economics, Industrial Economics, Evolutionary Economics, Geographical Economics, and Anti-Trust and Industrial Policy, to name the most important areas of research. Indeed, inter-firm networks, board interlocks, strategic knowledge exchange, the influence of proximity on firms' behavior, the relation between centrality and performance or size and performance, and the collusive (anti-competitive) effects of strategic alliances are all issues investigated by those disciplines from different (and sometimes the same) perspectives. We hope that, by focusing on a specific (albeit big) case study, our work could also facilitate an inter-disciplinary debate. Though the approach is essentially academic, we believe that our work is worth also for other two types of readers: the officers working for regulating institutions and the policy makers. The former could draw some suggestions to improve their current analyses of the collusive behaviors and settings. In fact, though we did not go deeply into their methods, at a first sigh they seem to focus only on the most evident situations, thus overlooking the middle and basic part of the pyramidal structures of inter-firm interlock networks. Our impression is that the disclosure of the whole pyramid shows a more massive adoption of this type of strategic alliances. Further, if this picture is combined with that corresponding to the pyramid of ownership inter-firm networks, industry structures appear under a new light, which is useful also to support the analyses and interventions of policy makers, because actually its effects vary considerably according to the topological features in terms of interlock and ownership coordination.

This book can be divided in three parts: one part is made by a "condensed content", which includes this introductory chapter, the literature review (Chap. 2), the overview (Chap. 3) of main feature, the comparisons across networks and hypotheses testing (Chap. 8), and the conclusions. Hence, the "efficient reader", who is interested mostly in the essential findings and not to the way in which they have been reached, can focus his/her attention only on this part.

Another part of the book is constituted by Chaps. 4–7 that deepen the analyses of the four networks: the ALL (resulting from the combination of the other three), the M2M (DINT), the D2D (BINT) and the M2D (the hybrid manager-director interlock). In each of these chapters, the following methods are applied: aggregate network analysis through the most known indexes, like size, density, average degree centrality, fragmentation, reciprocity, centralization, etc., and some less known indexes. Further, analyzed are the inter-sectoral and inter-country networks, built by collapsing groups of companies into same sectors and same countries, respectively. Network method applications proceed then to analyze: (i) components' and cliques' structure; (ii) distribution of topological or non-topological parameters; (iii) key-players represented as bridging companies; and finally, (iv) assortativity. Moreover, there are also statistical descriptive analysis of the whole aggregates, plus correlation and cluster analysis. Finally, the third part is made by Data Appendix and Methodological Appendix, which provide a good support for the reader who wishes to work on the same data or replicate the application of our methods to other business, economic, or social networks. Data Appendix contains tables and figures at a very disaggregated level or for not crucial findings, and it is available only as Electronic supplementary material (see below about how to access it).

We wish to thank Springer's editors for their patience and the support they gave us along our path of building this project. A special thank should be also given to Mark Biggiero, who implemented many algorithms in Python that are of significant imsportance, especially those to calculate structural equivalence, collected in the STREQ software and those in the ASEN software that were not taken from NetworkX. Further, he made also a simple but extremely useful Graph Converter, which efficiently transforms one of the following four formats in one another: Edgelist, DL, Matrix, and NetworkX Graph object. Without his precious help, this book would have contained less analyses and would have required much more efforts in managing data.

Chapter 2
A Knowledge-Based View of Inter-Firm Interlock Coordination

2.1 A Knowledge-Based View of Inter-Firm Networks

Board interlock (BINT), that is, sharing a director with one or more companies, is one of many ways in which companies do coordinate their behavior (Cropper et al., 2008; Ebers, 1997; Knoke, 2012; Nooteboom, 1999, 2004; Parmigiani & Rivera-Santos, 2001). This specific type has been investigated since long time ago and from different perspectives (Boyd et al., 2011; Domhoff, 1967; Jeidel, 1905; Mills, 1956; Mizruchi, 1996; Porter, 1956). The one we have chosen is the meso-level of an industry and its adjacent sectors, evidenced through its structural (network) dimension and the main content channeled through shared directors: knowledge. In fact, according to the Knowledge-Based View (KBV) of the firm (Curado & Bontis, 2006; Nooteboom, 2010; Rafael et al., 2008), knowledge is a fundamental—and likely, the most important—source of organizations' growth, competitiveness and power, be them profit or not-for-profit ones. The KBV is not yet a structured and sound theoretical framework; rather, it should be meant not too much related to the original and current approach rooted in Management and Organization Sciences (MOS), but rather as a broader perspective taking contributions also from Evolutionary Economics (Dosi et al., 2000; Teece, 2009, 2012).

In this chapter, we outline the application of this KBV to these three forms of inter-firm interlock coordination, demark its boundaries with other views, trace back to the main contributions, address to the main research stream crossing this field and to some main hypotheses that then we will test in Chap. 8. Therefore, this one and that final chapter are strictly related. Though knowledge should be distinguished from information (Biggiero, 2009, 2012; von Krogh & Roos, 1996; von Krogh et al., 1998; Yolles, 2006; Zeleny, 2005, 2006, 2007), at the level of width assumed in this work, we can comprehend in the word "knowledge" also the flow of information, which can or cannot be transformed into knowledge and eventually absorbed in an organization's learning process (Lane et al., 1998; Nooteboom, 2000, 2010; Todorova & Durisin, 2007; Zahra & George, 2002). In a large part of economic, managerial and sociological literature, knowledge is considered a crucial factor of

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competitiveness and innovativeness. A widely accepted idea in such research fields is that the complexity that characterizes the knowledge society and economy makes organizations more and more depending on others' resources, among which knowledge is crucial, especially in knowledge-intensive industries. Therefore, *capitalism is becoming network capitalism, characterized by a lot of formal or informal, intentional or unintentional inter-firm (or, more broadly, inter-organizational) networks* (Tung & Worm, 2001; Oleinik, 2004; Schweitzer, 2017).

The phenomenon of BINT claimed a lot of attention since the beginning of the twentieth century, because it was interpreted as a way to build collusive strategic behavior, thus producing extra-profits by violating a minimum degree of competition and therefore exploiting customers. Hence, the Clayton Act of 1914 included BINT among the practices to be sanctioned by the antitrust law, and since there, it has been updated in various forms, especially concerning the thresholds applied to the companies' size parameters and industry definition. In the last section of this chapter, we come back to this issue and advance some aspect of current view that seems not well appropriate to deal with the reality of interlock forms of inter-firm coordination that we have evidenced in this book.

Later and independently from standard economics and the law approaches to BINTs, since the fifties, MOS started to deepen this topic in many ways: the composition of BINTs with respect to internal or external directors, the motivations to issue a BINT, the effects on companies' behavior, etc. A first important systematization was finally found in the Theory of Resource Dependence (Pfeffer, 1983; Pfeffer & Salancik, 1978), meant as a form of controlling environmental uncertainty and guaranteeing crucial resources. Other authors (Mills, 1956; Mace, 1971; Domhoff, 1967; Zeitlin, 1974; Levine, 1972; Bearden et al., 1975; Mariolis, 1975; Sonquist & Koenig, 1975; Mintz & Schwarts, 1981; Mizruchi, 1982; Scott & Griff, 1984; Useem, 1984; Stokman et al., 1985; Carroll & Sapinski, 2011; Huijzer & Heemskirk, 2021; etc.), by taking a more macro perspective, contended that the aim is not control, but rather consolidating the class (élite) power, presumably against workers or other social classes. Then yet others (Davies, 1994; Davis, 1991; Galaskiewicz & Wasserman, 1989; Gilder, 2013; Haunschild, 1993; Hermalin & Weisbach, 1998; Kenis & Knoke, 2002; Pfeffer, 1972; Shropshire, 2010; Westphal et al., 2001) underline the relevance of BINTs as a channel for knowledge sharing and transfer, thus implicitly or explicitly assuming the KBV perspective.[1]

By assuming the KBV, we believe that, though it could be that in some cases it is nor the primary and neither the intentional purpose, *a knowledge sharing/creation/transfer is (at least almost) always involved in all them*, though the extent of sharing or creation or transfer can vary in each case. The deepening on the quantity and quality of tacit or explicit shared/created/transferred knowledge is definitely out of the scope of our work. As well, we did not gather data about previous affiliations of shared directors, so to infer a power unbalance between the two (or more) partners involved in BINTs. Further, we do not investigate on the consequences

[1] Though a bit dated, to summarize the state of the art see Mizrouchi (1996) and, more recently, Carroll & Sapinski (2011) and Simoni & Caiazza (2012).

of them for strategic or managerial decision-making, if not for the ultimate consequences in terms of profitability. In short, *our approach is meso*, but at the same time, *being shaped at industry level, it is very different from all the studies that have so far adopted a meso-approach*, because they mix companies operating indistinctively in various sectors. Further, our work is different from all the previous ones (see, e.g., Davies, 1996; Hallock, 1997; Burt, 2006; Alhares et al., 2020; Huijzer & Heemskerk, 2021, etc.)*,* because *we consider all limited liability companies, instead of restricting the sample only to public or listed or largest companies.*

The industry perspective and the inclusion of all limited liability companies are two relevant aspects, because it is highly reasonable that the features of an interlocked coordination be very dependent on an industry structure, at least on its main traits, like concentration degree, vertical integration of the filiere, product and process technology, etc. Therefore, when a study mixes industries into a same sample, the relationship between interlocks and industry structure is lost, and thus, it becomes hard to find the factors explaining them, at least at a meso-(industry) level. However, if it is important to keep an industry approach, we also argue that it is as well important to distinguish inter-industry interlocks, thus following the distinction in terms of intra- and inter-industry relationships, which in BINTs literature (Crossan & Apaydin, 2010; Haynes & Hillman, 2010; Ruigrok et al., 2006a, 2006b) have been called also horizontal and vertical interlocks, respectively. We keep this distinction for all the three types of interlocks, not only BINTs, and this is a further novelty of our work. Though vertical interlocks could suggest a link potentially related to a vertical supply chain, our work shows that it is not quite so all the time: sometimes the links seem very unrelated industry-wise. Therefore, we intend to stick to the nomenclature of "internal" and "external" links.

Inter-industry relationships have been identified by extending the analysis to the interlock neighbors of the EU28 Aerospace Industry (see next chapter and the Methodological Appendix).[2] In the descriptive Chaps. 4–7 of all network layers (based on different types of links, that is, types of interlocked coordination), we underline that horizontal (internal) interlocks correspond to a self-reference or self-organizing aspect of the industry coordination. From the theoretical perspective of Second-Order Cybernetics (Biggiero, 1998, 2001, 2018; Heylighen & Joslyn, 2001; Yolles, 2006), the same distinction can be operated also in geographical terms, thus distinguishing between intra- and inter-country interlocks, which in fact showed a very different propensity of companies to establish these types of coordination. Hence, in those chapters, *the three forms of interlocks will be distinguished in terms of internal and external to the EU Aerospace Industry and to single countries*—and even to the EU28 as a block and the Anglo-American block. In some cases, especially while testing hypotheses in Chap. 8, we have also introduced the distinction between continental Europe—France and Germany in particular—and the rest of EU.

As concerning the inclusion of *all* liability companies, it gives a tremendous advantage, because the public or listed or largest companies are only a very small

[2] However, to keep the analysis synthetic and reduce complexity, we have aggregated neighbors into sectors, not industries.

fraction of all limited liability companies in each country, and thus, focusing only on them does not allow to understand an interlock coordination structure at industry level. Indeed, our work demonstrates that *the presupposition that BINTs concern only such a fraction is false*. Indeed, one can contend that, from a statistical point of view, it represents anyway the large majority of the phenomenon. However: firstly, until we do not study it, we do not know yet precisely what that share is when referred to BINT coordination and not to standard economic attributes, like size, assets, etc.; secondly, even though the BINT coordination employed by non-largest companies resulted to be less than 20%, that share could be fundamental to understand the remaining 80%, because it could connect those largest interlocked companies in many different ways, hence transforming the essential picture of that 80% too. This is exactly an example of the different perspectives between (standard) statistics and network perspectives, when identifying with the former the analysis of the companies' attributes and with the latter their connection patterns. As we will see, this argument becomes even more relevant when concerning the other two forms of inter-firm interlocks.

This book innovate in the way to apply SNA methods to study a whole industry. Most SNA contributions, in fact, remain at the level of small groups of companies (Elouaer, 2006; Mentzer et al., 2020; Sankar et al., 2015; Takes & Heemskerk, 2016) or adopt only very few and simple methods of SNA, while this deals with the whole industry plus its worldwide neighbors and applies a plenty of methods. Further, it is one of the few SNA studies considering multi-layer networks (Dickison et al., 2016), where the layers here are represented by BINT, DINT, and HINT. Moreover, this work applies also basic statistical methods and some concepts from industry studies, like that of concentration. Hence, we can say that *our work crosses the following research streams* (Fig. 2.1): SNA, BINT, inter-firm networks and knowledge networks. In the descriptive part of the book, which is done in Chaps. 4–7, we call them D2D (Director-to-Director), M2M (Manager-to-Manager) and M2D (Manager-to-Director), respectively, meaning that a same person covers the same specific position in the two (or more) interlocked companies or, in the third case, a different position.

The remaining part of this chapter is organized as follows. Firstly, we outline the research stream of inter-firm knowledge networks, then the approach to BINTs from the KBV. Next, we address to DINT and HINT coordination forms, the so far neglected ways of interlocked coordination. Finally, we recall the issue of relationships between BINTs and firms economic–financial performance, and we relate it to the antitrust literature and the view of BINT from the standpoint of standard economics.

2.2 Inter-Firm Knowledge Networks

The KBV of inter-firm networks dates back more than 20 years and the development of its specific literature has been summarized by Biggiero (2016a, 2016b), to whom we address the reader. Indeed, a large part of this literature has focused on

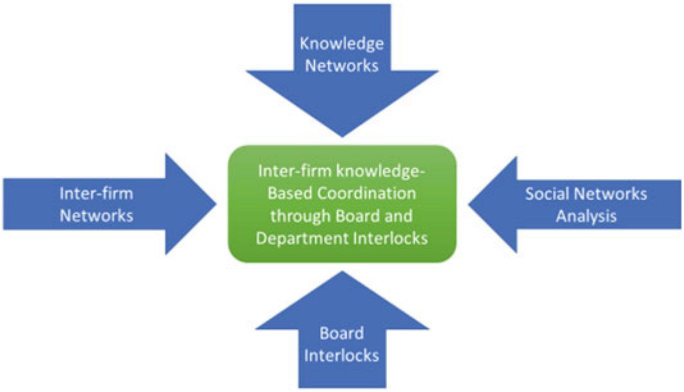

Fig. 2.1 Four research streams converging in this book

innovation networks and on the role of proximity in its various aspects. We will deal with this latter issue in Sect. 7 of Chap. 8 to test some hypotheses on the role of proximity for interlock coordination forms, thus the essential contributions of the corresponding literature are discussed there. Another research stream concerns industrial clusters, which actually are inter-firm networks identified on a territorial and industrial base (Biggiero, 1998; Tallman et al., 2004; Karlsson et al., 2005; Arkin, 2009; Giuliani, 2007, 2013). Advancements in that line shows that, even for industrial clusters, knowledge creation/sharing/transfer is a fundamental factor of competitiveness (Biggiero, 2006; Carayannis et al., 2008; Grandinetti & Camuffo, 2011). Actually, even EASIN is structured into about 45 industrial clusters (EACP, 2022) and the same happens in the US (Turkina et al., 2016). In this book, we deal with the geographical dimension too, but not at cluster level, rather at the more aggregate levels of single countries within and outside EU28, and of large geographical blocks, like the European, the Anglo-American, and the North-American.

Besides the proximity and geographical aspects, the research path that leads to consider interlock coordination networks as instantiations of inter-firm knowledge networks starts from the works by Powell (1996), Mowery et al. (1996) and Gulati (1999), which have been particularly influential to underline the formation of inter-firm networks. Though Transaction Cost Economics and Resource Dependence Theory provided some theoretical framework to explain the existence of intermediate relations between hierarchies and markets, it was necessary a step forward that underlined the external growth of firms seeking for the acquisition—not necessarily the possession—of critical resources. Another fundamental concern was considering knowledge as a critical resource and, as stressed above, the acknowledgment that knowledge is not reducible to information. Since then, a huge literature started distinguishing many types of knowledge: besides the distinction between tacit versus explicit, Brown and Duguid (2001) distinguished 'sticky' versus 'leaky', with sticky knowledge being that which is difficult to move, while leaky knowledge refers to the undesirable flow of knowledge to external sources. Drawing from and combining these previous research streams with others related to the pragmatist philosophy of science and the advancements of cognitive sciences, Biggiero (2009) outlined a view of (social) organizations as cognitive systems in a deep and wide sense of "cognition", including sensemaking and learning.[3] Further, Biggiero (2012) underlines the dual nature of knowledge as possession and as practice, noticing that tacit knowledge is particularly related to this latter dimension and is a human-embodied cognition. This distinction and deepening turns out to be especially appropriate for the topic of this book, because it deals precisely with our three forms of interlocked coordination, which are precisely three forms of person-based coordination of inter-firm relationships. The emphasis on the role of people and human-embodied cognition is one of the distinctive point of Relational Economics, a new perspective on firms' behavior and organizational governance (Biggiero, 2022; Biggiero et al., 2022).

All the previous research streams support the idea that, besides other types of resources, *knowledge is a fundamental resource created and exchanged within inter-firm networks.* This conviction oriented researches in two main directions: the first one was towards high-tech industries, which were logically supposed to be the ones where knowledge had to be more important, and thus, inter-firm knowledge transfer more evident (Balland et al., 2016; Salavisa et al., 2012; Xue, 2018). The second direction points at innovation networks, like R&D collaboration networks, where as well knowledge creation and transfer is the explicit purpose of inter-firm networks. This book is very consistent with both aspects. The Aerospace Industry is indubitably one of the more high-tech and innovation-oriented industries, where product complexity is so high that, despite the huge size of some companies, they are forced to heavily employ external resources and to acquire them not much through pure market transactions, but rather through alliances and various forms of agreements.[4] Some recent contributions analyze this industry just in terms of inter-firm knowledge network: Sammarra & Biggiero (2008), Broekel & Boschma (2011), Pizzurno & Alberti (2015).

Within firms of an inter-firm network, Huggins & Johnston (2010) further distinguish between *social capital*, which "concerns resources related to the social relations and networks held by […] individuals within a particular firm", and *network capital*, which concerns resources "more strategically held by the firm as a whole". This distinction sounds particularly interesting for the present work, because BINTs are supposed to be the outcomes of decisions made for both purposes: on one side the acquisition of strategic resources, thus matching network capital requirements, and on the other side the enactment of the social relations of actual board members, thus employing their social capital to choose the ones that could better link the two (or more) companies. Most likely, if the companies had previous ownership relationships, and especially if one were controlled by the other, the choice would result very restricted and led by the shareholder company. We can add that, especially

[3] Others, like von Krogh & Roos (1996), von Krogh et al. (1998) and Magalhaes & Sanchez (2009) grounded that distinction on autopoiesis theory and the constructivist philosophy of science.

[4] On the Aerospace Industry, there is a vast literature accumulated especially during last 20 years. For recent reviews, see Biggiero & Angelini (2015, 2016), Biggiero & Magnuszewski (2021).

in high-tech industries like the aerospace, where operative knowledge is a fundamental factor of competitiveness, even DINTs accomplish the same two purposes. The predominant diffusion of this type of interlock showed in our study suggests this argument.

2.3 Board Interlocks from the Knowledge-Based View

A KBV on BINTs is growingly diffusing in MOS literature, while it is rather absent in economic and sociological literature, which has more emphasized its disturbances of market efficiency (Thepot, 2021) and the formation of national and transnational corporate elites (Davis & Greve, 1997; Carroll & Fennema, 2002; Davis et al., 2003; Carroll et al., 2011), respectively. In this book, we overlook these two perspectives, though they are both strongly connected to knowledge issues, because *power interests require as well knowledge to be discovered, established and consolidated, and efficiency is primarily influenced by knowledge distribution.* Lamb and Roundy (2016) offer a recent review on BINTs, which for this book is particularly important, because it emphasizes just their knowledge-based aspects. We address to that paper to gain a wide and deep view of many aspects that will remain mostly implicit in our book, basically encapsulated into the wide concept of "knowledge". They assume a positive view of BINTs effects on companies' behavior and performance, effects that are particularly depending just on the knowledge acquisition (and hopefully absorption) processes. Conversely, as we will comment below in Sect. 7 of this chapter, others draw the opposite view from very similar premises. Lamb and Roundy (2016) underlie that BINTs are complex inter-organizational relationships, which can: (i) help firms manage environmental uncertainty and dependence (Useem, 1984), (ii) provide access to diverse and unique information (Haunschild & Beckman, 1998), (iii) enable the spread of new corporate practices (Davis, 1991; Palmer et al., 1993), and (iv) serve as a signal of a firm's quality (Dalton, 2003; Higgins & Gulati, 2003; Kang & Kim, 2008). Moreover, BINTs can facilitate key processes, such as diffusion (Davis, 1991; Strang & Soule, 1998) and learning (Haunschild & Beckman, 2002), which can in turn impact a firm's performance (Davis & Cobb, 2010; Hillman et al., 2009; Pfeffer, 1983).

Shropshire (2010) underlies that interlocked firms share similar strategies and behaviors, including acquisitions (Haunschild, 1993), diversification (Chen et al., 2009), poison pills and golden parachutes (Davis, 1991; Davis & Greve, 1997), defections between stock exchanges (Rao et al., 2000) and decision processes (Westphal et al., 2001). Carpenter and Westphal (2001) and many others speculate about the best contextual conditions triggering a BINT or enhancing its development, but so far there is no conclusive result, and basically their perspective is always only micro and non-positional in a network, thus they not directly matter for our work.

Simoni & Caiazza (2012) conducted a longitudinal analysis of the whole population of Italian listed firms covering the period from 1998 to 2006 and found "evidence that firms tend to select a new director that already seats on another board to consolidate their knowledge on the industry". If we distinguish intra-industry as similar and inter-industry as different, the classical homophily hypothesis so much developed in the SNA literature would be confirmed. We will go back to this issue in Sect. 7 of Chap. 8 as a hypothesis testing of our own data, showing that it is confirmed again: the Proportional Proximity Hypothesis (PPH) much better than the Optimal Proximity Hypothesis (OPH). They found also evidence of a preferential BINT propensity between the financial and the other sectors, which we also test against our data in Sect. 8 of Chap. 8. Here too, we will confirm what we call the Pivotal Finance Hypothesis (PFH), though the financial sector comes at the second place after the manufacturing sector.

Interestingly, they found also evidence of a preferential attachment mechanism that leads companies to share directors with highly connected instead of lowly connected companies, so to increase their access to others' knowledge. Conversely, they did not find evidence that "board interlocks are a preferential channel for firms to increase their exposure to knowledge variety". Then, in a next work, Simoni & Caiazza (2013) found that during seven years between 1999 and 2006 that network remained substantially invariant in its main structural features. We guess that it depends on the usual methodological choice that "biases" all the same type of studies done so far in the BINT literature: analysing only the top of the iceberg, made by largest/listed/public companies. Over few years (or even few decades), it is not so surprising that the network formed by such companies is rather stable and invariant, especially during time of rather stable economic development. For example, it could be that future analyses done on time series crossing the big financial crisis of 2008–2009 will not confirm that invariance, or at least not for most features. Indeed, the biggest changes occur in the middle-bottom part of the iceberg, which is made by the non-listed companies.

Further, also *the exclusion of neighbors has relevant methodological and empirical implications*, because the BINT connectivity of Italy or any country with the others can matter a lot on the inner structure of a country's BINT network. Indeed, all the studies that we have reviewed are not very (or not at all) clear on this respect. For example, we have distinguished the EASIN and EASINT networks, because the former considers only EU28 Aerospace companies connected among themselves, thus excluding hundreds companies that still belong to EU28 Aerospace Industry, but are connected only with neighbors in other countries or other sectors (for more detail, see Chap. 3 and the Methodological Appendix). Now, as we show extensively, those two networks differ considerably under all respects: statistically and structurally. Therefore, that choice can produce very different descriptions and lead to positive or negative results of the various hypotheses testing. Because of this limit and that of restricting the study only to limited companies, we suggest to take very cautiously the findings discussed here, based on the existing literature on BINTs. The extension of the analysis to the relationships with neighbors and between neighbors and to the non-listed companies could disclose different findings, which in part are already shown in this book and discussed in Chap. 8 and in the conclusions. In fact, some results contradict previous studies and common opinions. This acknowledgement is extremely important, because our analysis includes also that 99% of non-listed companies that have been overlooked so far by other studies.

Though almost completely "terra incognita", we add here below also some remarks on how the tacit/explicit, the strategic/operative and the technological/market/managerial classifications of knowledge can be applied to BINTs—but skipping the other two interlocked coordination forms, because they have been so far neglected. According to O'Hagan & Green (2004), Easterby-Smith & Lyles (2011) and Aalbers & Klaasse (2018), *boards' directors handle more tacit than explicit knowledge, as actually it is reasonable to expect when the objects of knowledge are complex*, as strategic decisions/actions actually are. These remarks bring us to the other categorization that between strategic and operative knowledge. This prevalent tacit–complex aspect of knowledge handled through BINTs connections does not prevent that there would also happen share of explicit-codified knowledge. In fact, while some author (O'Hagan & Green, 2002) considers the knowledge channeled through BINT ipso fact as tacit, it is likely that a not-irrelevant part of that is not tacit, because materialized into documents and formalized methods.

Conversely, it is likely that *the major part of DINT activities is objectified into codes, methods, procedures and standards, because this type of knowledge is more characteristic of operative knowledge*. However, it is worth noting that even operative knowledge can be more or less complex. When it is complex, then it should be accompanied by a tacit knowledge support, which is just what shared managers presumably do. In other words, a database of codified knowledge leaves still a large part of ambiguity and uncertainty for its application, a part that is filled in by the interpreting and leading work of shared managers. Supposedly, the company that produced a given codified knowledge will appoint its manager, who would accompany and "decipher" databases and codes.

As concerning the categorization of knowledge according to its functional purpose, namely technological or market or managerial, which has been applied to Aerospace (Biggiero & Sammarra, 2010; Sammarra & Biggiero, 2008), a DINT likely deals mostly with technological and secondary with managerial knowledge, leaving market knowledge to a residual. This hypothesis could be easily tested by checking departments involved by shared managers. We saw at first sight that the involved departments were almost all technical departments, like production, ICT, quality assurance, etc. Unfortunately, the software we created to automatically find the shared managerial positions from Orbis database raw data did not keep trace of that information, so we are unable to test this hypothesis as of now. On the contrary, it is likely that shared directors' positions channel mostly market, and to a lesser extent managerial and technological knowledge (Howard et al., 2016). However, this hypothesis could be strongly influenced by the technological characteristics of each industry in which the BINT is occurring, because if a company's technological advancement/choice were a strategic factor, it could be that a shared directors' coordination is used also or primarily for acquiring technological knowledge. This is a clear example of the rationale that leads us to argue that interlocked coordination forms should be studied also (and primarily) at industry level.

2.4 Social Network Analysis

SNA is a set of methods that focus on connections among elements instead of on their attributes (Carrington et al., 2005; Scott, 1992; Scott & Carrington, 2011; Wasserman & Faust, 1994; Wasserman & Galaskiewicz, 1994). Therefore, they are the right methods to discover and explain structures, and to find (dis)advantages coming from a position that an element can cover within a given structure (Zaheer et al., 2010). The novelty (and even reluctance) to adopt a network perspective for studying economic phenomena has been underlined by Schweitzer et al. (2009), then deepened by Biggiero (2016a, 2016b), who argues that the acknowledgement of the structural (relational) dimension came relatively late, due to a number of positive but heavily impacting consequences on the dominant paradigm in economics, namely neoclassical economic theory. He claims that *being free from the "neoclassical chains", MOS have adopted SNA methods much earlier and faster than economics,* as witnessed by (Borgatti & Foster, 2003). In a recent contribution, Biggiero (2022) suggests that SNA and other relational methodologies can be crucial to renew the theory of firms and inter-firm relationships. In the same direction, some scholars (Biggiero et al., 2022; Wieland, 2020) propose a new approach to economic theory and management studies, namely Relational Economics & Organizational Governance, which escapes from the view of standard economics and its applications into the fields of the theory of firms' behavior and industry studies. An outcome that this new theoretical perspective would bring is that of dissolving differences between economics and MOS in the field of the theory of firms and inter-firm relationships, so to build a new unified and integrated theoretical framework.

Despite huge and growing number of MOS papers adopting SNA, besides Grandori's (1999) readings and the massive Handbook of Inter-Organizational Relations (Cropper et al., 2008), *there are almost no monographs presenting a unitary view of the state of the art on the debates and applications of SNA in the field of the theory of firms and inter-firm relationships.* Few noticeable exceptions are Ebers' (1997), Nooteboom's (2004), and Knoke's (2012) books, which explicitly consider BINTs, and to which we address our reader for a wide view. Further, the book by Rossignoli and Ricciardi (2015) outlines the major theoretical frameworks, mostly Transaction Cost Economics and Resource Dependence Theory, and some specific applicative aspects. As noted by Bergenholtz & Waldstrøm, (2011), most old contributions employ the network view only conceptually or even just metaphorically, as done also by the books by Axelsson & Easton (2018) on industrial networks, and Todeva (2011) on business networks. Let say that an empirically grounded and theoretically sound network approach to inter-firm networks and its coordination mechanisms is still lacking.

Fortunately, there is a specialized literature—fragmented in many papers—focusing on BINTs from a SNA viewpoint. A good and wide review is provided by Carroll & Sapinski (2011), to whom we address the reader as well. Here, we only underline some contributions that more closely match with our work. Working on large corporations in the US, Mariolis & Jones (1982) found that the BINT connectivity degree of American corporates was lowly correlated with other variables, though the topology and correlations kept rather stable during the time series, and that banks centrality is more stable than non-bank companies. Moreover, confirming Mintz and Schwartz (1981a, 1981b) previous studies, they found that banks do indeed play a pivotal role in the whole network. As said above, this finding is confirmed by many other studies as well and, only to some extent, also by our analysis. More recently, by studying French listed companies, Elouaer-Mrizak (2012) found that indeed *big companies—whose size was measured with market capitalization—were the central nodes in the network, and that their geo-location was also very relevant*. Because *both findings are confirmed also by our study*, which employs a different sample and measures size with the number of employees, turnover, equity capital and assets, it could be argued that they have some good chance to be generalized.

Conversely, while *we found that the degree of BINTs connectivity is country-specific* (see Sect. 11 of Chap. 8), *we did not find any confirmation—except for France—that the continental Europe (CONEU) countries, and especially Germany, should have a connectivity with the Financial sector higher than the other countries, and especially the Anglo-American ones* (see Sect. 9 of Chap. 8). Actually, Windolf (2014) study is consistent with ours, because it shows that over time in Germany the connectivity of (and dependence from) banks reduced dramatically for the largest companies. We have produced other interesting results, but they cannot be compared with previous SNA-related literature, because they are new. Some other findings, which refer to the debate on the effects of BINTs on performance, are mentioned below in this chapter. Notice that for all the topics we analysed in our work, we did not limit only to BINTs, but rather we systematically extend the analysis to DINTs and HINTs, and to the combination of all of them.

2.5 Department Interlocks

In a DINT, one or more managers is shared by two or more companies in some of their departments. Such shared positions aim at facilitating the operative coordination between companies, because a same person is responsible for the application of procedures, standards, codes, etc. As we will see in next chapters, this solution is adopted by large groups of companies, that this way become fully and reciprocally connected. Although formation of large cliques occurs also for BINTs, here it is even more accentuated in terms of clique size and the number of positions covered by each single person (see next chapter for more details).

Department interlocks have not been a popular notion in literature, actually there is no trace, as of yet, of any study that would look at this kind of relationship. Although in the past there was a mention of inter-company relations based on top-management (Pettigrew, 1992), the study actually interpreted the top management as what we see as directors—because they were the ones in strategic positions. The management per se was looked at only in terms of composition, without the essential inter-firm perspective. In fact, as mentioned by Kor & Misanyi (2008) and Sanchez & Barroso-Castro (2015), many authors point out lack of distinction of various levels of management in inter-firm studies, though such a distinction would be very important for top the management and research. Therefore, this study enters an uncharted territory and aims to look at a field that has not yet been explored. The purposes (listed above) that Lamb and Roundy (2016) listed for the adoption of BINTs hold as well for DINTs, with the difference that they are achieved through operative instead of strategic knowledge. It should be underlined that, especially in high-tech industries, this latter can be even more important than the former. Therefore, DINT coordination is, in our specific case, even more important than BINT coordination. Consistently, DINT coordination provides both social and network capital, as defined by Huggins & Johnston (2010).

2.6 Hybrid Manager-Director Coordination

Each type of link is a carrier of different kind of information with its own distinguishable potential, but while BINTs and DINTs share a person covering the same hierarchical level in the org. chart, in HINTs two different ranks are combined in a single person. Therefore, more than for the other two interlock forms, where the knowledge exchange could be informally unbalanced, *the hybrid manager–director links create a formal exchange imbalance, because one company provides strategic knowledge by "hosting" the manager into its board, and the other company could be defined as an "exploiter", because its manager carries operative knowledge in return*. Therefore, we have called this phenomenon the AKE: *asymmetric knowledge exchange*. The exploiter, therefore, locates himself in a more favorable position where he obtains access to crucial strategic knowledge, not necessarily giving much back.

The idea of looking empirically at asymmetric inter-firm relations has been inspired by Brennecke & Rank (2017), who proposed to trace placement of executive management into other companies' board of directors, arguing that "each type of interlock goes along with unique knowledge-based, social influence-related and institutional benefits and costs". Therefore, considering their potential importance, our study aims to deepen the approach and include not only the executive level of management, but also all the other, lower levels, which could also transfer valuable operative knowledge.

Such assumption is reasonable, because power imbalances are often related to monitoring practice, what can be interpreted through both resource dependence and agency theories (Hillman & Dalziel, 2003), where a company with more power may observe without own disclosure. Contrarily to traditional, undirected approach to interlock links, the asymmetric links are hence directed. It is important, though, to remember that our study looks only at *potential* knowledge sharing/transfer, which does not guarantee that it actually occurs, we are rather interested in looking at the knowledge exchange channels which provide such capacity. However, although such links may represent only the potential, it is still important to study them to support understanding of basic building blocks of inter-firm networks.

2.7 The Effects of Board Interlocks on Firm Performance

So far, we have taken for granted that, following the principle that more knowledge is better than less knowledge, the more interlock coordination a company has the better will be its performance. However, as for many other scientific phenomena, especially in social sciences, a seemingly obvious relation like this can be wrong, because there are many other intervening factors accompanying these forms of coordination that can play in the opposite direction. This is exactly the type of arguments raised by the approaches to BINTs assumed by economics and law studies, which underline the collusive content and motivation of BINTs, and the consequent negative effects on market and firm's efficiency. We have expressed and tested this view with the Low Performance Hypothesis (LPH). We will briefly address to those issues in the next section, while here below we focus on the proofs about the relation between interlock coordination and business performance.

This issue has been investigated since long and many times, but the results are still inconclusive. As Zona et al. (2015) remark, authors who follow the RDT tend to expect a positive effect, because it is supposed that BINTs relax external constraints, while those who follow the Agency Cost Theory (hereafter, ACT) do expect the opposite, because it is supposed that BINTs enhance opportunistic behavior. Though the connection with the authors' theoretical background is not so strong, actually Horton et al. (2012), who side for RDT, found positive relationship, while Fich and Shivnasani (2006) and Devos et al. (2009), who sides on the opposite view, found a negative relationship. However, others, like Meeusen & Cuyvers (1985) and Fligstein & Brantley (1992), found no relationship at all. Baysinger & Butler (1980) find a positive effect of interlocks on profitability, while others such as Richardson (1987) show the opposite. By studying Fortune 500 top companies, Abdollahian et al. (2017) found that "interlock metrics can significantly alter outcomes, for better or worse, accounting for approximately 11% of performance success".

In their own test, Zona and colleagues (2015) selected 145 Italian manufacturing companies consistently traded during 6 years at stock exchange and then tested some hypotheses considering some variables as moderators: some on the RDT and some on the ACT side. They built a regression model in which they measured profitability in terms of Return on Assets (ROA) and industry concentration through Herfindhal–Hirshman Index (HHI). By integrating insights from both theories, they found that "interlocks may enhance and reduce corporate performance depending on the relative available resources at the interlocking firms. Board interlocks increase performance of the resource-constrained firms, especially when such board ties are targeted to resource-rich counterparts. Moreover, they decrease performance of the resource-rich firm when the interlocked partners are resource constrained. Thus, interlocking directorates may be both beneficial and detrimental to firm performance depending on the relative available resources".

By analyzing 131 firms from various sectors listed in the Saudi Financial Market during the period of 2016, Hamdan (2018) found two interesting results: (i) "the effectiveness of directors, in terms of their monitoring role, deteriorates when increasing the number of interlocks per director; (ii) a positive effect exerted by foreign ownership in terms of turning around the otherwise negative relationship between board interlocking and firm performance". A director sitting in many boards can pay only little attention to each of them and likely not in an equal share. Further, a company with many "overboarded" directors[5] will suffer of less effectiveness of its board work and likely will be subject to powerful external pressures. However, one could contend that, in exchange, that company can *potentially* acquire a lot of strategic knowledge, even more precious than others, just because coming from people so much involved into other strategic contexts and so fully immersed into corporate power elite. Even more, if the "board mix" of its directors include a significant variety of sectors and countries. So, what will be the net effects of the positive and negative forces just evidenced? Hamdan's and others' studies do not provide any answer to this question, which indeed grasps only a piece of the complexity of BINTs, especially when deepening into its micro-analytic aspects.

A third empirically based study on 200 Canadian companies that is worth to be mentioned here (albeit old) is that of Richardson (1987), who argues that the effect of BINTs on performance depends on the forces that caused each BINT: if they have been issued to serve some inter-organizational function, then the effects are positive, while if the causes rely on pure power purposes—be them in the sense of supporting corporate elite or of resulting from internal corporate power games—then the effects are negative. Now, in his language, serving inter-organizational functions correspond to what is generally meant as inter-firm coordination in the modern (above recalled) debate on inter-firm networks. However, in the other studies (including ours), it is not operated the distinction of BINT issued because of pure internal corporate power games.

Each of these three contributions—Zona & colleagues, Hamdan and Richardson—contains interesting suggestions to refine the test of the BINT-performance relation and, at the same time, lacks some aspect and has some flaws. The study of Zona & colleagues requires to look at mutual power and dependence aspects of the interlocked companies; Hamdan requires to count how many shared positions a director is involved in and also considering the existence of ownership relationships, especially those foreigners-owned; and Richardson requires to distinguish the causes for which the BINT has been established, approximated by checking whether a ceased shared position between the two companies has been replaced or not. The problem is that such requirements[6] are very burdening if applied to large

[5] Actually, that of "overboarding" is a phenomenon that is very strong and diffused in the networks studied in this book (see next chapter).

[6] Indeed, the analyzes of Zona & Richardson require also some further variable to be handled.

samples like ours, because of the many variables and data to be retrieved, which indeed are even harder to be got for non-listed companies.

Besides the remarkable data requirements, there are some flaws common to these three studies put here in special evidence, but in general common to most studies. We have discussed some of these flaws above, but it is useful to synthetically recall them here: (i) they concern only largest/public/listed companies; (ii) they mix all sectors; (iii) they check only one performance index; (iv) they consider only BINTs. Conversely, our test (see Sect. 7 of Chap. 8) is somehow specular to them, because it overlooks the micro-analytic variables just discussed, but it: (i) concerns all limited liability companies of a specific industry, (ii) employs three performance indexes, and (iii) extends the test to DINTs and HINTs and to the industry neighbors.

When considering all the companies, *regardless of their size or degree of interlock connectivity*, we have found that: (i) in some of the various forms of network that we have analyzed,[7] there was no any significant association between the degree of interlock connectivity and any performance index; (ii) profit margin (PM) and all but one ROCE results were not correlated with firm's performance in any network; (iii) HINTs are not correlated with any performance index; (iv) BINTs connectivity is mildly but positively correlated with ROCE, but not with ROE; (v) conversely, in the extended network—the one including the industry neighbors—ROE is lowly negatively correlated with BINT and DINT. Now, if we consider that the neighbors are very heterogeneous in terms of industries and that they are four times the EASIN companies, the most reliable and sound finding from a methodological point of view is just the one that shows *a positive association between BINTs connectivity and business performance, at least in terms of ROE*. In most other cases, the LPH seems to be confirmed and prevailing. However, we have also deepened the analysis by distinguishing companies in terms of ranges of interlock connectivity, a methodological choice that revealed to be fruitful of more interesting results, and that implicitly confirms that the usual limitation to largest companies is rather biased. This way, we could consider a possible nonlinear relationship with the connectivity degree. In fact, among other results, it resulted that for the strategic knowledge coordination through BINT in EASIN and its neighbors, the LPH can be rejected in terms of PM and is unclear for the other two performance indexes. Further, a company's degree of operative knowledge coordination through DINTs is positively and significantly correlated with its economic-financial performance when considering only the pure EU28 Aerospace Industry. Moreover, when including its neighbors partners, the LPH must be as well rejected and even inversed: the more connected through operative coordination forms, the more profitable is a company. Hence, we see that the association between interlock coordination and business performance is very sensitive to: i) the type of correlation (linear or nonlinear); ii) the type of economic-financial index; iii) the type of topological index; iv) the type of link (binary or

[7] The main ones are 8 networks: BINT, DINT, HINT, and ALL (its combination) for the EASIN and the extended network, which includes also the neighbors. For most analyzes, we have distinguished also EASINT, which add to EASIN also the companies that are connected only with neighbors and not even with other EASIN companies. See next chapter.

weighted); v) the type of interlock (BINT, DINT, HINT); vi) the specific aggregate (network) against which running the tests. This complexity can explain the inconclusiveness of revious studies and reminds once more the funamental requirement of considering all limited liability companies, and also distinguishing the various aggregates. We show and discuss all these results in the sections 5 and 6 of Chap. 8 and will come back on them also in the conclusive chapter.

The focus on a single industry confers to our study also the role of bridge between MOS or sociology-rooted studies on one side and economics or law-rooted studies on the other side. Actually, authors whose disciplinary background is rooted in one or the other side tend to have opposite expectations about the interlock–performance relation. Indeed, at a closer sight it appears clear that a positive relation is implied by what we could call a central tenet of SNA: higher centrality should be associated with some advantage, which in this case means better performance. On the contrary, the perspective of economics stresses the negative effects.

2.8 The Antitrust Literature and the View from Standard Economics

BINTs might have a potential anti-competitive effect deriving from the increased ability to collude. Actually, this is the other side of the coin of a firm's capacity to coordinate its behavior with others: the shared positions can serve not only to acquire more knowledge to the aim of being more competitive, but rather also to reduce competition and manipulate prices at the expense of customers. Indeed, the two aims can perfectly coexist in the same coordination action. Though we will not deepen our analysis to investigate on the ways in which countries' governmental institutions have faced with these issues, in this section we make some short comments.

Actually, in the US, the Federal Trade Commission recently revised the old Clayton's Act (Sect. 8) by addressing the prohibition of BINTs in the case that each involved corporation has capital, surplus and undivided profits aggregating more than $37,382,000 and each corporation's competitive sales are at least $3,738,200. This statute does not apply if the competitive sales of either of the competing companies are less than that amount (as adjusted annually) or 2% of that company's total sales, or if the competitive sales of each of the competing companies are less than 4% of that company's total sales. Indeed, the cases brought to litigation are very seldom.

In the EU, Petersen (2016) and Thepot (2021) argued strongly in favor of a strict EU legislation viewing BINT cases as anti-competitive behaviors. We did not check which, if any, of the US or EU companies match the criteria to be sanctioned by the current legislations, nor we have investigated the ways in which the corresponding authorities do bring forth their investigations. This work could be done in a future research agenda, perhaps with the active support of single countries and the EU or the US regulations institutions. However, as the reader will see in Chaps. 3 and 5, in all the main countries—and especially in the US—there are hundreds BINTs.

Indeed, *though there is some BINT between few very large companies and some others between small–medium companies, most of them hold between a large with many small–medium companies, so likely they do not violate current legislation.*

If this remark is reassuring on one side, it is worrying on the other side, because it raises many doubts about the effectiveness of these rules. In fact, if the aim is limiting the power of some single giant company, then it could be well suited. However, *if the aim is (also) keeping the market competitive, then it does not seem so well suited, because such BINT-based clusters, though each one is covering relatively small shares of production, as a whole they are likely not irrelevant for the efficiency degree at market level*. Further, as we show extensively in Chaps. 3, 5–7, many of such clusters do connect forming further quite large sub-networks. We did not check the degree of overlap between such sub-networks and industry segments at the EU or global levels, but certainly their size of hundreds of companies can heavily influence industry competition and efficiency. At the same time, we should notice that the thresholds established for sanctioning large companies can be misleading, because they are often very diversified, and thus, the total amount of operating revenues or equity capital can indicate not appropriately the true market power. Conversely, a cluster of many small-medium specialized companies can exert a considerable influence power.

Further, we notice that:

(a) the large majority of interlocked companies have a small size (see Chaps. 3 and 4);
(b) the large majority of inter-firm coordination through shared positions occur not in BINT, but rather in DINT; that is, they concern shared managers (see Chaps. 2 and 4);
(c) in high-tech industries like Aerospace, DINT can be much more important than BINT, even to allow anti-competitive behaviors, because codes and standards can have a strategic relevance. Therefore, the regulation authorities had to deal with this type of links too;
(d) in the US and the EU, only horizontal interlocks—that is, intra-industry or internal links, as we called them—are under regulation, while many others occur vertically, between the EU28 Aerospace Industry and other countries, primarily the US;
(e) any kind of inter-firm alliance or agreement can potentially be used to reduce competition between the dealing parties, so why to prevent or restrict only ownership or BINT types of connections?

We will come back on these remarks in the conclusive chapter, because we believe that they could help stimulating a reconsideration of the industry concept and of the effectiveness of current forms of regulations.

2.9 Summary

Among the many ways used by firms to coordinate their strategic and operative relationships, there is the option of sharing a director or a manager: in the former case, we consequently have a board interlock (BINT), while in the latter a department interlock (DINT), to which we can add also the hybrid case in which a manager of a company is placed into a board of another company (HINT). In our study applied to the EU28 Aerospace Industry and its global neighbors, BINTs represent about 11% of all connections, DINTs 88%, and HINTs the remaining 1%. The latter is, quantitatively speaking, almost irrelevant, but it is qualitatively very important, because it is mostly employed by companies that cover particularly important positions in the network formed by all the types of connections. Unlikely of other coordination forms, that are more constrained, specified by formal contract and based more on quantitative parameters, what is common to all the three forms—BINT, DINT, HINT—is being person-based, thus more depending on individuals' specificity and on the relations that they are able to establish, the knowledge that they can channel and the purposes that they can pursue. There are various reasons to choose one of those forms of coordination—reasons that change for each of the three types—but in each one the acquisition, sharing, creation or transfer of knowledge is somehow inevitable and important, though not necessarily always intentional and evaluated. In a certain sense, we could say that it happens beyond and despite individuals' will.

When concerning BINTs, what is "exchanged" is mostly strategic knowledge, while it is mostly operative through DINTs, and it is an unfair (asymmetric) knowledge exchange occurring through HINTs, because operative is exchanged with strategic knowledge, which is supposed to be more precious. Noteworthy, this language, especially if taken literally and synthetically, can be misleading, because the "exchange" can be unequal in all cases, and likely, it is not really ever measured. Indeed, if the purpose of knowledge acquisition is even not so intentional, a fortiori the exchange is not precisely measured or measured at all, at least as concerning strategic knowledge. It would be more properly the case of talking of a more or less intentional and effective knowledge sharing, whose real effect on the company depends on its absorptive capacity and on other circumstances. Likely, the operative knowledge diffused through DINTs could be more tangible and codified than the strategic knowledge shared in BINTs.

This knowledge-based view of interlock coordination forms is deeply rooted in the rich and multi-disciplinary approach to organizations as cognitive systems and repositories of strategic and operative knowledge, activated by dynamic capabilities. This is one of the four research streams that cross in our work, the others being the specific literature on BINTs, the inter-firm networks (in particular as knowledge networks), and the social network analysis (SNA). Therefore, our study looks at the EU28 Aerospace Industry and its global neighbors as a multi-layer network, whose layers are BINTs, DINTs, and HINTs. Hence, our approach is meso, but at the same time, being shaped at industry level, it is very different from all the studies that have so far adopted a meso-approach, because they mix companies operating indistinctively in various sectors and select only the largest companies, usually listed or public companies. Conversely, we considered all limited liability companies, thus dealing with about three thousands companies within the EU28 Aerospace Industry and more than six thousand neighbors all over the world and from any sectors. This methodological choice represents a big challenge in terms of applied SNA and, at the same time, allows considering the influence exerted by the technological and economic specificities on the BINT-DINT-HINT networks.

In our study, we extensively and intensively describe this multi-layer network and we run some hypotheses testing. Part of them are common topics of the BINTs literature—which we extend also to DINTs and HINTs—while others are new. Among the former group, we found confirmation that the big companies are more connected than small–medium ones, and that geo-location is very relevant to decide with whom should one establish a connection. Actually, we found that the degree of BINTs connectivity is country-specific, but we did not find any confirmation—except of France—that the continental Europe countries, and especially Germany, should have a connectivity with the Financial Sector higher than the other countries, and especially the Anglo-American countries.

We have extensively tested also the crucial and long lasting (and still inconclusive) topic of the relationship between BINT connectivity and business performance. If considering all companies together, then the most important and sound finding is a positive association of BINTs with business performance, at least in terms of ROE. Further, at a deeper look, after extending the test to the neighbors and clustering companies according to their degree of connectivity, we have found interesting results for BINTs and DINTs suggesting a curvilinear relationship with three performance indexes: profit margin (PM), ROCE and ROE.

Finally, we have discussed the question of the potential negative consequences of interlock coordination forms on an industry efficiency, due to collusive behavior. We have remarked that they are somehow inevitable, but their evaluation is far from being well suited in current regulations: They are, in fact, limited only to BINT and to connections between very large companies, thus excluding clusters of small–medium companies and DINT-HINT connections.

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Chapter 3
Overview on the EU28 Aerospace Industry Network and Its Neighbors

3.1 A Brief Overview of the Industry

The European aeronautics industry develops and manufactures civil and military aircrafts, helicopters, drones, aero-engines and other systems and equipment.[1] The industry includes companies that provide support services, such as maintenance and training. At its early stages, this industry was growing rather slowly, and only later achieved its potential. In fact, in 2008, the EU27 Aerospace Industry employed 375,300 people and the turnover amounted to 127.8 billion EUR. The value-added came up to EUR 34.5. As compared with all of the EU27-Manufacturing industries, the Aerospace Industry commanded a share of around 1.8% of value-added and 1.2% of the number of employees. According to Eurostat statistics, the production of the EU28 grew between 2001 and 2008 at an annual—price adjusted—average rate of 1.5%. The number of employees grew only slightly at a rate of 0.1% per annum (European Commission, 2009). More recently (European Commission, 2022), the aeronautics industry became one of the most essential European high-tech sectors on the global market providing more than half a million of jobs and in 2013 alone generated turnover at the level of approximately 140 billion EUR, numbers that increased enormously in 2019. Being one of the global leaders, in 2019 the EU28 had a production surplus that was exported all over the world. As we will see in the next section, this industry is highly concentrated geographically, with a very important role played by UK. Therefore, after the Brexit, it could be that the strength of EU27 Aerospace Industry is significantly lower.

Concentration. On the EU 2016 R&D Scoreboard (including 1000 companies), 24 European companies cover an astonishing 80% of all European Aerospace and defense revenues and about 65% of workforce (EU Commission, 2016). We update

[1] This first section of overview draws mostly from Alfonso-Gil (2007), Biggiero & Angelini (2015), Biggiero & Magnuszewski (2021), Giuri et al. (2007).

L. Biggiero and R. Magnuszewski, *Inter-firm Networks*, Relational Economics and Organization Governance, https://doi.org/10.1007/978-3-031-17389-9_3

and improve this analysis by calculating the Hirshman-Herfindhal Index (HHI),[2] which resulted to be rather high (0.68) in terms of production concentration. As when the distribution is strongly heavy-tailed (HT), it is useful to accompany HHI with traditional measures (Cremers et al., 2008), so we have calculated the TURN share of the early 4, early 8, early 20 and early 50 companies: 49%, 70%, 81% and 93%, respectively. This way it appears even more evident that the production of our EASIN industry is extremely concentrated and aligned to the estimation of the EU Commission.[3]

Profitability. According to the European Commission, although the employment costs are relatively high, productivity is considerable making the industry quite profitable. According to Eurostat, in 2019, profit share and net return on equity (after taxes) of non-financial corporations were 38.98% and 17.85%, respectively. Conversely, the early 100 EASIN companies in terms of TURN score very much lower: 4.38 and 7.78%, respectively. However, if we select only listed companies, which indeed are only 15 companies, then those numbers raise up to 7.74 and 19.13, respectively. Hence, while profitability in terms of profit margin is five times smaller, ROE is even a bit higher. Likely, even profit share could be considered aligned to EU28 corporations, because while our source database (see the Methodological Appendix) records net profit (after taxes), Eurostat records gross profit (before taxes). Indeed, if we consider all companies with available data, which are much less than 50% but anyway lacking mostly the micro-firms, both ROE and profit margin crashes down to 2.8%, suggesting that, despite this is a very rich and strategically crucial industry largely supported also by public funds, *the hundreds small suppliers serving the big or the middle players are economically and financially weak and poor*, like in most other industries. Put differently, *the fringe of the core of this industry does not gain from the advantageous positions of the leader companies.* They are exposed to high competition and likely also high mortality rates as in all other industries. Perhaps, the smartest of them can move to upper positions alongside the production chains, where likely they can benefit of some "protection" or benefit by middle players. Otherwise, if they acquired enough valuable knowledge and if they find the right opportunities, they "spend" it in other sectors, where they could score better economic performance and more stability.

Industrial cluster structure. The geographical scope of our work is national and international, and so we do not deal with the local or regional level. However, we want to underline that, as witnessed by the Aerospace and Defense Industries Association of Europe (ASD, 2017), which counts more than 45 clusters, the Aerospace Industry has a clustered structure (Beaudry, 2001; Cooke & Ehret, 2009; Hickie, 2006; Jackson, 2004; Niosi & Zhegu, 2005; Turkina et al., 2016), which makes

[2] We address the reader to the Methodological Appendix to know how HHI is calculated and normalized. Anyway, see Curry & George (1983) and Tirole (1988).

[3] Besides the partially different samples, part of the discrepancy could be due to the fact that we could apply the calculation only to those 40% of companies for whom we have TURN (turnover or operating revenues) data.

it a clear case of "glocal" industry (Biggiero, 2006; Swyngedouw, 2004): local production through industrial clusters for a global market. Actually, this "glocal" regime seems a property characterizing not only EASIN, but also the US Aerospace Industry. What is even more interesting and emerging very clearly from our research, is that the inter-firm strategic and operative coordination of the EU and the American Aerospace companies seem rather inter-connected, though not so much as it appears at first sight by looking at the number of involved companies and related connections. As we will show already in this chapter—and much deeper in the next chapter—American companies involved by EASIN's strategic and operative coordination are extremely numerous, but at the very end they are very much self-referential, that is, mostly engaged into their own coordination, rather than inter-connected with EASIN companies. Put differently, though all of them are connected directly with EASIN companies, the intensity of such connections, that is the number of multiple positions of interlock coordination that they hold, is not so high. As we will see below in this chapter, some countries—above all, the US—have a propensity/capacity to coordinate their strategic and operative behavior much higher among themselves than between them and EASIN.

This is a very important result for two main reasons. The first reason is that it reappraises the strategic and operative influence that the US, and now even the UK, have on such a strategic industry as EASIN. The second one concerns the theory of inter-firm relationships, because it provides precise and extensive quantitative data about these forms of coordination, which could be contrasted in future with other forms, namely R&D projects and ownership. In fact, Biggiero & Angelini (2015) have shown that companies and university departments (and other kind of institutions) are very much inter-connected forming a dense and persistent EU Aerospace research area. As well, and from a methodological point of view in a way fully homogeneous with this research, Biggiero & Magnuszewski (2021) have shown that between the US and EASIN occurs a strong degree of interdependence with respect to ownership relationships. We will go back on these issues in the conclusive chapter of this book.

Coordination requirements. Because of its high-tech nature (Paoli & Prencipe, 1999), and thus, design and product complexity (Acha et al., 2007; Prencipe, 1997) and high entry barriers (Niosi & Zhegu, 2002; Prencipe, 1997), strategic alliances are very important in the Aerospace Industry (Dussauge & Garrette, 1995; Jordan & Lowe, 2004; Smith & Rogers, 2004). In fact, whatever the scientific approach adopted, literature on strategic alliances underlines the need to externalize risks and costs and to build inter-firm agreements (Das & Teng, 1998, 2002; Franco & Haase, 2012; Knoke, 2012; Mowery et al., 1996). According to, the EU Aerospace research area (Barber & Guffarth, 2013, 2014) would have to rely heavily on both internal and external relations, including trade, ownership, R&D and shared people (interlocks). Our study will not be delving too much into explaining mechanisms and processes that determine the structure, but rather will limit to a more descriptive approach, though extending on the analytical side in Chap. 8. Issues concerning board interlocks which are still controversial, we will apply correlations in the next chapters to check how interlocks interact with economic variables.

3.2 A Statistical Description

EASIN. Having considered that data on employees refers to only 51.2% of companies (Table 3.1a in Data Appendix),[4] it still can be noted that the European Aerospace Industry Network's employment is huge: 894,000 people, split over 3143 companies.[5] As well enormous are total assets, which amount to 618.3 billion US$, though limited to 65% of companies. Turnover amounts to 430 US$ billion (but corresponding to only 42% of companies), while equity capital (115 billion US$) seems more representative than other variables, like the total value of assets, because it covers 69% of companies. Conversely, the value of cash flow (25.7 billion) is the least representative variable (33% of companies). The major players in Europe are the UK (more than 27% of companies, top 3 in terms of TASS, TURN, EM, EC and CF[6]), France (5th in terms of number of companies, but an unquestionable leader in terms of economical indexes), Germany, Spain, Italy, Poland and slightly behind the Netherlands and Sweden. More specifically, data show that the UK, France and the NL hold the highest shares of TASS and EC,[7] while the UK and France hold the highest shares in terms of EM and CF, and finally, France, the Netherlands and the UK hold the highest shares of TURN. As it is apparent, the UK is always among the top three countries, but again, it is unclear the extent to which this depends on its truly prominent position or on the better data availability relatively to others. The percent share of EASIN's 3143 companies per country is represented in Fig. 3.1a, whereas country distribution of the connect part of EASIN is presented in Fig. 3.1b—it is noticeable that the top 8 in both cases is composed of the same countries, just in different order. Only Germany and Italy swapped places—Germany owns more when considered are its isolates, Italy when considered are the connected companies—what would be according to the literature on board interlocks available for those two countries (Chap. 2). Because the same countries are in the top when isolates are considered and when they are not, EASIN's connectivity seems not to be purely country-related, but there is indication of other factors that influence companies' need for strategic bonding (see also the last section of Chap. 8).

[4] The values in brackets in the tables indicate the % of companies, out of total companies in that specific country, for which the data of that variable are available. As it can be seen, the situation changes considerably per variable and per country: the worst degree of reliability occurs for cash flow where for two key-players like the Netherlands and the UK available data concern only 3 and 11% of companies, respectively.

[5] A further problem in comparing these and other sources' data is that related to the degree of diversification of some companies—especially, but not exclusively, the largest ones—into other sectors. Indeed, it is possible that data on which Aerospace and Defense Industries Association and EU Commission built their statistics do take into account only the Aerospace part of such companies, while Orbis (the database from where our data come from—see Methodological Appendix) in no way does such a distinction.

[6] All abbreviations are explained in the list of abbreviations at the beginning of the book.

[7] Though the term "capital" could be referred to many firm's variables, in this paper, it is referred only to equity capital and its shares represent ownership links. Of course, in case that a company

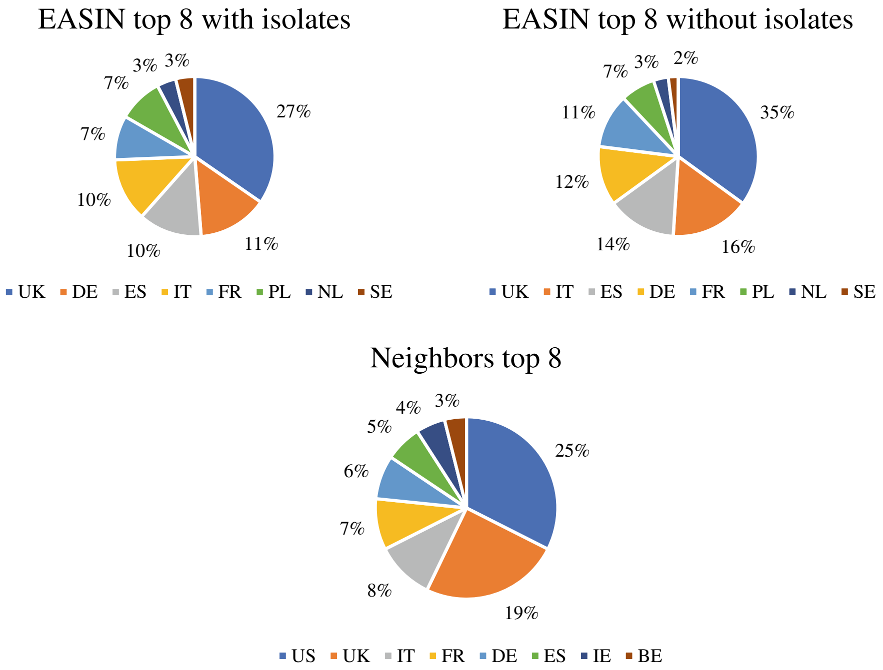


Fig. 3.1 **a**–**c** Share of top 8 countries in terms of number of companies in EASIN with isolates (**a**), without isolates (**b**) and neighbors (**c**). *Legend* The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables "the others", which are included in Tables 3.1a and 3.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 8

Besides the high number (1741) of isolated companies in EASIN, there are 1402 companies (the EASIN Integrated—please check the Methodological Appendix) who are connected with any others—be it themselves or companies from other sectors (Table 3.1 in Data Appendix), out of which 555 (18%) companies connect horizontally (internally) with each other—thus creating the EASIN network. Within them, there is a set of 99 (3%) companies who are connected only in such way, the complement to the 555 companies subset have both types of connections. The remaining 847 (27%) EASIN companies, in reference to the subset of 1402, form only external links. The complexity of this situation is better explained in Table 3.1 and Fig. 3.2. The connected 1402 EASIN companies hold external coordination relationships with 6637 non-EASIN ones, which in the jargon of network analysis are called "neighbors". All of the introduced companies thus form a total set of 9780 units.

As we can see, the coverage of available data of EASIN's connected companies (Table 3.1b) is a bit higher and reported values are high, proportionally much higher

is self-owned, its entire capital is not shared with any other company (while it could be with single individuals), thus without any in- or out-flow of capital.

Table 3.1 Number of companies in various contexts

Case	Set of companies	# of companies	% of total
1	Total number of all EASIN companies	3143	32
2	EASIN companies connected within EASIN	555	5
3	EASIN isolates within EASIN	2588	26
4	EASIN companies connected in E+N	1402	14
5	EASIN companies connected in E+N only with neighbors	847	8
6	EASIN isolates in E+N	1741	17
7	Neighbors in E+N	6637	67
8	All connected companies in E+N	8039	82
9	All connected companies in E+N + EASIN isolates	9780	100

than the total (Table 3.3 in Data Appendix): a bit less than half of EASIN companies that are connected cover 85% of TASS and TURN, 75% of EM, 82% of EC and CF.

Isolates. The above results tell us that the isolates are EASIN's smallest and less relevant companies, and same holds true when they are compared with neighbors. In the extended network, our work deals only with the 8039 connected companies, because the inclusion of the 1741 isolates does not change significantly (maximum difference of 1–2%, compare Tables 3.3a, b in Data Appendix) any of the economic attributes, and so our focus is on the features of the connected companies: namely, the who and why adopts forms of inter-firm coordination through managers and directors. Per country cross section of the isolated companies is presented in Fig. 3.3 (Fig. 3.2).

Neighbors. Values of the whole set of companies (EASIN + NEIGH) in terms of all economic attributes, when compared with the previous EASIN tabs (in the Data Appendix), grow significantly: TASS 9 times, TURN more than 4 times, EM about 3 times, CF 5 times and EC 10 times. There is a clear conclusion that stands out after

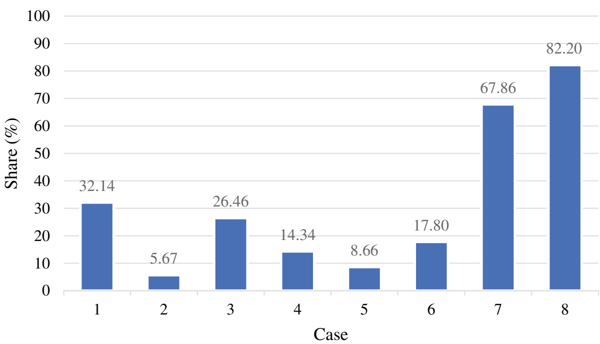


Fig. 3.2 Shares of the complete dataset in various contexts

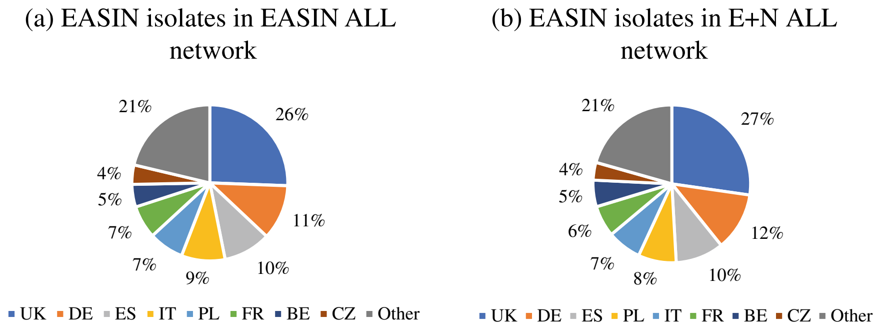


Fig. 3.3 **a**, **b** Per country cross section of isolates in EASIN (**a**) and EASIN + NEIGH (**b**)

the initial analysis—*the combined values of economic attributes of neighbors are much larger than EASIN's attributes*. The neighbors themselves are mostly (69%) from the EU28. Although EASIN is a huge industry in terms of both capital and employees, its neighbors when aggregated have almost twice as many companies and possess about ten times more EC, three times more EM, about four and a half more TURN, almost nine times more TASS and five times more of CF (Table 3.2a in Data Appendix). Such difference in economic capabilities is of no surprise, it is predictable based on literature—among neighbors, there is a strong presence of the resourceful Financial sector whose economic attributes are very high, as presented in Table 3.2b (in Data Appendix) and Fig. 3.4. Indeed, apparent is the significant presence of banks, holdings and other financial operators: 547 out of 4587 in the EU28 and 101 out of 2050 in the non-EU part. However, it is not their number, but the economic attributes that those relatively few companies and organizations do bring to the neighbors' stock. In Europe, they stand for 57% of TASS, 30% of EC, 14% of CF and 6% of TURN and EM. Clearly, it is those micro-size companies, in terms of EM, that own a lot of TASS and EC. In the rest of the world, the economic data availability is too insignificant to consider analyzing those companies deeply, except for pointing out that majority of them come from the US—55%. In Europe, most of the Financial companies come from France and the UK (more than 100), but it is France and Sweden (which is the last one in terms of number of companies in our top 8) that are the most prominent.

EASIN + NEIGH. The following pie charts highlight the situation in more aggregated form showing the relative economic capacity of EASIN as compared to its neighbors, represented as the percent share of the total per each economic attribute. The neighbors are presented there through a cross section of sectors with particular attention given to those most prominent ones. Although EASIN is not a sector, but rather just an industry within a particular geographical context, it is added to the analysis because it is after all the focal point of the entire book. It is apparent, that EASIN is always present in the top 3 along with, usually, Financial and Manufacturing sector.

From Table 3.2, Figs. 3.5 and 3.6, we can clearly grasp another fundamental trait of the whole extended network: *companies are very unevenly distributed across*

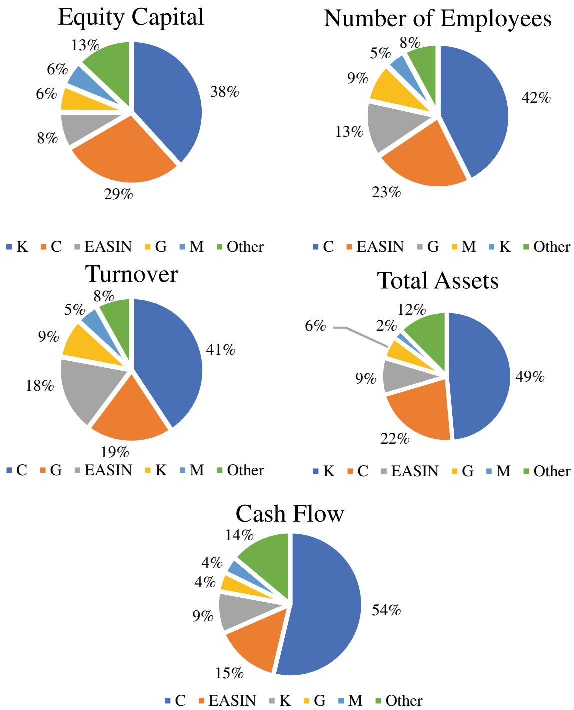


Fig. 3.4 a–e Economic attributes of EASIN compared with all its neighbors, which are grouped into their respective sectors

sectors and countries. The Manufacturing sector (the C symbol) is made of 2158 companies, covering 27% of the whole, and much more than the connected part of EASIN itself, which has only 17% despite the whole network originated from it. The second true sector—EASIN is not a sector but has been included for comparison nonetheless—is the Professional Activities (the M symbol) with 9%, followed by the Financial (the K symbol) with 8%, and the Wholesale sector (the G symbol) with 6%. It means that these four sectors are those most responsible for the inter-firm coordination, regardless yet of which specific type.

With about 1630 companies each, the US and the UK score also the highest share (20%) of connected companies (Table 3.2), but it should be reminded that while the American is only neighbors, the British is only half neighbors. Then, Italy follows with 9% and France with 7%, but actually, when we separate the EASIN companies, we see (the fifth column) that while the US increases its share among neighbors, the UK lowers to 12%, Italy and France lower to 6%, and Germany and Spain to 3%, because the majority of their companies are inside EASIN. So, when below and in next chapters we will talk of neighbors, we must know that *neighbors are 27% Manufacturing companies and 25% American companies*, followed by some of the most important EU (and EASIN) countries: the UK, Italy and France.

Another very relevant feature concerns the share of individual countries within the global (but EASIN-related) Manufacturing sector: 59% of them are American

Table 3.2 Distribution of total and manufacturing companies over top 8 countries

Country	# of companies	Country share (%)	# of EASIN companies	Share on neighbors (%)	# of C[a] companies	Share of C sector (%)	Share of C on single country (%)
US	1629	20	–	25	1266	59	78
UK	1623	20	854	12	231	11	14
IT	729	9	299	6	108	5	15
CA	105	1	–	2	80	4	76
ES	503	6	322	3	76	4	15
FR	589	7	219	6	73	3	12
DE	506	6	336	3	47	2	9
PL	223	3	210	0	36	2	16
Total	8039	100	1402	100	2158	100	27

Legend [a]EASIN companies are excluded

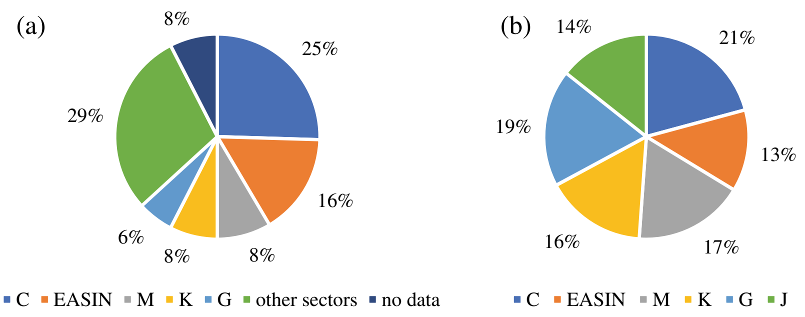


Fig. 3.5 **a**, **b** Distribution of companies (**a**) and countries (**b**) by main sectors. *Legend* The numbers present **a** % of all companies; **b** % of countries involved in that sector (countries can be present in many sectors, so the number here does not add to 100%)

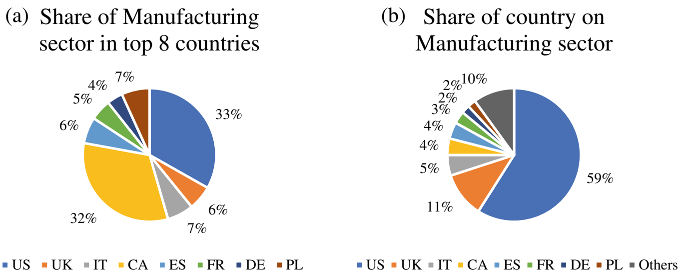


Fig. 3.6 **a**, **b** Focus on the Manufacturing sector

and 11% are from the UK. So, it can be easily said that *the Manufacturing sector influencing (and also being influenced by) EASIN is prevalently Anglo-American.* It means that, when in next chapters we will see the Manufacturing sector, we will be substantially speaking of those two countries, which, however, are very different under other respects, one of which is that the US overall is also extremely specialized in the Manufacturing sector, which covers 78% of their involved companies, while for the UK that share is only 14%, aligned with the other main countries.

Though the Manufacturing sector is mostly relevant (Fig. 3.6a) to the US and the UK (in terms of our network), for the rest of the countries it does not exceed 10%. Looking at the sector's cross section (Fig. 3.6b), it is immediately visible that the US prominence is unquestionable. The sector involves the largest number (74%) of countries of the 61 present in the extended network. It is followed by Professional Activities, Finance and Wholesale, with whom we are familiarizing, and actually, they will be rather important in almost all other aspects.

3.3 Basic Structural Aspects

Companies. In both versions—that is, EASIN or EASIN + NEIGH—our object of study is a multi-layer network, whose layers are made by three distinguishable subnetworks with different types of links. They are distinguished according to building logic, which is based on assigning positions covered by individuals who are engaged in them:

- D2D, directors-to-directors, with BINT links, what represents a director sitting in boards of two companies. Being located in the boards, these people share strategic information and thus, are supposed to coordinate strategic behaviors;
- M2M, managers-to-managers, with DINT links, what represents a manager appointed in departments of two companies. By covering managerial positions, these people are supposed to share functional knowledge and coordinate operating behavior, which indeed might be extremely important in high-tech industries, such as the Aerospace;
- M2D, managers-to-directors, with HINT links, what represents a person appointed as a manager in a (department of a) company and as a director in the board of another company, thus connecting the two companies in a hybrid way, because the connection occurs between two different hierarchical levels: lower in the company where the person covers a managerial position and higher where s/he sits in the board.

The former two are symmetric (undirected), because their relationships represent collaboration between hierarchical peers. Conversely, M2D refers to a relationship that, albeit is a collaboration, and therefore could be bidirectional, holds between different hierarchical levels. Hence, we argue that, from the point of view of influence power, the two connected companies are not in a symmetric position. As discussed in Chap. 2, we found theoretical and empirical support from Brennecke and Rank

(2017). We will say much more on this point in Chap. 7, when dealing with this type of network.

It should be underlined that in the end, companies are connected by a complex web of relationships. More specifically, two main sources of complexity come from the four following aspects:

- Between two companies can occur more than one *type* of relationships: for instance, DINT and BINT, as it is well shown by the case of, i.e., companies of the Airbus group;
- Between two companies can occur more than one of the *same* type of relationships: for instance, two DINTs (when sharing two, different managers), same example as above;
- A same director could be member of more than two boards, thus connecting more than two companies, even up to two and a half hundred;
- A same person could cover, at the same time, two positions at different hierarchical levels within the same company: that is, s/he can be a manager and a director at the same time.[8] Further, that person could further cover a shared position in DINT with one company and BINT with another, and even both with the same company.

Because two companies can be connected by more than one director or manager, we have analyzed not only the mere existence of a relationship, but also its intensity: to the former aim, we build and examine the binary, while to the latter aim, the weighted versions of the four networks. They are four, because one per each type of link—M2M, D2D, M2D—plus the multi-layer network—the ALL version—which resulted by merging them together. Such four networks are then doubled according to the binary and the weighted versions, and further split into two aggregates: the EASIN and the EASIN + NEIGH. Finally, these two are distinguished into the whole network and a focus only on its main component. Additionally for better understanding, we have added also the EASIN Integrated (EASINT) network, which will be explained later. As discussed in the previous chapter, while D2D has been studied for a long time in economic and management literature, M2M and M2D are almost unknown.

A very concrete and immediate consequence of all these aspects is that, except for counting in terms of weighted links, which is commented later on, companies and people distributions will not square to 100%, because of many occurrences of multiple connections and multiple roles (shared positions as manager/director, sometimes in BINT or DINT or HINT interlocks). Many more details are given in the Methodological Appendix, which contains also indications of how we collected and grouped the data, so that a reader would be able to replicate the same approach for another industry, or any other target group.

[8] We remind that we chose to assimilate all executives to managers to simplify the analysis, which otherwise would have to consider six types of relationships. Further, this choice is legitimate by the fact that executives involved in inter-firm relationships are, in this industry, anyway very few: about few dozens.

When considering only EASIN companies (Table 3.3), the large majority of them (85%) are involved in M2M shared positions, then 55% in D2D, and more residual 20% in M2D—we remind once more that this (and other distributions) does not sum up to 100% because of companies being involved in more than one type of link. Interestingly, all these percentages increase substantially when extending also to neighbors. Conversely, the distribution between connected and isolated companies for each type of network sums up to 100%. In this respect, either for EASIN only or for the extended network, the ranking sees M2M as the one with the largest share of companies connected through shared positions: 15% in EASIN and 71% in the extended network. It is followed by D2D with 10% and 52%, respectively, in EASIN and the extended network, and then M2D with 4% and 45%.

The following three figures (Figs. 3.7, 3.8 and 3.9) summarize the main data concerning the amount and distribution of companies in the extended (EASIN +

Table 3.3 Distribution of connected and isolated companies among the various types of networks

Network	# of companies	Share[a]	Isolates	Share[a]	Share of connected[b] (%)	# of all companies
M2M EASIN	471	85	2672	1.03	15	3143
M2M EASIN MC	27	51	–	–	–	–
M2M E+N	6973	87	2807	1.61	71	9780
M2M E+N MC	3238	79	–	–	–	–
D2D EASIN	305	55	2838	1.10	10	3143
D2D EASIN MC	12	23	–	–	–	–
D2D E+N	5042	63	4738	2.72	52	9780
D2D E+N MC	770	19	–	–	–	–
M2D EASIN	112	20	3031	1.17	4	3143
M2D EASIN MC	10	19	–	–	–	–
M2D E+N	4414	55	5366	3.08	5	9780
M2D E+N MC	1641	40	–	–	–	–
ALL EASIN	555	100	2588	1.00	8	3143
ALL EASIN MC	53	100	–	–	–	–
ALL E+N	8039	100	1741	1.00	82	9780
ALL E+N MC	4078	100	–	–	–	–

Legend [a]This share refers to the total of the same category: for example, in the category EASIN, the D2D network covers 55%, it should be taken into account that they do not sum up to 100, because the same company can repeat for different networks, because it can hold more than one type of link or it can be isolated in one network and not in the ALL network

[b]Share of connected companies over all companies

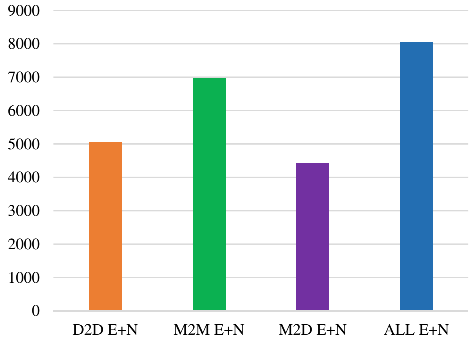


Fig. 3.7 Size of the four extended networks

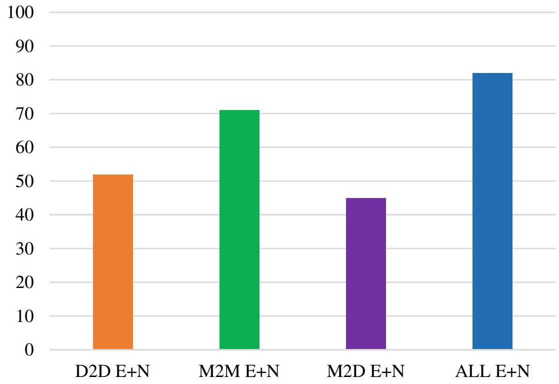


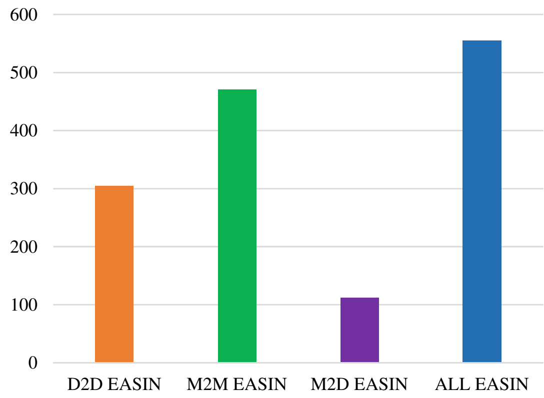
Fig. 3.8 Share of connected companies within the four extended networks

NEIGH) and EASIN networks by distinguishing the three types of inter-firm coordination. It is easy to see that the *DINT (inter-department) is the coordination form used by most companies, followed by BINT (inter-board) and then HINT (hybrid coordination)*. It means that the need to coordinate operative activities is much more important and diffused than the need to coordinate strategic behavior. Right below, we will see that *such differences become much more accentuated when measuring the relative importance of these forms of coordination in terms of the number of links and not in terms of number of companies involved*. Even more extreme will be the difference when we will consider not only the number of links holding between two companies, but also their intensity, measured by the multiple connections (positions) holding at the same time: that is, more than one director or more than one manager, or both.

Links. The distribution of weighted links is the only "squared" distribution, where the sum of the different types of links/networks sum up to 100%[9] in the ALL version.

[9] The reason is that, in the binary ALL version, if two companies had both a DINT and a BINT link, only one link would be considered in the end—its either companies are connected at all or not, does not matter in how many ways, in consequence only one of the links is considered dropping the other. Therefore, the total number of binary links of the ALL version is somehow underestimated. In the

Fig. 3.9 Size of the four EASIN networks



In fact, the ALL version of EASIN only or EASIN + NEIGH contains all the links, and thus, its composition in terms of BINT, DINT and HINT links is exhaustive (Table 3.4). *The EASIN network is coordinated through the significant number of 2519 links, most of which (57%) are made by shared managerial positions, 38% by board positions, and the remaining 5% by hybrid (M2D) positions.* Notice that it would be slightly inappropriate to identify positions and people, as to say 2519 people (or links), because a single manager could cover multiple positions. Thus, it is more correct to speak of managerial positions rather than managers. In the final section of this chapter, we deepen on the relations between positions and people, while more clarifications about the many complex relations among all these seemingly simple concepts are provided in the Methodological Appendix.

The network extended to neighbors is coordinated by the astronomic number of 3.154 million links, who are made by managerial in the large majority (88%), 11% by directorial and only 1% by the hybrid positions. Therefore, the ALL EASIN + NEIGH network—that is, the multi-layer network including all the three types of links—is largely dominated by the M2M network (Fig. 3.10). However, for the peculiarities of structural (topological) aspects, we cannot conclude in a way that would seem obvious: that M2D positions are irrelevant and D2D very marginal. From a pure statistical and quantitative perspective that conclusion would be true, but from a network perspective D2D and M2D could add interesting information, because D2D could integrate parts of M2M that otherwise would be disconnected, thus changing the whole topology and the degree centrality of single companies

present tab, we decided, for the purpose of correspondence, to keep the values of binary links that result in the network outline tabs of Chaps. 4, 5, 6 and 7, but also to add a column Sum which shows sums of networks' binary absolute density—which we then use to show distribution of networks. Additionally, the M2M and D2D networks' links are symmetric, and thus if they were treated as traditionally undirected those numbers would be halved, see the Methodological Appendix for more details. We also remind, that links of MC in the ALL networks and sum of links of all individual MCs put together are two entirely different things, creating different structures and so different numbers of nodes and links.

Table 3.4 Distribution of binary and weighted links among the various types of networks

Binary	D2D	%	M2M	%	M2D	%	Sum	ALL
EASIN MC	44	25	114	68	12	7	170	222
EASIN	600	38	904	57	87	5	1591	1151
E+N MC	109,340	30	255,748	68	10,715	2	375,803	319,228
E+N	244,744	43	301,358	54	17,024	3	563,126	357,390
Weighted	D2D	%	M2M	%	M2D	%	Sum	ALL
EASIN MC	52	12	420	86	12	2	484	771
EASIN	888	35	1536	62	95	3	2519	2519
E+N MC	117,072	5	2,393,312	94	13,496	1	2,523,880	3,103,018
E+N	354,364	11	2,779,408	88	20,966	1	3,154,738	3,154,738

Legend % represent share of "Sum"
Please note, that Sum is different from the "ALL" column (which is de facto a sum of the previous three versions as well). The differences are based on topology, some of the links from individual networks can have the same source and target, and so in ALL, they overlay and their effect is lost in topological terms, Sum, therefore, sums them up—thus accounting for their added weights. In a main component (MC), the most important aspect is topology and its peculiarities, it is the largest in the ALL version because there it utilizes all the connections provided by individual networks, the Sum of values just adds weights together, but cannot consider all the available binary links

or groups of them. Further, being directed (asymmetric), M2D did add a direction to merged (ALL) network and evidence fragmentations or non-reachability that previously were undetectable.

Though it is true that the number of companies grows more than 3 times from 3143 up to 9780, *the number of people involved grows almost thirty time*s from 247 up to 7344, and *the number of links grows 1252 times from 2519 up to 3.154 million.* It is also extremely interesting that, while in EASIN only 31% of links are in the main component, here that share grows up to 98%. Though the size of the main component

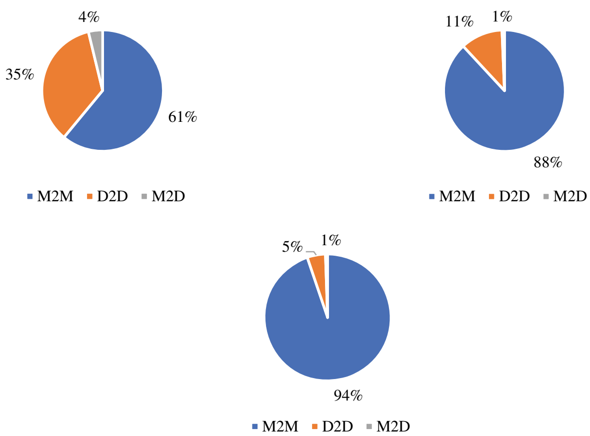


Fig. 3.10 **a**–**c** Distribution of weighted links between the three variants of networks in EASIN (**a**), EASIN + NEIGH (**b**) and the main component of EASIN + NEIGH (**c**)

increases 77 times respect to the EASIN network, the growth of its binary and even more, weighted links is incomparable. This fact shows a clear phase transition in the density of the whole network and even more accentuated, of its main component (Fig. 3.11).

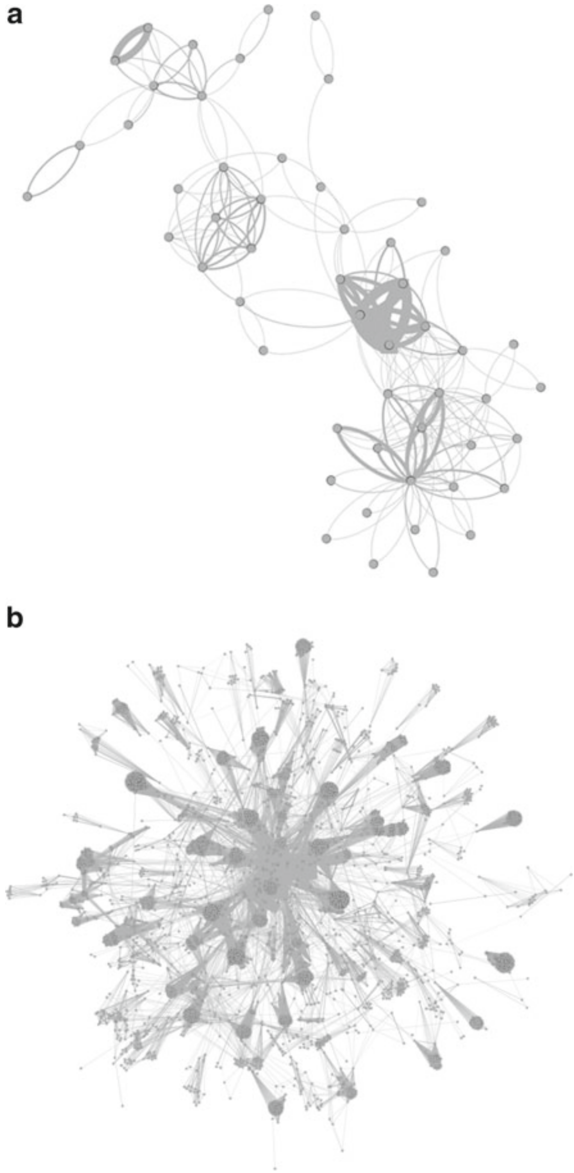


Fig. 3.11 **a**, **b** Main components of EASIN (**a**) and EASIN + NEIGH (**b**)

Coordination capacity/propensity. We can now combine the most important data regarding companies and their links from a sectoral perspective (Table 3.5a). Here, we see that Interestingly, such propensity is more than double of that occurring in the Wholesale sector, more than three times than in the Financial sector, about five times more than in the Professional Activities sector, and more than ten times of what concerns EASIN companies. Even more interestingly, if we consider only cross-sectoral coordination, that is external links, such a huge difference dramatically reduces and the ranking changes too: among the early sectors (including EASINT), the highest propensity to coordinate is related to Wholesale companies (31 links per company), followed by the Financial companies (19 links), and the Manufacturing and Professional Activities companies, both about 14 links. Even in this sense, EASIN comes last with about 8 links per company. Actually, what makes the true difference is the extremely high propensity (83 links per company) of Manufacturing companies to address coordination among themselves instead that toward other sectors.

If we shift from binary to weighted links, that is considering also the intensity of coordination efforts, then we see that (Table 3.5b), though the primacy remains with the Manufacturing sector, the sectoral ranking and quantities change dramatically and show remarkable surprises. So, the data on average coordination efforts, meaning with these words that we take into account also the intensity of coordination, that is, the number of different positions holding between each pair of companies, provides a set of very important information. The first one concerns the *astonishing average number of links per Manufacturing company (1244), which characterizes only Manufacturing sector's internal links, because when links refer to cross-sectoral relationships, then the number dramatically lowers to 15 per company.* The second point is that EASINT holds no more the second position in ranking, because it falls onto the 14th position in terms of total number of links (and even worse in terms of average number of internal links per company). The third point is that the second position is covered by the ICT (J) sector, followed by the Wholesale (G) sector, while Financial (K) and the Professional Activities (M) sectors fall to the sixth and tenth position, respectively. The fourth point to underline is that, while the coefficient of variation of the average number of external links is pretty normal (0.53), that of internal and total links are very abnormal (3.24 and 2.35, respectively), mostly due to the extremely high level of average internal links of the Manufacturing sector, followed by the high level of the ICT and Wholesale sectors.

A first implication of this data is that companies of the Manufacturing sector, which has the primary importance in terms of number of companies (27%) and number of links (88%), have an extremely high reciprocal coordination, which lowers a bit less than the average of other sectors when coordination concerns inter-sectoral relationships. Now, because we have seen (Fig. 3.6) that 59% of those companies are American and 11% British, then we know that, *despite Anglo-American companies are very important in terms of presence within the strategic and operative coordination efforts involved by EASIN, its effective influence is much lower and aligned with that of other countries and other sectors.* There are three more consequences to stress right now: the first one is that, because out-going and in-coming edges are very near, the previous statement holds even for the influence that EASIN can exert on

Table 3.5a Companies' binary propensity to coordinate by sectors

Sectors	Countries	Companies	# of (binary) links per company		
			Internal links	External in-coming	Total links
C	45	2158	82.53	14.44	97.69
EASINT	28	1402	0.82	7.87	8.69
M	38	708	2.57	14.52	17.09
K	35	644	13.28	18.87	32.14
G	40	470	9.92	31.04	41.12
N	29	393	6.30	17.32	23.62
J	31	363	14.02	13.09	27.11
L	28	351	2.53	11.93	15.09
H	29	242	7.67	19.29	26.96
F	27	169	2.85	17.17	20.05
S	19	100	0.45	13.29	13.74
A	14	64	4.44	16.06	21.00
D	12	64	2.00	11.30	13.48
I	17	63	1.59	17.21	19.11
P	16	63	0.63	10.08	10.71
R	12	49	0.16	15.94	16.10
Q	12	32	0.31	15.72	16.03
B	8	18	1.22	23.94	25.17
E	8	17	0.12	12.47	12.59
T	1	10	0.00	40.30	40.30
O	5	9	0.22	42.78	43.22
U	2	2	0.00	5.00	9.00
No data	39	648[a]			
Total	61	8039			

Legend [a]For 648 companies, we lack the sector classification. Such companies are split over 39 countries

the Anglo-American Manufacturing companies. The second consequence concerns the relevance that the presence of this huge amount of coordination efforts Anglo-American Manufacturing companies has for the analyzes of the extended network (E+N) that we will run in this book: they will appear very important in most statistical and topological findings. It should be remembered though, that because of its extremely high propensity to self-referential coordination (which will be confirmed in next chapter by looking at its very high degree of closure), its effective influence on and from EASIN and other sectors/countries is much lower, though of primary relevance, of course. The third consequence is strictly structural: the way in which such a self-reference occurs is through the formation of cliques or quasi-cliques, which in fact will be found in large quantity and in very big size.

Table 3.5b Companies' weighted propensity to coordinate by sectors

Sectors	Countries	Companies	# of (weighted) links per company		
			Internal links	External out-going	Total links
C	45	2158	1207.13	15.17	1244.16
J	31	363	193.13	11.31	214.97
G	40	470	143.02	31.20	193.07
B	8	18	17.67	23.00	123.39
H	29	242	74.11	19.09	110.68
K	35	644	59.59	18.84	100.46
O	5	9	0.22	43.00	63.00
T	1	10	0.00	40.20	44.70
N	29	393	13.96	16.77	39.64
M	38	708	5.31	14.20	30.38
F	27	169	5.05	17.20	29.60
I	17	63	3.27	17.52	29.46
A	14	64	7.72	16.56	28.84
EASINT	28	1402	1.80	7.40	25.61
Q	12	32	0.63	15.63	23.78
L	28	351	3.55	12.56	21.08
D	12	64	4.27	11.48	20.23
E	8	17	0.24	12.47	19.59
R	12	49	0.20	15.78	19.55
S	19	100	0.92	12.83	17.57
P	16	63	1.24	9.24	15.21
U	2	2	0.00	9.00	11.50

The second main implication is *the existence of a high sectoral variety of the propensity to coordinate, especially in terms of self-coordination*: in fact, the early three sectors in terms of total links have also distinctively the highest degree of self-coordination (Table 3.5b). Even the Financial sector has a considerable propensity to coordinate (100 links per company), mostly (60 links per company) for self-coordination, and a propensity to coordinate other sectors that is less than half of the influence received from other sectors: 19 versus 41 links per company. As we have already noticed, in BINT literature self-links are usually referred to as horizontal-relations and external links are the vertical-relations—especially in the literature on antitrust (Flath, 1992; Murphy, 1978; Petersen, 2016). However, because of the complexity of relations in our networks, we will follow Borgatti and stay with the "internal" vs. "external" distinction. In fact, not all the external links have to necessarily be vertical—this would require further investigation, i.e., of supply-chain relations—and, secondly, our networks often mix different levels of aggregation (industries, sectors, etc.), so in order to maintain integrity, we will not apply the literature's nomenclature here.

The final implication concerns *EASIN's low propensity to any type of interlock coordination*: its companies have a very low (about 2 links per company) propensity to internal coordination and a very moderate (about 8 links per company) propensity to coordinate externally others, while a three times level (24 links per company) of propensity to be coordinated externally by other sectors, which nevertheless is less than the average level (30 links per company).[10] It seems to indicate a low capacity of EASIN to strategically and operatively interact and coordinate with its neighbors. It can be interpreted as a sign of competitive weakness or a lack of the right managerial skills and resources to search for the right partners. Actually, there is a huge literature concerning the managerial skills and knowledge required to employ an effective process of partner selection and evaluation (Bouncken et al., 2017; Duisters et al., 2011), and then to design effective and stable relationships (Cooper & Gardner, 1993; Low, 1997; Mengoni et al., 2017).

We can apply the same type of analysis to countries instead of sectors. Firstly, we focus on EASIN and then on all the countries. Because here too the ranking changes significantly between binary and weighted links and because these latter are definitely more important, we comment only this latter (Table 3.6), leaving to the reader considerations concerning the binary findings, whose corresponding Tables 3.6 and 3.7 are in Data Appendix. Two of the three variables—internal and total links per company—are rather (if not very much) homogeneous, while the distribution of external links per company is a bit more heterogeneous. In any case, the NL ranks in the first place, followed by rather distant FR. Interestingly, two other important EASIN countries, DE and the UK, cover only the fifth and the sixth place, respectively, and IT only the 17th. It means that there is a very different propensity to coordinate across EASIN countries, which moreover is not so much correlated with the relevance in economic terms. This data also suggest that, though the UK is the largest EASIN country (27%) in terms of number of companies (see Fig. 3.1), due to the not particularly high propensity to coordinate within EASIN or across neighbors, Brexit could not worsen too much EASIN's degree of horizontal and vertical coordination.

When moving to the extended network and focusing on the weighted links (Table 3.7), the situation changes considerably in various directions. Firstly, all the three variables score a high variance: the coefficient of variation is 3.4, 3 and 2.4 for the internal, external and total links per company, respectively. As it happens for the sectoral dimension, this is due mostly to the American companies, which score an astonishing 1718 average number of total links per company, perfectly consistent with the 1244 average number total links per Manufacturing company, where American companies have 59% share. However, and this is the second novelty, there is another out-layer, which is not the UK as one could expect: it is CA (Canada), which with its 1130 average number of total links per company is the second country

[10] We provide here additional information that cannot be extracted by the reader himself from the attached tables.

Table 3.6 Companies' weighted propensity to coordinate by EASIN countries

Countries	# of companies	# of (weighted) links per company		
		Internal links	External out-going	Total links
UK	192	4.85	0.71	5.56
FR	43	4.35	4.16	8.84
DE	41	2.68	2.85	5.66
ES	67	2.84	0.48	3.31
NL	15	7.47	4.73	12.93
IT	64	1.81	0.30	2.11
BE	15	0.93	2.47	3.40
AT	5	7.20	1.60	8.80
PL	22	1.18	0.23	1.41
RO	13	1.23	0.85	2.31
PT	11	1.64	0.82	2.45
CZ	13	1.69	0.15	1.85
SE	8	1.75	0.88	2.63
MT	2	0.00	6.00	6.00
DK	5	0.40	1.20	2.20
HU	7	1.57	0.00	1.57
SI	5	0.80	1.40	2.20
LV	6	1.67	0.00	1.67
FI	3	2.67	0.33	3.00
BG	4	2.00	0.00	2.00
IE	6	0.67	0.67	1.33
EE	3	1.67	0.67	2.33
GR	1	0.00	5.00	5.00
LT	2	1.00	0.00	1.00
SK	2	1.00	0.00	1.00
Total	555	1848	671	2519

in terms of coordination capacity, and then only on the third place comes the UK, whereas the whole EASIN is only 13th. Hence, *the propensity to coordinate its own activity with other companies is far more a peculiarity of North-American companies*, but with a big difference between the two countries: while American companies are almost completely self-referential (1621 average horizontal vs. 92 vertical links per company), Canadian companies show the far higher propensity to coordinate (or be coordinated by) companies in other countries: 97 average internal versus 1030 external links per company. *EASIN has a propensity to influence other countries about one third of the mean, confirming its weak capacity to influence the strategies and operations of the international Aerospace Industry*.

Table 3.7 Average coordination (weighted) links per company by early 20 EASIN + NEIGH countries

Countries	# of companies	# of (weighted) links per company		
		Internal links	External out-going	Total links
US	1629	1621.17	91.67	1717.77
CA	105	97.06	1030.08	1129.67
UK	1244	67.58	19.67	87.25
EASINT	1402	1.80	25.38	27.18
FR	480	28.60	11.25	39.85
IE	243	50.17	13.73	63.90
IT	552	15.40	7.21	22.62
DE	377	10.11	10.86	22.40
BE	186	23.32	7.52	31.72
ES	354	8.57	4.66	13.22
NL	97	15.28	23.46	38.74
SE	81	9.22	32.07	41.30
AU	35	9.51	79.57	89.63
HK	30	40.27	57.90	98.17
PT	110	12.74	3.68	16.42
SK	59	22.97	3.15	26.92
DK	101	11.66	2.56	14.76
PL	149	5.15	4.20	9.80
CY	38	32.47	2.24	34.71
SG	21	3.33	53.86	57.19
Total	8039	2,796,793	2,796,793	3,154,738

All the shared managers and directors involved in the three types of interlock at the whole EASIN+NEIGH level sum up to 7344 individuals (Fig. 3.12). Some of them covers a unique role as shared manager for DINTs or shared director for BINTs, while others play only the hybrid manager/director role for HINTs, and finally some others are engaged into the role of shared manager and shared manager/director or shared director and shared manager/director. This is the reason why it is rather complicated to understand the picture and some of the shares do not sum up to 100%. As for the links, the distribution shares square to 100% only when considering all the positions for the whole network (Table 3.8).

Therefore, it turns better to start commenting just from the EASIN+NEIGH network (Table 3.9 in Data Appendix). Out of the 7344 coordinators, 83% (6130) are appointed in neighbor companies and the large majority (85%) are managers, while 23% are directors and 16% are hybrid. However, the managers who play only that role are 12 percentage points less and the directors who play only that role are less than half. Hence, because directors are 27% of managers, the hybrid role covers a

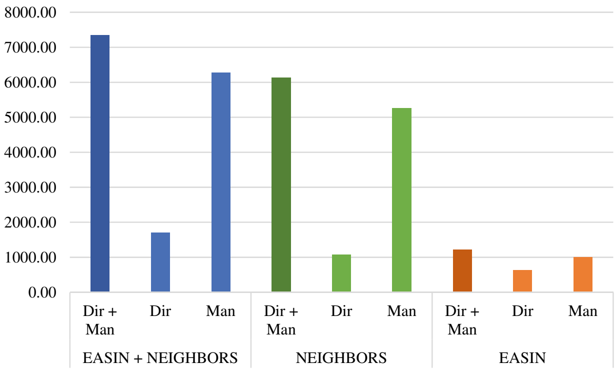


Fig. 3.12 Distribution of coordinating positions among EASIN and neighbors

Table 3.8 EASIN, EASIN Integrated, EASIN + NEIGH and neighbors

Networks		M2M	D2D	M2D	ALL
EASIN + NEIGH	Binary links	301,358	244,744	17,024	357,390
EASINT		18,670	12,272	2906	24,639
EASIN		904	600	87	1151
EASIN + NEIGH	Weighted links	2,779,408	354,364	20,966	3,154,738
EASINT		49,578	17,188	3873	70,639
EASIN		1536	888	95	2519
EASIN + NEIGH	# of companies	6975	5043	4423	8039
EASINT		1181	748	429	1402
EASIN		471	307	112	555
Networks		M2M	D2D	M2D	ALL
Neighbors	Binary links	282,688	232,472	14,118	332,751
	Weighted links	2,729,830	337,176	17,093	3,084,099
	# of companies	5794	4295	3994	6637

bigger share among the former than the latter. Actually, coordinators playing only the hybrid role are only 255. Interestingly, these compositions are very different in EASIN, where the proportion of directors is more than double than in the extended network. Because hybrid roles have a double proportion too (39 instead of 16%), strategic knowledge is proportionately more activated by EASIN than NEIGH coordinators, though it flows also between the two groups of companies, as shown with the link distribution analysis.

Quite interestingly, the 1214 coordinators appointed in EASIN companies dedicate their efforts mostly in the interlock with its neighbors: 82% if managers, 79% if directors, and 90% if hybrid. Therefore, the biggest effort of the EU28 companies was in coordinating and exchanging operative and strategic knowledge through interlocks with neighbors, mostly Anglo- and North-American companies rather than among themselves. This finding will be confirmed by the analyses of interlock topologies run in the four chapters, where it will be further shown that the Anglo- and North-American block does just the opposite: it is more self-referential than open to establish interlocks with the CONEU (Continental Europe) block.

Remarkably, almost 90 managers coordinate more than 110 operative positions each (Table 3.10 in Data Appendix), an incredible number when considering that such positions correspond as well to departments, where concrete and (supposedly) frequent decisions should be made. Conversely, when looking at directors, only 10 people seat in at least 110 boards, but there is one who is member of 256 boards and another one of 153. However, 83% of coordinators have only one or two positions, and thus, as it will be shown in the next chapter, the distribution of positions among people (coordinators) does follow a clearly heavy-tail form. Still in the next chapter, it will be explained that this polarized distribution is allowed by the existence of some huge cliques in the D2D (board interlock) and M2M (department interlock) networks.

3.4 An Integrated View of the Main Analytical Aggregates—EASIN, EASINT, Neighbors and EASIN + NEIGH

Let us sum up the main aggregates. We call EASIN the set of 3143 EU28 Aerospace Industry companies belonging in 2019 to the NACE code 30.30 in the ORBIS database provided by Bureau van Dijk. Out of them, only 555 companies are connected *one another* through one or more type of interlock. When considering interlock coordination established by EASIN companies with aerospace companies outside EU28 or with non-aerospace companies (wherever they are placed), then 6637 neighbors are selected (Table 3.8). Notice that such neighbors not only connect with the 555 companies that were coordinating when overlooking neighbors, but rather they connect also with 847 companies that in EASIN were isolated, thus bringing the count of connected companies to 1402 and the total number of EASIN + NEIGH companies to 8039. We call this aggregate as "EASIN Integrated" (EASINT), which is an "intermediate aggregate" between EASIN and EASIN + NEIGH necessary for some statistical analyses. Therefore, NEIGH companies are the large majority (83%) of all EASIN + NEIGH companies, and companies connected in EASIN are the 40% of EASINT.

If we shift from reasoning in terms of number of companies to reasoning in terms of weighted links, that is of shared positions, which measure the *intensity of the coordination effort*, the composition of the three aggregates is much more unbalanced on the side of NEIGH, which cover 98% of share, EASINT almost 2%, and EASIN an irrelevant share of 0.08% (Fig. 3.13). Therefore, it is evident that when, in the following chapters, we will analyze the EASIN + NEIGH network, we will be examining almost exclusively NEIGH. On one side, it is a very impressive fact by itself that EASINT—namely 1402 EASIN companies—activates almost 6 times more of coordination partners and 1261 times more of shared positions. On the other side, the focus on EASIN is almost completely lost in the extended networks, though we will evidence the specific role of EASIN within all the analyses. Further, we will see that *most coordination efforts are made by the US and are self-referential, that is, established among American companies themselves.*

However, to keep the focus on EASIN, and especially to take into account the effects on EASIN companies of their integration with the NEIGH, we decided to distinguish also the aggregate of EASINT. It gives a particular focus to all EASIN companies, the same ones as in the internally connected EASIN, but this time with reference to the extended network—EASINT companies are looked at more precisely through the perspective of all their existing connections—additionally including EASIN companies connected only to NEIGH.

The EASINT aggregate is necessary to run statistic-based analysis in a methodologically correct way: that is, correlations, cluster analyzes, and financial performance analyzes. Though the same set of companies, the centrality indexes of EASINT companies refer to EASIN + NEIGH network, rather than to EASIN. This necessity and its effects will be definitely clear in Chap. 8.

Noteworthy, the share of M2D links of the EASINT over the whole network is much bigger than that of the other two types of links: 17% (M2D) versus 5% (D2D), 6% (M2M), and 7% of the ALL network in terms of binary links, and 18% (M2D) versus 5% (D2D), 2% (M2M and ALL) in terms of weighted links (Table 3.8). This fact is rather interesting and contributes to distinguishing

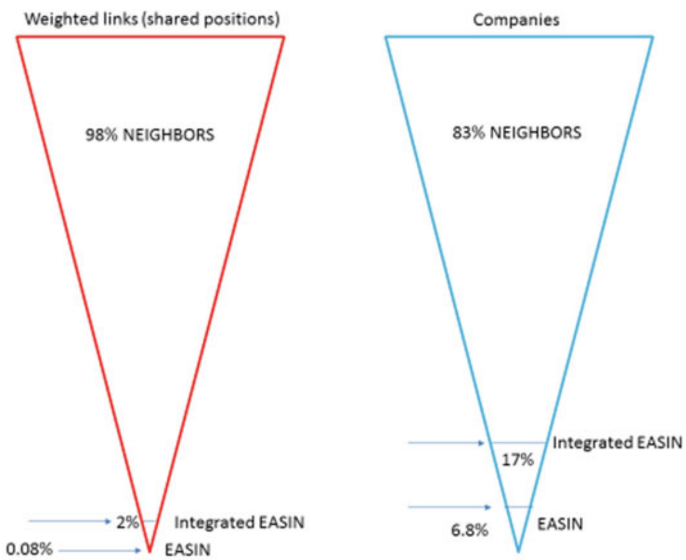


Fig. 3.13 Shares of EASIN and EASINT on EASIN + NEIGH

asymmetric coordination from the other two types of symmetric coordination forms. It means that the quasi-irrelevant quantitative influence of EASIN for the strategic or operative coordination of the global network becomes much more relevant when dealing with asymmetric coordination. Conversely, its share is lower (10 vs. 17%) than in the other two types of coordination when considering the number of companies. This means that *EASIN companies which coordinate with NEIGH through asymmetric coordinations have a much higher propensity/capacity to establish those relationships*. It means also that the EASIN companies that build interlocks only with neighbors are the gatekeepers through which EASIN's strategic knowledge is taken by neighbors in exchange of operative knowledge. As we will show in Chap. 7, when zooming on the M2D network, *the relative major relevance of asymmetric interlock sees EASIN companies mostly in the role of exploited instead of exploiting part*.

3.5 Summary

The EU28 Aerospace Industry network (EASIN) is a huge and very important industry for the technological development, the economic and defense matters in the whole European Union, as witnessed by its more than 894,000 employees (according to our data[11]) distributed over 3143 companies. It is an economically and geographically concentrated industry: the early four companies have 49% of production share and 27% of companies reside in UK. The profitability of its (very few) listed companies is aligned to that of the same type of companies in the EU28, while it declines considerably moving to non-listed but anyway largest companies, and finally drops down when considering all companies.

The number of companies (6637) and the combined values of their economic attributes makes the set of neighbors much larger, powerful and enormously more interconnected than EASIN. Companies are very unevenly distributed across sectors and countries, with a strong prevalence of the Manufacturing sector (2158 companies) and the US country (1629 companies), two sets that are highly overlapped (1266 companies).

EASIN and its neighbors companies do coordinate their behavior through three types of relationships: DINT, which refers to the inter-department coordination through shared managers; BINT, which is the strategic inter-board links, known generally as interlocking directorates; HINT, which is a hybrid inter-firm relationship, hybrid in the sense that who is manager in a company is a board member in another one. Each type of coordination generates a corresponding network, and because two companies can have more than one type of link, a fourth network results from the merge of all the three types.

[11] To explain differences in numbers compared to the EU Commission, please consider the differences in interpreting what an Aerospace Industry actually is and its definition and fact that apparently our study got a broader definition of it.

The share of EASIN companies that use people coordination only with the non-EASIN companies is higher than those which use it also among themselves. In both EASIN and EASIN + NEIGH, the large majority of companies is involved with M2M (DINT) shared positions, then D2D (BINT), and more residually in M2D (HINT). The EASIN network is coordinated through the significant number of 2519 shared positions, most of which (61%) are made by managerial, 35% by directorial, and the remaining 4% by hybrid (M2D) positions. The network extended to neighbors is coordinated by the astronomic number of 3.154 million links, which are made by managerial in the large majority (88%), 11% by directorial and only 1% by the hybrid positions.

Companies have a very different capacity/propensity to coordinate their own activities, either in sectoral or geographical dimension: the 2158 Manufacturing companies have the astonishing average number of 1244 partners per each one, which are almost exclusively oriented toward other Manufacturing companies. Now, because we know that they are mostly Anglo-American, then it comes that, despite such companies are very important in terms of presence within the strategic and operative coordination efforts involved by EASIN, EASIN's effective influence is much lower and aligned with that of other countries and other sectors. On its own, EASIN shows a low propensity to any type of coordination, which can be interpreted as a sign of competitive weakness or a lack of the right managerial skills and resources to search for the right partners. The number of companies connected in the EASIN network compose only about 7% of the whole extended network, whereas after including those connected also with neighbors their share grows to 17%. Thus, there are many more companies connected with neighbors, then those who connected only with other EASIN companies.

In terms of countries, the propensity to coordinate its own activity with other companies is far more a peculiarity of North-American companies, while EASIN companies are much below the average capacity.

In the extended network, 7344 individuals (6272 managers and 1710 directors) are employed directly into presented coordination forms, mostly (83%) among neighbors. The positions among coordinators are another clear example of uneven distribution of inter-firm coordination: 90 managers coordinate more than 110 operative positions each. Inter-board positions are less polarized, because only 10 people seat in at least 110 boards, but anyway one director is member of 256 boards and another one of 153.

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Chapter 4
Network Analysis of the ALL (Merged) Network

4.1 Network Outline

EASIN. As we have seen already in the previous chapter, out of the 3143 companies, only 18% (555 companies) have some kind of people coordination relationship (PCR) among themselves. Now, we deepen the network analysis of the EASIN and its main component (MC), which indeed is very small (about 10%), respect to the typical structure of socio-economic networks, where it is supposed to include usually more than 50% of nodes. Normalized density is very small (0.4%), but it grows 20 times in the main component, while absolute (binary) density, which indicates the number of connections among companies, is 1151 for the whole network and 222 for the main component (Table 4.1a). However, the weighted absolute density, which measures the intensity of coordination efforts through multiple positions occurring between each couple of companies, grows up to 2519 for the whole network and 771 in the main component. Hence, it is clear that within the main component, the inter-connections between companies are much stronger: the average number of partners (ADc) grows from 2 to 4.2 in binary terms and from 4.5 to 14.5 when considered is also the intensity of coordination.[1] This can be interpreted as a company's capacity/propensity to acquire its strategic or operative knowledge through interlock coordination, and we see that such a propensity is much higher for the companies operating into the MC, especially due (as we will see below and in next chapters) to the presence of very large cliques, that is, clusters of fully connected companies. Indeed, because 50 companies of this MC constitute a SCC (Strongly Connected Component), each of them can access—directly or indirectly—the knowledge of all others. It means that in the MC—and often also in many other components: there is a huge knowledge

[1] It is worth reminding that a position does not coincide with a person—be s/he a director or a manager—in a one-to-one relationship, because that one person could as well link many different companies. The relation is frequently one-to-many, that is, one person to many positions. This holds even more when considering weighted (multiple) relationships between companies: In these cases, the relation is many-to-many, because, let say, many managers can link many companies. See the Methodological Appendix.

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diffusion and sharing. We did not measure how much knowledge is conveyed by people (coordinators) or shared positions, so the number of links in binary versions or, better, of shared positions in weighted versions, can be held as an appreoxinate value of the knowledge flow in each network or sub-network, be it a clique, component or other type of cluster.

Direct relationships are very much uniformly distributed in the whole network, meaning that no company has a dramatic proportion of degree centrality respect to the others, and thus, no overwhelming number of interlocks. Such low centralization values hold either for who influences or who is influenced by others' coordination, as represented by the Out_Dc and the In_Dc_CE indexes, respectively. However, they become slightly concentrated in the main component: about 8% according to the most

Table 4.1a EASIN: main indexes of network analysis

Index	EASIN ^{b}	EASIN MC ^{b}	EASIN ^{w}	EASIN MC ^{w}
Size	555	53	555	53
Density (rel.)	0.004	0.081	–	–
Density (abs.)	1151	222	2,519	771
Fragmentation	0.987	0.056	0.712	0.779
Av. Link value	1	1	2.189	3.473
ADc	2.074	4.189	4.539	14.547
Out_Dc_CE (Fre)	0.027	0.251	0.04	0.041
In_Dc_CE (Fre)	0.027	0.251	0.04	0.043
Out_Dc_CE (Sni)	0.002	0.079	–	–
In_Dc_CE (Sni)	0.002	0.064	–	–
Bc_CE	0.004	0.395	0.004	0.404
RWB_CE	–	0.513	–	0.361
Out_Eig_CE	0.385	0.317	0.576	0.546
In_Eig_CE	0.370	0.296	0.579	0.546
Out_Katz_CE	0.009	0.025	0.128	0.539
In_Katz_CE	0.007	0.025	0.125	0.539
Reciprocity	0.971	0.955	0.987	0.987
Geo-reciprocity	0.951	0.942	0.948	0.945
GORC	0.081	0.343	0.001	0.335
Diameter	12	12	24	24
Apl	3.468	4.521	4.705	6.017
GCL	0.788	0.617	1.99	4.2
SW	415	3.64	–	–

appropriate index.[2] Moreover, when considering also the indirect connections and the relevance of adjacent nodes' centrality (measured by the eigenvector centralization binary), influence power of coordination grows very much, to a remarkable 39% in the whole network, lowering a bit in the main component, meaning that inside it partners' distribution is less unbalanced. This is due to long coordination chains that extend to 12 steps (diameter) and have an average of 3.5 (4.5 in the MC), as witnessed by the average distance (Apl). Further, when considering its intensity, centralization grows to a considerable 58%,[3] meaning that the coordination efforts are rather concentrated in the hands of few companies.[4]

Nearly, the same occurs in terms of intermediating influence power (Bc and RWB centralization indexes): while it is irrelevant in the whole network, it becomes very relevant (about 40%) in the MC—in both binary and weighted terms. It means that the highest access to knowledge and influence power occurs in companies placed in the middle of many coordination chains, whose length and width is rather uniform, because the whole network is homogeneous under this respect—GORC is 0.061. However, when looking at the MC, it becomes rather heterogeneous (GORC 0.384), and the same proportion holds in the weighted version.

EASIN is definitely non-hierarchical, because most direct and indirect relationships are reciprocal or circular: these measures are expressed by arc- and geo-reciprocity values (see the Methodological Appendix). Despite non-hierarchical structure, the whole network is extremely fragmented, because it is divided into 188 components (see Sect. 4.3 on components analysis), whose large majority is made of dyads. In fact, when considering only the main component, the fragmentation index drops down to 5.6%. Accordingly, the diameter is determined by the structure of the main component, which is 12 in binary terms and 24 in weighted terms: it means that from a source of an influencing company that appoints some its persons to some other company to the least influenced company of the longest path—made by 12 companies—potentially 24 positions are involved.

Considered the moderate size of the whole network, average distance is pretty high (3.5) and it becomes very high (4.5) in the small main component. The global clustering index (GCL) is very high—0.79 and 0.62, respectively—and the small-world index (SW) of the whole network is rather high (415). It means something very important: *the strategic and operative knowledge created and transferred through the various coordination efforts are spread rather easily and extensively across the EASIN's 555 inter-connected companies*. Conversely, in the MC, it is concentrated around few companies, and because seven of the companies with outstanding length of coordination chains (LORC index in Data Appendix) are composed in 83% by

[2] We refer to the Snijders' centralization index, which is much more appropriate than the Freeman's index when networks are large and multi-centered, as this and the E+N ones. For more in depth, see the Methodological Appendix.

[3] The Katz centralization index is, especially in the binary version, much lower, because it takes into account a reduction of power due to the length of coordination chains. This fact should lead us to give a more attenuate evaluation of the eigenvector index.

[4] The same degree for out- and in-edge is due to the fact that 99% of links are symmetric, because they are DINT and BINT.

the Airbus group and come mostly from Spain, France and the UK, not surprisingly that group seems to be the most influential and able to access strategic and operative knowledge through interlock coordination.

EASIN + *NEIGH*. When extending the network to the 6637 neighbors (Table 4.1b), the size of connected companies grows from 555 to 8039, a growth that is accompanied by a number of phase transition effects, one of which concerns the (MC) size, which grows much more than the whole network—77 versus 14 times. The number of binary links reaches the really enormous level of 357,390 connections, mostly (89%) occurring within the MC: hence, there is a phase transition also in absolute density, which grows 44 versus 78 times, respectively. Even more remarkably, weighted density reaches the astronomic level of 3.155 million of shared positions, which reside almost all (98%) within the MC. As we have seen in the previous chapter, this is realized by 7344 individuals, out of whom 1710 are directors, and 6272 are executives/managers. Here, too, another phase transition occurs, because they grow 87 and 50 times respect to EASIN.

The presence of neighbors brings the average link value to 8.8 and 9.7, for the whole and the MC network, respectively, which means that *each coordination relationship involves on average almost 10 different positions, mostly made by shared managers*, because we know that DINTs are 88% of all connections. In the whole E+N network, each company has an average capacity/propensity to establish a coordination relationship with 44 other companies, a number that grows to 78 in the MC. What is even more astonishing is that, if we consider each coordination effort, in the whole network, each company employs on average 392 shared positions, which almost doubles to 760 in the MC.

In the whole network, centralization is rather low in any of its forms: binary and weighted, direct and indirect. With the exception of both forms of betweenness centralization (the geodesic and the non-geodesic), which in the MC score the considerable level of 19 and 27%, centralization is very low even in the MC. It means that *no one company or a group of companies can strongly and exclusively influence or be influenced by the interlock coordination of others, but there still are few of them that can indeed access and transfer strategic and operative knowledge quite better than others.* Actually, it should be considered that, in so large networks, even very small fractions of centrality or centralization indicate a large gap in the connectivity between the few highly and the most lowly connected points. Therefore, the 6% of Eigenvector centralization is remarkable, though it is due to the high length and connectivity of coordination chains of some leader companies. In fact, Katz centralization, which attenuates that effect, is irrelevant in the binary network and a bit lower in the weighted, meaning that the chains of leader companies occurs with higher strength.

Reciprocity is nearly full in all the variants (whole and MC, binary and weighted), and therefore, knowledge is shared between almost all peers of companies. However, due to high fragmentation and long average distance, it remains entrapped into clusters and plenty of disconnected components, as we will show in Sect. 4.3. In fact, in major part, the fragmentation is due to the high number of components: 844, where

Table 4.1b EASIN + NEIGH: main indexes of network analysis

Index	EASIN + NEIGH [b]	EASIN + NEIGH MC [b]	EASIN + NEIGH [w]	EASIN + NEIGH MC [w]
Size	8039	4078	8039	4078
Density (rel.)	0.006	0.019	–	–
Density (abs.)	357,390	319,228	3,154,738	3,103,018
Fragmentation	0.751	0.037^	0.768	0.769^
Av. Link value	1	1	8.827	9.720
ADc	44	78	392	760
Out_Dc_CE (Fre)	0.034	0.059	0.002	0.004
In_Dc_CE (Fre)	0.033	0.058	0.002	0.004
Out_Dc_CE (Sni)	0.015	0.034	–	–
In_Dc_CE (Sni)	0.015	0.034	–	–
Bc_CE	0.053	0.207	0.042	0.164
RWB_CE	–	0.187	–	0.266
Out_Eig_CE	0.061	0.059	0.062	0.060
In_Eig_CE	0.061	0.059	0.062	0.060
Out_Katz_CE	0.001	0.001	0.053	0.053
In_Katz_CE	0.001	0.001	0.053	0.053
Reciprocity	0.977	0.980	0.997	0.998
Geo-reciprocity	0.038	0.037	0.051	0.051
GORC	0.260	0.384	0.000	0.156
Diameter	16		–	-
Apl	4.313	4.322	–	–
GCL	0.919	0.899	–	–
SW	45	12	–	–

Legend b = binary links; MC = main component; w = weighted links; ADc = average degree centrality; In_ or Out_Dc_CE = degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; In_ or Out_Eig_CE = eigenvector centralization; In_ or Out_Katz_CE = Katz centralization; Geo-reciprocity = arc reciprocity in the geodesic matrix; GORC = centralization of the Out_reaching capacity; Apl = Average path length; GCL = global clustering coefficient; SW = Small-World index. Weighted diameter, Apl and GCL were not calculated due to technical reasons; ^ = distance weighted fragmentation

within them enclosed are 869 strongly connected components (SCCs).[5] Average distance is aligned with that of EASIN, while the diameter is a little bit longer (16), and it contributes to a significant GORC centralization in the binary version (0.16). There are indeed few large out-components, meaning that some huge strategic alliances extend their influence across the whole network and, even more, in the MC.

[5] As we will see, so many SCCs (out of which some very big) are due to the existence of some huge cliques in the M2M and D2D networks.

Global clustering is extremely high, meaning that this form of strategic alliance through shared people is very much clustered into groups of companies, which can be properly called strategic groups. However, since average distance is considerably high even within the main component, the whole network has a rather low SW structure. Put differently, *despite the high number of people involved and the enormous number of links that their coordination does generate, strategic knowledge is not frequently transferred between different clusters*. This conclusion seems very reasonable with the idea that, in a high-tech industry like this, knowledge creation, accessibility and transfer are fundamental issues for development of the industry, but at the same time, at the level of single companies or strategic groups, knowledge appropriability and exclusivity are even more important competitiveness factors. Therefore, we argue that, especially as concerning strategic knowledge, it is very reasonable that the SW index is low.

4.2 Correlation Analysis

From the point of view of social network analysis, being central is considered a competitive advantage that can be acquired only by economically competitive companies, which often (but not necessarily) are large companies, because they can exploit scale economies and market power. Actually, we have seen in the previous chapter that EASIN is an extremely concentrated market, and thus, it is reasonable to expect a confirmation of the association between economic size attributes and centrality indexes. Therefore, we have checked whether such a correlation holds for EASIN Integrated[6](EASINT), and then also for EASIN + NEIGH and its MC. Then, we checked also for more focused correlations, restricted to the most important sectors or to top200 companies.

EASIN Integrated. In this network,[7] there is a significantly high positive (0.62 in average) correlation between weighted In_ and Out_Dc with all the four economic size attributes (Table 4.2)[8] and particularly with EC (0.67 in both cases). Because also binary In_ and Out_Dc have an average positive correlation of 0.47 with all the four attributes, we can affirm that, in the ALL EASIN Integrated network, the largest are also the highest connected companies. In Chap. 7, in which we will test seven different hypotheses, we will summarize the results all the correlations of this type—between centrality indexes and size attributes—in each network (EASIN, EASINT, E+N) of each type of interlock. We will call it Size Proportional Connectivity Hypothesis (SPCH), according to which (at least some of) the degree of connectivity varies

[6] We remind, that EASIN Integrated means indexes of EASIN companies with reference to E+N network indexes.

[7] We have tested the same correlations also for EASIN, and there was no any significant change in any of the cases; they were in almost all cases a bit smaller.

[8] *P*-values and percent of complete observations are in Table 4.1a in Data Appendix.

Table 4.2 Correlations in EASIN Integrated

	EC	EM	TURN	TASS	Average
LORC	−0.03	−0.01	−0.03	−0.01	–
BIDc	0.48**	0.42**	0.51**	0.45**	0.47
BODc	0.49**	0.44**	0.53**	0.47**	
WIDc	0.67**	0.58**	0.63**	0.58**	0.62
WODc	0.67**	0.55**	0.65**	0.58**	
BBc	0.33**	0.27**	0.21**	0.21**	0.28
WBc	0.39**	0.24**	0.32**	0.27**	
BRc	0.01	0.02	−0.01	0.01	–

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

proportionally with (some of the) company size attribute.[9] There is also an average moderate positive correlation (0.28) between binary and weighted Bc on one side and the four attributes on the other. It confirms that, despite the extremely high fragmentation, in the ALL EASIN network, the largest companies have also a significant intermediating power, and it is mostly residing in large companies. Conversely, bridging centrality (BRc) and local out-reaching capacity (LORC) are uncorrelated with any size attributes.

EASIN + NEIGH MC and EASIN + NEIGH. When looking at the MC of the E+N network (Table 4.3, *P*-values and percent of complete observations are in Table 4.1c in Data Appendix), which has a very high size, we see that there is a small but not irrelevant average positive correlation between binary (0.18) and weighted (0.15) In_ and Out_Dc with all the four size attributes, so that, to some extent, even in ALL E+N MC, the largest companies are also the most connected. In this network, the positive correlation between binary and weighted Bc and the four size attributes grows to 0.34, and thus, the largest companies have also a significant intermediating power. That growth is due to the enormous expansion of network size respect to EASIN, which gives to intermediating companies much more power, even thanks to the extremely low fragmentation. Conversely, bridging centrality (BRc) and local out-reaching capacity (LORC) stay still uncorrelated with any size attributes. The same values and comments hold for the E+N network too (Table 4.4, *P*-values and percent of complete observations are in Table 4.1d in Data Appendix).

Neighbors sectoral correlations. If the previous correlation coefficients were considered too small, one could suppose that it depends on the high degree of diversification of large companies, especially by the significant presence of non-manufacturing companies, namely from the Wholesale and financial sectors. The rationale is that the real degree centrality of manufacturing companies is much higher, but to get it, we had to run sectoral correlations. Because the same reasoning could be applied in terms of single industries, we calculated correlations restricting the

[9] In Chap. 7, to test the SPCH, we will integrate the results of these correlations with other analyzes.

Table 4.3 Correlations in EASIN + NEIGH MC

	EC	EM	TURN	TASS	Average
LORC	−0.01	0.01	0.00	0.00	–
BIDc	0.14**	0.22**	0.20**	0.16**	0.18
BODc	0.14**	0.23**	0.21**	0.17**	
WIDc	0.12**	0.18**	0.15**	0.17**	0.15
WODc	0.12**	0.17**	0.15**	0.17**	
BBc	0.17**	0.46**	0.32**	0.38**	0.34
WBc	0.21**	0.46**	0.33**	0.40**	
BRc	0.01	0.01	0.00	0.02	–

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 4.4 Correlations in EASIN + NEIGH

	EC	EM	TURN	TASS	Average
LORC	−0.02	0.01	−0.03	−0.01	–
BIDc	0.15**	0.24**	0.19**	0.12**	0.19
BODc	0.16**	0.25**	0.21**	0.16**	
WIDc	0.14**	0.20**	0.17**	0.13**	0.16
WODc	0.14**	0.19**	0.17**	0.14**	
BBc	0.17**	0.46**	0.32**	0.29**	0.31
WBc	0.17**	0.46**	0.32**	0.29**	
BRc	0.02	0.03	0.02	0.03	–

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

analysis to only the Aerospace Industry. In all these cases, therefore, only neighbors have been considered.

Our hypothesis revealed true, because *coefficients about doubled for all Dc and Bc indexes when correlations are restricted to the Manufacturing sector* (Table 4.5). Conversely, no improvements are recorded if the reference sector is the Financial or the Professional Activities (see Table 4.5a and b in Data Appendix), meaning that what matters is the technological (or knowledge) closeness (similarity) to the Aerospace Industry and/or its internal degree of industrial homogeneity. As a further confirmation of our hypothesis, correlations with the Aerospace Industry (Tables 4.3 and 4.6 in Data Appendix) much more than double with respect to those of E+N, which include all the sectors.

Top 200. Correlations of top 200 companies are very much aligned to those of all companies (see Table 4.4 in Data Appendix). Being very much correlated to one another, whatever the attribute chosen as the ordering criterion, results are very similar. Interestingly, this closeness occurs also when the chosen criterion is bridging centrality, for which anyway the value of correlation is around zero. This correlations

Table 4.5 Correlations limited to the Manufacturing (C) sector

	EC	EM	TURN	TASS	Average
LORC	−0.03	0.01	−0.03	−0.01	–
BIDc	0.28**	0.38**	0.31**	0.37**	0.34
BODc	0.28**	0.38**	0.31**	0.38**	
WIDc	0.21**	0.28**	0.22**	0.33**	0.26
WODc	0.21**	0.27**	0.21**	0.33**	
BBc	0.25**	0.67**	0.42**	0.62**	0.51
WBc	0.32**	0.69**	0.43**	0.64**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 4.6 Correlations limited to the Aerospace Industry (NACE:3030)

	EC	EM	TURN	TASS	Average
LORC	0.01	−0.01	−0.02	0.01	–
BIDc	0.39**	0.40**	0.46**	0.45**	0.44
BODc	0.40**	0.42**	0.47**	0.47**	
WIDc	0.45**	0.38**	0.42**	0.54**	0.47
WODc	0.46**	0.38**	0.42**	0.56**	
BBc	0.32**	0.80**	0.73**	0.79**	0.62
WBc	0.42**	0.81**	0.75**	0.83**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

similarity across the ordering criterion of top 200 companies holds for all the three variants (EASIN, EASIN + NEIGH MC, EASIN + NEIGH) of the ALL network. We have supposed that it depends on the fact that most missing data, which (see the first section in Methodological Appendix) concern only the four economic attributes (EM, TURN, EC, TASS) and occur mostly for lowly connected companies. Because the acknowledgment of this aspect matters also for many other explanations of the features of our networks, we have deepened this point.

Analysis of companies with missing attributes and small companies. The analysis of missing data on economic attributes is synthesized in Tables 4.7, 4.8 and 4.9, which show that *companies with missing data are placed in definitely peripheral positions in the network*: Dc, Bc and BRc are irrelevant. Further, we underline that: (i) 68% of all companies with missing attributive data (equal to about 31% of all companies at all) belong to the Manufacturing sector; (ii) further, 1784 companies (71% of them) belong to the Aerospace Industry; (iii) 1590 companies are in the USA, followed by 476 of the UK companies, and both of them to a large extent belong exactly to the Aerospace Industry. This information should be also considered in any analysis, f.e., that Manufacturing sector has potential for larger economic size, etc.

Table 4.7 Number and share of companies with missing values across main sectors

Sector	# of companies	Share (%)	WODc	WTDc	BBc	BRc
C	2498	68	0.0008	0.0016	0.0001	0.0001
G	208	6	0.0002	0.0004	0.0001	0.0001
K	202	5	0.0001	0.0002	0.0001	0.0001
J	155	4	0.0002	0.0005	0.0001	0.0001
M	151	4	0.0000	0.0000	0.0001	0.0001
H	106	3	0.0001	0.0002	0.0001	0.0001
N	98	3	0.0000	0.0000	0.0001	0.0001
L	62	2	0.0000	0.0000	0.0000	0.0000
S	57	2	0.0000	0.0000	0.0007	0.0007
F	46	1	0.0000	0.0000	0.0002	0.0002
P	23	1	0.0000	0.0000	0.0004	0.0004

Legend Network indexes presented as averages. B = binary; W = weighted; O = out-; T = total; Dc = degree centrality; Bc = betweenness centrality; BRc = bridging centrality. Sectors symbols explained in the list of abbreviations

Table 4.8 Number and share of companies with missing values across main industries

NACE	# of companies	Share (%)	WODc	WTDc	BBc	BRc
3030	1784	48	0.0005	0.0010	0.0001	0.0000
2651	317	9	0.0020	0.0039	0.0001	0.0000
2892	140	4	0.0014	0.0027	0.0000	0.0000
6420	115	3	0.0001	0.0003	0.0001	0.0000
6201	85	2	0.0004	0.0008	0.0001	0.0000
4671	55	1	0.0006	0.0011	0.0001	0.0000

Legend Network indexes presented as averages. B = binary; W = weighted; O = out-; T = total; Dc = degree centrality; Bc = betweenness centrality; BRc = bridging centrality

4.3 Components and Cliques

As discussed above, the extremely high fragmentation evidenced in Table 4.1b is due mostly to the relatively high number of disconnected components (Table 4.11), which rounds between 7 and 12% in the extended versions and more than triples in EASIN. Therefore, it means that, *even considering together all the three forms (BINT, DINT, HINT) of relationships, that is, at the highest degree of its integration in a single multi-layer network, coordination is established within a huge number of separate groups that, likely, correspond to either strategic, operative or hierarchical groups of coordination.* Within this ocean of independent groups, there are few very large components, where coordination occurs among hundreds or even thousands of companies. Actually, in most networks, components are distributed according to a

Table 4.9 Number and share of companies with missing values across main countries

Country	# of companies	Share (%)	WODc	WTDc	BBc	BRc
US	1590	39	0.0009	0.0018	0.0002	0.0000
UK	476	12	0.0000	0.0001	0.0000	0.0000
DE	387	9	0.0000	0.0000	0.0001	0.0000
ES	212	5	0.0000	0.0000	0.0000	0.0000
FR	159	4	0.0000	0.0000	0.0000	0.0000
IT	137	3	0.0000	0.0000	0.0000	0.0000
PL	133	3	0.0000	0.0000	0.0000	0.0000
BE	126	3	0.0000	0.0000	0.0004	0.0000
CA	93	2	0.0006	0.0012	0.0001	0.0000
CZ	87	2	0.0000	0.0000	0.0000	0.0000
IE	80	2	0.0000	0.0001	0.0001	0.0000
NL	65	2	0.0000	0.0000	0.0000	0.0000
CH	49	1	0.0000	0.0000	0.0001	0.0000

Legend Network indexes presented as averages. B = binary; W = weighted; O = out-; T = total; Dc = degree centrality; Bc = betweenness centrality; BRc = bridging centrality. Country symbols according to the official EU Commission glossary

heavy-tail structure (Sect. 4.9). In fact, between 32 and 43% of all components are made of dyads, a percentage that grows up from 57 to 74% when considering only EASIN.

The extended versions of each network—ALL, M2M, D2D and M2D—record a share of companies in the main component much bigger than EASIN networks, because the inclusion of neighbors produces always a phase transition effect on

Table 4.10 Overview on distribution of components

Network		Network size	# of components	Share of components (%)	MC # of companies	Share of the MC (%)	# of dyads	Share of dyads on total (%)
ALL	E+N	8039	844	10	4,078	51	341	40
	EASIN	555	188	34	53	10	133	71
D2D	E+N	5043	624	12	770	15	244	39
	EASIN	307	116	38	12	4	80	69
M2M	E+N	6975	823	12	3238	46	352	43
	EASIN	473	171	36	27	6	127	74
M2D	E+N	4414	328	7	1641	37	105	32
	EASIN	112	37	33	10	9	21	57

density and connectivity growth. Interestingly, *by far the largest share (46%) occurs in DINT, meaning that the need of operative coordination due to technological aspects generates a positive network externality in creating and transferring codes and standards through shared managers among technological departments.* Conversely, the network with the lowest relative (and also absolute) size of the main component (15%) is D2D, likely because sharing strategic knowledge cannot be too much extended.

We can advance a hypothesis relating these findings with the diffused idea that one of the main traits of social—and especially knowledge—networks is a proportion of nodes in the main component higher than 50%. It could be argued that it depends on the degree of relevance of that knowledge: if it was very high, then social actors could prefer to keep it more restrictive, thus limiting the size of the main component and at the same time fragmenting it in small groups (disconnected components). At least, this hypothesis could explain what happens in our networks, where operative knowledge (0.46) is much more shared than hierarchical (hybrid) knowledge (0.37) and even more, than pure strategic knowledge (0.15). When considering only EASIN companies, such shares reduce considerably, though the differences between D2D and the other two types of knowledge remain very high, thus confirming our hypothesis.

Table 4.10 shows that, in the extended networks, the relative majority of components are dyads, a share that grows to the absolute majority (0.57) for M2D, and to the large majority for M2M, ALL and D2D (0.74, 0.71 and 0.69, respectively). This fragmentation in dyads and the simultaneous considerable size of the main component suggests right now that components size follows a non-linear distribution. This hypothesis is confirmed in the section concerning the heavy-tail structure of all the four networks, at least for their extended versions. The way how components from EASIN network transfer into E+N network (Table 4.11) shows in all cases the importance of the main component, where most of the main companies end up. The second largest component, except for D2D, is made up of only few EASIN companies, which means that strategically companies can isolate themselves from the world to maintain their independence, however, in order to be on par operatively they must be "belong" with the largest group and efficiently exchange state-of-the-art practices.

What characterizes the ALL network is an astonishing number of cliques in the extended network and also in its main component (Table 4.12a): 1122 weak and 852 strong cliques and 1073 weak and 860 strong cliques, respectively.[10] When considering only EASIN, these numbers crash down to 79 and 72, respectively. However, their share on the network size keeps constant in the extended and only EASIN networks: 14 and 11 for the weak and strong cliques, respectively. Such shares almost double when considering the main component of the extended version and

[10] Likely, these numbers are dramatically underestimated, due to the fact that in those cases the software Ucinet could not count size-3 and size-4 cliques, basically due to the abnormal high number of size-3 cliques in the main component of the M2D extended network. It is substantially impossible to estimate the total number, which could be doubled or tripled or on the contrary, be only lowly increased due to "merging effects" between M2D size-3 cliques once that other (M2M and D2D) connections are added and combined.

Table 4.11 Companies' distribution from EASIN to EASIN + NEIGH MC and 2° largest component

Network	Type of network	EASIN nodes	E+N MC nodes	E+N 2° largest component nodes
All EASIN companies	ALL	3143	379	5
–	M2M	3143	274	0
–	D2D	3143	11	29
–	M2D	3143	76	3
EASIN MC	ALL	53	53	0
–	M2M	27	27	0
–	D2D	12	0	12
–	M2D	10	10	0
EASIN NO MC	ALL	502	206	2
–	M2M	444	158	0
–	D2D	293	4	13
–	M2D	102	28	0
EASIN isolated	ALL	2588	120	3
–	M2M	2672	89	0
–	D2D	2838	7	4
–	M2D	3031	38	3

almost disappear in the main component of the only EASIN. It means that *operative and strategic coordination through shared managers and directors occur by means of fully cohesive groups*, whose median size is supposed to be very remarkable: difficult to be calculated precisely, but certainly much bigger than 23 and 10 members in the extended network for the weak and strong cliques, respectively, dropping down to 3.8 in the only EASIN for both types.

Indeed, the average values are not really representative, because cliques are often distributed in a heavy-tail way (Sect. 4.9), as it is shown by the high coefficient of variation (Table 4.12b), and as it is deepened in the dedicated section. Here, we can underline that its distribution is polarized between an abnormal maximal size (253 companies) for both weak and strong type in the extended network and in its main component. It means that *6% of companies of the main component in the ALL network are supposed to share a substantial part of their strategic and operative knowledge*. At least, the portion conveyed by shared managers and directors. At the same time, such concentration of coordination and knowledge share into a single group is accompanied by 176 cliques of minimum size, a number that keeps still very high even into the main component: 141 and 148 for weak and strong type, respectively.

Table 4.12a Overview of cliques' distribution

Network		# of cliques		Size of max cliques		# of minimum size cliques		Average		Coefficient of variation	
		Weak	Strong	Weak	Strong	Weak	Strong	Weak	Strong	Weak	Strong
ALL	E+N	1122'^	852'^	253	253	176'	176'	23.02	10.04	1.39	1.68
	E+N MC	1073'^	860'^	253	253	141'	148'	21.68	13.2	1.45	1.91
	EASIN	79	72	7	7	44	41	3.82	3.78	0.29	0.23
D2D	E+N	492		253		153		10.58		2.07	
	E+N MC	21		253		2		43.1		1.48	
	EASIN	40		7		25		3.68		0.28	
M2M	E+N	1,197		248		322		10.52		1.84	
	E+N MC	684		248		138		12.18		2.01	
	EASIN	53		7		32		1.09		0.29	
M2D	E+N	45'^	0	6	0	>6686^	0		–	–	–
	E+N MC	6686	0	6	0	5915	0	3.11	–	0.1	–
	EASIN	4	0	3	0	4	0		–	–	–

Legend Minimum clique size is 3, but in the cases marked with it was possible to calculate only minimum size 5. The numbers marked with ^ are those mostly underestimated due to the uncounted presence of size-3 cliques

Table 4.12b Distribution of cliques in the four types of networks

Network		# of companies	Density WA	Share of cliques on network size (%)		Share of max size clique on the MC (%)	
				Weak	Strong	Weak	Strong
ALL	E+N	8039	3,154,738	14	11	6	6
	E+N MC	4078	3,103,018	26	21	6	6
	EASIN	555	2519	14	13	–	
D2D	E+N	5043	354,364	10		33	
	E+N MC	770	117,070	3		33	
	EASIN	307	888	13		–	
M2M	E+N	6975	2,779,408	17		8	
	E+N MC	3238	2,393,312	21		8	
	EASIN	473	1536	11		–	
M2D	E+N	4423	20,966	1	0	0	–
	E+N MC	1641	13,496	7	0	0	–
	EASIN	112	95	4	0	–	

Legend W = weighted; A = absolute

Besides the merged (ALL) network, the clique distribution changes considerably in its three constituents and especially in the M2D. While the analysis is deepened in the dedicated sections of the next few chapters, here, we provide a short comment, aimed at comparing them. Among the three networks, the operative coordination network (M2M) has the highest number of cliques: 1197 in EASIN + NEIGH and 684 in its main component. Even considering only EASIN, the 53 cliques are more than in the other two networks. This massive presence is confirmed also in terms of relative share (17%) on the size of the extended network. In this network, there is a very large clique of 248 companies, which is placed into the main component. Conversely, when considering only EASIN, then there are only 53 cliques, and the largest one is made of only 7 companies. In the extended network, the largest cliques coexist with a big number of minimum size cliques: 322 in the whole network and 138 in the main component. The average size is about 10 members, but with a high coefficient of variation (about 2 in the extended version and in its main component).

Now, the presence of such huge cliques generates a remarkable distortion on all centrality indexes, because they dramatically increase the connectivity of its members, even though most of them, as shown in Fig. 4.1a and b, are connected with only other members of the same clique. Therefore, some key-companies that play the role of bridges across cliques appear less central or less connected than clique members. As well, huge cliques create problems also to the discovery of statistical clusters through cluster analysis (see Sect. 4.6), because cliques are a sort of "natural clusters". These distortions occur not only in the M2M and D2D networks, but also in the ALL networks, because DINTs cover 88% of all weighted links and BINTs cover 11%.

In fact, M2D is a completely different network under all respects (see Chap. 6). Not only it is a directed network and one incomparably sparser than the other two, but in the main component of the extended network, there is an abnormal number (5915) of size-3 weak cliques, plus 771 cliques of higher size.[11] Noteworthy and reasonably, in all M2D networks, there are no strong cliques at all, because a hierarchical strong clique would be a sort of paradox or limit case. It would mean that company A controls (in a broad sense) company B that in turn controls company C that in turn controls company A, and the other way round. So, it would become non-hierarchical, because hierarchy means asymmetry, while the definition of strong clique implies symmetry. We will come back to this important point in Chap. 6.

Finally, we have completed the components and cliques analysis by checking whether there is a close relationship between them or conversely, whether a clique size is largely independent on the component size. To this aim, we have run a regression analysis, which actually shows that *such a relationship does exist and is very strong*: clique size explains 86% of components size; in the D2D it lowers a bit to 75%; and in the M2M, it perfectly explains it (99.7%).

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[11] While for the main component network of 1641 nodes, the software was able to calculate all of them, for the full extended network of 4423, it could not run the calculation. So, in the M2D extended network, we could only count 45 size ≥ 5 weak cliques, almost all of them of size-5. Of course, the 6686 size ≥ 3 cliques found in the main component keep also in the fully extended networks, because it is built by adding other 822 components.

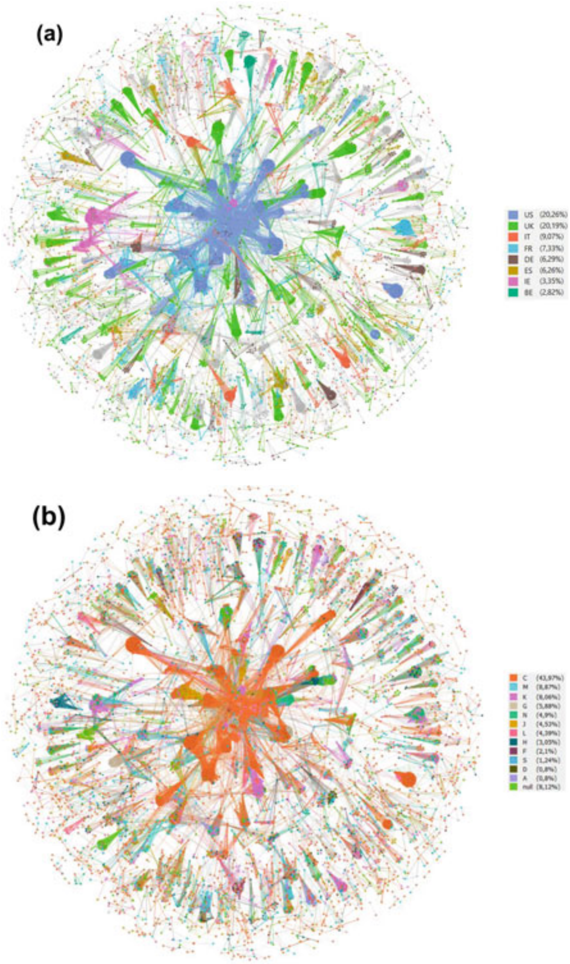


Fig. 4.1 **a** Clique structure of the ALL EASIN + NEIGH network with top 8 country evidence. *Legend* Percent values represent share of total number of companies aggregated per each country, **b** Clique structure of the ALL EASIN + NEIGH network with sectoral evidence. *Legend* Percent values represent share of total number of companies aggregated per each sector, null represents companies with no sectoral data

A visual inspection of the topology of this whole multi-layer network (Fig. 4.1)a and b provides a clear view of what has been said so far with numbers: the cliques are represented by the circular structures connected to the rest of the network with lines. The high number of large cliques is clearly visible, with its large concentration in the MC. Further, there appears evident also something that we have mentioned in Chap. 3 and that will be deepened below in this chapter: both in terms of countries and sectors, large cliques present high tendency to stick with one same country and sector.

It means that *companies of large cliques are not only structurally equivalent, but they are also extremely homogeneous in sectoral and geographical terms*. Therefore, this reinforces the idea that *large cliques are very strong strategic and operative groups, where knowledge is created and transferred very easily, due to common* *languages and technological similarities.* Alongside the book, we will develop this analysis of the strong inner geographical and sectoral homogeneity of cliques, and then in the conclusive chapter, we will relate it to the scientific literature discussed in Chap. 2.

4.4 Inter-sectoral Network

In this section, after having aggregated companies accordingly to the 21 sectors,[12] we analyze the inter-sectoral network,[13] which has an extremely dense structure of 434 binary connections (Table 4.13): basically, it is almost a clique, where more than 3 million coordination relationships are channeled. On average, each sector is connected with almost every other one, what activates more than 138 thousand coordination relationships per sector. However, this average weighted coordination capacity is misleading, because it is HT distributed (the coefficient of variation of weighted In_ and Out_Dc centrality is more than 4 and values span over 5 orders of magnitude): the Manufacturing (C) sector confirms to be the most influential, scoring a weighted Out_Dc about 30 times the Wholesale sector, short followed by those of Information (J), Finance (K), and EASIN (Table 4.6 in Data Appendix). This analysis tells us that the Manufacturing sector in general has the highest capacity to directly influence the others and also to be influenced by them. In terms of random walk betweenness centrality (RWBc), it has also the highest intermediating capacity (0.53), followed by the Financial sector (0.16) and EASIN (0.13).[14] The over-whelming position covered by the Manufacturing sector is well expressed by the weighted eigenvector centralization indexes, which amount to almost 1. The binary measures do not represent real heterogeneity, because actually most sectors in such case have the same number of links and are connected to most of all others.[15]

Average distance is low and global clustering nearly maximum, but not enough to make a high small-world index, just because, again, most sectors are directly connected with most others. Further, being a quasi-clique, disconnectedness degree (DD) and fragmentation are zero, while reciprocity and geo-reciprocity are about 1. Conversely, no sector has an accentuated influence in terms of the number of quantity and extension of influenced sectors (GORC), especially when considering also the intensity of coordination relationships.

[12] Methodological Appendix includes description on how that network has been prepared. Notice that this one and all other inter-sectoral or inter-country networks include self-links.

[13] Nodes are 22 because, besides the 21 sectors, there is also EASINT.

[14] Because of some reasons, when directed networks are super dense, like this one, and when their links' weights or degree centrality spans over 2–3 magnitudes, like this one again, then binary degree centrality and centralization measures are not useful, and betweenness centrality and centralization (either binary or weighted) can be rather misleading. Conversely, RWBc (also called flow centrality) and centralization work very well.

[15] See the previous footnote.

Table 4.13 Inter-sectoral network of the ALL network

Index	Binary	Weighted
Size	22	
Density (norm)	0.94	
Density (abs)	434	3,037,127
Disconnectedness degree	0	
Fragmentation	0	0.094^
Av. Link value	6998	
ADc	19.73	138,051
Out_Dc_CE (Fre)	0.113	–
In_Dc_CE (Fre)	0.113	–
Out_Dc_CE (Sni)	0.173	–
In_Dc_CE (Sni)	0.233	–
Bc_CE	0.005	0.437
RWB_CE	0.008	0.480
Out_Eig_CE	0.021	0.999
In_Eig_CE	0.021	0.998
Reciprocity	0.945	1
Geo-reciprocity	1	1
GORC	0.195	0.140
Apl	1.104	5.303
GCL	0.931	640
SW	1.269	

Legend ^ distance weighted fragmentation

Table 4.14a is particularly interesting, because it shows that 65% of binary coordination occurs within instead of across sectors, a percentage that grows up to 92% when considering the multiple people (managers or directors) who are employed to coordinate each single pair of companies. Put differently, though EASIN activates all possible sectors to coordinate its own strategic and operative activities, *the coordination across such sectors is limited to 35%, and when considering multiple coordinators per each single pair of companies, inter-sectoral coordination falls down to a low 8%*. Even more interesting is deepening the analysis at single sector level, and in particular at the most important one, that of Manufacturing (C), which is absolutely predominant by accounting for 66% of total links. The crucial point is that it has a share of 84% of internal links, which amount to 178 thousand links, which in turn cover 87% of total internal links. In short: *the Manufacturing sector is by far the biggest one in terms of coordination efforts, and because it employs such efforts among Manufacturing companies themselves, it is also influencing mostly the share of the total internal links*. If we consider the intensity (links weights) of coordination effort (Table 4.14b), the relevance of the Manufacturing sector covers 88% of all links and reaches the astonishing number of 2,684,893 connections. Because the corresponding share of total internal links is extremely high (97%), the Manufacturing sector covers 93% of total internal links. We can sum up all this data underlying that, despite the Manufacturing sector covers 27% of companies (Table 2.2 of Chap. 2), sector is involved into the majority of binary links (66%) and the largest majority (88%) of coordination efforts. Further, the largest majority of such links are self-referential, because they occur within that sector and not between that and the other sectors.

Because a majority share of self-links characterizes most sectors, it is worth wondering whether the self-referential interlock coordination is correlated with some

Table 4.14a Share of internal (binary) links across sectors

Sector	IDB	ShITB (%)	EODB	EIDB	TDB	ShTB (%)	ShIB (%)
C	178,092	87	32,730	31,165	210,822	66	84
G	4662	2	14,663	14,589	19,325	6	24
K	8551	4	12,131	12,150	20,701	7	41
EASINT	1151	1	10,380	11,039	12,190	4	9
M	1818	1	10,057	10,282	12,100	4	15
N	2475	1	6591	6806	9281	3	27
J	5091	2	4107	4751	9842	3	52
H	1855	1	4619	4669	6524	2	28
L	887	0	4409	4188	5296	2	17
F	481	0	2907	2901	3388	1	14
S	45	0	1283	1329	1374	0	3
A	284	0	1060	1028	1344	0	21
I	100	0	1104	1084	1204	0	8
D	128	0	735	723	863	0	15
R	8	0	773	781	789	0	1
P	40	0	582	635	675	0	6
Q	10	0	500	503	513	0	2
B	22	0	414	431	453	0	5
T	0	0	402	403	403	0	0
O	2	0	387	385	389	0	1
E	2	0	212	212	214	0	1
U	0	0	18	10	18	0	0
Total	205,704	100	110,064	110,064	317,708	100	65

Legend Total links per sector are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB

Table 4.14b Share of internal (weighted) links across sectors

Sector	IDW	ShITW (%)	EODW	EIDW	TDW	ShTW (%)	ShIW (%)
C	2,604,980	93	79,913	74,589	2,684,893	88	97
G	67,221	2	23,524	22,887	90,745	3	74
J	70,107	2	7066	7928	78,035	3	90
K	38,376	1	25,210	26,319	64,695	2	59
EASINT	2519	0	30,458	33,384	35,903	1	7
H	17,934	1	8851	8719	26,785	1	67
M	3763	0	16,719	17,746	21,509	1	17
N	5485	0	9806	10,092	15,577	1	35
L	1245	0	6153	5998	7398	0	17
F	853	0	4149	4090	5002	0	17
B	318	0	1871	1903	2221	0	14
I	206	0	1650	1629	1856	0	11
A	494	0	1352	1266	1846	0	27
S	92	0	1610	1665	1757	0	5
D	273	0	1015	1022	1295	0	21
P	78	0	807	880	958	0	8
R	10	0	946	948	958	0	1
Q	20	0	731	741	761	0	3
O	2	0	517	565	567	0	0
T	0	0	447	438	447	0	0
E	4	0	329	325	333	0	1
U	0	0	23	13	23	0	0
Total	2,813,980	100	223,147	223,147	3,043,564	100	92

Legend Total links per sector are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations
ShIntTW = IDW/Total TDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIntW = IDW/TDW

of the most important economic or topological variables (Table 4.15). We see that the degree of closure (indicated by ShIntB and ShIntW, for binary and weighted, respectively) of a sector is very highly positively correlated with its size in terms of number of companies and other economic-financial variables, reaching an absolute peak of 0.96 with CF, but in general a bit lower in weighted terms and especially in correlation with TASS. Conversely, it is only moderately positively correlated (0.44) with the number of countries involved in sectors. As for the total number of links, it is highly correlated with the degree of closure when this is calculated in binary terms—0.79 and 0.76 for binary and weighted links, respectively—while it is moderately correlated (0.6 and 0.55) when the degree of closure is calculated in

Table 4.15 Correlations between some crucial variables and the degree of sectoral closure

	EC	EM	TURN	TASS	CF	Count.	Comp.	IDB	ShIB	IDW	ShIW	TDB	TDW
EC	1	0.62	0.68	0.97	0.69	0.57	0.68	0.59	0.68	0.56	0.55	0.63	0.57
EM	0.62	1	0.98	0.45	0.95	0.61	0.95	0.87	0.69	0.87	0.54	0.91	0.88
TURN	0.68	0.98	1	0.52	0.93	0.64	0.91	0.85	0.71	0.84	0.61	0.89	0.85
TASS	0.97	0.45	0.52	1	0.52	0.48	0.53	0.40	0.55	0.37	0.46	0.44	0.38
CF	0.69	0.95	0.93	0.52	1	0.55	0.92	0.96	0.78	0.96	0.57	0.98	0.96
Count.	0.57	0.61	0.64	0.48	0.55	1	0.73	0.46	0.76	0.44	0.76	0.53	0.45
Comp.	0.68	0.95	0.91	0.53	0.92	0.73	1	0.80	0.75	0.79	0.57	0.84	0.80
IDB	0.59	0.87	0.85	0.40	0.96	0.46	0.8	1	0.77	1	0.55	1	1
ShIB	0.68	0.69	0.71	0.55	0.78	0.76	0.75	0.77	1	0.75	0.92	0.79	0.76
IDW	0.56	0.87	0.84	0.37	0.96	0.44	0.79	1	0.75	1	0.54	0.99	1
ShIW	0.55	0.54	0.61	0.46	0.57	0.76	0.57	0.55	0.92	0.54	1	0.6	0.55
TDB	0.63	0.91	0.89	0.44	0.98	0.53	0.84	1	0.79	0.99	0.60	1	0.99
TDW	0.57	0.88	0.85	0.38	0.96	0.45	0.80	1	0.76	1	0.55	0.99	1

Legend Acronyms explained in the list of abbreviations. Count. = # of countries involved; Comp. = # of companies. All indexes, except those related to economic size attributes, are statistically significant with $* P \leq 0.05$

weighted terms. Therefore, the bigger the sector in terms of number and size of its companies and the more interlocked are such companies, the more self-referential it is in exchanging strategic and operative knowledge through BINTs, DINTs, and HINTs.

As it can be seen in Fig. 4.2 and Table 4.16, the highest coordination effort, which accounts for about 20% of all cross-sectoral connections, occurs between EASIN and the Manufacturing sector, which is involved in almost all major efforts of coordination: It takes place with the Wholesale (G) sector with more than 17.5 thousand positions, the Financial (K) with more than 13 thousand, and the Professional Activities (M) sector with about 7.5 thousand positions. This confirms the pivotal role of the Manufacturing (C) sector, much more relevant than the Financial (K), which instead has the primary role and position in the extended EASIN network built on the ownership relationship (Biggiero & Magnuszewski, 2021). This is somehow surprising, because part of the literature (Chap. 1, subsection on Financial companies) underlines that board interlocks are due significantly to the need of Financial companies to monitor and control their clients. However, it could be that this non-dominant role is due to the fact that, in the ALL network, most (88%) of weighted links are due to operative (M2M) coordination, thus obscuring the typical strategic coordination required by the financer-credited company relationship. In Chap. 5, we will test this hypothesis by analyzing the inter-sectoral graph of the D2D network, so to check if, at least limitedly to board interlock, the financial sector becomes the most important one.

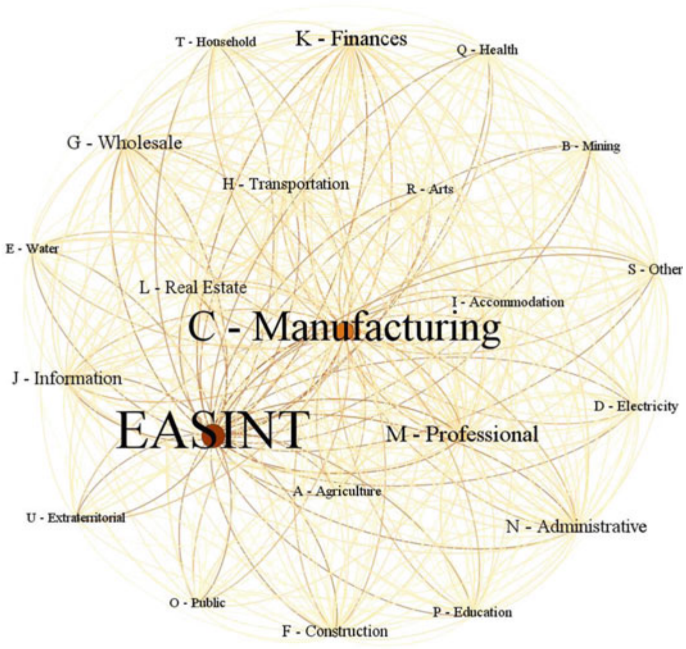


Fig. 4.2 Inter-sectoral graph of EASIN + NEIGH coordination. *Legend* The size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of board interlocks (directors), department interlocks (managers), and the hybrid forms department-board

4.5 Inter-country Network

EASIN. Unlike the inter-sectoral network, for the inter-country network, it is possible and interesting to group companies in terms of countries and analyze the reciprocal influence even within EASIN (Table 4.17). The first interesting point is that, though EASIN refers to the 28 EU countries in 2019, three of them are not present in any of the three forms of inter-firm coordination through people that we have considered in our study: namely we lack Cyprus, Croatia and Luxembourg.[16] They show up later in EASIN + NEIGH among EASIN's neighbors. The second remark is that its normalized density is high (0.26), but nevertheless less than 1/3 than that of the E+N inter-sectoral network and even strictly less than the E+Ninter-country network. EASIN inter-country is a fully connected and almost fully reciprocal network, where on average, each country has 5 partners, with whom it holds 33 links.

[16] It is worth clarifying that these missing countries are not due to an absolute lack, but rather to companies that are not connected either among themselves within the same country or with companies from other countries.

Table 4.16 Major 20 cross-sectoral coordination efforts

Source	Target	Weight
C	EASINT	24,796
EASINT	C	22,506
G	C	17,711
C	G	17,614
C	K	13,213
K	C	12,137
C	M	7936
M	C	7215
C	H	4376
C	J	4269
H	C	4239
K	N	3905
N	K	3761
J	C	3371
K	M	2218
M	K	2211
M	EASINT	1729
EASINT	M	1646
K	EASINT	1628
EASINT	K	1539

As confirmed by the high values of the various indexes of centralization, especially when considering the weight (intensity) of coordination, a visual inspection of Fig. 4.3 tells us that the UK plays the most pivotal role (Table 7 in Data Appendix): 0.67 binary Out_Dc vs 0.5 of DE, 0.46 FR and IT; five times the values of DE and IT (and more than double of FR) when Out_Dc is calculated in weighted terms; almost 1 in terms of out-eigenvector and out-Katz centrality and the highest binary and one of the highest weighted Bc. In short: *either in purely structural or in the mix of structural and economic aspects, the UK plays by far the most fundamental role in the EASIN's strategic and operative coordination*. Its structural and mixed structural-economic relevance are even superior to its relevance in statistical terms related to the number of companies or its economic attributes (EC, TURN, TASS, CF). Therefore, the damage made by Brexit on EASIN, considering this perspective, is enormous, even after considering an aspect that we are going to show right below: the UK companies tend to be rather self-referential. In fact, the results discussed here are cleaned from the aspect of the degree of closure of the UK companies in terms of coordination propensity, which actually is higher than the mean EASIN. Here, we have just considered the influence power of the UK as a whole on the strategic and operative coordination of other EASIN countries.

Table 4.17 Inter-country network of EASIN

Index	Binary	Weighted
Size	25	
Density (norm)	0.21	
Density (abs)	123	2,519
Disconnectedness degree	0.01	
Fragmentation	0.367	0.476
Av. Link value	1	20.48
ADc	4.92	100.76
Out_Dc_CE (Fre)	0.481	–
In_Dc_CE (Fre)	0.437	–
Out_Dc_CE (Sni)	0.194	–
In_Dc_CE (Sni)	0.157	–
Bc_CE	0.259	0.184
Out_Eig_CE	0.286	0.988
In_Eig_CE	0.288	0.991
Reciprocity	0.764	0.998
Georeciprocity	1	1
GORC	0.304	0.226
Apl	1.908	3.442
GCL	0.653	689
SW	2.047	

Actually, if we look at the degree of "closure" of countries (Tables 4.18a and 4.18b), we see that in EASIN, it is 74% in binary terms and 73% in weighted terms, meaning that the proportion keeps similar also considering the intensity of coordination. The country with the major number of links is the UK (39%), followed (quite surprisingly) by Spain (14%), then France (11%) and Italy (8%). Interestingly, among the top 5 countries, the UK, Spain and Italy are rather self-organized, because they have a share of internal links > 82%, while France and Germany are more open: 54 and 61%, respectively. When considering the intensity of coordination, the degree of closure keeps still high (>86%) for the UK, Spain and Italy, while lowers (<50%) for France and Germany. The other countries have a share of internal links that varies between 0 and 100%, and it does not seem to be related to the country size in terms of companies or links.

When looking at the cross-country coordination (Table 4.19), we see that France is particularly frequent among the most intensive relationships: firstly with Germany, then with the UK and the Netherlands. The second country for presence in the list in major 20 relationships is the UK, and interestingly, Germany appears only 4 times, and there is no Italy, though it is one of the major players in EASIN.

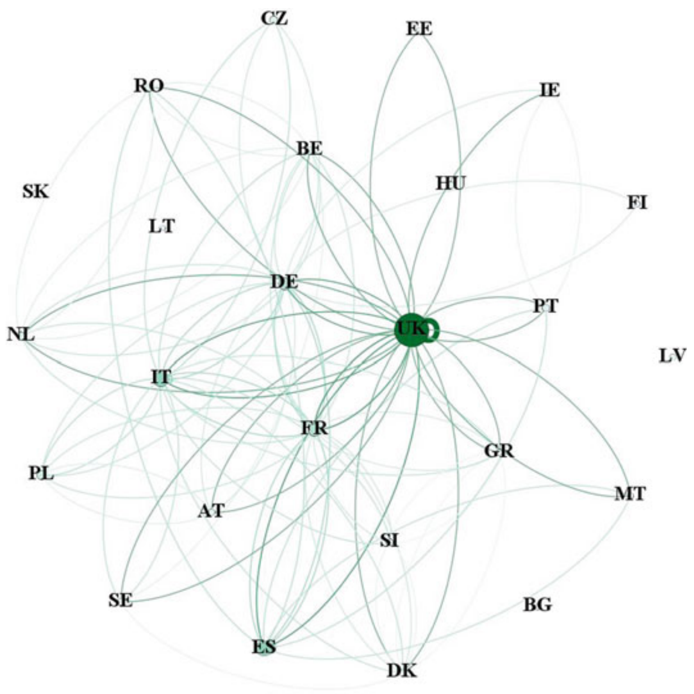


Fig. 4.3 Inter-country graph of EASIN coordination. *Legend* The size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of board interlocks (directors), department interlocks (managers) and the hybrid forms department-board

EASIN + NEIGH. In the extended network (Table 4.20), there are 61 countries,[17] that is, 36 more than in EASIN. This network is much denser (0.315) than EASIN's inter-country network, without any disconnected country (DD = 0), almost not fragmented, but with a similar degree of distance weighted fragmentation. Having a size three times bigger than EASIN inter-country and almost 1000 times bigger than that one in terms of absolute density (including self-links), while the countries' average capacity to form coordination partnerships (binary ADc) is only 4 times bigger than that of countries in EASIN inter-country, the intensity of coordination efforts within those partnerships is 500 times: on average, a country shares 51,000 positions (mostly through managers) with other countries. Further, the number of positions in a single partnership grows from 20 within EASIN to 2644 in the extended inter-country network.

This inter-country network is rather centralized in binary terms and fully centralized in weighted terms (eigenvector centralization), much more than that of EASIN inter-country, and here, the US plays the same pivotal role that the UK plays in

[17] Nodes are 62, because, in order to understand the mutual influence between EASIN and the other countries, we have included EASINT as a separated node.

Table 4.18a Share of internal (binary) links across countries

Countries	IDB	ShITB (%)	EODB	EIDB	TDB	ShTB (%)	ShIB (%)
UK	366	43	77	80	446	39	82
ES	138	16	24	26	164	14	84
FR	66	8	56	51	122	11	54
IT	81	10	16	16	97	8	84
DE	46	5	30	26	76	7	61
NL	36	4	20	17	56	5	64
BE	8	1	20	20	28	2	29
PL	22	3	5	5	27	2	81
CZ	20	2	2	2	22	2	91
RO	12	1	10	9	22	2	55
PT	10	1	4	9	19	2	53
SI	4	0	7	7	11	1	36
AT	4	0	6	6	10	1	40
SE	4	0	3	5	9	1	44
DK	2	0	6	5	8	1	25
HU	8	1	0	0	8	1	100
IE	4	0	2	4	8	1	50
MT	0	0	7	7	7	1	0
LV	6	1	0	0	6	1	100
GR	0	0	5	5	5	0	0
BG	4	0	0	0	4	0	100
EE	2	0	1	1	3	0	67
FI	2	0	1	1	3	0	67
LT	2	0	0	0	2	0	100
SK	2	0	0	0	2	0	100
Total	849	100	302	302	1,151	100	74

Legend Total links per country are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB

that network (see Table 8 in Data Appendix): weighted Dc is far bigger than any other country, and eigenvector centrality is 1. Consistently to the fact that neighbor countries have been identified in relation with EASIN, that is one of the major 5 nodes in terms of direct centrality, and it has almost the same crucial role of the US in terms of various measures of Bc—especially when considering all the weighted links (weighted RWBc). Because the centralization of weighted RWBc is rather high (0.456), it appears clearly that *the US and EASIN (0.45 and 0.42 RWBc , respectively)*

Table 4.18b Share of internal (weighted) links across countries

Countries	IDW	ShITW (%)	EODW	EIDW	TDW	ShTW (%)	ShIW (%)
UK	931	50	116	137	1068	42	87
FR	187	10	193	179	380	15	49
DE	110	6	122	117	232	9	47
ES	190	10	31	32	222	9	86
NL	112	6	82	71	194	8	58
IT	116	6	18	19	135	5	86
BE	14	1	32	37	51	2	27
AT	36	2	8	8	44	2	82
PL	26	1	5	5	31	1	84
RO	16	1	14	11	30	1	53
PT	18	1	5	9	27	1	67
CZ	22	1	2	2	24	1	92
SE	14	1	5	7	21	1	67
MT	0	0	12	12	12	0	0
DK	2	0	9	6	11	0	18
HU	11	1	0	0	11	0	100
SI	4	0	7	7	11	0	36
LV	10	1	0	0	10	0	100
FI	8	0	1	1	9	0	89
BG	8	0	0	0	8	0	100
IE	4	0	2	4	8	0	50
EE	5	0	2	2	7	0	71
GR	0	0	5	5	5	0	0
LT	2	0	0	0	2	0	100
SK	2	0	0	0	2	0	100
Total	1848	100	671	671	2519	100	73

Legend Total links per country are a sum of internal and the larger of external links. Acronyms explained in the list of abbreviations
ShITW = IDW/Total TDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

are by far the two key geographical areas in the world strategic and operative coordination. These two areas access and filter all the corresponding flows of strategic and operative knowledge activated by EASIN, which are circulating at global level. It should be underlined, however, the very important role covered by the UK and FR, which have half of EASIN's capacity to intermediate such flows, despite being just two single countries and moreover, gaining also the advantages of having other companies directly inside EASIN.

Table 4.19 Major 20 inter-country coordination efforts

Source	Target	Weight
FR	DE	77
DE	FR	76
FR	UK	56
UK	FR	49
FR	NL	32
NL	FR	32
DE	NL	24
NL	DE	24
NL	UK	17
ES	UK	16
BE	FR	14
FR	BE	13
UK	ES	13
UK	NL	11
UK	MT	10
MT	UK	10
RO	ES	10
BE	UK	8
DE	UK	8

The countries' degree of closure. In the extended network, the countries degree of closure is much higher than in the analogous measure for only EASIN and the sectors degree of closure (Tables 4.21a and 4.21b): in binary terms 76% and in weighted terms 89%. Between the US companies, it occurs 64% of connections, which raises up to 89% when considering its intensity. Hence, *the US companies are predominant within neighbors' strategic and operative coordination*: 88% of coordination occurs between the US companies, a share that grows up to an astonishing 94% when considering also the intensity (multiplicity) of coordination connections, corresponding to 2,798,249 links. However, it does not mean that they influence so much EASIN and also other non-US neighbors, because they are extremely self-referential: 2,640,880 links, what corresponds to 94% of all total internal links of the whole EASIN + NEIGH network.

The second country is the UK with 11% of all links, but when considering also the intensity of coordination, its place is taken by Canada with a share of 4%, corresponding to 118,615 links. So, we can conclude that neighbors' coordination effort is a North-American affair, but with an interesting difference: The degree of closure of Canada is only 4% versus the 94% of the US. The result is that, if we look at the number of (multiple forms of) connections exchanged by the US and Canada with other countries (including EASIN), we see that they are very near: about 150 and

Table 4.20 Inter-country network of EASIN + NEIGH

Index	Binary	Weighted
Size	62	
Density (norm)	0.315	
Density (abs)	1193	3,154,738
Disconnectedness degree	0	
Fragmentation	0.016	0.410
Av. Link value	1	2644
ADc	19.24	50,883
Out_Dc_CE (Fre)	0.679	–
In_Dc_CE (Fre)	0.712	–
Out_Dc_CE (Sni)	0.366	–
In_Dc_CE (Sni)	0.377	–
Bc_CE	0.265	0.131
RWBc	0.163	0.456
Out_Eig_CE	0.135	0.998
In_Eig_CE	0.136	0.998
Reciprocity	0.935	1
Georeciprocity	0.016	0.032
GORC	0.113	0.051
Apl	1.695	3.995
GCL	0.798	6.140
SW	3.344	

108 thousand, respectively. Therefore, in terms of degree of interaction with other countries, the US and Canada exert almost the same degree of influence.

It is also noteworthy that, while *the degree of closure is extremely variable across countries*, the ratio between the direct influences pushed to or received from the other countries, if measured in terms of out- or in-degree centrality, rounds approximately on the same level. Moreover, this alignment happens also for EASIN inter-country and E+N inter-sector, either binary or weighted. If we measure the degree of indirect influence through eigenvector centrality, we see that (Tables 7 and 8 in Data Appendix) countries with the highest economic size attributes are also in the lead in terms of this binary index, both in its in- and out- variation. However, if considered is its weighted version (Table 7 in Data Appendix), then the UK has almost full centrality[18]—it is creating the central “elite” by intensively exchanging relations with other well-connected peers.

Cross-country coordination efforts. When deepening the analysis to the major 30 cross-country coordination efforts (Table 4.22b), the US becomes the most important player, especially in partnership with Canada with which it covers about one third of

[18] Although the value shows 1.00—signifying full centrality, it is rather a matter of a rounding error.

Table 4.21a Share of internal (binary) links across early 20 countries

Countries	IDB	ShIB (%)	EODB	EIDB	TDB	ShTB (%)	ShIB (%)
US	199,687	73	26,093	27,668	227,355	64	88
UK	28,383	10	10,884	10,487	39,267	11	72
FR	13,090	5	3708	3516	16,798	5	78
EASINT	1151	0	12,093	11,394	13,244	4	9
CA	830	0	9157	9192	10,022	3	8
IT	6033	2	3141	2728	9174	3	66
IE	6348	2	1985	1936	8333	2	76
DE	3037	1	2539	2829	5866	2	52
BE	3407	1	1045	1066	4473	1	76
ES	1777	1	1255	1170	3032	1	59
NL	940	0	1239	1394	2334	1	40
SE	429	0	1185	1143	1614	0	27
HK	464	0	907	898	1371	0	34
PL	630	0	601	634	1264	0	50
SK	1051	0	173	205	1256	0	84
PT	797	0	336	316	1133	0	70
DK	850	0	230	254	1104	0	77
CY	958	0	58	57	1016	0	94
AU	74	0	940	916	1014	0	7
CZ	465	0	288	373	838	0	55
Total	272,652	100	84,738	84,738	357,390	100	76

Legend Total links per country are a sum of internal and the larger value of external links
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB

all EASIN + NEIGH external connections. The following major players are the UK and EASIN, which recur rather frequently in that list. Italy and France then follow, but with a difference that France is much more connected to the US than Italy. Interestingly, *when focusing specifically on EASIN's coordination partners* (Table 4.22b)*, we find in the first three ranks the US, the UK and Canada, with the former far more important than the two latter*. Right after, the other main EU countries follow in the ranking. Even more interestingly, it seems that, though the difference is not large, there is systematically more influence of other countries on, rather than from EASIN.

If we turn our analysis to correlations (Table 4.23), we see that, regardless if binary or weighted, *the country-based degree of closure is positively but very lowly (if any) correlated with all the other variables, including the number of companies and the total number of internal links*. Coefficients vary from a maximum of 0.31 of correlation between the share of internal weighted links and the total number of

Table 4.21b Share of internal (weighted) links across early 20 countries

Countries	IDW	ShITW (%)	EODW	EIDW	TDW	ShTW (%)	ShIW (%)
US	2,640,880	94	149,336	157,369	2,798,249	89	94
CA	10,191	1	108,158	108,424	118,615	4	9
UK	84,064	3	24,471	20,147	108,535	3	77
EASINT	2519	1	35,585	32,535	38,104	1	7
FR	13,728	1	5401	5132	19,129	1	72
IE	12,191	1	3337	3252	15,528	1	79
IT	8503	0	3981	3108	12,484	1	68
DE	3812	0	4095	4633	8445	0	45
BE	4338	0	1398	1562	5900	0	74
ES	3033	0	1648	1449	4681	0	65
NL	1482	0	2276	2272	3758	0	39
SE	747	0	2598	2366	3345	0	22
AU	333	0	2785	2804	3137	0	11
HK	1208	0	1737	1711	2945	0	41
PT	1401	0	405	404	1806	0	78
SK	1355	0	186	233	1588	0	85
DK	1178	0	259	313	1491	0	79
PL	768	0	626	692	1460	0	53
CY	1234	0	85	81	1319	0	94
SG	70	0	1131	1014	1201	0	6
Total	2,796,793	100	357,945	357,945	3,154,738	100	89

Legend Total links per country are a sum of internal and the larger of external links. Acronyms explained in the list of abbreviations
ShITW = IDW/Total TDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

internal binary links and a minimum of 0.1 between the share of internal binary links and CF.

It is interesting to compare the sector and country-based degree of closure of the E+N network. As we can see, on average, they are both very high and rather close: the country-based degree of closure is a bit higher in binary terms (0.76 versus 0.65) and a bit lower in weighted terms (0.89 versus 0.92). However, in terms of correlations with either the economic or topological variables, the country-based aggregation is very lowly (albeit always positively) correlated, while the sector-based aggregation is in general highly and sometimes moderately correlated.

Table 4.22a Major 30 cross-country coordination efforts in EASIN + NEIGH

Source	Target	Weight
US	CA	105,013
CA	US	104,875
US	EASINT	22,487
EASINT	US	20,044
US	UK	15,787
UK	US	12,015
UK	EASINT	4900
EASINT	UK	4797
US	FR	2994
FR	US	2720
DE	US	2000
US	DE	1884
CA	EASINT	1706
US	SE	1631
EASINT	CA	1522
AU	US	1474
SE	US	1466
US	AU	1464
HK	IE	1365
IE	HK	1365
US	IT	1313
IT	EASINT	966
EASINT	IT	934
DE	EASINT	775
IT	US	771
FR	EASINT	731
EASINT	ES	717
ES	EASINT	702
EASINT	DE	690
EASINT	FR	688

4.6 Cluster Analysis

We applied cluster analysis to EASIN, EASIN Integrated (EASINT) and EASIN + NEIGH versions of the four networks. In this chapter, we concern the ALL networks and their analysis results are casted over three clusters[19] whose features are further

[19] The methodological procedure to create the clustering analysis is explained in the Methodological Appendix.

Table 4.22b Major coordination efforts related to EASIN

Countries	EASINT	
	To	From
US	22,487	20,044
UK	4900	4797
CA	1706	1522
IT	966	934
ES	702	717
DE	775	690
FR	731	688
IE	541	543
NL	373	308
BE	347	302
PL	188	183
PT	170	166
CZ	152	160
SE	139	139
AU	140	136
DK	109	101
CH	82	95
RO	90	81
BG	79	75
FI	51	68

analyzed by projecting each cluster within its network, thus evidencing where they are placed and also by distinguishing their geographical and sectoral aspects.

EASIN. Employed here were binary out-degree centrality (BODc), jointly with binary in-degree centrality (BIDc), binary out-degree closeness centrality (BOCc) and TURN.[20] The results are presented below (Fig. 4.5, Tables 4.24 and 4.25).

Cluster 1. This cluster collects 77% of EASIN companies, which are those with the lowest relative topological and economic attributes. They are mostly members of small dyadic, triadic or at times bit larger components, but they are the still rather a "background" of the main actors in the network. They come from all EASIN countries, without any one of them dominating (Figs. 4.6, 4.7 and 4.8).

Cluster 2. This cluster represents the opposite group of Cluster 1, where two companies (0.6% of all) are the top of the network, with both the highest topological and economic attributes. They are members of the biggest component in the network, and they come from France and the Netherlands—they are, respectively, Airbus and Airbus SE.

[20] Normalized respect to highest value decreased by one decimal place to level with other parameters.

Table 4.23 Correlations between crucial variables and the degree of country's closure

	IDB	EIDB	EODB	IDW	EIDW	EODW	EC	EM	TURN	TASS	CF	ShIB	ShIW	Comp	TDB	TDW
IDB	1	0.85	0.88	0.99	0.80	0.81	0.57	0.67	0.77	0.68	0.76	0.25	0.26	0.69	0.97	0.99
EIDB	0.85	1	1	0.82	0.91	0.90	0.71	0.83	0.91	0.77	0.89	0.14	0.14	0.90	0.82	0.82
EODB	0.88	1	1	0.84	0.91	0.91	0.69	0.82	0.91	0.77	0.88	0.15	0.15	0.89	0.84	0.85
IDW	0.99	0.82	0.84	1	0.79	0.81	0.49	0.63	0.71	0.60	0.69	0.24	0.25	0.63	0.98	1
EIDW	0.80	0.91	0.91	0.79	1	1	0.48	0.62	0.69	0.56	0.67	0.12	0.12	0.65	0.80	0.81
EODW	0.81	0.90	0.91	0.81	1	1	0.47	0.61	0.68	0.55	0.66	0.13	0.13	0.64	0.82	0.83
EC	0.57	0.71	0.69	0.49	0.48	0.47	1	0.65	0.86	0.88	0.89	0.06	0.03	0.75	0.47	0.46
EM	0.67	0.83	0.82	0.63	0.62	0.61	0.65	1	0.90	0.85	0.82	0.20	0.17	0.88	0.67	0.63
TURN	0.77	0.91	0.91	0.71	0.69	0.68	0.86	0.9	1	0.90	0.96	0.14	0.12	0.94	0.72	0.70
TASS	0.68	0.77	0.77	0.60	0.56	0.55	0.88	0.85	0.90	1	0.90	0.20	0.16	0.81	0.61	0.58
CF	0.76	0.89	0.88	0.69	0.67	0.66	0.89	0.82	0.96	0.90	1	0.10	0.08	0.90	0.68	0.68
ShIB	0.25	0.14	0.15	0.24	0.12	0.13	0.06	0.20	0.14	0.20	0.10	1	0.99	0.17	0.30	0.25
ShIW	0.26	0.14	0.15	0.25	0.12	0.13	0.03	0.17	0.12	0.16	0.08	0.99	1	0.15	0.31	0.26
Comp	0.69	0.90	0.89	0.63	0.65	0.64	0.75	0.88	0.94	0.81	0.90	0.17	0.15	1	0.63	0.62
TDB	0.97	0.82	0.84	0.98	0.80	0.82	0.47	0.67	0.72	0.61	0.68	0.30	0.31	0.63	1	0.99
TDW	0.99	0.82	0.85	1	0.81	0.83	0.46	0.63	0.70	0.58	0.68	0.25	0.26	0.62	0.99	1

Legend Acronyms explained in the list of abbreviations. Comp. = # of companies. All indexes, except economic attributes, are statistically significant with * $P \leq 0.05$

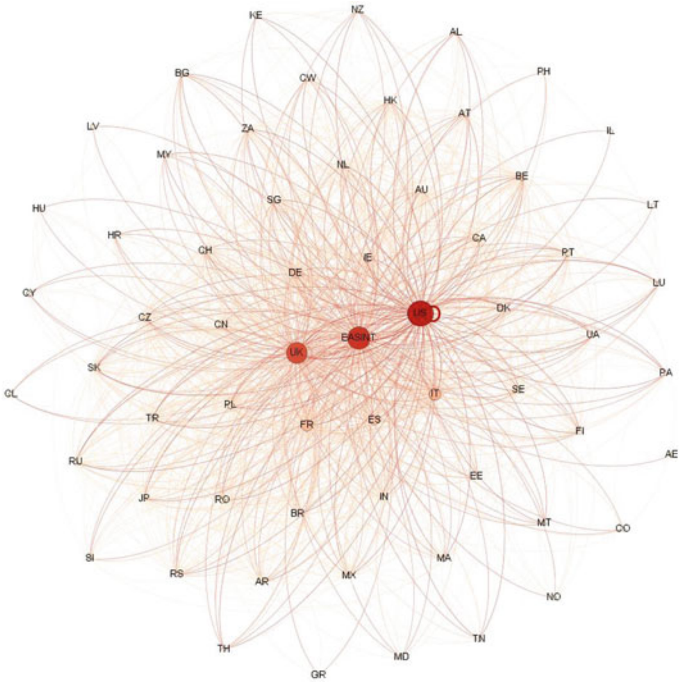


Fig. 4.4 Inter-country graph of EASIN + NEIGH coordination. *Legend* The size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of board interlocks (directors), department interlocks (managers), and the hybrid forms department-board

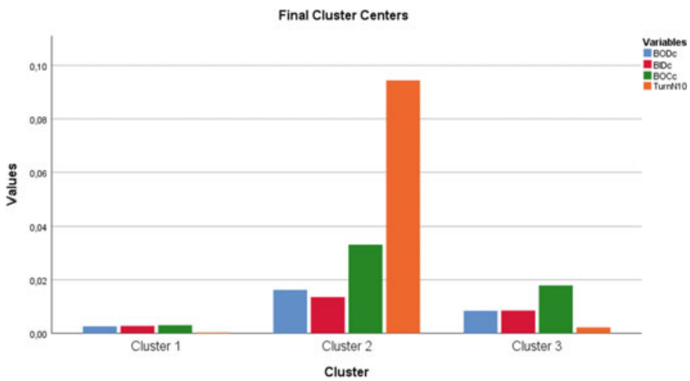


Fig. 4.5 EASIN clusters

Table 4.24 EASIN attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	8039	8	51	41
TURN	2,260,123++	6	71	23
EM	3400+	14	52	34
EC	1,279,861++	5	70	25
TASS	6,048,787++	3	66	31

Legend +,000; ++,000,000 current US$

Table 4.25 EASIN clusters statistics

General	BIDc	BODc	BOCc	TURN	*C1*	BIDc	BODc	BOCc	TURN
Average	2	2	0.005	998++	Average	1	1	0.002	189++
Min	0	0	0.000	− 8+	Min	0	0	0.000	− 8+
Max	17	17	0.038	79,591++	Max	5	4	0.011	15,826++
Median	1	1	0.002	9 ++	Median	1	1	0.001	5++
C2	BIDc	BODc	BOCc	TURN	*C3*	BIDc	BODc	BOCc	TURN
Average	11	12	0.033	23,630++	Average	4	4	0.016	2,184++
Min	7	8	0.029	976++	Min	1	1	0.008	0
Max	17	17	0.038	70,624++	Max	9	9	0.031	79,591++
Median	10	12	0.033	14,235++	Median	5	5	0.014	92++

Legend +,000; ++,000,000 current US$

Cluster 3. This cluster includes all the in-between 22% of companies, which have both topological and economic attributes at medium-levels. They are members of the rather large components, including the main one, and come majorly from the UK, France, Germany and Spain.

EASIN Integrated. In order to keep the two versions of EASIN comparable, we have selected the same indexes for this analysis. The summary of results is available in (Fig. 4.9 and Table 4.26). In general, the results are expected to be similar, because this analysis includes a similar set of companies, however, now, the network indexes are taken not from the EASIN network, but from the EASIN + NEIGH so that we could get an insight into companies' true connectivity with others, not only within their own industry like before. Since they are the same companies as in EASIN, plus some others that now got connected only to neighbors, we will not highlight them in the network graphically, but rather just comment on them.

Cluster 1. This cluster is the equivalent of Cluster 2 from EASIN analysis, where two most central companies stand-out immensely both with their centrality indexes and economic size attributes. The ratio of differences between them and the general level is much more leveled.

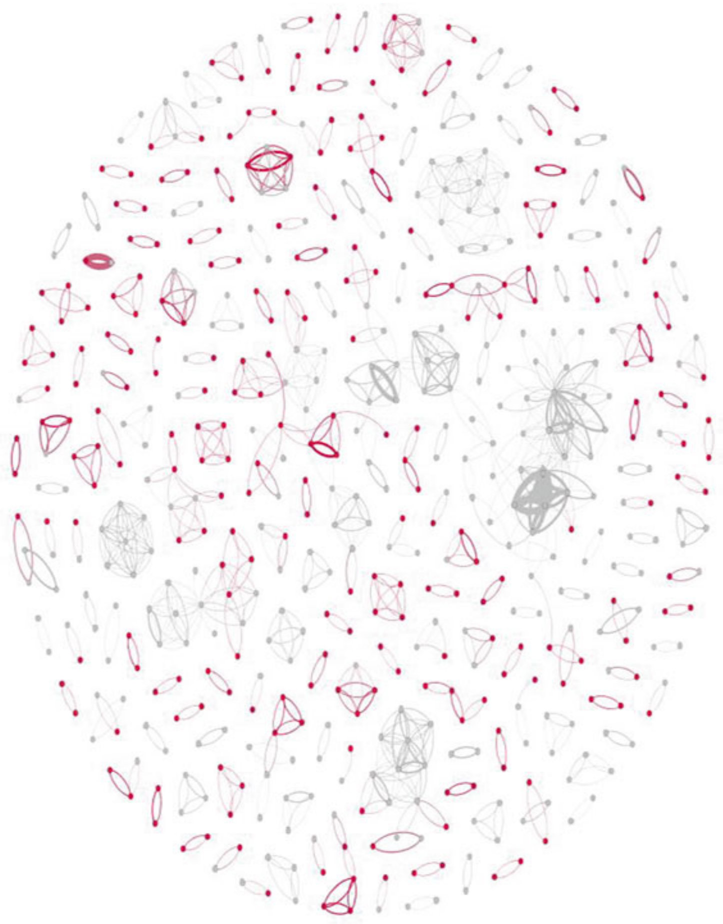


Fig. 4.6 Cluster 1 in EASIN

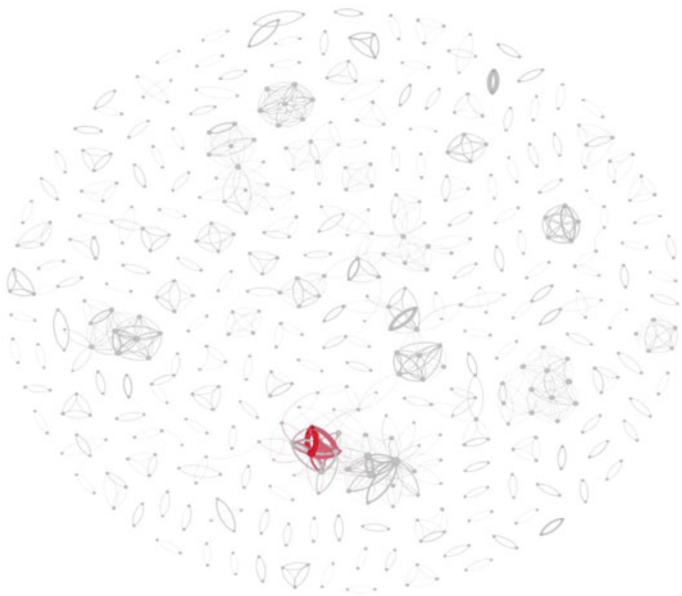


Fig. 4.7 Cluster 2 in EASIN

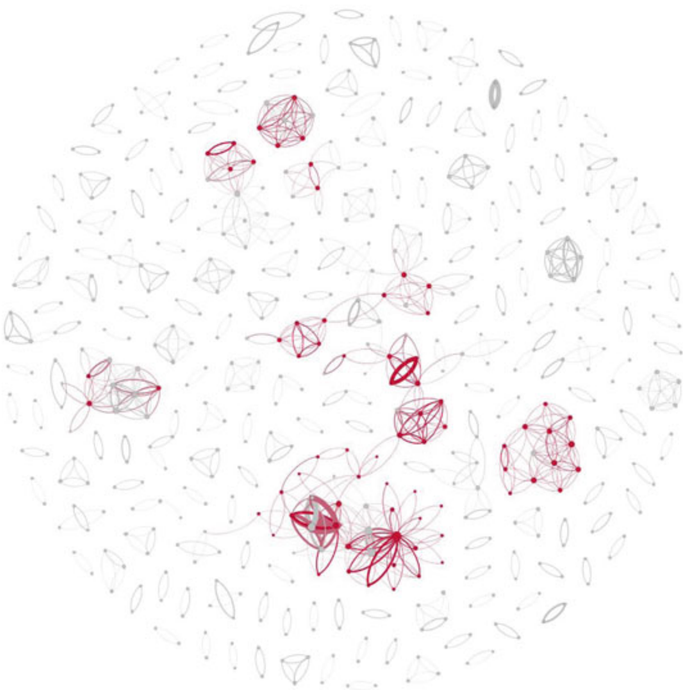


Fig. 4.8 Cluster 3 in EASIN

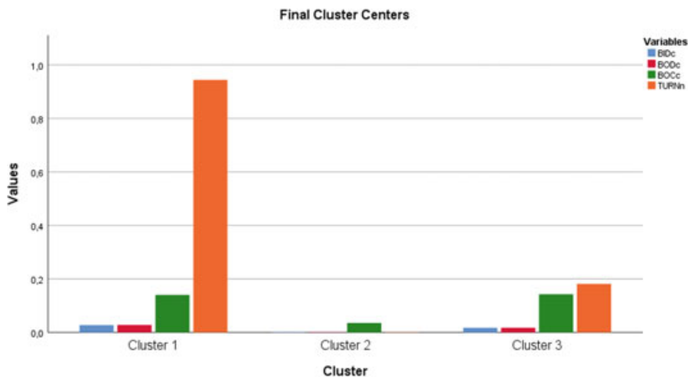


Fig. 4.9 EASINT clusters

Table 4.26 EASINT clusters statistics

General	LORC	BODc	BOKc	TURN	*C1*	LORC	BODc	BOKc	TURN
Average	12	11	0.037	479++	Average	26	24	0.112	730++
Min	0	0	0.000	− 8+	Min	1	1	0.059	0
Max	313	318	0.165	79,591++	Max	274	275	0.165	21,765++
Median	3	3	0.001	3++	Median	9	8	0.114	27++
C2	LORC	BODc	BOKc	TURN	*C3*	LORC	BODc	BOKc	TURN
Average	4	4	0.000	18++	Average	206	208	0.147	50++
Min	0	0	0.000	− 8 +	Min	128	128	0.134	30++
Max	111	101	0.008	2650++	Max	313	318	0.160	80++
Median	2	2	0.000	853+	Median	178	179	0.146	70++

Legend + ,000; ++,000,000 current US$

Cluster 2. This cluster composes the large majority of EASINT—it includes 98% of the analyzed companies. Those companies have relatively very small network indexes and very small economic size attribute.

Cluster 3. This cluster includes also small, made up of 1% of companies group, which has medium direct centrality indexes, similar to Cluster 1 long-range centrality indexes (meaning they are also members of some larger components) and a medium—but still much smaller than Cluster 1—economic size attribute.

EASIN + NEIGH. After many experimental attempts, we found that, measured in normalized values, LORC (the width and length of descendants from each company), binary out-degree centrality (BODc) and binary out-Katz centrality (BOKc) better discriminate among all companies. The focus here is on the out-indexes, as in the extended network, they turned out to give better, more general results, the inclusion of the in-indexes would require inclusion of many more clusters, and the analysis would be much over-extended for contents of this book. Their overview is below (Fig. 4.10, Tables 4.27 and 4.28).

Cluster 1. This cluster is made up by 8% of companies, and they have large reaching capacity and low out-degree and Katz centralities. The last two parameters are comparable with the other two clusters, as confirmed by Table 4.28. It is apparent that due to the extremely high global clustering, actually most of the analyzed here companies are decently connected (BODc and BOKc), so the analysis will focus rather on their distinctive abilities to produce longer chains, which are represented by the LORC index. Therefore, with the smallest number of companies with respect to the other two clusters, C*luster 1 represents the group of "connector" companies in the whole network*. They are the ones, who have access to intermediating bridges that are linked to other parts of the network—this will be additionally highlighted in the following section on bridging analysis. Those companies are not only connected to their own cliques, but also to the outside, thus forming longer chain connections, themselves being entry and exit points, as may be observable in Fig. 4.10. *This positional advantage is well represented by LORC. They are largely present not only in the whole network, but also in the main component*.

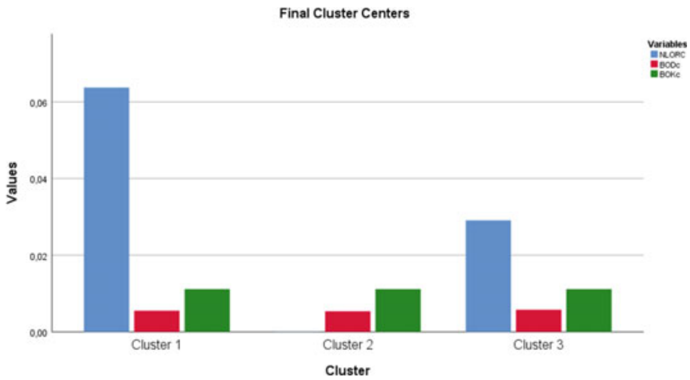


Fig. 4.10 EASIN + NEIGH clusters

Table 4.27 EASIN + NEIGH attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	555	82	1	17
TURN	324,195++	14	36	49
EM	547+	25	24	51
EC	86,623++	25	31	44
TASS	446,326++	20	30	50

Legend + ,000; ++,000,000 current US$

Table 4.28 EASIN + NEIGH clusters statistics

General	LORC	BODc	BOKc	*C1*	LORC	BODc	BOKc
Average	35,343	44	1.01	Average	131,657	44	1.01
Min	0	0	1	Min	96,062	0	1
Max	233,000	318	1.071	Max	233,000	261	1.059
Median	287	11	1.002	Median	132,899	14	1.003
C2	LORC	BODc	BOKc	*C3*	LORC	BODc	BOKc
Average	109	43	1.01	Average	60,090	46	1.01
Min	0	0	1	Min	30,533	0	1
Max	30,209	318	1.071	Max	95,734	275	1.062
Median	7	11	1.002	Median	55,729	9	1.002

Considering Fig. 4.11, which shows extracts from the whole network, it becomes apparent that companies of this cluster form the bridges usually between companies of the same origin, rarely forming inter-country or inter-sectoral relations. Consistently with what we showed in the previous two section about the propensity to self-referential coordination, the most dominant countries in this cluster are the US and the UK, while in terms of sectors (Fig. 4.12), Manufacturing and ICT sectors form the largest closely connected groups. Confirming what we showed previously, the single-colored, most often Manufacturing sector groups come largely from the US. European companies (most visibly from the UK, France, Ireland or Italy) participate in larger variety of industries, though also tend to relate to other same-sector companies. It is worth reminding that each of the companies has also a number of other relations, which were omitted after the extraction, and that in the original network, most of those grouped companies were initially highly dispersed (Fig. 4.11).

Cluster 2. Companies of the second cluster are the most present in the whole network, constituting its 51%. They lack almost entirely the LORC parameter, which means that they do not generate any longer-wider chains within the network. At the opposite, they are the ones that form small components outside or even within the MC, but in this latter case, they are enclosed within their own cliques or components and are hardly reachable from outside. When in business groups, they are usually the members that revolve around main companies of that group.

Almost all companies of Cluster 2 are members of the same country groups and represent the same sectors in the partitions of the network where they are gathered together. Interestingly, however, companies of the largest and most frequent country groups—the UK and the US—are at times connected also to each other, where the UK or sometimes even French groups intermediate between few of the US ones. In Cluster 1, this same situation occurred, but only for some of the companies, and in Cluster 2, this bridging happens, but this time for entire groups of companies. In terms of sectors, companies of Cluster 2 are better mixed up, except for the most central Manufacturing sector (Figs. 4.13 and 4.14).

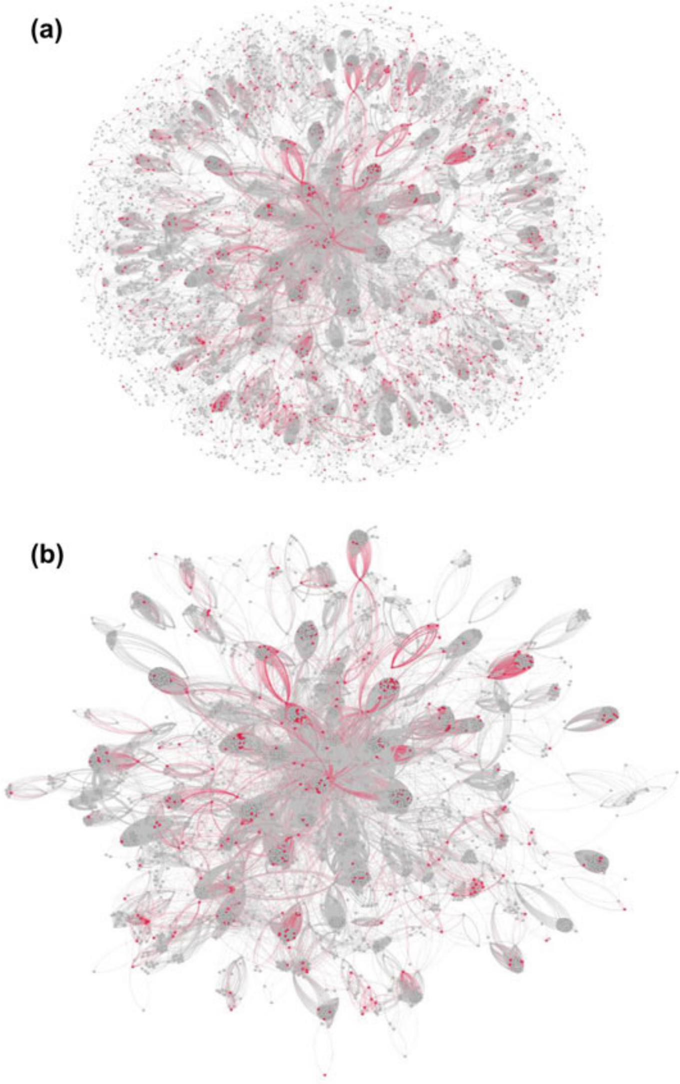
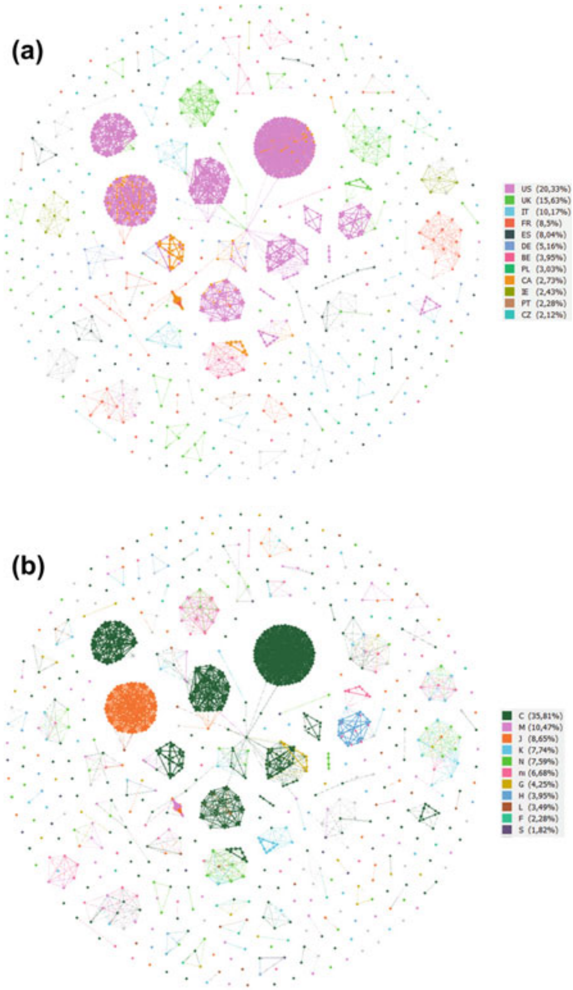


Fig. 4.11 **a, b** Cluster 1 in EASIN + NEIGH (**a**) and in EASIN + NEIGH MC (**b**)

Cluster 3. This cluster represents companies that are both medium in quantity (41%) and in the topological indexes. They have half LORC compared to the Cluster 1, meaning they also connect different groups, but not as extensively as the most connected companies, both in the whole network and in the main component. In terms of countries, the same trends as before prevail. Companies from all the countries, except for only few tightly connected sections of the network, stick almost exclusively to their national relatives. As already noticed above, this is extremely relevant when

Fig. 4.12 **a, b** Cluster 1 by evidencing countries (**a**) and sectors (**b**)



considering that this network includes all types of links. Sector-wise, the trait of the same color is apparent mostly in the MC of the extracted network, and in other larger contracted sections floating around it, though in this case, there is more inter-twining in the smaller parts. An example of such mix is happening in the UK, where a big group in the MC, which is connected to the US group, is made up of several different sectors, including H, K and others, or in a French free-floating section outside the MC, which is also a blend of *K*, *N* and others (Figs. 4.15 and 4.16).

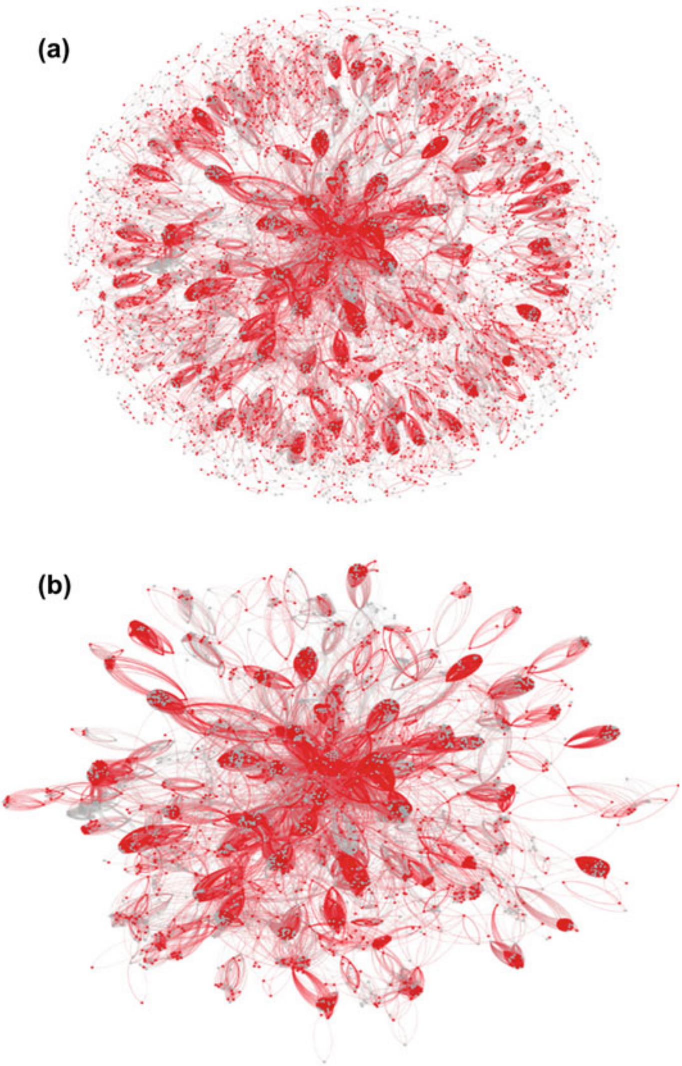


Fig. 4.13 **a, b** Cluster 2 in EASIN + NEIGH (**a**) and in EASIN + NEIGH MC (**b**)

4.7 Bridging Companies as Key-Players[21]

Bridging companies in EASIN + NEIGH. In order to not duplicate the bridging analysis, in this network selected are only the top 200 companies in terms of the highest bridging centrality index (BRc). In fact, the bridging analysis carried out per

[21] There are various ways to define and find key-players within a network. In the Methodological Appendix, we discuss our choice to use the bridging centrality index.

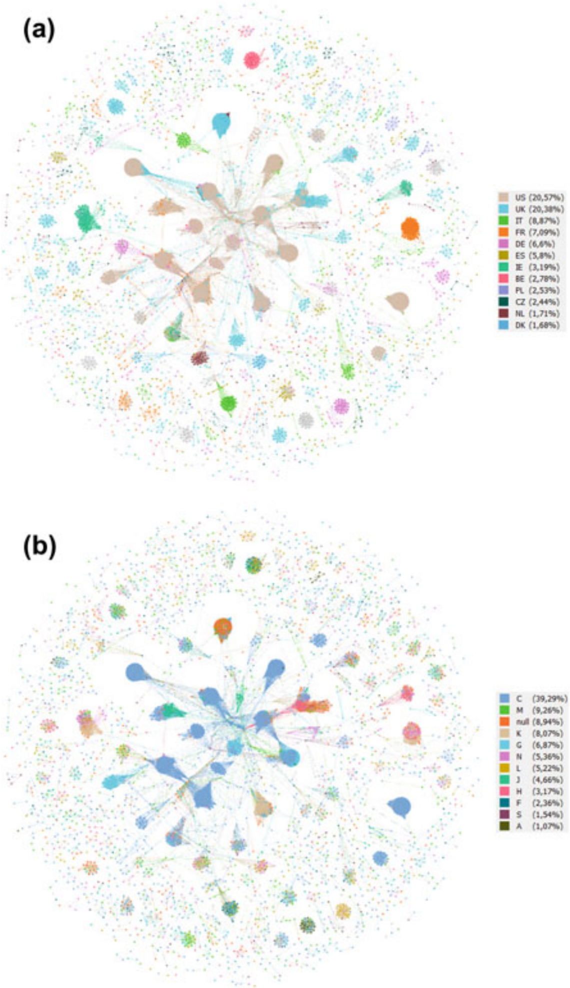


Fig. 4.14 **a, b** Cluster 2 by evidencing countries (**a**) and sectors (**b**). *Legend* Symbol “null” includes companies with no data on country of origin or sector

each particular variation of the network in the next chapters includes highlight of all companies with bridging centrality index which is higher than 0.[22] These top 200 bridging companies (Fig. 4.17) play a special role in the global Aerospace Industry, because they transfer very precious strategic and operative knowledge across clusters of companies that—as we previously have seen—most often are structured into the form of large cliques. Since the previous clique analysis has evidenced that such cliques tend to be very homogeneous in terms of countries and sectors, it means that *the top bridging companies transfer that knowledge across blocks of countries and sectors*. Noteworthy, as we have seen in the section on correlation analysis, values

[22] It is worth reminding that bridging centrality results from the combination of Bc and bridging coefficient. It means that it is not only necessary to have a high Bc, but also to bridge large clusters.

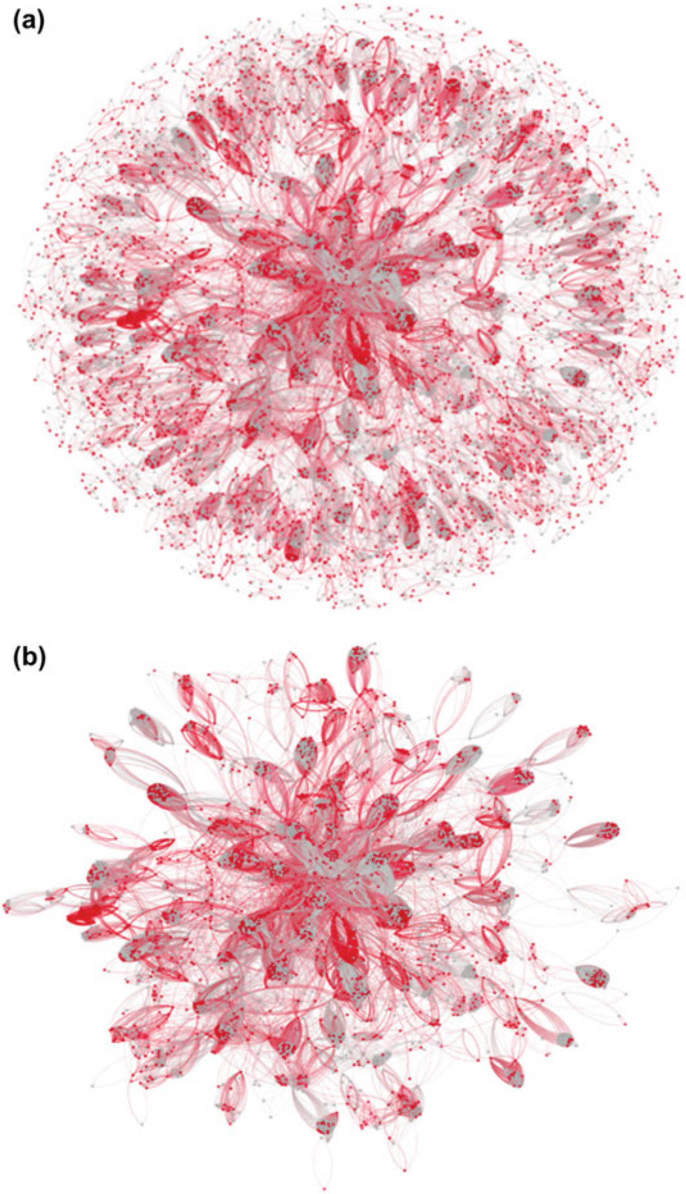


Fig. 4.15 a, b Cluster 3 in EASIN + NEIGH (**a**) and in EASIN + NEIGH MC (**b**)

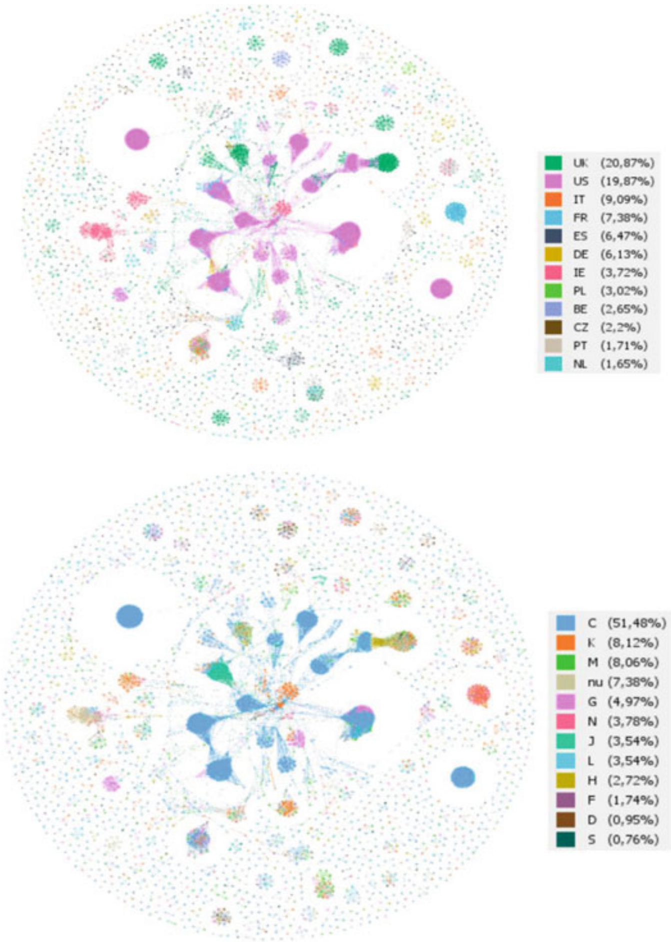


Fig. 4.16 **a, b** Cluster 3 by evidencing countries (**a**) and sectors (**b**). *Legend* Symbol "null" includes companies with no data on country of origin or sector

of bridging centrality are not correlated with economic size attributes—which are presented in Table 4.29, meaning that some highly bridging companies can be also of small size.

The top 200 most effective companies in connecting clusters (Fig. 4.18a) are almost in *one third from the UK, and a bit more than 10% come from France, the US and Italy*. In terms of sectors (Fig. 4.18b), almost 55% of those companies represent Manufacturing (*C*), then in only 11%, the Professional Activities (*M*), 6% are the Financial (*K*) and 4% the Wholesale (*G*) sector. In case, a link happens between the top 200 BRc companies, which connects distant clusters through different bridging companies, it is apparent that the companies usually connect to others of the same

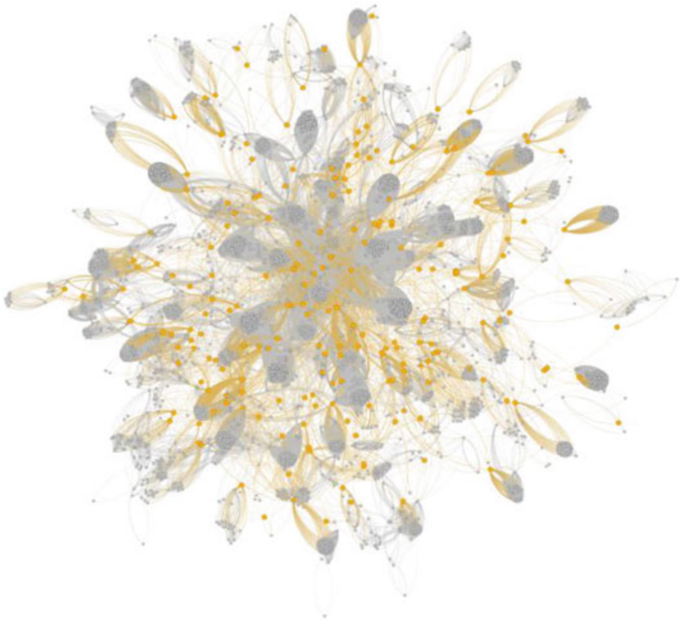


Fig. 4.17 Bridging companies in EASIN + NEIGH network. *Legend* Top 200 companies according to BRc are evidenced with orange color

Table 4.29 Economic size attributes of the top 200 companies according to BRc

Index	EC	EM	TURN	TASS	CF
Average	311++	2+	1267++	2770++	88++
Min	−8617++	1	0	0	−237++
Max	27,241++	161+	84,818++	149++	4775++
Median	5++	104	26++	15++	2++
Std. Dev	2435++	16+	7787++	16,698++	488++

Legend + ,000; ++,000,000 current US$

color, but upon the visual inspection, it may be noted that sectors do mix-up more freely than countries (Fig. 4.18).

Further, we can see that the extract itself has a connected and disconnected parts, where the floating disconnected companies are those that are the sole connectors of their cliques, and most likely attach them to some longer chains of relationships, without having any relations to other bridging companies from their own cliques or to other bridging companies from different cliques. Hence, *among the top 200 bridging companies, there are companies that by themselves coordinate their own cluster or others who form relations with other bridging companies, forming in fact a group of connectors, with an outstanding potential for strategic coordination*

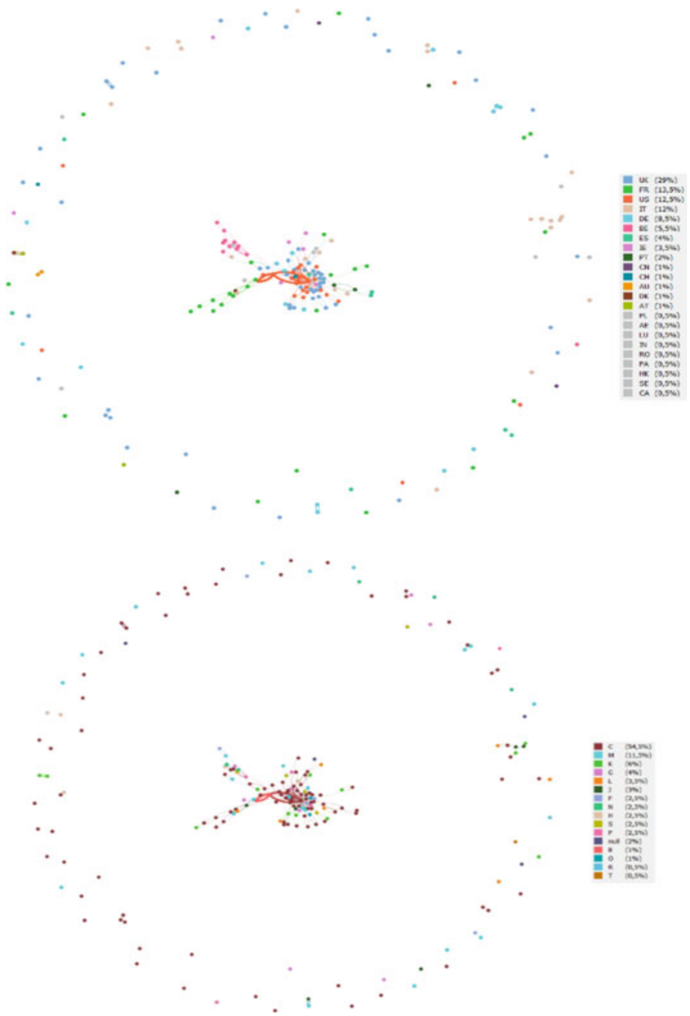


Fig. 4.18 a, b Top 200 bridging companies in the EASIN + NEIGH, evidenced by countries (**a**) and sectors (**b**). *Legend* Symbol "null" represents companies with no data on sector

and information sharing. The other companies that are connected to other bridging companies represent situations where a clique may have more than one exit points and so all of the exit points as members of one clique must be related to each other, or alternatively, the bridging companies represent two different cliques that are directly connected to each other. In fact, *the central section of the connected part is actually a bridging clique itself, which is formed by companies that are bridging that clique to other cliques, being* de facto *a hub for cliques*. In total, those top 200 companies generate 9417 bridging links, which are 2.6% of all the links in the EASIN + NEIGH network, and between themselves, they exchange 310 links—less than 0.1% of the whole. It means that indeed, a very small group of bridging companies has access to unique strategic position.

4.8 The Different Composition of the Main Component

As we have seen in Sect. 4.1, the MC has rather different topological properties than the rest of the E+N network: with only 50% of companies, it comprises 98% of coordination efforts. Further, it is much more centralized, and as we have seen, it includes the largest cliques. Here, we see that there is also a different composition in sectoral and geographical terms: among the four main sectors (C, K, M, G), while the Financial sector holds the same share, that of Manufacturing companies are 51% in the MC and only 18% in the small components, while the Professional Activities and the Wholesale sectors are much more present in the latter than the former (Table 4.30a). This is consistent with the fact that the propensity to coordinate of Manufacturing companies is very much higher than the others, and that the average link value is much higher in MC than in the minor components.

From a geographical perspective, the composition differences in terms of the main countries are striking too (Table 4.30b): The share of American companies almost disappears (from 43 to 1%), as also that of Ireland and Canada. So, the North-American companies are concentrated into the MC. Conversely, the UK keeps a significant presence in both partitions: 0.17 in MC and 0.21 in the minor components. The shares of France and Germany are higher in the latter than in the former, but much smaller than those of the UK. All in all, the geographical distribution of countries across the minor components is rather balanced, with a significant presence of the main EU countries and a very residual presence of American companies. Even this geographical different composition is consistent with the fact that the propensity to coordinate of American companies is very much higher than the others, and that the average link value is much higher in MC than in the minor components.

In sum, from a geographical perspective, we have three markedly distinct "blocks" of companies: The first block is that of the 555 EASIN companies, which is made in 70% by continental EU and 20% by Anglo-Irish companies; then, the block of about 4000 MC companies, which are made by 66% of Anglo- and North-American and 30% by EU continental companies; and finally, the block of other 4000 companies operating within the minor components, which have a very similar composition of EASIN—73% by EU continental and 23% by Anglo-Irish companies. Such differences are very important, because a vast and growing stream of Organization Studies (Baum, 2011; Moonen, 2021; Rugman & Verbeke, 2004) evidences that strategies, structures and operations are rather country-specific and do change considerably between the continental EU and the Anglo-American world. Further, Corporate Governance literature (Maher & Andersson, 1999; OECD, 2015; World Bank, 2014) underlines too that rules on board compositions and voting rights are rather country-specific, especially between those two parts of the world. Both issues suggest that coordination propensity is substantially influenced by the institutional

Table 4.30 Sectoral (**a**) and geographical (**b**) composition of MC versus other components

Sectors	MC (%)	Other (in %)	Countries^	MC (in %)	Others (%)
C	50.6	17.5	US	43.4	0.8
K	10.8	10.6	UK	17	21
M	8.8	15.7	IT	7.1	9.9
G	6.1	10	IE	5.6	1.3
J	4.9	7.5	FR	3.8	11.5
N	4.6	9	DE	3.2	8.8
L	3.5	8.8	BE	2.9	2.7
H	3.2	5.1	CA	2.8	0
F	2.2	3.6	ES	2.5	8.9
S	1	2.5	PT	1.6	1.7
I	0.8	1.4	NL	1.5	1.5
D	0.7	1.5	DK	1.3	1.8
A	0.6	1.7	CH	0.9	0.5
P	0.6	1.6	SE	0.8	1.8
R	0.5	1.2	HK	0.8	0.1
Q	0.3	0.8	AU	0.6	0.4
B	0.2	0.4	CN	0.6	0.2
T	0.2	0.2	BR	0.4	0.1
O	0.1	0.2	PL	0.4	4.6
E	0.1	0.6	AT	0.3	0.8

Legend ^ early 20 countries

assets, management style and strategic orientation of single countries, especially between continental EU and the Anglo-American world.

These factors can contribute to explain the existence of the huge cliques in the MC of the extended network, which becomes much smaller in EASIN. It seems that they are strictly related to the Anglo-American companies, which, moreover, are rather self-referential, that is, tend to coordinate among themselves rather than with companies in other countries and are mostly Manufacturing and Financial. We will go back to this aspect in Chap. 7, in order to support the explanations of the results of the five tested hypotheses.

4.9 Heavy-Tail Scale-Free Distribution Analysis

Consistently with what has been found in specialized literature (Barabasi, 2016; Newman, 2010), the ALL network, as many (most?) socio-economic networks, is shaped in a heavy-tail scale-free (HTSF) structure. Besides many other conceptual and methodological implications discussed recently by Biggiero & Urbani (2021), the HT property means that distribution of (direct) links is polarized between few extremely highly and most very lowly connected nodes. This is exactly the case of our networks: not only of the present one combining the three types of links, but also all the other networks corresponding to each type of link. In fact, there are relatively few highly and a plethora of lowly connected companies. Further, as argued by some authors (Biggiero & Angelini, 2015; Biggiero & Magnuszewski, 2021; Biggiero & Urbani, 2021; Caldarelly, 2007), it seems that many socio-economic networks are HT shaped also in terms of other topological parameters, that is, not only in terms of Dc, which was considered the first and canonical parameter to depict a network as HT or even SF.[23] Moreover, we will show that the HT—and often a strict SF—structure characterizes also non-topological parameters, like economic size attributes. We start this section by showing the HTSF distribution of the main topological parameters, then followed by components and cliques' distribution. Then, we show the HTSF structure of directors and managers positions, and finally the distributions related to the main economic attributes. For each parameter, we have checked the HTSF structure for both EASIN and EASIN + NEIGH versions.

Topological parameters. As for the topological parameters, we have checked for the HTSF structure of the following: binary and weighted In_Dc, Out_Dc, Tot_Dc, binary Bc. Interestingly, in the EASIN + NEIGH network, there is a high HTSF distribution for Bc, while for all the other Dc indexes, the degree of HT is only moderate. We argue that this is due to the same factor that determines a low correlation, as discussed above: that is, the real degree of connectivity of many highly diversified neighbor companies is captured only partially by the EASIN-induced connections. This fact penalizes especially very large companies, whose Dc then results to be not so high to polarize the distribution. Conversely, when focusing on the only EASIN network (Fig. 4.19b, c, d and f), this effect largely (not completely) dissolves, and in fact, its HT distribution results to be particularly accentuated for the binary values of In_ and Out_Dc, while a bit attenuated for the weighted values and even more, for the binary Bc.

Components and Cliques. The following three figs show that EASIN components and cliques size distribution are moderately HT for the former ($R^2 = 0.61$), while very much for the latter ($R^2 > 0.93$). The fitness of the interpolating line of the log–log plot is only moderate for E+N, but indeed, if we consider that, because of computational overload, we could not calculate cliques of size-3 and 4, we can be rather sure that if such values were included, the outcome would be with an $R^2 > 0.9$ (Fig. 4.20).

Shared positions. Let us remind that for "shared position", we mean a specific link joining two companies through a strategic (BINT, HINT) or operative (DINT) coordination. Now, because a manager or a director can coordinate more than a single pair of companies (see Chap. 2 and the Methodological Appendix), we wondered

[23] The SF structure is a special case of the family of HT distributions. We have measured the degree of SF in terms of the R^2 of the linear regression of the log–log distribution (see the Methodological Appendix). Because there is an ongoing debate among graph theorists about the accuracy of that synthetic measure, in each figure, we have reported the regression equation with its R^2, and then used the acronym HT to indicate that, if not a full SF, there is at least a heavy-tail shape.

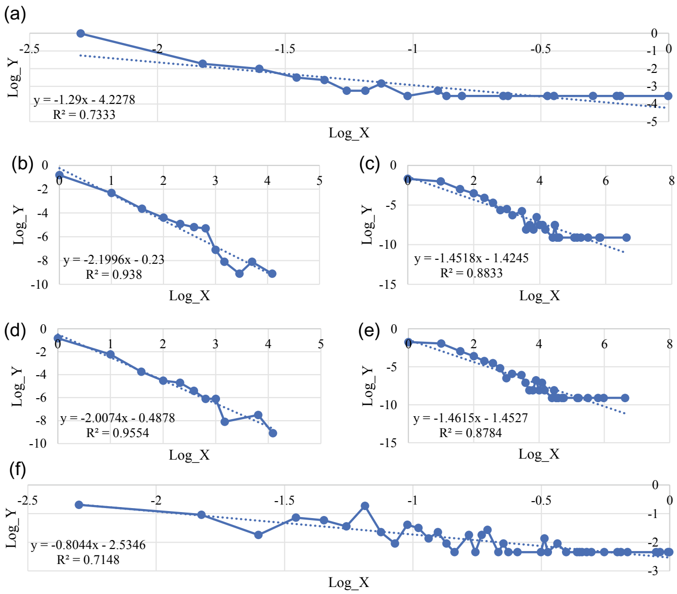


Fig. 4.19 **a–f** Heavy-tail (HT) distribution of the BBc of EASIN + NEIGH network, HT distribution of the binary, **b** and weighted, **c** In_Dc of EASIN network, HT distribution of the binary, **d** and weighted, **e** Out_Dc of EASIN network, **f** HT distribution of the Bc of EASIN network

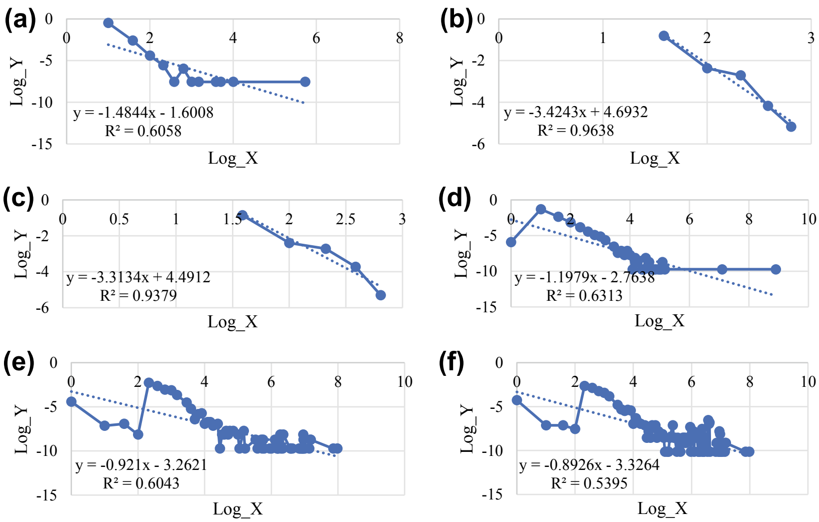


Fig. 4.20 **a–f** HT components, **a** and strong cliques **b** distribution by size of EASINHT weak cliques **c** and components, **d** distribution by size of EASINHT strong cliques **e** and weak cliques **f** distribution by size of EASIN + NEIGH

whether also the number of coordinating roles played by them does follow a HT shape. The answer shown by the following figs is definitely positive either in EASIN or in EASIN + NEIGH. In fact, the distribution of the sum of directors and managers positions or only managers' positions is only moderately HT ($R^2 = 0.67$ and $R^2 = 0.61$, respectively), that considering only directors has $R^2 = 0.84$. When considering only EASIN, such values of R^2 become 0.91, 0.61 and 0.76, respectively. Thus, we can conclude that managers' and (even more) directors' coordination tends to occur through very few people that concentrate a tremendous power of influence and knowledge into their hands, and a large majority of people who coordinate just two or three companies. This distribution is fully consistent with the HTSF distribution of components and cliques just discussed above (Fig. 4.21).

Economic individual attributes. There is a noteworthy HTSF size (Fig. 4.22) distribution also of the three main economic attributes: EM, TURN, EC. At the first sight, it seems that the R^2 values are only moderately: from 0.55 to 0.71, depending on the variable and on the EASIN + NEIGH or EASIN network. However, if we consider that for about 50% of companies, we do not have the corresponding values and more importantly, that most missing values occur in very small companies, we can run the same reasoning offered before for cliques size distribution, namely that we are almost sure that, if such data were available, then the R^2 values would only rise

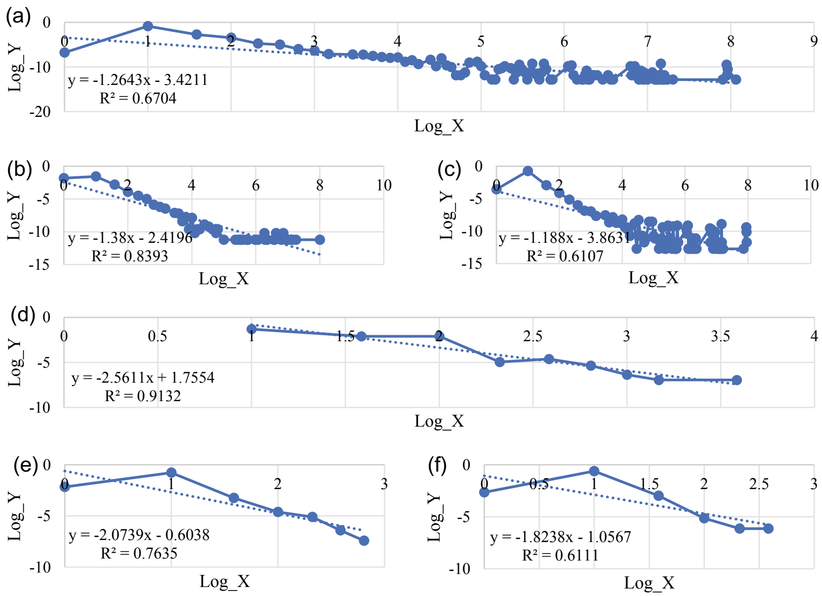


Fig. 4.21 **a–f** HT distribution of the sum of directors and managers positions of EASIN + NEIGH, HT distribution of directors, **b** and managers, **c** positions of EASIN + NEIGH, **d** HT distribution of the sum of directors and managers positions of EASIN, HT distribution of directors, **e** and managers, **f** positions of EASIN

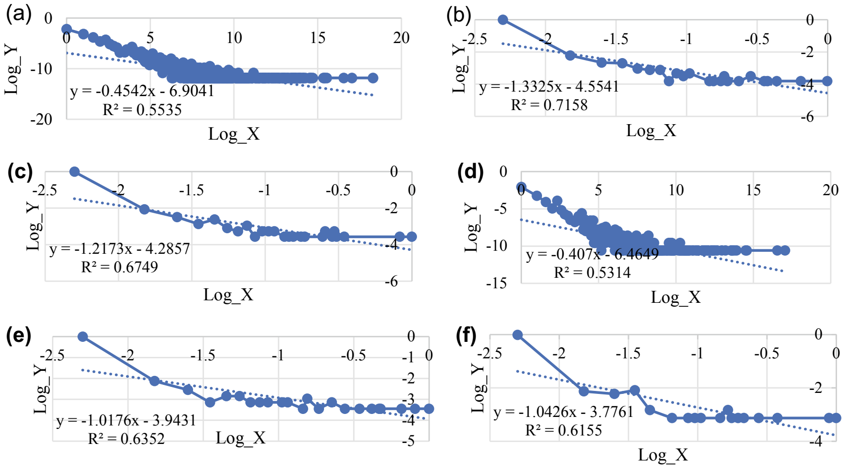


Fig. 4.22 a–f HT distribution of EASIN + NEIGH in terms of EM (**a**) and EC (**b**), HT distribution of EASIN + NEIGH in terms of TURN (**c**) and TASS (**d**), HT distribution of EASIN in terms of EC (**e**) and TURN (**f**)

and probably by much. Without those data, we are substantially cutting or reducing the vertical tail.

4.10 Summary

EASIN is a sparse, fragmented, reciprocal and homogeneous network, with relatively long coordination chains. Each relationship holds on average two positions, and each company has an average capacity/propensity to establish a coordination with two other companies. Conversely, its MC is very different: besides a much higher average number of partners and intensity of coordination effort per each of them, the strategic and operative knowledge channeled through coordination efforts flow freely almost within the whole MC. This structure generates a significant concentration in direct coordination relationships and an even higher concentration of intermediate coordination power: that is, few companies access and can filter a huge amount of strategic and operative knowledge. In the whole network, the strategic and operative knowledge channeled through coordination is spread rather easily and extensively across the companies: that is, the 53 connected EASIN MC companies share most strategic and operative knowledge. Under this fundamental respect, they can be considered a compact unity. Conversely, for the 90% of connected companies, the strategic and operative knowledge created and shared through the three forms of interlock is entrapped into a number of small islands, and mostly in dyadic relationships.

In the extended network, the average capacity to establish coordination is very high, and the addition of neighbors changes radically the network structure and generates various kinds of phase transitions. Centralization is low, so that no one company or groups of companies can influence or be influenced by others coordination behavior, but few of them can significantly access and transfer strategic and operative knowledge, especially for the companies that have a high capacity to intermediate knowledge flows, and even more in the MC. However, outside the MC, knowledge remains mostly entrapped into hundreds components that largely correspond to complete or quasi-complete clusters.

In the EASIN network, either the major creation and exchange of knowledge with direct partners or the preferential access to the knowledge flowing across other partners is prevalently in the hands of the largest companies. This competitive advantage varies with a company's size in terms of typical economic attributes, and especially in terms of TURN. When considered are also EASIN's connections to neighbors in EASINT perspective, it turns out that companies' connectivity is correlated with EC, so indeed it seems like the best connected are the largest of them also in terms of that economic attribute. The number of EASINT companies, so those who interact also with neighbors, grows to 1402.

Having many partners overall is a condition mildly associated with a high economic size, however, in the EASIN + NEIGH network and in its MC. A strong association holds especially with those companies that can be particularly able to stay in the middle of many coordination chains, that is, knowledge flows. However, the association between connectivity and size attributes grows dramatically when neighbor companis are selected in the Manufacturing sector and, even more, in the world Aerospace industry.

All the networks, and this merged one in particular, are characterized by a high fragmentation in disconnected components, whose size is unevenly (heavy-tail scale-free) distributed. The far largest share (0.46) of MC is in the M2M, meaning that the need of operative coordination due to technological aspects generates a positive network externality in creating and transferring codes and standards through shared managers among technological departments. In fact, the smallest share is in the D2D network, likely because the sharing of strategic knowledge cannot be too much extended.

Even considering together all the three forms of relationships, coordination is established within a huge number of separate groups that, likely, correspond to either strategic, operative, or hierarchical groups of coordination, and that partly overlap. The largest majority is made by just couples of companies, but few of them are huge. What characterizes the ALL network is an astonishing number of cliques in the extended network and also in its main component. Operative and strategic coordination through shared managers and directors occurs by means of fully cohesive groups, some of which are very big: for example, 6% of companies in the main component, which contains 51% of companies and 89% of links, are fully reciprocally coordinated in strategic and operative ways: they behave as a unity. The size distribution of cliques explains the size distribution of components, thus confirming that the formation of strategic and operative groups is the fundamental process that drives the structuration of the whole industry. Companies of large cliques are mostly structurally equivalent, and they are also extremely homogeneous in sectoral and geographical terms, thus reinforcing the idea that they are very strong strategic and operative groups, where knowledge is created and transferred very easily, due to common languages and technological similarities.

In terms of inter-sectoral connections, the whole network is a quasi-clique, where almost each sector coordinates its activities with all the others. Despite this seemingly parity, when considering the intensity of coordination efforts, the Manufacturing sector appears to be definitely the most important in terms of direct and indirect influence power. The coordination across such sectors is limited to 35% and when considering multiple coordinators per each single pair of companies, inter-sectoral coordination falls down to a risible 8%. The Manufacturing sector is not only far more the biggest one in terms of coordination efforts, but because it employs such efforts among Manufacturing companies themselves, it is also influencing mostly the share of the total internal links.

In terms of inter-country connections, either in purely structural or in the mix of structural and economic aspects, the UK plays the far more fundamental role in EASIN's strategic and operative coordination. A consequence of Brexit on the EU Aerospace Industry is that it will result not only smaller in terms of number of companies and economic size attributes but also much less interlockingly coordinated than before. This result will hold also when taking into account that the UK companies have a propensity to address their coordination efforts to themselves rather than to companies of other countries. At global level, the US and EASIN (0.45 and 0.42 RWBc, respectively) are by far the two key geographical areas in the world strategic and operative coordination. These two areas access and filter all the corresponding flows of strategic and operative knowledge activated by EASIN and circulating worldwide.

The US companies are largely predominant within neighbors' strategic and operative coordination links, but since they are extremely self-referential, that is oriented to share managers and directors mostly among themselves, then its real influence on global coordination is limited to 44% of all (out-going) positions, which is still very strong, but less than half of the weight including also those addressed to themselves. It means that the US is still very influential in the global strategic and operative coordination, but not much more than the second most influential, which quite surprisingly is Canada (30%), almost fully oriented toward the global production, then EASIN (9%) as well with a low degree of closure, and then the UK (6%), which (like the US) is mostly self-referential. Interestingly, the degree of closure is extremely variable across countries, and it is positively but very lowly (if any) correlated with all the other variables, including the number of companies and the total number of internal links. When focusing specifically on EASIN's coordination partners, we find in the first three ranks the US, the UK and CA.

At the global level, we have identified a homogeneous Cluster 1 gathering the group of "connector" companies, which are not only connected to their own cliques, but also to the outside, thus forming longer chain connections, themselves being entry and exit points. Companies of the second cluster are the most present in the whole network, constituting its 51% and are members of the same country groups. The third cluster collects 41% of companies, which score middle values of the selected variables: they do not coordinate many other companies, neither directly nor indirectly. In EASIN and EASINT, the cluster analysis shows similar outcomes, with a strong indication of heavy-tail features.

At the global level, the most important bridging companies, which are key-players in the strategic and operative coordination of the global Aerospace Industry activated by EASIN, coordinate their own cluster or others who form relations with other bridging companies, forming in fact a group of connectors, with an outstanding potential for strategic coordination and information sharing. They belong mostly to the Manufacturing sector and to the UK more than the US, followed by France and Italy. There is also a cluster of bridging companies, which can be seen as a club of super-connectors that channel a large part of global strategic and operative knowledge.

There are two types of neighbors, depending on whether they operate within the main component or minor components: the former is dominated by the Anglo- and North-American companies, with a minor weight of continental EU countries, and the reverse for the latter block. Because we know that into the MC coordination knowledge flows much easier across clusters of companies than in minor components and MC companies are bigger than the others, this difference of composition between the two blocks of continental EU and Anglo- and North America assumes a crucial relevance. It also helps to formulate hypotheses that put the formation of the huge cliques and the high self-reference in the propensity of coordination in relation with the different institutional-organizational contexts characterizing the two blocks.

The analysis of the distribution of main topological and attributive parameters showed that the multi-layer network is shaped in a heavy-tail structure for all of them and for many of them also in a scale-free structure. This aspect has a lot of implications, first of all that of resilience: the core structure is robust and has a high probability to keep connected even after some problem in the "fringe" of small or lowly connected companies. However, these types of networks are fragile with respect to a loss of a highly connected or large node. This could be the case of the Brexit, because the UK has a considerable share of companies of EASIN, EASINT, EASIN + NEIGH and most importantly EASIN + NEIGH MC, and some of them are also in the "rich club" of mostly connected and largest companies.

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Chapter 5
Inter-Departmental Coordination Through Shared Managers

5.1 Network Outline and Statistical Analysis

EASIN. Looking at EASIN's companies connected in this chapter (Table 5.1 in Data Appendix) with respect to the EASIN + NEIGH network, which will now be interpreted as EASIN Integrated (EASINT), it becomes apparent that they are resource-wise the larger part of the entire EASIN. First observation shows that *there are more companies connected* via *managers than there are* via *directors, more exactly over a third of EASIN companies use that sort of strategic alliance form.* Their share of economic attributes of the whole EASIN is 78% of EC, 82% of TURN, 79% of CF, 81% of TASS, all of that achieved with 72% of EM—meaning that they engage most of EASIN's economic resources. In terms of most noticeable actors of that set it is the UK, which is the most present country, followed by Italy, Germany, France and Poland. Although the UK is the leader in terms of number of companies, the greatest overall economic accumulation resides in France and the UK is usually the second one to follow. This form of inter-company integration, much looser in its attachment and mutual responsibility than board interlocks, is more in line with governmental policies of some countries like Poland, who are more involved here than in D2D. This tells us that the M2M and D2D sets will have some parts similar, and some much different, there is no absolute contrast or similarity. As we will demonstrate in Chap. 8, managerial interlocks can often function as a lighter substitute for board interlocks, so countries which do not adopt BINT do often engage in DINT relations, but overall if BINTs are present, then that does not exclude the presence of DINTs (Fig. 5.1).

Neighbors. Similar trait concerns also the neighbors (Table 5.2a in Data Appendix) where they are more present here than in D2D—5766 in total—where two-thirds come from the EU28 and the remaining part comes from the rest of the world. First observation here concerns *the most present countries, where once again it is the US and the UK with 1624 and 1166 companies, being respectively 28% and 20% of the whole network. The UK is the leader of the European part with 30% of its shares, and the US with its 83% clearly stands out in the non-European part. In case of*

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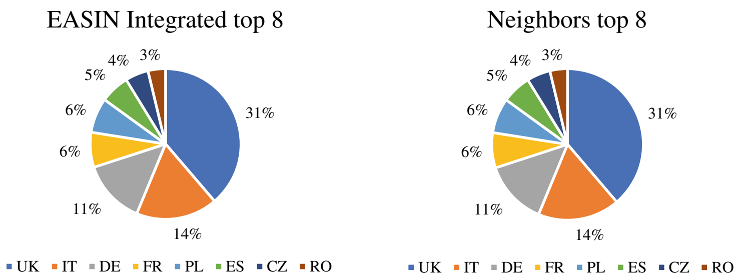


Fig. 5.1 **a, b** Share of top 8 countries in terms of number of companies in EASIN without isolates (**a**) and neighbors (**b**). *Legend* The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables "the others", which are included in Tables 5.1 and 5.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 8

neighbors, it is the UK that is the leader both in quantity and in economic attributes in Europe, and France although fourth in quantity is the second one in attributes. In the non-EU28 part, the US is prime in terms of attributes with no other country being any close to it. In terms of the economic attributes, overall the EU holds 56% of EC, 57% of EM, 49% of TURN, 65% of TASS and 56% of CF. These numbers are almost all slightly above half of the economic attributes, considering that the other half is dominated by the US; this tells a lot about the nature of managerial integration of EASIN with its neighbors.

The Financial sector neighbors (Table 5.2b in Data Appendix) are in major part located in Europe—82% out of 529 companies. They are distributed more evenly than previously, with the UK (22% in Europe and 18% globally) and the US (10% globally) being once again in lead in terms of number of companies. In Europe, the next places are occupied by Ireland, Germany, France and Italy, whereas in the rest of the world, it is Switzerland, Canada, Brazil and Singapore. Due to the lack of attributive data, there is no further reason to analyze financial proportions.

EASIN + NEIGH. The overall economic size of actors participating in the EASIN + NEIGH network is presented in Table 5.3 (in Data Appendix). When put together, all companies engaged in M2M EASIN + NEIGH network represent on average 97% of economic attributes of companies engaged in the ALL version (Fig. 5.3). It means that almost all "tangible" (as opposed to the "intangible" tacit knowledge and know-how) economic resources of all companies engaged with EASIN through any type of people-based coordination are being accessed in a way through managers.

The following pie charts (Fig. 5.2) highlight the situation in more aggregated form showing the relative economic size of EASIN as compared to its neighbors, represented as the percent share of the total per each economic attribute. The neighbors are presented through a cross section of sectors with particular attention given to those most prominent ones, the strength of the whole EU28 compared to the rest of the world is already provided in tables which can be found in the Data Appendix, so it will not be duplicated here. Although EASIN is not a sector, but rather just an industry within a particular geographical context, it is still added to the analysis because it is after all the focal point of the entire book. It is apparent that EASIN is always present in the top 3 along with, usually, Financial and Manufacturing sectors.

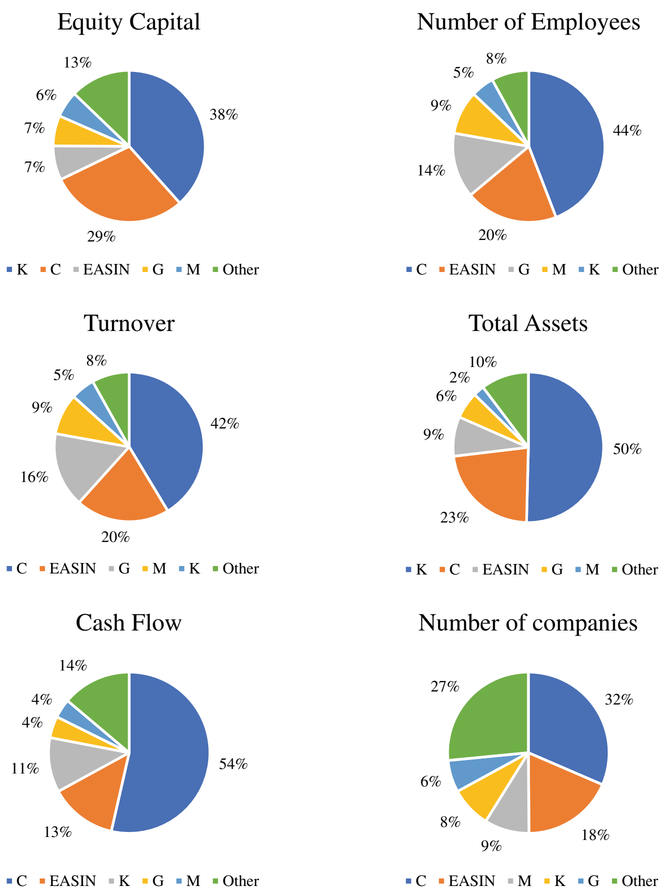


Fig. 5.2 a–f Economic attributes of EASIN Integrated compared with its neighbors, which are grouped into their respective sectors. *Legend* The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables "the others", which are included in Tables 5.1a and 5.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 5

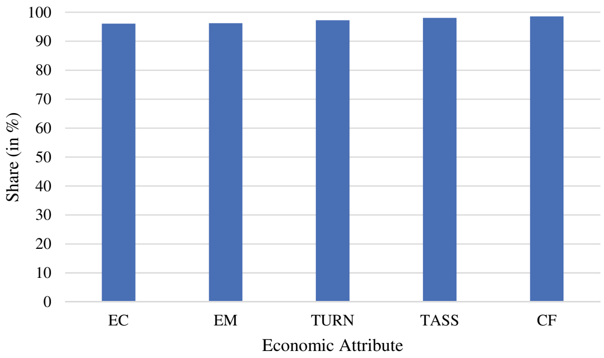


Fig. 5.3 Economic attributes of M2M E + N companies as proportion of ALL E + N companies

5.2 Correlation Analysis

EASINT.[1] Integrated EASIN[2] includes 1181 companies and (as usual) has full data for the topological indexes and a very high number for EC and TASS: 923 and 919, respectively. Conversely, substantially lower for EM, TURN and CF: 691, 626 and 505, respectively. Therefore, for some combinations of these three variables and eigenvector centrality, there can be insufficient significance (see Tables in Data Appendix). All the main centrality indexes become remarkably positively correlated with all economic size attributes. The coefficient is particularly high (0.67) for Dc with EC and (0.63) with TURN (Table 5.1). It means that within the EU28 Aerospace Industry, *inter-departmental coordination is proportionate to a company's economic size. This result can be interpreted with the fact that the effort to create and exchange operative knowledge in terms of quality standards, codes, programs, delivery time,* etc. *grows with company size*, so that larger companies are called for a major effort than smaller companies. The reduction of correlation coefficients in combination with eigenvector and Katz centralities suggests that the paths of connections starting from large companies proceed with small companies, which then have smaller connectivity. Put differently, *the transfer of operative knowledge declines alongside its transmission chains*. This is also confirmed by the absence (or mild negative) correlation with LORC.

Conversely, there is a positive and remarkable correlation with Bc, meaning that *the larger the firm, the easier it can access operative knowledge flow and, at the same time, filter and orient it*. However, such advantageous intermediary positions

[1] Due to the systematic lack of data on economic attributes, as for all analyses involving economic attributes, the true number of cases counted for correlations is much lower than the number of companies belonging to the specific network. The proportion of available cases of each correlation is in Data Appendix, jointly with the P-values.

[2] See the last section of Methodological Appendix to well understand the differences in EASINT and understand why it is necessary to use this aggregate for correlations. EASIN of M2M has less than half companies than its corresponding EASINT and refers to different network.

Table 5.1 Correlations in EASIN integrated

	EC	EM	TURN	TASS	CF	Average
LORC	−0.01	−0.03	−0.04	−0.04	−0.01	–
BDc	0.50**	0.44**	0.56**	0.50**	0.47**	0.49
WDc	0.67**	0.52**	0.63**	0.56**	0.61**	0.49
BBc	0.35**	0.29**	0.25**	0.25**	0.35**	0.60
WBc	0.21**	0.15**	0.20**	0.19**	0.15**	0.60
BRc	0.00	0.00	0.00	0.00	0.00	–

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

do not correlate also with bridging centrality, meaning that those companies do not cover positions that have a privilege access to companies' clusters.

EASIN + NEIGH MC. The MC of the extended network (Table 5.2) is about three times bigger than EASINT: It comprises 3238 companies (out of which only between 28 and 44% are covered by size attribute data). We see that, compared to EASINT, correlations are only mildly positively correlated with Dc, especially in the weighted version. It means that the addition of many neighbors weakens such associations, though we know (see i.e. Table 4.1 in Chap. 4) that MC companies are larger, more connected and more important—and thus, supposedly more integrated with the Aerospace Industry—than those outside of it. However, they are also more diversified in terms of sectors. Conversely, the Bc of the whole EASIN + NEIGH MC is remarkably correlated with companies' size, meaning that *though they do not generate and exchange much operative knowledge in direct relationships, they can easily and largely access the flow of that knowledge proportionately to their economic size*. Further, as for the ALL network and M2M EASIN Integrated, BRc is not correlated with economic size.

EASIN + NEIGH. Finally, if we move to EASIN + NEIGH network, which is made up of 6975 companies (but with observations shares that vary from 36% for EM and TURN to 56% for EC and TASS), correlation with Dc becomes negative (though very low), meaning that *companies' propensity to establish inter-departmental coordination is not associated with their size* (Table 5.3). Because the largest majority of

Table 5.2 Correlations in EASIN + NEIGH MC

	EC	EM	TURN	TASS	Average
LORC	– 0.04	−0.04	−0.06	−0.05	-0.03
BDc	0.05	0.15**	0.11**	0.11**	0.11
WDc	0.11**	0.16**	0.13**	0.18**	0.15
BBc	0.18**	0.48**	0.33**	0.41**	0.34
WBc	0.17**	0.43**	0.31**	0.37**	
BRc	0.00	0.00	−0.01	0.02	–

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

the 3737 companies out of the MC are diversified neighbors, it seems reasonable to suppose that in other sectors—or even in Manufacturing apart from Aerospace—the need for operative coordination is much lower than in EASIN, or at least it is not so associated with a company's size. This supposition is rather confirmed by the correlation analyses that we have done isolating some sectors and even focusing only on the Aerospace Industry alone. As in the MC, the association between size and Bc is rather high, *meaning that large companies occupy important positions in acquiring and transferring this type of operative knowledge*. Interestingly, BRc is not irrelevant (0.18), suggesting that unlike in MC, some of the companies with high intermediation power (Bc) connect also large clusters of companies, namely some big cliques, as we will show in the next sections.

Top 200. The level and signs of correlations change dramatically if we consider only the top 200 companies of the EASIN + NEIGH. As we discussed in the previous chapter, we explore the results of different types of ordering of the top 200, and then focus on those that produce interesting results. Here, they are EM or TASS and one peculiar topological parameter: bridging centrality (BRc). When ordered in terms of TASS (Table 5.4a), the correlations between binary and weighted Dc on one side and EM or TASS on the other become positive, and especially for the binary Dc and EM reach 0.23, which is a quite important value. Bc keeps around 0.29, which is near the same level as for the correlations of all the companies. However, here we lose that significant (0.18) correlation with bridging centrality shown by the whole: evidently, *large companies do not play the role of crucial connectors between clusters of companies, be them cliques—which in this network can be very large (see the corresponding analysis below in this chapter)—or other types of subnetworks.* The same lack of correlation occurs also if the ordering criterion of top 200 is that of EM or BRc itself. It means that company size does not guarantee that important role. If we order the top 200 in terms of EM (Table 5.4b), what we found in the previous Table is confirmed and slightly reinforced.

The situation changes drastically if we use bridging centrality as the ordering criterion (Table 5.4c). Here, the correlation between company size and Dc centrality is extremely high, especially when size is expressed in terms of EM or TURN: more than 0.8 for the binary and more than 0.89 for the weighted indexes, respectively.

Table 5.3 Correlations in EASIN + NEIGH

	EC	EM	TURN	TASS	Average
LORC	−0.03	0.02	−0.11	−0.08	–
BDc	−0.07**	−0.05**	−0.10**	−0.09**	−0.08
WDc	−0.07**	−0.04**	−0.06**	−0.07**	−0.06
BBc	0.25**	0.41**	0.15**	0.29**	0.28
WBc	0.25**	0.42**	0.16**	0.29**	
BRc	0.16	0.29	0.09	0.19	–

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 5.4a Correlations ordered by TASS in EASIN + NEIGH

	EC	EM	TURN	TASS	Average
LORC	−0.01	−0.01	−0.03	−0.04	–
BDc	0.00	0.23	0.17	0.06	–
WDc	0.03	0.16	0.13	0.06	–
BBc	0.14**	0.51**	0.32**	0.27**	0.29
WBc	0.12**	0.44**	0.29**	0.24**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 5.4b Correlations ordered by EM in EASIN + NEIGH

	EC	EM	TURN	TASS	Average
LORC	−0.10	−0.06	−0.08	−0.06	–
BDc	0.15*	0.21**	0.19**	0.22**	0.19
WDc	0.14	0.17*	0.15*	0.18*	0.16
BBc	0.25**	0.49**	0.33**	0.44**	0.36
WBc	0.22**	0.43**	0.31**	0.39**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

It means that *among the companies that determine the 0.18 coefficient at the whole network level, there is an extremely high correlation between Dc and Bc on one side and company size in terms of EM and TASS:* 0.55 and 0.9 in binary and weighted terms for Dc 0.96 and 0.93 for Bc.

Sectoral and industrial correlations. Interestingly, when focusing only on the Manufacturing sector (Table 5.5a), there is a significant, though only mild correlation between binary (0.28) and weighted (0.24) Dc and economic attributes size. The correlation grows up to 0.5 when considering Bc, with very high values (0.68 and 0.64) when the economic parameters are EM and TASS, respectively. Therefore, we see that *among the Manufacturing companies, there is a strong association between the capacity to intermediate the flow of operative knowledge and firm size.*

Table 5.4c Correlations ordered by the degree of BRc in EASIN + NEIGH

	EC	EM	TURN	TASS	Average
LORC	−0.04	−0.02	−0.03	0.00	–
BDc	0.37**	0.80**	0.83**	0.55**	0.64
WDc	0.60**	0.89**	0.93**	0.90**	0.83
BBc	0.62**	0.90**	0.93**	0.96**	0.83
WBc	0.56**	0.86**	0.89**	0.93**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

This relationship between centrality and firm size grows further when, within the Manufacturing sector, we select only on the Aerospace Industry (NACE:3030, Table 5.5b): The correlation with binary and weighted Dc almost doubles (0.45 and 0.46, respectively) and that with binary Bc reaches the peak of 0.82 and 0.83 for EM and TASS, respectively. Therefore, the remarks done for the ALL network apply perfectly to this M2M network too, and indeed this should be not surprising, because inter-departmental links are about 80% of all links, and as well the companies involved are the majority of all. Interestingly, LORC results to be systematically uncorrelated with any of the economic size parameter for any correlation set. It means that *the length and size of chains departing or arriving to a company have no relationship with its economic size. Put differently, it seems that a company can have a short or long chain of companies connected through their department, regardless of its size in terms of EC, TURN, EM or TASS*. This result is to some extent consistent with that of BRc, though they can be different in some cases, like in the case in which included were all companies (Table 5.3), where LORC continues to be (negatively) uncorrelated, while BRc assumes a mild and positive value (0.18).

Correlations are much lower in the Professional Activities (M) sector (Table 5.5c), but still relevantly grow again in the Financial (*K*) sector (Table 5.5d): In particular, there is a high correlation with the size in terms of EM, which reaches a peak of 0.83 when associated with binary Bc and a not trascurable 0.3 with binary Dc.

Table 5.5a Correlations limited to the manufacturing (C) sector

	EC	EM	TURN	TASS	Average
LORC	−0.04	−0.04	−0.05	−0.04	–
BDc	0.18**	0.32**	0.24**	0.34**	0.28
WDc	0.18**	0.25*	0.19**	0.32**	0.24
BBc	0.26**	0.68**	0.42**	0.64**	0.49
WBc	0.26**	0.62**	0.40**	0.59**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 5.5b Correlations limited to the Aerospace Industry (NACE:3030)

	EC	EM	TURN	TASS	Average
LORC	0.00	−0.03	−0.05	−0.03	-0.02
BDc	0.41**	0.42**	0.48**	0.50**	0.45
WDc	0.46**	0.38**	0.43**	0.58**	0.46
BBc	0.39**	0.82**	0.74**	0.83**	0.66
WBc	0.35**	0.73**	0.69**	0.75**	
BRc	0.09**	0.08*	0.08*	0.10**	0.09

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 5.5c Correlations limited to the professional activities (M) sector

	EC	EM	TURN	TASS	Average
LORC	−0.04	−0.01	−0.03	−0.06	–
BDc	0.13**	−0.02	0.01	0.13**	0.06
WDc	0.13**	0.00	0.06	0.16**	0.09
BBc	0.16**	0.02	0.13*	0.20**	0.11
WBc	0.05	0.02	0.01	0.05	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

Table 5.5d Correlations limited to the financial (K) sector

	EC	EM	TURN	TASS	Average
LORC	0.00	−0.03	0.02	−0.04	–
BDc	0.04	0.30**	0.08	0.05	0.12
WDc	0.08	0.21**	0.09	0.08	0.12
BBc	0.35**	0.83**	0.46**	0.46**	0.53
WBc	0.35**	0.76**	0.46**	0.47**	

Legend Statistical significance: * $P \leq 0.05$, ** $P \leq 0.01$

5.3 Network Analysis

EASIN. Among the three types of coordination, this form (Table 5.6a) involves the largest number of EASIN companies: 473 respect to the 305 of D2D and 112 of M2D. These companies interact through 904 links, which activate 1536 shared positions. It corresponds to a very low relative density (0.4%), with an average of about 2 positions per company, which grows up to 3.2 considering multiple positions. The binary version of this network lacks any kind of centralization, except for the eigenvector type (0.37), due to the fact that few higher centralized companies are connected with other highly connected ones. The main cause of this lack of centralization comes from the extremely high fragmentation (0.99), occurring through the presence of 171 disconnected components. However, the distance weighted fragmentation is half, meaning that more intensive coordination occurs among larger and closer components, namely the main component (MC), as witnessed by the binary and weighted average degree centrality (ADc) of the whole network and its MC and the diameter weight, which increases 4 times due to multiple links. Consistently, average distance is rather short (1.89), but with a diameter rather high (6) for such a small network. When considering the weighted version, Katz centralization increases from 0.01 to 0.5 and the eigenvector to 0.57, meaning that the most important companies and their neighbors make a particularly intensive coordination effort. It means that *there are few companies that produce a considerable effort in establishing standards and codes and diffuse them to their neighbors by appointing shared managers*. This fact, and more generally all the operative coordination forms, indicates that even when dealing with the application of standards and codes, explicit (codified) knowledge is not enough: there is required also human intervention. The MC is very small (27 companies) and highly centralized under all respects: few companies concentrate most operative knowledge flows. The main component is a joint of two business groups—Airbus and Safran, and companies related to them. It can be said that *EASIN standards and codes are established by these 27 companies, and especially by the most central heads of the business groups. This is a definitely high source of power, due to the crucial relevance of operative knowledge in Aerospace Industry.*

EASIN + NEIGH. In the extended version (Table 5.6b), more than 700 EASIN companies that were isolated, now become connected through neighbors, meaning that *operative coordination extends its effects also to those companies that do not receive it directly from EASIN companies.* Actually, they are coordinated by the neighbors, thus sharing their operative knowledge, which in part originate only in NEIGH, but in part is generated by other EASIN companies that bring their operative knowledge to those companies through the neighbors. These 700 ex-isolated EASIN companies activate about 2800 relationships, which involve 4000 shared managers, definitely a relevant number. Consequently, the number of connected companies grows 16 times, reaching the size of 6975. Here we witness, in fact, another case of phase transition, because the number of binary shared positions grows 334 times, reaching the enormous number of 0.3 million links, which become the astronomic number of 2.779 million in the weighted version. Moreover, they have also a very

Table 5.6a M2M EASIN: main indexes of network analysis

Index	$EASIN^{b}$	$EASIN\ MC^{b}$	$EASIN^{w}$	$EASIN\ MC^{w}$
Size	471	27	471	27
Density (norm)	0.004	0.162	–	–
Density (abs)	904	114	1,536	420
Fragmentation	0.991	0.000	0.472	0.589
Av. link value	1	1	1.699	3.684
ADc	1.918	4.222	3.256	15.556
Dc_CE (Fre)	0.028	0.430	–	–
Dc_CE (Sni)	0.002	0.336	–	–
Bc_CE	0.002	0.503	0.002	0.462
Eig_CE	0.367	0.237	0.567	0.499
Katz_CE	0.012	0.021	0.500	0.172
RWB_CE	–	0.519	–	0.556
GORC	0.032	0.270	0.027	0.283
Diameter	6	5	22	22
Apl	1.893	2.433	2.807	4.211
GCL	0.840	0.700	0.840	0.700
SW	239	1.842	–	–

high capacity of intermediating operative knowledge: almost 179 thousand links in binary terms and more than 264 thousand in weighted terms. Even more interestingly, *the whole EASIN MC "migrates" into the EASIN + NEIGH MC, meaning that the EASIN core companies (Airbus and Safran groups) remain crucial players also in the extended network and this way they benefit from the knowledge brought by neighbors*. Further, the companies that in EASIN were placed in other, smaller components—the ones out of the MC—belong also to the EASIN + NEIGH MC, thus, doing a big jump in terms of knowledge acquisition and coordination power.

Due to the phase transition in connectedness, fragmentation substantially lowers to 0.784, despite the high (823) number of disconnected components (see Table 4.10 in Chap. 4). The degree of fragmentation is then still high, but much lower than that of EASIN, because of the enormous increase of the MC share. Now, *because many companies that in EASIN were isolated or placed in separated small components are indeed connected by neighbors into the MC, then the operative knowledge seemingly*

Table 5.6b M2M EASIN + NEIGH: main indexes of network analysis

Index	EASIN + NEIGH^{b}	EASIN + NEIGH MC^{b}	EASIN + NEIGH^{w}	EASIN + NEIGH MC^{w}
Size	6975	3238	6975	3238
Density (norm)	0.006	0.024	–	–
Density (abs)	301,358	255,748	2,779,408	2,393,312
Fragmentation	0.784	0.000	0.753	0.754
Av. link value	1	1	9.223	9.358
ADc	43	78.986	398	739.143
Dc_CE (Fre)	0.039	0.072	–	–
Dc_CE (Sni)	0.027	0.069	–	–
Bc_CE	0.041	0.192	0.040	0.185
RWB_CE	–	0.21	–	0.26
Eig_CE	0.061	0.059	0.062	0.059
Katz_CE	0.001	0.001	0.045	0.046
GORC	0.224	0.3	0.100	0.167
Diameter	12	12	270	270
Apl	4.048	4.062	–	–
GCL	0.961	0.940	0.961	0.940
SW	44	9	–	–

Legend b = binary links, MC = main component, w = weighted links; ADc = average degree centrality; Dc_CE = out_degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; RWB_CE = random-walk betweenness centralization; Eig_CE = eigenvector centralization; Katz_CE = Katz centralization; GORC = centralization of the hierarchical degree according to the reaching capacity; Apl = average path length; GCL = global clustering coefficient; SW = small-worldliness index. Some of the indexes are missing due to computational limitations *unrelated, because dispersed into a plethora of small islands, appears now, even for most EASIN companies, integral part of a large and strongly coordinated operative knowledge generated and diffused into the MC*.

Still because of the same reason, average distance does not increase much, reaching about 2 steps. However, due to the much larger average size of components, and in particular of the main component, which here includes 46% of companies, the diameter doubles to 12 steps, which weights 270 considering multiple links. Indeed, this aspect of the global operative coordination induced by the EU28 Aerospace Industry fits with one of the topological traits supposed to characterize all socio-economic networks and in particular knowledge (or cognitive) networks (Gallo, 2012; Jackson & Rogers, 2007). Another one is the HT structure of links distribution and even of other topological and attributive parameters (see below Sect. 5.6). Another clear trait matching this one with the class of knowledge networks is the SW structure, which in fact, though not very high, is 44, and much higher (239) for EASIN.

It is very important to underline that the average number of links per company—a parameter that we call also coordination propensity—is much higher than in EASIN: 43 vs. 1.9, that is, companies of the extended network have a propensity to establish operative coordination that is 22 times bigger. This difference is even more astonishing when considering the intensity of the coordination effort, that is, all the multiple shared positions that could be issued: It is 124 times bigger. This is due to a fact that we have already discussed in the previous chapter: *Neighbor companies—and among them Anglo-American and Manufacturing companies—have a very high propensity to coordinate their activities with EASIN companies, but especially among themselves*.

Due to the high fragmentation from hundreds of disconnected components, centralization is very low in both, binary and weighted, versions, while binary GORC (0.22) shows that there are some companies from which start very long and wide coordination paths, while most others are rather short-small. Likely, those with long and wide paths are companies that can generate and trigger the dissemination of technical or commercial standards. However, weighted GORC is much lower, meaning that the longest, widest subnetworks channel relatively less operative knowledge than the others.

EASIN + NEIGH MC. The MC is huge, because it comprises 3238 companies, which hold almost 256 thousand relationships (85% of global operative coordination) that, in turn, activate more than 2393 thousand shared managerial positions—about 86% of total. A truly huge number, meaning that there is a primary attention, skills and resources employed to create and transfer operative knowledge throughout this compact core. As witnessed by main centralization indexes that grow slightly, few companies have a more important position than others, but, due to MC big size, not so much like in the EASIN MC. A remarkable level (0.19) of the intermediating power is well shown by binary and weighted Bc, and even more when considering not only the shortest paths, as it should be done in this phenomenal domain: RWB_CE is 0.21 and 0.26 in binary and weighted terms, respectively. Likely, the same companies that are supposed to generate more knowledge with their neighbors are also those that

Table 5.7 Inter-sectoral network of the M2M network

Index	Binary	Weighted
Size	22	
Density (norm)	0.478	
Density (abs)	221	2,725,932
Disconnectedness degree	0	
Fragmentation	0	0.115
Av. link value	1	6460
ADc	19.18	123,906
Dc_CE (Fre)	0.141	–
Dc_CE (Sni)	0.385	–
Bc_CE	0.008	0.327
RWB_CE	0.015	0.480
Eig_CE	0.026	0.999
GORC	0.256	0.141
Apl	1.130	4.338
GCL	0.920	–
SW	1.259	

Legend Look above

are more central between all the knowledge flows. In short, *operative knowledge is largely created by a relatively restricted number of companies residing within the MC: a core of the core. The MC itself is so big that it could be considered enough to technologically coordinate the essential part of the global Aerospace Industry activated by EU28 countries.*

5.4 Inter-Sectoral Network

After grouping companies into sectors (see Methodological Appendix), we have built the corresponding inter-sectoral network (Table 5.7). This network is extremely dense (0.48) and accounts for more than 157 thousand inter-sector manager interlocks. It is a fully connected network, extremely clustered and with short coordination chains (1.13). Despite these traits, it is not a balanced network, because *after EASIN that covers the most important position, few other sectors also cover crucial central positions (Fig. 5.4): besides the Manufacturing (C), which is the most prominent one, also the Wholesale (G), the Financial (K) and the Professional Activities (M) sectors are very relevant either in terms of number of companies or intensity of coordination.* This concentration is grasped by looking at the moderate centralization indexes in terms of Snijders' degree (0.39) and GORC. When considering the weighted version, which counts also the intensity of coordination, EASIN (see Table 5.11 in

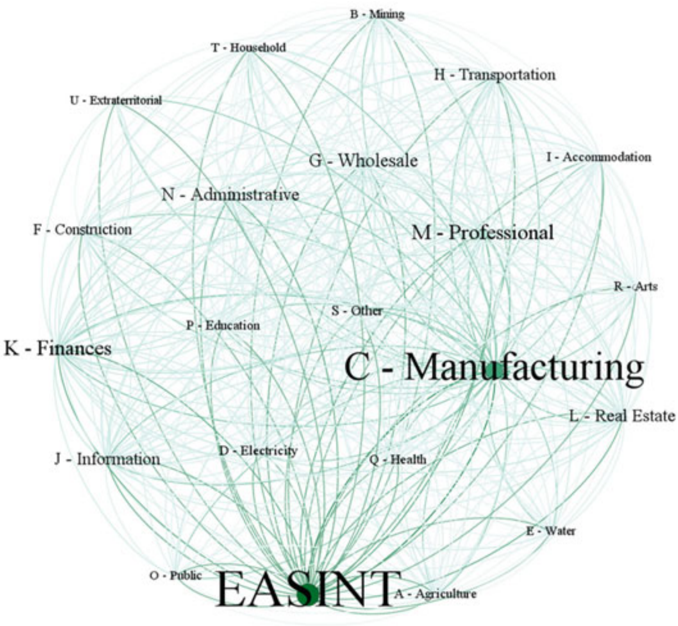


Fig. 5.4 Inter-sectoral graph of EASIN + NEIGH coordination. *Legend* the size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of department interlocks

Data Appendix) dominates so much this network to determine almost the maximum values for the high eigenvector centralization. In terms of weighted Bc, the degree of centralization is remarkable, but more moderate: (0.33) for (geodesic-based) Bc and 0.48 for RWB_CE (Table 5.7).

The sector with by far the greatest number of coordination connections is the Manufacturing, with almost 200 thousand (binary) links (Table 5.8a), equals to 72% of total connections, followed by the Wholesale (only 6%), then the Financial, the Professional Activities and EASIN. It should be underlined that these sectors concern only neighbors, because EASIN is considered apart. Now, it is noteworthy that in terms of inter-sectoral connections, the ranking still sees the Manufacturing and the Wholesale sectors at the first two places, but two aspects become very different: (i) the ranking distances are much smaller than those of total links, because the Manufacturing has just about the double connections of the Wholesale and not eleven times; (ii) the third position is covered by EASIN. This happens because 88% of Manufacturing links are self-links, that is, are links occurring between Manufacturing companies themselves, while for EASIN companies that share is only 10%. It means that Manufacturing companies which we know from the previous chapter (and will confirm in the following section specifically for this form of coordination) are mostly American and establish inter-departmental coordination mostly among themselves. This situation is even accentuated when considering also the intensity of coordination efforts (Table 5.8b): here we see that almost the totality (98%) of shared positions of Manufacturing companies is established among themselves, while only 6% are of EASIN. Consequently, though the first rank in inter-sectoral coordination is still covered by the Manufacturing sector with about 60 thousand shared managers, the second position is covered by EASIN with about 23 thousand positions. The Wholesale and the Financial sectors follow. *This shows an opposite orientation of EASIN and neighbor Manufacturing companies regarding operative knowledge creation and transfer: The former is oriented toward neighbors of diverse sectors, while the latter is self-referential. Those traits explain also how it is possible that, despite the enormous difference in terms of number of connections, in the inter-sectoral network, EASIN covers a more important position than the Manufacturing sector*, as it can be seen also from Fig. 5.4. However, the Manufacturing sector is the main partner of EASIN (Table 5.9), with whom it establishes 18.6 thousand positions to manage operative knowledge, which is the biggest inter-sectoral relationship. On the other hand, the pivotal role of the Manufacturing sector can be drawn also from the fact that the following six positions in that ranking see that sector always involved.

Companies' propensity for adopting operative coordination. If we look at company's average propensity/capacity to establish operative coordination in each sector (Table 5.10), we see that Manufacturing companies have the extraordinary propensity to issue 1211 shared positions, which crash down to only 30 when the partner company is in another sector. The second highest propensity is that of ICT (218) and Wholesale companies (206), which both are rather unbalanced toward its same sector partners. The same Table shows that the Manufacturing, Wholesale, Finance and Professional Activities sectors have the major diversification in geographical terms (Table 5.11).

5.5 Inter-Country Network

EASIN. There are only 25 countries in the EASIN inter-country network, because, out of the EU28, three countries have no companies connecting to companies from other countries—they are Cyprus, Croatia and Luxembourg. Another eight countries have only self-referential coordination (see Fig. 5.5 for visual inspection).[3] There are 64 coordination connections between the 25 countries, corresponding to a 0.107 normalized density, less than one fourth of that of the inter-sectoral network, which as well was built on the E + N network. The intensity of coordination effort is of 1536 shared managers, including those between companies within the same country, meaning, that on average, every inter-country connection involves 14.6 positions. Still on average, each country establishes 4 relationships, which involve about 61 shared managers.

[3] These seven countries appear as isolated nodes with self-links, and they determine a positive disconnectedness degree and a 0.55 fragmentation (0.42 when distance weighted).

Table 5.8a Share of internal (binary) links across sectors

Sector	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
C	173,510	90	24,637	198,147	72	88
G	4602	2	12,924	17,526	6	26
K	4332	2	6782	11,114	4	39
M	1230	1	7873	9103	3	14
EASINT	904	0	8195	9099	3	10
J	4888	3	2554	7442	3	66
L	838	0	3520	4358	2	19
N	668	0	3472	4140	2	16
H	1584	1	2031	3615	1	44
F	438	0	2463	2901	1	15
I	100	0	1063	1163	0	9
A	236	0	808	1044	0	23
S	28	0	770	798	0	4
D	90	0	572	662	0	14
P	38	0	482	520	0	7
R	8	0	400	408	0	2
Q	6	0	401	407	0	1
O	2	0	355	357	0	1
B	22	0	297	319	0	7
E	2	0	191	193	0	1
T	0	0	134	134	0	0
U	0	0	10	10	0	0
Total	193,526	100	79,934	273,460	100	71

Legend Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB

This network is moderately centralized in binary terms either directly (Dc_CE Fre 0.34 and Sni 0.26) or indirectly: Bc_CE 0.14, Eig_CE 0.28 and GORC 0.26. It becomes much more centralized when considering the intensity of coordination effort: due mostly to the UK, it reaches 0.99 in terms of weighted eigenvector centralization. Actually, the UK is by far the most important country, followed by FR, DE, IT and the NL, thus confirming also in topological way what holds as well in statistical way, as evidenced in section one. So, we can say that EASIN operative coordination is made to a large extent by the UK, which makes a massive effort, especially through direct links. In fact, if we look at the capacity to intermediate the flow of operative knowledge, we see that IT, which is at the fourth place in terms of shared managers (direct links, WDcA in Table 5.11 in Data Appendix), climbs at the first place in

Table 5.8b Share of internal (weighted) links across sectors

Sector	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
C	2,387,786	92	59,921	2,447,707	90	98
G	65,440	3	19,900	85,340	3	77
J	65,132	3	4446	69,578	3	94
K	25,760	1	15,532	41,292	2	62
EASINT	1536	0	23,205	24,741	1	6
H	15,904	1	4450	20,354	1	78
M	1560	0	10,834	12,394	0	13
N	2712	0	4294	7006	0	39
L	980	0	4175	5155	0	19
F	718	0	3211	3929	0	18
B	238	0	1434	1672	0	14
I	172	0	1410	1582	0	11
A	368	0	865	1233	0	30
S	36	0	815	851	0	4
D	158	0	622	780	0	20
P	46	0	528	574	0	8
Q	12	0	506	518	0	2
R	8	0	432	440	0	2
O	2	0	381	383	0	1
E	2	0	255	257	0	1
T	0	0	136	136	0	0
U	0	0	10	10	0	0
Total	2,568,570	100	157,362	2,725,932	100	94

Legend Acronyms explained in the list of abbreviations
ShITW = IDW/Total IDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

terms of weighted Bc (WBcA). The UK becomes second and FR and DE third and fourth. This tells us that the creation of standards, which likely are done in direct relationships, is mostly done by the UK, but the transfer of (and also the access to) such standards is made more by IT. In short: *EASIN operative knowledge is largely created into and by the UK, but then its inter-country diffusion is more balanced among the four main EU28 countries, among which IT covers a prominent position.*

Despite its much higher number of links and companies—377 relationships engaging 522 shared managers (Tables 5.12a and 5.12b) and 178 companies—the UK's influence on other EASIN countries is only on the third place with 66 managers shared with other countries. The first place is covered by FR (128), followed by DE (90 shared managers). Then, after the UK, there comes the NL (42) and PL (26).

Table 5.9 Major 20 cross-sectoral coordination efforts

Source	Target	Weight
EASINT	C	18,632
G	C	16,235
C	K	10,001
C	M	5410
J	C	2589
H	C	2200
C	B	1065
N	K	949
K	M	934
F	C	910
EASINT	M	834
K	EASINT	772
C	N	757
M	G	719
G	K	703
L	K	692
M	N	590
L	C	589
EASINT	H	557
G	EASINT	534

Legend Each of them is symmetric

Interestingly, IT is only 7th after ES, though it has a primary role in terms of intermediation power of operative knowledge flow. The reason of this is that, among the main countries, the UK and IT have the highest "degree of closure", that is, share of internal links out of all links: 89% the UK, 87% IT. This major propensity of French companies to coordinate operative knowledge with companies of other countries is confirmed also by looking at the more intensive bilateral relationships (Table 5.13): FR is in the first three ranks.

Operative coordination propensity per country. Within EASIN (Table 5.14), companies' propensity to employ operative coordination is quite high and quite differentiated, with some remarkable exceptions, such as Austria, Bulgaria, Estonia and Belgium with high scores, and several others with scores lower than 1. The country that was important in the statistical analysis—the UK—turned out, overall, not to be so in terms of propensity once it has been calculated including all of the UK's isolates.

EASIN + NEIGH. The size of this extended inter-country network (Table 5.15) is almost that of the ALL network, thus witnessing how pervasive is operative coordination. In fact, as we will see in the next chapter, the size of the analogous D2D network is 47 (countries), thus indicating that the strategic coordination is restricted

Table 5.10 Companies' weighted propensity to coordinate across sectors

Sectors	# of countries	# of companies	# of (weighted) links per company		
			IDW	EDW	Total
A	13	52	7.08	16.63	23.71
B	7	17	14.00	84.35	98.35
C	42	2021	1181.49	29.65	1211.14
D	11	57	2.77	10.91	13.68
E	7	15	0.13	17.00	17.13
EASINT	27	1181	1.30	19.65	20.95
F	23	146	4.92	21.99	26.91
G	37	413	158.45	48.18	206.63
H	24	196	81.14	22.70	103.85
I	15	59	2.92	23.90	26.81
J	28	319	204.18	13.94	218.11
K	33	525	49.07	29.58	78.65
L	25	310	3.16	13.47	16.63
M	36	576	2.71	18.81	21.52
N	26	315	8.61	13.63	0.02
O	5	9	0.22	42.33	42.56
P	15	50	0.92	10.56	11.48
Q	10	27	0.44	18.74	19.19
R	11	42	0.19	10.29	10.48
S	14	78	0.46	10.45	10.91
T	1	9	0.00	15.11	15.11
U	2	2	0.00	5.00	5.00
No Data	36	556	–	–	–
Total	60	6975	368.25	22.56	390.81

Legend Acronyms explained in the list of abbreviations

to a smaller geographical area. Unlike the EASIN inter-country network, this one is almost not fragmented and has a rather high degree of degree centralization: 0.68 and 0.61 for the Freeman's and the Snijders' methods, respectively. This is clearly due to EASIN, which has 58 neighbors (represented by its binary Dc) and the UK and the US, which have 48 and 45 neighbors, respectively (Table 5.11 in Data Appendix). However, if we look at the weighted links, the US has the overwhelming relevance, because they account for 23% of companies and 45% of coordination effort between countries, which means weighted direct relationships (Table 5.17 and 5.18). This unbalance between the two shares is due to the extremely higher coordination propensity of American companies with respect to all other companies. Indeed, according to the absolute number of shared positions, the US share is 92%, but it largely

Table 5.11 Inter-country network of EASIN

Index	Binary	Weighted
Size	25	
Density (norm.)	0.107	
Density (abs.)	64	1536
Disconnectedness degree	0.01	
Fragmentation	0.547	0.462
Av. link value	14.63	
ADc	4.20	61.44
Dc_CE (Fre)	0.339	–
Dc_CE (Sni)	0.258	–
Bc_CE	0.142	0.187
Eig_CE	0.284	0.985
GORC	0.257	0.169
Apl	1.860	3.154
GCL	0.694	–
SW	5.193	

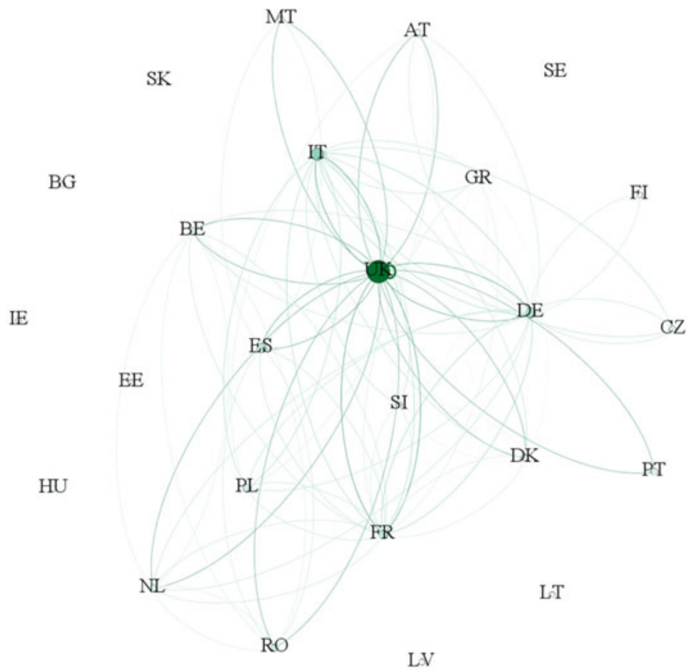


Fig. 5.5 Inter-country graph of EASIN coordination. *Legend* the size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of department interlocks

Table 5.12a Share of internal (binary) links across countries

Country	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
UK	334	48	43	377	42	89
IT	80	11	12	92	10	87
ES	48	7	12	60	7	80
FR	48	7	36	84	9	57
DE	46	7	26	72	8	64
NL	36	5	14	50	6	72
PL	22	3	5	27	3	81
CZ	18	3	2	20	2	90
RO	12	2	9	21	2	57
PT	10	1	1	11	1	91
BE	8	1	18	26	3	31
HU	6	1	0	6	1	100
AT	4	1	6	10	1	40
BG	4	1	0	4	0	100
LV	4	1	0	4	0	100
SI	4	1	7	11	1	36
DK	2	0	5	7	1	29
EE	2	0	0	2	0	100
FI	2	0	1	3	0	67
IE	2	0	0	2	0	100
LT	2	0	0	2	0	100
SE	2	0	0	2	0	100
SK	2	0	0	2	0	100
GR	0	0	4	4	0	0
MT	0	0	5	5	1	0
Total	698	100	206	904	100	77

Legend Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB

depends on the fact that 95% of such positions are not occurring across countries, but rather within the US itself (Tables 5.16a and 5.16b). In other words, 95% of operative coordination efforts of American companies is addressed to other American companies.

When ranked in terms of coordination efforts, the main countries immediately following the US are CA, the UK, EASINT, IT and DE. The abnormal high level (0.998) of weighted eigenvector centralization depends on the abnormal number of self-links in the US. To "neutralize" that distortion, it is better to use the binary version

Table 5.12b Share of internal (weighted) links across countries

Country	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
UK	456	41	66	522	34	87
FR	140	13	128	268	17	52
DE	110	10	90	200	13	55
IT	110	10	12	122	8	90
NL	76	7	42	118	8	64
ES	58	5	14	72	5	81
AT	36	3	8	44	3	82
PL	26	2	5	31	2	84
CZ	20	2	2	22	1	91
RO	14	1	11	25	2	56
BE	12	1	26	38	2	32
PT	12	1	1	13	1	92
FI	8	1	1	9	1	89
HU	6	1	0	6	0	100
BG	4	0	0	4	0	100
LV	4	0	0	4	0	100
SI	4	0	7	11	1	36
DK	2	0	6	8	1	25
EE	2	0	0	2	0	100
IE	2	0	0	2	0	100
LT	2	0	0	2	0	100
SE	2	0	0	2	0	100
SK	2	0	0	2	0	100
GR	0	0	4	4	0	0
MT	0	0	5	5	0	0
Total	1108	100	428	1536	100	72

Legend Acronyms explained in the list of abbreviations
ShITW = IDW/Total IDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

(0.142) and imagine that the "true" level is at some intermediate point between the binary and weighted version. Actually, the ranking of binary eigenvector is very close to that of binary Dc, but with important ranks covered also by FR and ES. Very interesting is also the degree of the mild (but significant) level of binary and weighted Bc centralization: 0.27 and 0.19, respectively. In this specific ranking, if considering the binary network, EASINT is definitely the first, then followed by the UK and the US and far distant from the others. If we consider the weighted version,

Table 5.13 Major 10 cross-country coordination efforts

Source	Target	Weight
DE	FR	61
UK	FR	29
NL	FR	19
NL	DE	13
FR	BE	12
ES	RO	8
AT	UK	6
DE	UK	6
UK	NL	6
UK	BE	5

Legend Each of them is symmetric

EASINT is still the first actor, but then, due to the neutralization of self-links (that in Bc do not count), do follow surprisingly ES, AU, CZ and CH.

It is very interesting to notice that 73% of the US external operative coordination is realized with CA (Table 5.17), which in turn holds with the US 98% of its coordination effort. Further, 7% of the US coordination is realized with the UK, which in turn employs 72% of its external operative coordination with the US. Therefore, it appears clear that 101,500 shared positions to exchange operative knowledge are an Anglo-North-American business. Only 13% of the US external operative coordination (corresponding to 17,145 shared positions) is realized with EASINT, thus showing that it is definitely secondary for the US and the Anglo-North-American area. Conversely, for EASINT that share represents 71% of its all external operative coordination, thus showing that *there is a sharp asymmetry in the operative knowledge exchange between the two blocks in favor of the Anglo-North-American area.*

Operative coordination propensity per country. While the average propensity of the whole extended network to adopt this coordination form is 399 shared positions per company (Table 5.18), only two countries have a much higher propensity than it: the US and Canada. At a closer view, it is further confirmed that EASINT is mostly interacting with the outside, similarly to France, the Netherlands, Romania and Austria in EU28 and Canada with Switzerland outside of it, whereas the rest of countries depends on internal relations. The country dependent on internal relations with the largest gap between internal/external relations is the US, which also has the most companies and therefore has the highest impact on the average (Fig. 5.6).

Table 5.14 Companies' weighted propensity to coordinate across EASIN countries

Country	# of companies	IDW	EDW	Total
AT	5	91.20	13.20	104.40
BE	13	10.77	9.85	20.62
BG	4	27.50	22.50	50.00
CZ	12	9.17	1.00	10.17
DE	41	1.85	1.02	2.88
DK	4	14.50	3.50	18.00
EE	2	18.00	4.00	22.00
ES	30	0.40	0.87	1.27
FI	3	8.67	1.67	10.33
FR	31	0.45	0.35	0.81
GR	1	12.00	1.00	13.00
HU	6	0.67	1.17	1.83
IE	2	4.00	0.50	4.50
IT	62	0.03	0.10	0.13
LT	2	3.00	0.00	3.00
LV	4	0.00	1.25	1.25
MT	2	2.00	0.00	2.00
NL	14	0.00	0.29	0.29
PL	22	0.18	0.00	0.18
PT	11	0.18	0.00	0.18
RO	13	0.15	0.00	0.15
SE	2	1.00	0.00	1.00
SI	5	0.40	0.00	0.40
SK	2	1.00	0.00	1.00
UK	178	0.11	0.01	0.12
Total	471	3.71	1.45	5.17

Legend Acronyms explained in the list of abbreviations

5.6 Cluster Analysis

In this chapter, we look at M2M networks in all variants (EASIN, EASIN Integrated and EASIN + NEIGH). Their analysis results are casted over three clusters[4] whose features are further analyzed by projecting each cluster within its network, thus evidencing where they are placed and distinguished are also their geographical and sectoral aspects.

[4] The methodological procedure to create the clustering analysis is explained in the Methodological Appendix.

Table 5.15 Inter-country network of EASIN + NEIGH

Index	Binary	Weighted
Size	61	
Density (norm)	0.153	
Density (abs)	560	2,779,408
Fragmentation	0.033	0.420
Av. link value		2,586
ADc	17.62	45,564
Dc_CE (Fre)	0.684	0.018
Dc_CE (Sni)	0.611	–
Bc_CE	0.272	0.193
Eig_CE	0.142	0.998
GORC	0.181	0.050
Apl	1.724	4.073
GCL	0.816	–
SW	2.221	

EASIN. Due to a major coverage of economic attributes, in this cluster analysis, we could employ also them (Fig. 5.7, Tables 5.19 and 5.20), so that after some experiments, we found the following key-parameters: BDc, BCc and TURN.[5] The results are further analyzed by projecting each cluster into the network, thus evidencing where they are placed.

Cluster 1. This cluster highlights the most frequent type of companies—those that cover 76% of the analyzed network. They are members of all the smaller components. Companies that are highlighted have medium connectivity—both short and long distance, as well as very low TURN (Fig. 5.8).

Cluster 2. It contains 1% of companies from the EASIN network, which are lowest in terms of connectivity—short and long distance, but by far have the highest TURN. Two of them are in the thickest part of the main component, and one of them is located in a smaller dyad (Fig. 5.9).

Cluster 3. It includes 23% of companies with the highest connectivity—it means that they are members of the largest components in the network, because they connect with many others in a close range, but also thanks to the larger size of their components they also well connect with their further members indirectly. Their TURN is, however, similar to the worse connected companies of Cluster 1 (Fig. 5.10).

EASIN Integrated. Out of all EASIN companies connected in the EASIN + NEIGH network, only a bit more than a half had the attributive data which allowed us to conduct the following analysis. Further, in the cluster analysis of EASIN Integrated with the use of the same parameters as in EASIN it turned out that only the binary degree centrality played any important role in distinguishing groups of companies

[5] Normalized respect to highest value, decreased by one decimal place to level with other parameters.

Table 5.16a Share of internal (binary) links across early 20 countries

Country	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
US	193,870	81	19,745	213,615	71	91
UK	22,162	9	6881	29,043	10	76
EASINT	904	1	8883	9787	3	9
CA	810	1	8489	9299	3	9
IT	5670	2	2608	8278	3	68
DE	3034	1	2421	5455	2	56
BE	3356	1	891	4247	1	79
IE	3110	1	948	4058	1	77
FR	1204	1	1563	2767	1	44
NL	926	0	1102	2028	1	46
ES	698	0	601	1299	0	54
PL	630	0	601	1231	0	51
SK	900	0	166	1066	0	84
PT	600	0	241	841	0	71
DK	668	0	161	829	0	81
BR	70	0	665	735	0	10
CH	106	0	498	604	0	18
CZ	342	0	255	597	0	57
CN	66	0	422	488	0	14
ZA	140	0	308	448	0	31
Total	46,680	100	41,063	87,743	100	53

Legend Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB

from one another, the closeness centrality and TURN did not vary visibly. In consequence, due to the clique-based structure of the EASIN + NEIGH network, it was possible to distinguish only roughly into what sizes of cliques the analyzed companies fell into after adding the neighbors into the equation. In consequence, Cluster 1 comprising 92% of companies showed the lowest BDc, Cluster 2 with almost 2% of companies had the highest connectivity, Cluster 3 with about 6% of companies showed about half of Cluster 2's connectivity—becoming the medium connected group. Compared to EASIN in this part, the lowest connected group expanded (shift from 76 to 92%) and the medium size shrinked from 23%.

This analysis very well resembles the heavy-tail structure of our networks, where top connectivity is reserved only for few most central companies, and the rest are at the opposite spectrum.

The cluster analysis is a great tool, which allows to gather together and present what we have already showed in previous analysis and show those results in a

Table 5.16b Share of internal (weighted) links across early 20 countries

Country	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
US	2,434,498	97	126,471	2,560,969	92	95
CA	8642	1	94,593	103,235	4	8
UK	25,022	1	12,765	37,787	1	66
EASINT	1536	1	24,021	25,557	1	6
IT	7656	0	2859	10,515	1	73
DE	3806	0	3880	7686	1	50
BE	4218	0	1143	5361	0	79
IE	3152	0	1100	4252	0	74
FR	1404	0	2660	4064	0	35
NL	1048	0	1559	2607	0	40
AU	154	0	1564	1718	0	9
ES	856	0	612	1468	0	58
PL	768	0	626	1394	0	55
SK	1148	0	178	1326	0	87
PT	838	0	260	1098	0	76
BR	136	0	830	966	0	14
SE	80	0	836	916	0	9
DK	716	0	170	886	0	81
ZA	162	0	662	824	0	20
CH	160	0	556	716	0	22
Total	2,497,876	100	281,532	2,779,408	100	90

Legend Acronyms explained in the list of abbreviations
ShITW = IDW/Total IDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

comprehensible, graphical way. The general insight stemming from it is: (1) EASIN exhibits a heavy-tail distribution of its topological and size attributes; (2) it is divided into numerous components, where majority is made of small ones, usually dyads, several of them are made up of several companies, and only few of them form larger structures; (3) the largest components are usually associated with companies, which exhibit also the largest economic size attributes; (4) there are only very few companies, who are both economically large and occupy an outstandingly advantageous network positions, where they are the "thick of the things" being surrounded by a fairly large immediate neighborhood and also being connected to longer chains, thus having access to further companies.

EASIN + NEIGH. The cluster analysis has identified three clusters (Fig. 5.11), whose basic statistics are summarized in Tables 5.21 and 5.22. Due to the lack of data on economic attributes of neighbors, we had to employ only topological parameters, namely LORC, binary degree centrality and Katz centrality. LORC makes the major

Table 5.17 Major 30 cross-country coordination efforts

Source	Target	Weight
US	CA	92,338
US	EASINT	17,145
UK	US	9161
UK	EASINT	1866
DE	US	1767
US	FR	1381
CA	EASINT	1258
US	AU	919
IT	EASINT	769
IT	US	769
EASINT	DE	683
SE	US	527
US	NL	440
US	ZA	400
FR	EASINT	297
NL	BE	290
BE	EASINT	273
US	BR	267
CH	US	226
US	BE	216
CA	UK	214
FR	CA	204
DE	IT	200
US	IE	192
EASINT	ES	188
PL	EASINT	183
EASINT	NL	177
NL	EASINT	177
BR	IT	172
IT	IE	168

Legend Each of them is symmetric

discrimination among the three clusters being extremely small for the largest cluster (Cluster 3), very large for the smallest cluster (Cluster 2), and large for Cluster 1, which covers one third of all companies. It means that the cluster that has the largest capacity to diffuse operative knowledge is rather small and is characterized also by a low number of partners. Further, they are mostly American and British Manufacturing companies that connect different parts of the whole network. More in-depth analysis of each cluster follows here below.

Table 5.18 Companies' weighted propensity to coordinate across early 20 EASIN + NEIGH countries

Country	# of companies	IDW	EDW	Total
US	1624	1499.08	77.88	1576.95
EASINT	1181	1.30	20.34	21.64
UK	1166	21.46	10.95	32.41
IT	515	14.87	5.55	20.42
DE	375	10.15	10.35	20.50
FR	282	4.98	9.43	14.41
IE	226	13.95	4.87	18.81
BE	178	23.70	6.42	30.12
ES	164	5.22	3.73	8.95
PL	149	5.15	4.20	9.36
CA	105	82.30	900.89	983.19
CZ	104	3.60	2.81	6.40
PT	103	8.14	2.52	10.66
DK	89	8.04	1.91	9.96
NL	86	12.19	18.13	30.31
RO	73	1.64	4.56	6.21
BG	55	5.31	2.38	7.69
SK	54	21.26	3.30	24.56
AT	36	2.78	9.47	12.25
CH	36	4.44	15.44	19.89
Total	6975	359.46	39.13	398.57

Legend Total links per country are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations

Cluster 1. Cluster 1 is made up of 38% of companies, and it is characterized by a medium-range network reach (LORC) and slightly larger direct connectivity than in the other 2 clusters. Katz is leveled for all clusters; hence, it will be irrelevant for this analysis. The highlighted companies are distributed across the whole network, and they also form large part of the main component (Fig. 5.12a and b). The reason why they are put together is because from their current positions, they can fairly easily access other, further companies outside their own cliques, but their chains are not too long. Between themselves, they are usually connected with companies from the same countries (Fig. 5.13a). Consistently with what discussed in the previous section, the most dominant countries in this group are the US and the UK, where all companies of the former tend to stick to each other, the latter form rather isolated components. The US companies are mostly from Manufacturing (C) sector (Table 5.13b), except two cases where they represent also the Financial companies (K) and information and communication (J).

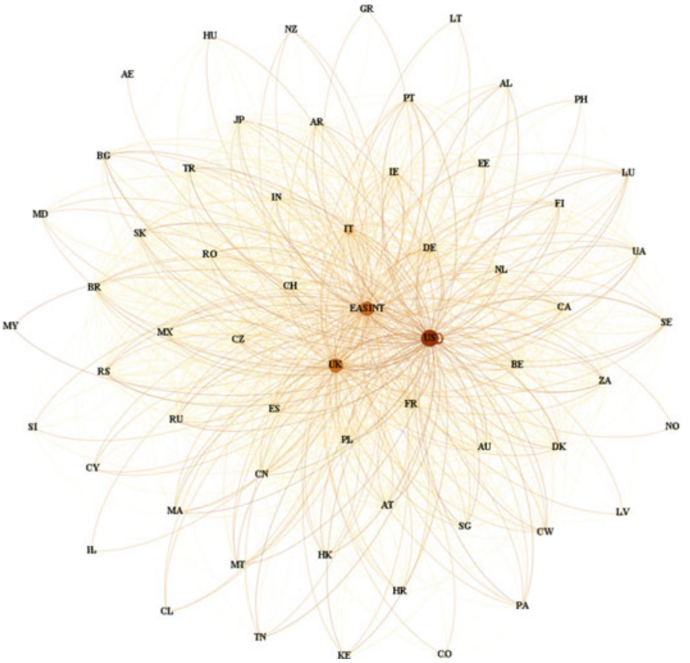


Fig. 5.6 Inter-country graph of EASIN + NEIGH coordination. *Legend* the size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of the department interlocks

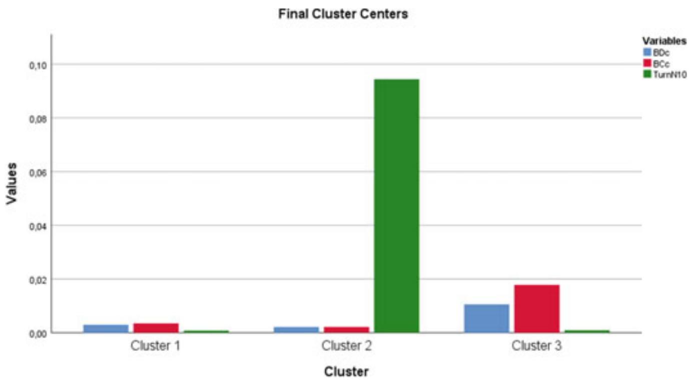


Fig. 5.7 EASIN clusters

Table 5.19 EASIN attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	267	76	1	23
TURN	313,768 + +	13	50	37
EM	518 +	23	31	46
EC	82,002 + +	25	22	53
TASS	424,913 + +	16	51	33

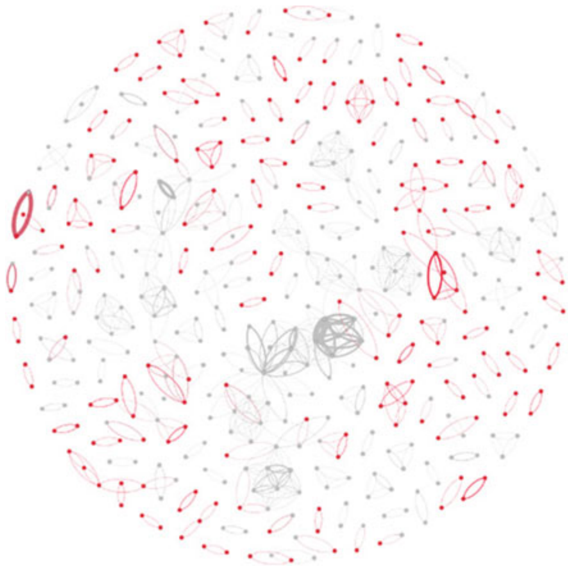
Legend + 000; + + 000,000 current US$

Table 5.20 EASIN clusters statistics

General	BDc	BCc	TURN	*C1*	BDc	BCc	TURN
Average	1.92	0.0054	1175 + +	Average	1.32	0.0032	191 + +
Min	1	0.0021	0	Min	1	0.0021	0
Max	15	0.0342	79,591 + +	Max	3	0.0109	15,826 + +
Median	1	0.0021	7 + +	Median	1	0.0021	5 + +
C2	BDc	BCc	TURN	*C3*	BDc	BCc	TURN
Average	5.33	0.0172	52,514 + +	Average	4.11	0.0158	1896 + +
Min	1	0.0021	7,327 + +	Min	1	0.0085	0
Max	11	0.0294	79,591 + +	Max	15	0.032	29,579 + +
Median	4	0.0203	70,624 + +	Median	4	0.0137	112 + +

Legend + 000; + + 000,000 current US$

Fig. 5.8 Cluster 1 in EASIN



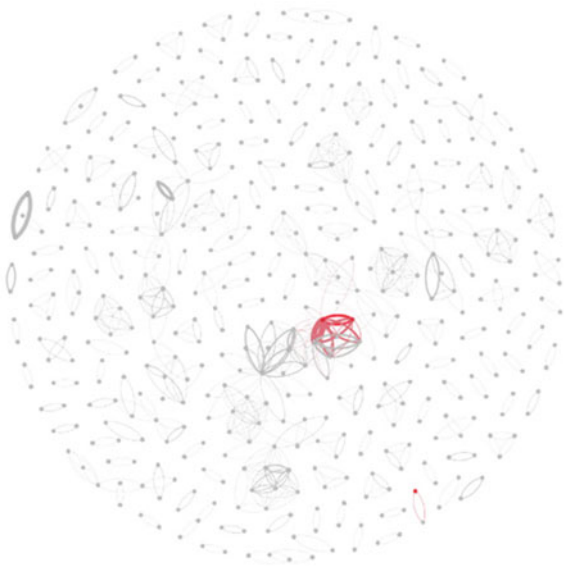


Fig. 5.9 EASIN cluster 2

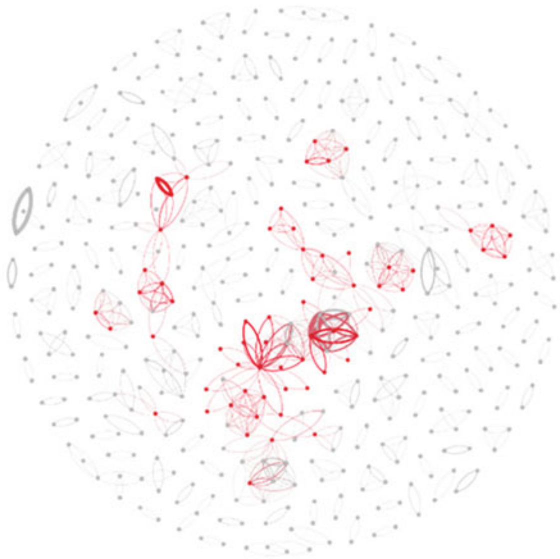


Fig. 5.10 Cluster 3 in EASIN

Cluster 2. Companies (7% of all) that belong to Cluster 2 have largest LORC, smallest BDc and comparable to rest of clusters Katz centrality. Considering that it is also the smallest cluster and taking into account its extremely high reachability, these companies work very well as connectors of distinct parts of the network. Indeed, they are often the ones that work as bridges in-between separate components/clusters both

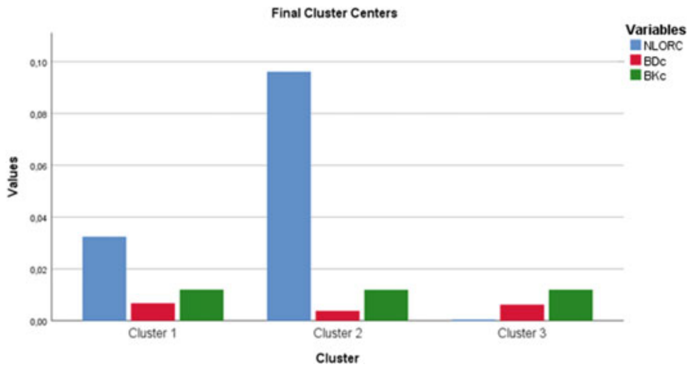


Fig. 5.11 EASIN + NEIGH clusters

Table 5.21 EASIN + NEIGH attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	6975	38	7	55
TURN	2,197,875 + +	36	2	62
EM	3,273 +	48	2	50
EC	1,229,488 + +	28	2	70
TASS	5,932,389 + +	28	1	71

Legend + 000; + + 000,000 current US$

Table 5.22 EASIN + NEIGH clusters statistics

General	LORC	BDc	BKc	*C1*	LORC	BDc	BKc
Average	36,730	43	1.010	Average	61,061	47	1.011
Min	0	1	1.000	Min	30,656	1	1.000
Max	224,833	313	1.074	Max	120,068	276	1.064
Median	41	10	1.002	Median	51,754	9	1.002
C2	LORC	BDc	BKc	*C3*	LORC	BDc	BKc
Average	180,897	26	1.006	Average	807	43	1.010
Min	121,419	1	1.000	Min	0	1	1.000
Max	224,833	233	1.055	Max	30,856	313	1.074
Median	184,307	7	1.002	Median	6	11	1.003

in the entire network and much more visibly in the main component (as it can be seen in a visual inspection of Fig. 5.14a and b).

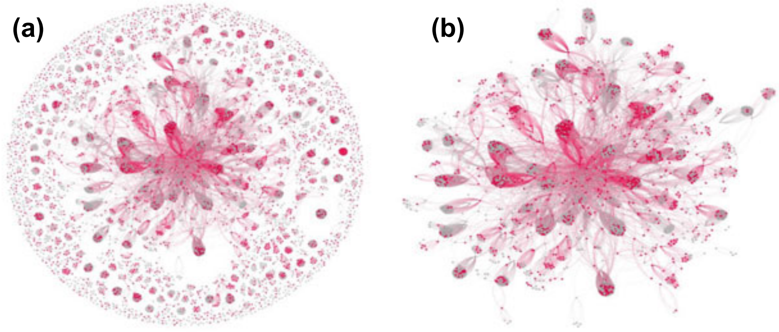


Fig. 5.12 **a, b** Cluster 1 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**). *Legend* Companies belonging to this cluster are evidenced in red

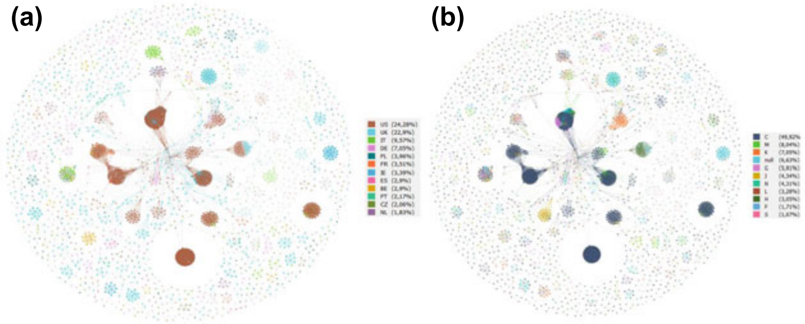


Fig. 5.13 **a, b** Cluster 1 by evidencing countries (**a**) and sectors (**b**). *Legend* Symbol “null” includes companies with no data on sector

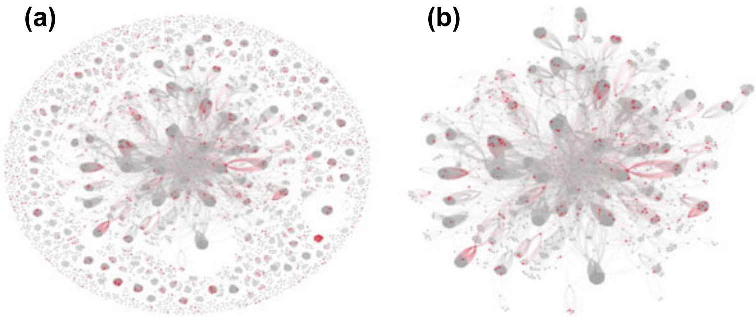


Fig. 5.14 **a, b** Cluster 2 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**)

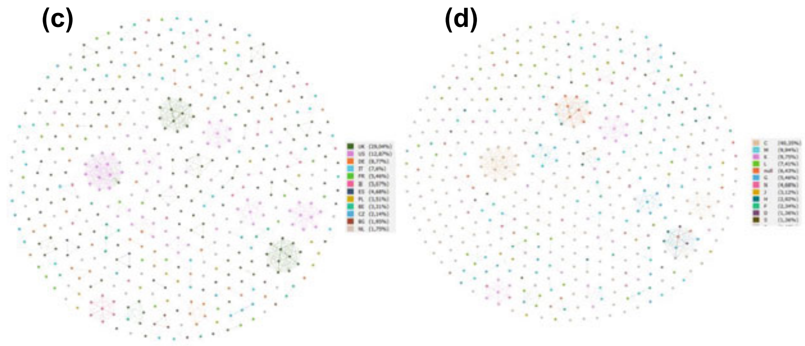


Fig. 5.15 a, b Cluster 2 by evidencing countries (**a**) and sectors (**b**). *Legend* Symbol "null" includes companies with no data on country of origin or sector

From a geographical perspective (Fig. 5.15a), it seems apparent that these "connectors" in big majority join groups of the same countries.[6] In terms of sectors (Fig. 5.15b), there are only two major, same color cliques present, the rest of components are a blend of different sectors. The "connectors" therefore get together more often companies from the same countries, but of different sectors.

Cluster 3. Companies of Cluster 3 (55% of all) are members of relatively largest cliques, but those that are not well connected with the rest of the network. Indeed, they are the most frequent type of companies and function as the "background" to the rest of the more engaged network actors. They are more independent, both in the whole network as well as in the main component. In terms of countries, yet again those companies form in major part a single-country cliques/components. In terms of sectors, in case of Manufacturing, Finances and information and communication, they tend to stick to their own type, otherwise companies freely blend with each other (Figs. 5.16, 5.17).

In summary, the cluster analysis highlighted that: (1) the extended network is also distributed in a heavy-tail way; (2) membership in clusters is heavily dependent on participation in cliques, their size and also on a role that is played within them; (3) there is no strong dependence on the main component, and all clusters have members who are present either in or out of it; (4) extracts of those clusters in large majority are self-referential, meaning that their members present large tendency to relate to others of the same type—either country—or sector-wise; (5) as a consequence of point 1 and 4 these clusters are all alike, the only factor that really distinguishes them being their size.

[6] In the figures, we see only the extract, which hides the effect that even in a dyad, the companies can be each still connected to their own big cliques/components.

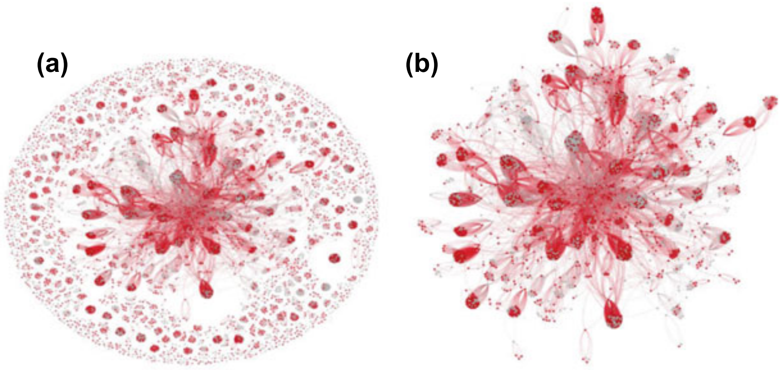


Fig. 5.16 **a, b** Cluster 3 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**)

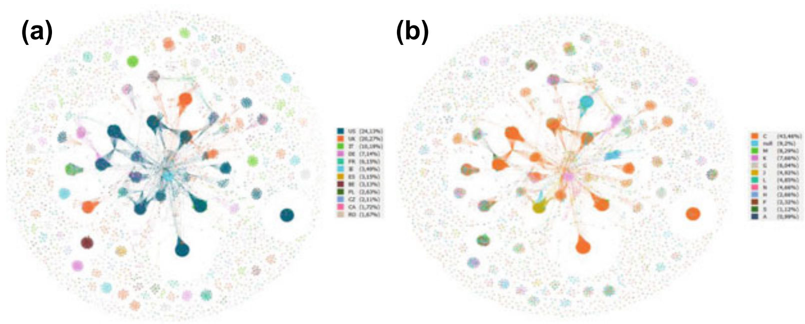


Fig. 5.17 **a, b** Cluster 3 by evidencing countries (**a**) and sectors (**b**). *Legend* Symbol "null" includes companies with no data on country of origin or sector

5.7 Cliques Analysis

In Chap. 4, we have shown that cliques and components are distributed in a very nonlinear and heavy-tail (HT) shape in the ALL (multi-layer) network, which thus includes this of inter-department coordination. Here below, we deepen the analysis on the three largest cliques within this inter-department network, and show that, even in this network, clique size is HT distributed. *The three biggest cliques are made of 248, 232 and 145 companies, and their existence explains the huge propensity of coordination* discussed in previous sections of this chapter. In fact, it is enough to be a member of one of these huge cliques to score a very high number of connections, and then, if most connections involve 5–10 shared positions, which we know means the intensity of coordination, it is not difficult to have companies with more than 1000 shared positions. It should be reminded that between managers and shared positions, there is a one-to-many correspondence. So, one company that has, let say,

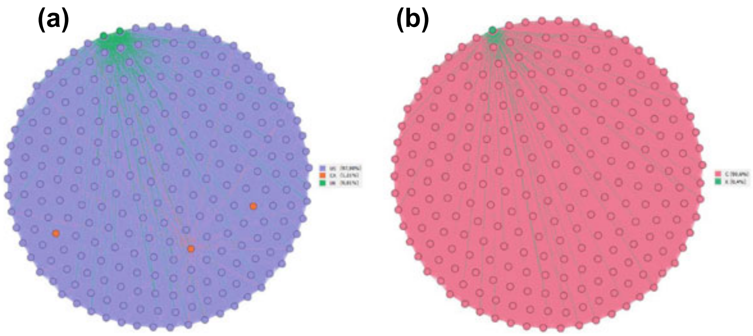


Fig. 5.18 **a, b** Composition of the largest clique in terms of countries (**a**) and sectors (**b**)

100 partner companies corresponding to 1000 shared positions could employ only 50 managers to hold them.

Clique size 248. This largest clique in the E + N network comes almost entirely from the North America, and it belongs almost completely to the Manufacturing sector, with one exception, a Financial company that comes from the UK. This is the most paradigmatic example of what we discussed in the section on inter-country network: Operative coordination is to a large extent an Anglo-North-American business. We can add also a Manufacturing business (Fig. 5.18).

Clique size 232. This clique is a bit more varied. It is also greatly dominated by the US companies, with better than before representation of the European ones—seven of them are from the UK, and one comes from Germany. There is also much more variety in terms of sectors, in two-thirds, the clique is made up of Manufacturing, one quarter of Wholesale, and the rest is marginal. The two, out of three, Financial companies are not US, because they come from the UK and Canada. Manufacturing comes almost entirely from the US, whereas Wholesale is distributed between the US and the remaining UK companies. Hence, this is an example of inter-sectoral and inter-country operative knowledge sharing/transfer, though to a small extent (Fig. 5.19).

Clique size 145. The clique with 145 companies has an almost identical composition of the first one, with the small variation that two companies come from Europe—both from Italy. It is almost entirely a Manufacturing sector, where the entire group is "served" by a single Financial and single Professional Activities company (Fig. 5.20).

5.8 Bridging Companies as Key-Players

The analysis of bridging centrality in the EASIN + NEIGH network includes 653 companies, which have a positive score of that index. Since almost entirely they were located in the MC, it is only that part of the network to which focus will be given (Fig. 5.21). By definition, highlighted are companies that often belong to the largest

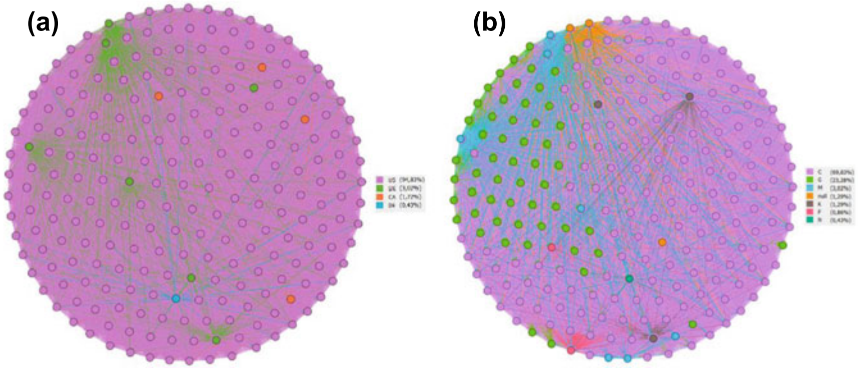


Fig. 5.19 **a, b** Composition of the second largest clique in terms of countries (**a**) and sectors (**b**). *Legend* Symbol “null” includes companies with no data on country of origin or sector

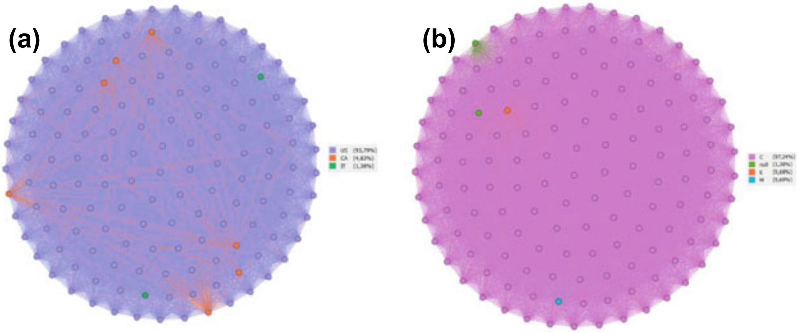


Fig. 5.20 **a, b** Composition of the third largest clique in terms of countries (**a**) and sectors (**b**). *Legend* Symbol “null” includes companies with no data on country of origin or sector

cliques, but have also connections to other parts of their network. Considering that the EASIN + NEIGH MC is larger and denser than in the analogous part of the other two (D2D and M2D) networks, it is here where those companies become most prominent. In terms of countries, those companies belong mostly to the US and the UK (35 and 29% respectively), and they not only are the most present, but they are also the most central ones (Fig. 5.22a). In fact, they are at the core of the main component, where they broker between many of the cliques from the rest of the world. More than a half of the bridging companies are from the Manufacturing sector (C) (Table 5.22b), and as well in this case, it is also the most central sector in the network. In essence, in terms of bridging various global cliques which are constructed through managerial relationships, it is the American Manufacturing companies that fulfill this role most often.

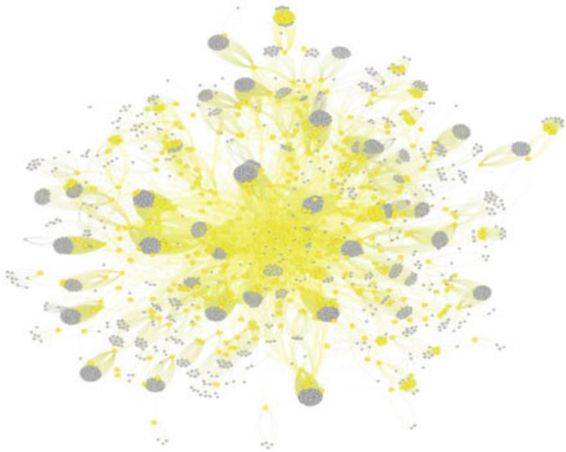


Fig. 5.21 Bridging companies in EASIN + NEIGH MC

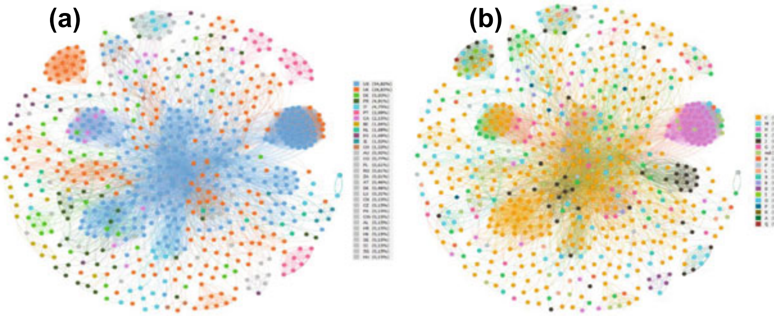


Fig. 5.22 **a, b** Bridging companies in EASIN + NEIGH MC evidenced by countries (**a**) and sectors (**b**). *Legend* Symbol "null" includes companies with no data on country of origin or sector

5.9 Heavy-Tail Scale-Free Analysis

EASIN. With respect to the attributive variables (see Figs. 5.1 to 5.12 in Data Appendix), EC, TASS and TURN have a moderate HTSF structure. Among topological parameters, cliques and degree centrality indexes have a high HTSF structure, while Bc and LORC only moderate, and components not any.

EASIN + NEIGH. With the exception of the EM variable, all other economic size parameters are distributed in a considerably high heavy-tail (HT) structure (see Figs. 5.13 to 5.24 in Data Appendix). Among topological parameters, only Bc has a good SF structure, and components and cliques have a moderate HTSF structure.

5.10 Assortativity

In these networks of departments interlock, there is a sharp difference between EASIN and the extended network (Table 8.3): this latter is extremely assortative (0.96), while the former moderately assortative (0.44 and 0.5 in binary and weighted terms, respectively). Noteworthy, in the main component of EASIN, the network becomes significantly disassortative (−0.57) in binary terms and lowly disassortative (−0.23) in weighted terms. All this means that *inter-departmental coordination occurs between companies of the same level of connectivity highly-highly and lowly-lowly, while in EASIN, this homogeneity of coordination decreases and into its main component it reverses: highly connected companies preferably coordinate their departments with lowly connected companies.* This depends on the fact that, when operations become more strictly related to Aerospace-specific technologies, then highly connected companies, which are also the largest companies that play the role of system integrators and are direct rivals of each other, do mostly refuse to coordinate their reciprocal operations, preferring instead to coordinate with small—and thus, lowly connected—suppliers. This preference attenuates when considering weighted links, because the much higher values presumably involved in coordination between highly connected companies counterbalance the pure structural (binary) dimension.

5.11 Summary

There are more companies connected via managers than there are via directors: their share of economic attributes of the whole EASIN is 78% of EC, 82% of TURN, 79% of CF, 81% of TASS, all of that achieved with 72% of EM. A great majority of economic resources, much larger share than in D2D network, is owned by companies that do seek out managerial collaboration, and the UK is the most connected country in this respect, followed by Italy, Germany, France and Poland. The number of EASINT companies grows from 471 to 1181 after adding to the EASIN network also companies connected only to neighbors.

In the EU28 Aerospace Industry, inter-departmental coordination with any other company is proportionate to a company's economic size. This result can be interpreted with the fact that the effort to create and exchange operative knowledge in terms of quality standards, codes, programs, delivery time, etc. grows with company size, so that larger companies are called for a major effort than smaller companies. It is also the larger companies in EASINT that find it easier to intermediate operative knowledge flows. In the EASIN + NEIGH MC, though companies do not generate and exchange much operative knowledge in direct relationships with their partners, they can, proportionately to their economic size, easily and largely access the flow of that knowledge circulating within the MC. There is a clear indication that the more diversified is the network, the lower is the correlation between a company's economic and topological size, except in terms of intermediation capacity, where it keeps considerable.

Through 904 relationships, which involve more than 1500 shared positions, the 85% of EASIN companies is engaged with operative coordination, thus showing the fundamental importance of this type of activity and of the related knowledge. Few companies are pivotal in generating this knowledge and, with their managers appointed in other companies through a net of coordination, diffusing it into the main component, where they concentrate a huge direct and indirect power. The extremely high fragmentation, which is due to a high number of (disconnected) components, suggests that there are many other autonomous sources of operative knowledge dispersed in small "islands" throughout the industry. Likely, they mirror the different technological areas of the Aerospace Industry, but this is a hypothesis to be tested in a future agenda. The whole EASIN MC "migrates" into the EASIN + NEIGH MC, meaning that EASIN's core companies remain crucial players also in the extended network and in this way they only additionally benefit from the knowledge brought to them by neighbors. The operative knowledge seemingly unrelated, because dispersed into a plethora of small islands, appears now even for most EASIN companies as they become an integral part of a large and strongly coordinated operative knowledge resource, generated and diffused within the main component.

In the extended version, the number of connected companies grows 16 times, reaching the size of 6975 (out of which 5766 are neighbors), thus keeping about the same proportion (0.87) on the whole multi-layer network as the EASIN subnetwork on its counterpart. More or less the same proportions repeat in terms of connections and their related intensity, therefore making operative coordination by far the most present coordination form. The degree of fragmentation is still high, but much lower than that of EASIN, because of the enormous increase of the MC's share. Operative knowledge is largely created by a relatively restricted number of companies residing into the MC: a core of the core. The MC itself is so big that it could be considered enough to technologically coordinate by itself the essential part of the global Aerospace Industry activated by EU28 countries.

After grouping companies by sectors, EASIN and Manufacturing are the most important actors in terms of number of companies or intensity of coordination, followed by Wholesale, Financial and Professional Activities sectors. However, there is an opposite orientation of EASIN and Manufacturing companies regarding operative knowledge creation and transfer: the former is oriented toward neighbors of diverse sectors, while the latter is self-referential. These traits explain also how it is possible that, despite the enormous difference in terms of number of connections, in the inter-sectoral network, EASIN covers a more important position than the Manufacturing sector.

EASIN operative knowledge is largely created within the UK, but then its inter-country diffusion is more balanced among the four main EU28 countries, among which IT covers a prominent position. Further, in terms of propensity to coordinate operative knowledge with other countries, FR and DE have the highest and the UK and IT the lowest values (among the main countries). In the extended network, there is a sharp asymmetry in the operative knowledge exchange between the two blocks—the continental EU and the Anglo-North-American area—in favor of the latter, and in particular the US, which has a dominant position. However, EASIN has the major capacity to intermediate operative knowledge flowing at global level, thus showing also the best capacity to access that knowledge, a fact that could more than compensate the minor capacity to create it in direct partnership.

At both EASIN and the global level, almost all topological variables are distributed in a HT form, a fact that guarantees a good resilience of the operative coordination structure and a good diffusion of the corresponding knowledge. However, due to its strong structural role, the Brexit should have damaged that flow and definitely reinforced the Anglo-American block.

Inter-departmental coordination occurs between companies of the same levels of connectivity: highly-highly and lowly-lowly connected, while in the pure EASIN, this homogeneity of coordination decreases. Within its main component, it reverses: Highly connected companies preferably coordinate their departments with lowly connected companies. It means that, though we have treated shared managers as symmetric relations, it is likely that those managers are appointed by highly connected or large companies to transfer standards and codes to subcontractors. The highly connected ones are also likely to be the larger companies, though they can be also medium-small size, but highly specialized subcontractors which have many connections just with the prime or main contractors. Conversely, when the companies are less technologically specific because they are not operating in a high-tech industry like the Aerospace, then they tend to coordinate by firms of the same large size when they create such standards or medium-small size when they collaborate to apply those standards. This is what happens especially among neighbors, and it is also very influenced by presence of huge cliques, which obviously push the assortative combinations.

If the intermediation capacity of the Anglo-American block resulted secondary to EASIN and the continental EU, its primacy is relaunched when considering bridging centrality, because among the 653 bridging companies, 35% and 29% are from the US and the UK, respectively. These are the true key positions in accessing, orienting and filtering operative knowledge in the global Aerospace Industry, though activated from EU28.

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Chapter 6
Inter-Board Coordination Through Shared Directors

6.1 Network Outline and Statistical Analysis

EASIN. In the scope of the "traditional" form of interlocks, although the number of EASIN companies engaged in those relations, either with their peers or neighbors or both, is much lower than in M2M (748 companies, which is only 24% of the whole EASIN), they still altogether employ 68% of EASIN's EM, generate 81% of its TURN, operate on 81% of CF, hold 81% of TASS, and their EC equals 79% (Table 6.1 in Data Appendix). The first insight shows that therefore it rather must be the larger companies utilizing the strategic coordination channels for their benefits, this notion shall be followed in the next sections of this chapter. In terms of countries' distribution among EASIN Integrated (Fig. 6.1a), the highest presence is noted for the UK, Spain, France, Italy and the Netherlands. Noteworthy, Germany here is not even in EASIN top 8, while it covers a considerable 7% among NEIGh top 8 countries.

Neighbors. Within this part of the set—constituted by 4295 companies, what is highlighted in Table 6.2a (in Data Appendix) and also in Fig. 6.1b, here as well the most prominent countries are the US, the UK, Spain, Ireland and Italy. Also in this set, once again the UK makes up for almost half of the European part, and a quarter of the whole global set. In terms of the non-European part clearly outstanding, and even more present than the UK, is the US making up 83% of the non-EU companies and 33% of the whole network. In general, there are almost six times more neighbors than the connected companies of the core industry, and in Europe only, there is three and a half times more of them than EASIN. They also control more economic resources: In Europe only, they have from two to six times larger size of attributes, and when it comes to the global part, they range from three to eleven times more.

The Financial sector neighbors (Table 6.2b in Data Appendix) are not that significant in quantity (about 10% of all neighbors), but they are substantial in terms of their economic attributes. Although this fact is well known and can be expected, their overview is useful to help the reader realize their true relative capabilities in respect to EASIN. They compose one third of both, the European and the global, parts in terms of EC, they make up 7% of the European TURN, 9% of the global one, they

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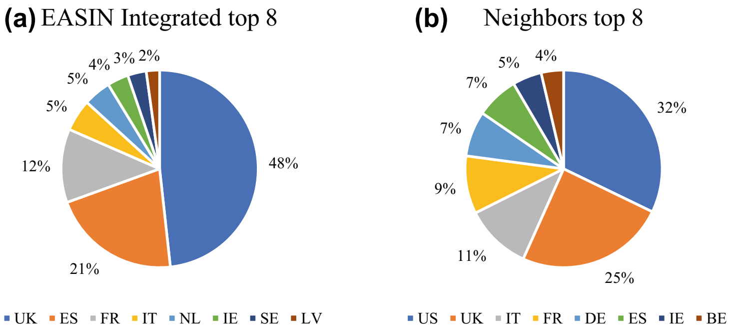

Fig. 6.1 **a**, **b** Share of top 8 countries in terms of number of companies in EASIN Integrated (**a**) and neighbors (**b**). *Legend*: The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables "the others", which are included in Tables 6.1 and 6.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 8

operate with 15% in terms of CF in Europe, 10% globally, they hold 55% of TASS in Europe and 47% in the whole world and all of that with only 5% of EM in Europe and 3% globally.

EASIN + NEIGH. More than a half of companies engaged in board interlocks comes from Europe (Table 6.3 in Data Appendix), but the country with the largest number of companies is the non-European US. It is closely followed by the UK, and the two together make up 57% of the whole board interlocks network. This provides an interesting insight of who are the most present actors that interact strategically with EASIN. It shall be later revealed that they are also the ones with the most intense coordination efforts with respect to EASIN. In terms of economic attributes in the whole structure, Europe holds 62% of EC, 65% of EM, 65% of TURN, 74% of TASS and 64% of CF, so although being the geographical domain of the EASIN, it represents only two-thirds of its network's economic size. When put together, all companies engaged in D2D EASIN + NEIGH network represent on average 84% of economic attributes of companies engaged in the ALL version (Fig. 6.3).

The following pie charts (Fig. 6.2) highlight the situation in more aggregated form showing the relative economic size of EASIN Integrated as compared to its neighbors, represented as the percent share of the total per each economic attribute. The neighbors are presented through a cross section of sectors with particular attention given to those most prominent ones, the strength of the whole EU28 compared to the rest of the world is already provided in tables which can be found in the Data Appendix, so it will not be duplicated here. Although EASIN is not a sector, but rather just an industry within a particular geographical context, it is still added to the analysis because it is after all the focal point of the entire book. It is apparent that EASIN is always present in the top 3 along with, usually, Financial and Manufacturing sectors (Fig. 6.3).

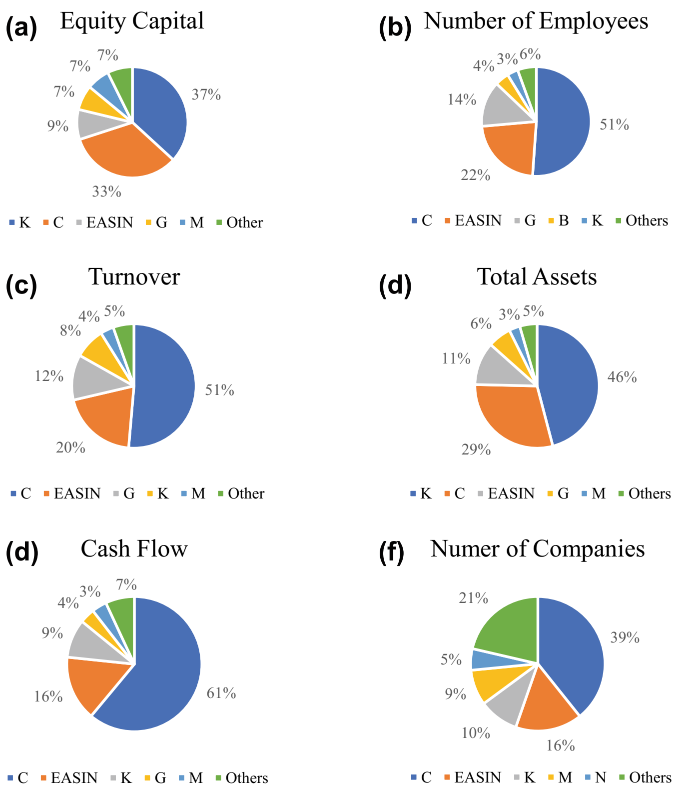

Fig. 6.2 **a–f** Economic attributes of EASIN Integrated compared with its neighbors, which are grouped into their respective sectors. *Legend*: The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables "the others", which are included in Tables 6.1a and 6.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 5

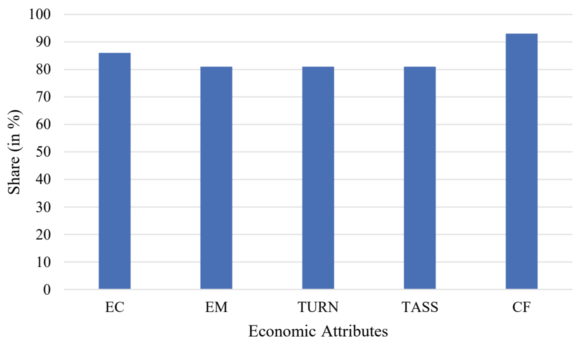

Fig. 6.3 Economic attributes of D2D E + N companies as proportion of ALL E + N companies

6.2 Correlation Analysis

EASINT. The *EASINT* network is made of 748 companies—with a range of 47–83% valid statistical observations for the economic size variables—out of which 441 are connected only with neighbors and not with any other EASIN companies. We remind that these numbers are specific for each type of coordination. In fact, as we have seen in the previous chapter, the size of integrated and pure EASIN for operative coordination is much bigger than that for strategic coordination, though the relative proportion is almost the same. There is a medium (0.55 and 0.46) positive association between the connectivity of strategic coordination and company size (Table 6.1). A bit weaker (0.30 and 0.31) is the association of Bc with size, especially when measured in terms of CF. It means that *highly connected companies establish the major strategic coordination with their partners and have also better access to all the strategic knowledge flowing into the whole network*. Further, *some of the companies with high intermediating capacity are placed in points of access to strategic knowledge by large companies' clusters, many of which are medium cliques*. Therefore, the power of such companies is very high and, within this network, it confirms SPCH (Size Proportional Connectivity Hypothesis) that we will test and discuss in Chap. 8—hypothesis testing.

In the *EASIN* network, which is made of 307 companies (with range 54–83% of valid statistical observations), there is a very positive correlation (0.66) between TURN and weighted Dc, followed by TASS (0.58) (Table 6.2). Therefore, we can say that *EASIN's largest companies are also the highly connected in terms of strategic coordination*. EC and EM are also remarkably positively correlated with intermediating capacity (0.6 and 0.55, respectively, for both binary and weighted Bc). Thus, we can also say that *the intermediating power of EASIN companies strategic knowledge flows varies with their size in terms of EC and EM*. Finally, bridging centrality is positively correlated with all the four attributes and becomes remarkable with EM size: thus, size is a key-factor also for the capacity to access, filter and orient strategic knowledge among clusters of companies.

EASIN + NEIGH MC. When we enlarge the size to the MC of the extended network, which is made of 770 companies (with range 8–15% of valid observations), we see (Table 6.3) that weighted Dc is positively, but lowly (0.20) correlated to EC

Table 6.1 Correlations in EASIN integrated

	EC	EM	TURN	TASS	Average
LORC	−0.07	−0.07	−0.07	−0.06	–
BDc	0.54^{**}	0.58^{**}	0.54^{**}	0.52^{**}	0.55
WDc	0.44^{**}	0.5^{**}	0.48^{**}	0.45^{**}	0.46^{**}
BBc	0.37^{**}	0.32^{**}	0.16^{**}	0.21^{**}	0.30^{**}
WBc	0.38^{**}	0.33^{**}	0.17^{**}	0.21^{**}	0.31
BRc	0.37^{**}	0.32^{**}	0.16^{**}	0.21^{**}	0.30

Legend: Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

Table 6.2 Correlations in EASIN

	EC	EM	TURN	TASS	Average
LORC	0.03	0.00	−0.01	0.00	–
BDc	0.35^{**}	0.31^{**}	0.26^{**}	0.24^{**}	0.29
WDc	0.43^{**}	0.49^{**}	0.66^{**}	0.58^{**}	0.54
BBc	0.60^{**}	0.55^{**}	0.23^{**}	0.28^{**}	0.41
WBc	0.59^{**}	0.55^{**}	0.23^{**}	0.27^{**}	
BRc	0.22^{**}	0.44^{**}	0.07	0.09	0.21

Legend: Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

Table 6.3 Correlations in EASIN + NEIGH MC

	EC	EM	TURN	TASS	Average
LORC	−0.06	0.07	−0.12	−0.09	–
BDc	0.09	−0.10	0.04	0.05	–
WDc	0.22^{*}	−0.08	0.20	0.15	0.12
BBc	0.12	0.20	0.07	0.31^{**}	0.18
WBc	0.12	0.20	0.07	0.31^{**}	
BRc	0.19^{*}	0.62^{**}	0.26^{*}	0.53^{**}	0.40

Legend: Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

and TURN, and a bit less (0.15) to TASS. However, these values are much lower than those of D2D EASIN and ALL EASIN + NEIGH MC. Analogously, binary and weighted Bc are positively correlated to economic attributes, but less than half of D2D EASIN and ALL EASIN + NEIGH MC. Conversely, BRc is considerably (0.40) positively correlated in the average of the four attributes and, more noticeable, double than EASIN. Notice that in ALL that variable is totally uncorrelated. More particularly and noteworthy, BRc is very highly positively correlated with EM size (0.62) and TASS size (0.53). In sum, we can say that *even in the EASIN + NEIGH MC, the SPCH is confirmed, because there is a positive (and sometimes rather high) correlation between economic size attributes and (direct and indirect) connectivity.*

EASIN + NEIGH. If we consider the whole extended network (5043 companies, with a modest range of valid observations), then *there is a mild positive correlation between binary and weighted Dc on one side and EM and TURN on the other*: 0.22 and 0.18 in the former case and a bit less in the latter (Table 6.4). A similar degree of correlation holds between Bc indexes on one side and EM and TURN on the other: 0.23 in the former and 0.16 in the latter case. BRc is about half of that in the MC, but sill about 0.19 in average of the four attributes reaches 0.29 for EM. Therefore, it seems clear that *the direct and indirect capacity to influence strategic coordination of the (EASIN-induced) global Aerospace Industry network is very much associated with company size in terms of employees.*

Table 6.4 Correlations in EASIN + NEIGH

	EC	EM	TURN	TASS	Average
LORC	−0.02	−0.01	−0.02	−0.02	–
BDc	0.12**	0.22**	0.18**	0.07**	0.15
WDc	0.08**	0.15**	0.17**	0.05**	0.11
BBc	0.11**	0.23**	0.16**	0.15**	0.16
WBc	0.11**	0.24**	0.16**	0.15**	
BRc	0.09**	0.29**	0.19**	0.18**	0.19

Legend: Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

Top 200. As we already did for the ALL and the M2M network, we have checked whether considering only the top 200 companies the correlations coefficients between topological and attributive parameters of the EASIN + NEIGH version do change. Because the ranking of top 200 varies with the ordering criterion, we considered the following ones: TASS (Table 6.5a) and EM size (Table 6.5b) or BRc (Table 6.5c). Respect with considering all companies (Table 6.4), in terms of TASS, all correlations become lower except BRc, which increases considerably. In terms of EM, all correlations increase substantially, excepted LORC, which remains always uncorrelated. The same happens in terms of BRc, whose correlation with TASS reaches a coefficient of 0.41.

Sectoral and industrial correlations. As we already did for the ALL and the M2M network, we have checked whether correlations coefficients do change when considering single sectors (Table 6.6a and tables in Sect. 6.2 in Data Appendix) or the Aerospace Industry (NACE:3030) only (Table 6.6b). With respect to all sectors (Table 6.4), *focusing only on the Manufacturing (C) sector increases the coefficients, with the exception of LORC and with a particular growth for Bc*. A further focus only on the Aerospace Industry within the Manufacturing sector shows a remarkable increase of the coefficients, especially in association with Bc and BRc, which in average scores 0.52 and 0.67, respectively. Even more considerable is the correlation between BRc on one side and EC and TASS on the other, which reaches 0.72 and 0.78, respectively. In means that within the Aerospace Industry, companies with high EC and TASS play a fundamental role in keeping connected clusters of other Aerospace Industry.

Conversely, coefficients slightly decrease when limiting the analysis to Professional Activities (Table 6.6c) or the Financial sector (Table 6.6d). In this latter, there is no association between company size and intermediating capacity, meaning that these Financial companies are not strategically coordinated for their own objectives, but rather they are present in support of the global (but EASIN-induced) Aerospace Industry. In other words, these coefficients do not indicate a low relevance of the Financial sector, which instead is shown in many ways across all the chapters of this book. They simply mirror the way in which such companies have been selected, a way that actually does not configure this set of companies as a true sector with its structural characteristics. Likely, this is why there is no correlation between economic

Table 6.5 **a** Correlations ordered by TASS in EASIN + NEIGH, **b** Correlations ordered by EM in EASIN + NEIGH, **c** Correlations ordered by the degree of BRc in EASIN + NEIGH

(**a**)

	EC	EM	TURN	TASS	Average
LORC	−0.01	0.08	0.01	0.01	–
BDc	0.10	0.17*	0.20**	0.00	0.12
WDc	0.06	0.09	0.18	−0.02	0.08
BBc	0.05	0.28**	0.17*	0.10	0.15
WBc	0.05	0.29**	0.17*	0.10	0.15
BRc	0.10	0.37**	0.24**	0.22**	0.23

(**b**)

	EC	EM	TURN	TASS	Average
LORC	−0.04	0.03	0.01	0.02	–
BDc	0.24**	0.22**	0.25**	0.17*	0.22
WDc	0.28**	0.19**	0.29**	0.20**	0.24
BBc	0.15*	0.32**	0.21**	0.25**	0.23
WBc	0.15*	0.33**	0.22**	0.25**	0.24
BRc	0.18*	0.37**	0.25**	0.39**	0.30

(**c**)

	EC	EM	TURN	TASS	Average
LORC	−0.09	0.03	−0.03	0.01	–
BDc	0.25*	0.21	0.27*	0.19	0.23
WDc	0.30**	0.14	0.31*	0.23*	0.25
BBc	0.10	0.20	0.05	0.30**	0.16
WBc	0.11	0.21	0.05	0.31**	0.17
BRc	0.13	0.34	0.17	0.41	–

Legend: Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

size and topological centrality. Through this lens should be also seen the Professional Activities sector, while the Manufacturing sector mirrors more reliably its structural characteristics, either because it is made by a much larger number of companies or because, from a technological viewpoint, it is much closer to the Aerospace Industry. Again, it seems that the key issue that makes the analyses more consistent and reliable is the degree of heterogeneity of the aggregate object of study: the higher that degree, the lower the consistency and reliability.

Table 6.6 **a** Correlations limited to the Manufacturing (C) sector, **b** Correlations limited to the Aerospace Industry (NACE:3030), **c** Correlations limited to the Professional Activities (M) sector, **d** Correlations limited to the Financial (K) sector

(**a**)

	EC	EM	TURN	TASS	Average
LORC	−0.02	0.01	−0.01	0.02	–
BDc	0.27**	0.29**	0.27**	0.27**	0.28
WDc	0.23**	0.20**	0.23**	0.22**	0.22
BBc	0.21**	0.41**	0.23**	0.40**	0.31
WBc	0.21**	0.42**	0.23**	0.40**	
BRc	0.16**	0.38**	0.21**	0.42**	0.29

(**b**)

	EC	EM	TURN	TASS	Average
LORC	0.02	0.06	0.06	0.07	–
BDc	0.33**	0.27**	0.29**	0.25**	0.29
WDc	0.26**	0.19**	0.22**	0.21**	0.22
BBc	0.60**	0.52**	0.41**	0.54**	0.52
WBc	0.60**	0.52**	0.41**	0.54**	
BRc	0.72**	0.63**	0.55**	0.78**	0.67

(**c**)

	EC	EM	TURN	TASS	Average
LORC	−0.04	−0.03	−0.05	−0.02	–
BDc	0.21**	0.01	0.06	0.21**	0.12
WDc	0.21**	−0.01	0.05	0.20**	0.11
BBc	0.14*	−0.01	0.05	0.11*	0.07
WBc	0.12*	−0.02	0.04	0.1	
BRc	0.18**	−0.01	0.01	0.13	0.08

(**d**)

	EC	EM	TURN	TASS	Average
LORC	−0.01	−0.04	−0.04	−0.05	–
BDc	0.09	0.21*	0.07	0.00	0.09
WDc	0.07	0.15	0.06	−0.01	–
BBc	0.00	−0.02	0.00	0.00	–
WBc	0.00	−0.02	0.00	0.00	
BRc	−0.01	−0.02	0.00	0.00	–

Legend: Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

6.3 Network Analysis

EASIN. Within EASIN companies, board interlock concerns a much smaller number of companies as compared to department interlock (Table 6.7a): 307 versus 471. This is very reasonable, because strategic coordination is a much more committing agreement than operative coordination, though the Aerospace Industry is very high tech. Perhaps, in a low-tech industry, such a gap could be smaller, because the need to adopt common standard would be not so crucial. With respect to fragmentation, there is no difference with DINT: Both are definitely very fragmented phenomena (0.99). However, if we consider the weighted measure of fragmentation, its value crashes down to 0.15. In fact, among 307 companies there are 116 components, mostly (70%) made by dyads, and the main component made by only 12 companies. Consequently, average distance is very short: 1.2. Normalized density is extremely low, because there are only 600 strategic relationships, which involve almost 900 directors. On average, there are only 2 partners per each company, which become 3 if we count in terms of the number of shared directors per company. Each relationship conveys on average less than 2 shared directors, as it happens also for shared managers. There is no centralization of any kind, except for the eigenvector type, which is strongly determined by the 12 companies residing into the MC, which are very centralized around the "Gotha" of the EU Aerospace Industry. Therefore, *EASIN strategic coordination is, as it was supposed to be, a very elitist phenomenon, with the power firmly concentrated in a pull of few companies.*

EASIN + NEIGH. When the EASIN network is extended to include 4295 neighbors (Table 6.7b), the number of connected companies grows up to about 5043, that is, 16 times more than in EASIN, due the fact that the 441 companies that in EASIN were isolated, now become connected to the neighbors. The phase transition in terms of absolute density appears clear when looking at binary relationships, which grow from 600 up to 244,744: that is, they increase 408 times in front of the 16 times of the companies. It is only slightly less in weighted terms: 399 times of increase. It means that the 63% of all the EASIN + NEIGH companies activated by EASIN companies with some kind of people-based coordination—that is, 5043 out of 8039 companies—coordinate their strategic behavior through 354,364 shared directors positions, which is indeed a huge number. Put differently, it could be said that out of *the 3143 EASIN companies, 307 coordinate their strategic behavior among themselves through 600 direct relationships, while they and other 441 EASIN companies do it through 4295 neighbors and 354,364 shared directors' positions, almost all established with neighbors.* It can be argued that *EASIN's strategic behavior is almost entirely coordinated by neighbor companies.*

This network is almost completely fragmented into 624 disconnected components, with only a moderate reduction to 0.72 when measuring it in terms of distance weighted. It means that even *the strategic coordination is extremely fragmented, with more compactness occurring only in the (relatively small) MC*. Due to the extremely high fragmentation, all kinds of centralization indexes are very low, including the eigenvector, regardless if binary or weighted. It means that strategic coordination

Table 6.7 **a** D2D EASIN: main indexes of network analysis, **b** D2D EASIN + NEIGH: main indexes of network analysis

(a)

Index	EASIN [b]	EASIN MC [b]	EASIN [w]	EASIN MC [w]
Size	307	12	307	12
Density (norm)	0.006	0.333	–	–
Density (abs)	300	22	444	26
Fragmentation	0.992	0.000	0.153	0.441
Av. link value	1	1	1.480	1.182
ADc	1.964	3.667	2.909	4.333
Dc_CE (Fre)	0.026	0.628	–	–
Dc_CE (Sni)	0.000	0.439	–	–
Bc_CE	0.001	0.618	0.001	0.584
Eig_CE	0.371	0.289	0.575	0.294
Katz_CE	0.021	0.171	0.561	0.215
RWB_CE	–	0.728	–	0.546
GORC	0.029	0.309	0.007	0.150
Diameter	3	3	6	6
Apl	1.180	1.788	1.521	2.304
GCL	0.939	0.759	1.472	0.999
SW	334	1.120	–	–

(continued)

Table 6.7 (continued)

(**b**)

Index	EASIN + NEIGH ^{b}	EASIN + NEIGH MC ^{b}	EASIN + NEIGH ^{w}	EASIN + NEIGH MC ^{w}
Size	5043	770	5043	770
Density (norm)	0.010	0.185	–	–
Density (abs)	244,744	109,338	354,364	117,070
Fragmentation	0.962	0.000	0.723	0.000
Av. link value	1	1	1.448	1.071
ADc	48.54	142	70.282	152
Dc_CE (Fre)	0.043	0.159	–	–
Dc_CE (Sni)	0.036	0.307	–	–
Bc_CE	0.015	0.624	0.015	0.625
RWB_CE	–	0.697	–	0.499
Eig_CE	0.060	0.043	0.083	0.044
Katz_CE	0.016	0.026	0.041	0.025
GORC	0.078	0.287	0.067	0.324
Diameter	10	7	18	15
Apl	3.613	3.978	–	–
GCL	0.985	0.986	–	1.160
SW	30	1.097	–	–

Legend: b = binary links, MC = main component, w = weighted links; ADc = average degree centrality; Dc_CE = degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; RWB_CE = random-walk betweenness centralization; Eig_CE = eigenvector centralization; Katz_CE = Katz centralization; GORC = hierarchical degree according to the reaching capacity; Apl = average path length; GCL = global clustering coefficient; SW = small-worldliness index. Some of the indexes are missing due to computational limitations occurs diffusely throughout the global Aerospace network activated by EASIN strategic alliances, but it is very much concentrated into the MC. Diameter (10 steps) and average distance (3.6) are rather large with respect to the not huge network size.

Each company, on average, has 49 partners with whom it establishes 70 shared directors' positions. Therefore, while the average number of partners is only a bit superior to that of operative coordination (43), *the number of shared positions is incomparably lower, because the average number of shared managerial positions is 398: almost six times more.*[1] We think that this is due to three factors: (i) the number of directors is usually much smaller than the number of managers; (ii) the complexity of the strategic work is much higher than that of operative management, so that not too many positions in different boards can be given to a single director; (iii) usually, one appointed director per single board is enough at least to access strategic knowledge and few directors to significantly orient the board; (iv) in a high-tech industry like the Aerospace, extension of the operative tasks affected by standards and codes is so large, that in a single partnership could be necessary various managers (besides his/her shared positions), likely appointed in different departments, to guarantee an effective operative coordination.

EASIN + NEIGH MC. Things substantially change within the MC, where normalized density is considerably high (18.5%), because the 770 companies have about 109 thousand relationships (alliances), corresponding to about 45% of total (binary) links, which generate 33% of shared positions, while involving only 15% of all companies. This is a crucial difference with operative coordination, whose MC includes 46% of companies, establishing 85% relationships that generate 86% of shared positions. Each company has on average 142 partners, while they are only 49 when considering the whole network—that is, including the disconnected components. It means that *the companies' elite residing in the MC has a very big capacity to create strategic knowledge directly with their partners, though* via *smaller effort per each partnership.* This ratio of 2.9 reduces to 2.2 when considered is the coordination effort (the shared positions). In fact, the average number of shared directors per single agreement (strategic alliance) lowers from 1.45 to 1.07, meaning something rather surprising: that in the MC, the effort of strategic coordination is lower than outside of it. This characteristic occurs also in EASIN, where the average number of shared directors in each agreement lowers from 1.48 to 1.18. Conversely, this does not happen in operative coordination agreements, where it doubles from 1.7 in the whole EASIN to 3.68 in its MC and in the extended network keep equal around 9.2.

The average distance is about 4 steps and the diameter 7 steps. Differently from the whole network, here direct centralization is significantly high (30.7% in terms of the Snijders' index) and extremely high in terms of intermediating power: 62% as betweenness centralization (Bc_CE) and 71% as RWB centralization. It means that *the companies' elite has not only the power to made most strategic decisions with their partners, but it has also the capacity to access most strategic knowledge decided*

[1] Let us remind once more the distinction among a company's partnership, the number of people (managers or directors) involved and the number of shared positions assigned to them. See Chap. 2 and the Methodological Appendix.

in other parts of the MC. Conversely, eigenvector and Katz centralizations are low, meaning that there are long chains within which companies are lowly connected. In fact, GORC centralization is considerably high (32%), meaning that few central companies have chains of coordination much longer than the others: that is, *strategic decisions made by the elite are then diffused alongside the MC through long chains of transmission*. They mostly come from the Manufacturing sector from the US and few of them from the UK.

6.4 Inter-Sectoral Network

After grouping companies into sectors (see Methodological Appendix), we have built the corresponding inter-sectoral network (Table 6.8). This network is very dense (0.45) and accounts for more than 268 thousand shared directors' positions. It is a fully connected network, extremely clustered and with short coordination chains. Despite these traits, it is not a balanced network, because few sectors cover crucial central positions (Fig. 6.4 and Table 6.12 in Data Appendix): besides the Manufacturing, which is by far the most prominent one, also the Financial sector is very relevant in terms of intensity of coordination with partners. The third position is covered by EASIN, but with a coordination capacity which is half of that of the Financial sector. This concentration is grasped by looking at the remarkably high centralization indexes in terms of Snijders' degree centralization (0.52) and eigenvector centralization (0.99). Weighted betweenness centralization and random-walk centralization are also rather centralized (0.39 and 0.40, respectively), meaning that even the access to strategic knowledge circulating into the network is again concentrated into the same three leading sectors. Therefore*, both the creation and transfer of strategic knowledge at the global level are made essentially by neighbor Manufacturing companies, which are mostly Anglo-American, then (much less) by neighbor Financial companies, which are mostly European (but not only EU28) and much less by EASIN companies.*

The two following Tables 6.9 (a and b) show a situation very similar to what we have seen in the previous chapter concerning operative knowledge: though the Manufacturing sector is by far the most prominent in terms of number of links, due to its extremely high (0.94) degree of self-reference (closure), its influence on the other sectors coordination is dramatically lowered in terms of absolute values. Consequently, in terms of the coordination efforts, though the sectoral ranking remains about the same (Manufacturing, Financial, EASIN, etc.), distances in the sectors' coordination propensity are reduced: 13,351 shared directors' positions, 8529, 6928, respectively. Interestingly, the fourth rank is covered by the Administrative (N) sector, before Professional Activities (M), because when strategic issues are called, then various types of institutions become important actors.

The biggest coordination effort occurs between the Manufacturing sector and EASIN (Table 6.10) by involving 3691 shared positions, then followed by the coordination between the Administrative and the Financial sectors with 2561 shared

Table 6.8 Inter-sectoral network of the D2D network

Index	Binary	Weighted
Size	22	
Density (norm)	0.450	
Density (abs)	208	268,500
Fragmentation	0	0.154
Av. link value	1	1291
ADc	9	12,204
Dc_CE (Fre)	0.197	–
Dc_CE (Sni)	0.518	–
Bc_CE	0.032	0.387
RWB_CE	0.051	0.396
Eig_CE	0.035	0.997
GORC	0.354	0.182
Apl	1.182	4.056
GCL	0.912	172
SW	1.279	

Legend: ADc = average degree centrality; Dc_CE = degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; RWB_CE = random-walk betweenness centralization; Eig_CE = eigenvector centralization; GORC = hierarchical degree according to the reaching capacity; Apl = average path length; GCL = global clustering coefficient; SW = small-worldliness index. Some of the indexes are missing due to computational limitations

inter-board positions. Then, again the Financial and the Manufacturing sectors recur as some of the most intensive strategic inter-sectoral coordination. We believe that this ranking is very significant of which sectors are most important in the strategic decision coordination of the global Aerospace Industry.

When we look at companies' average propensity/capacity to establish strategic coordination in each sector (Table 6.11), similarly to the operative coordination, the Manufacturing sector is by far the most inclined to do so with its 125 positions, and with the average level of 58, it makes it at least twice as much inclined to form relations respect to other sectors. Out of those 125 positions, 117 are formed internally (with other Manufacturing companies), what confirms the networks' propensity to form cliques with others of the same type, as shown in the section on cliques' analysis. The second one in terms of number of companies and also in terms of propensity—if we would consider only sectors with a size larger than 100—is the Financial (K) sector, with a total score of 45, which is already below the total average. Overall, the total average score of 58 is, when a looked at its internal vs external composition, highly inclined toward the former form, what is confirmed in other types of analysis (look at f.e. the section with cluster analysis).

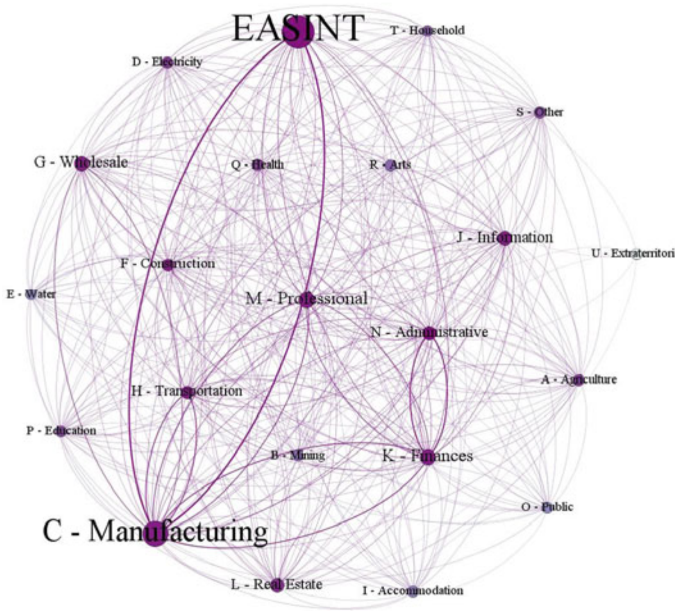

Fig. 6.4 Inter-sectoral graph of EASIN + NEIGH coordination. *Legend*: the size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of board interlocks

6.5 Inter-Country Network

EASIN. The number of countries involved in the strategic coordination of EASIN is much smaller than in the operative coordination (M2M): 16 versus 25. The number of partners and shared positions is about half (Table 6.12): 30 and 796 versus 64 and 1536. This difference sounds very reasonable, due to the much smaller average size of boards with respect to the average size of departments and due to the more complex tasks of directors respect to managers. Like the inter-country network of operative coordination, there are some isolated countries (BG, HU, LV), whose companies are connected only among themselves (Fig. 6.5). Consequently, there is a very small disconnectedness degree (DD), a moderate degree (0.35) of binary fragmentation and a bit higher distance weighted fragmentation (0.56). Each country has on average almost two partner countries, with whom it establishes about 50 shared directors' positions. In each bilateral country partnership, about 19 shared positions are involved in average.

This network is lowly centralized in terms of direct relationships (Dc_CE_Sni), but it is extremely centralized in terms of weighted eigenvector (0.99) and Katz (0.88) indexes. This extremely high centralization is due definitely to the UK (see Table 6.13 in Data Appendix and Fig. 6.5), which is connected to 9 out of the 16 partners and employs 507 shared directors' positions. Measured in this way, the

Table 6.9 **a** Share of internal (binary) links across sectors, **b** Share of internal (weighted) links across sectors

(**a**)

Sector	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
C	157,414	90	10,532	167,946	77	94
K	6992	4	6727	13,719	6	51
J	4742	3	2049	6791	3	70
N	2210	1	3745	5955	3	37
EASINT	600	0	5188	5788	3	10
H	1672	1	2996	4668	2	36
M	1098	1	3474	4572	2	24
G	638	0	2005	2643	1	24
L	170	0	1163	1333	1	13
F	86	0	641	727	0	12
S	24	0	578	602	0	4
R	2	0	486	488	0	0
D	44	0	340	384	0	11
A	68	0	302	370	0	18
B	16	0	315	331	0	5
T	0	0	300	300	0	0
P	22	0	186	208	0	11
Q	8	0	195	203	0	4
I	28	0	169	197	0	14
O	0	0	101	101	0	0
E	2	0	61	63	0	3
U	0	0	3	3	0	0
Total	175,836	100	41,556	217,392	100	81

(**b**)

Sector	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
C	215,044	89	13,351	228,395	77	94
K	11,876	5	8529	20,405	7	58
EASINT	888	0	6928	7816	3	11
N	2718	1	4941	7659	3	35
M	2030	1	5174	7204	2	28
J	4868	2	2205	7073	2	69
H	1982	1	3914	5896	2	34
G	1750	1	2590	4340	1	40
L	250	0	1490	1740	1	14

(continued)

Table 6.9 (continued)

(**b**)						
Sector	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
F	110	0	753	863	0	13
S	54	0	688	742	0	7
B	76	0	420	496	0	15
R	2	0	487	489	0	0
D	68	0	361	429	0	16
A	72	0	350	422	0	17
T	0	0	300	300	0	0
P	28	0	241	269	0	10
Q	8	0	200	208	0	4
I	28	0	176	204	0	14
O	0	0	127	127	0	0
E	2	0	64	66	0	3
U	0	0	3	3	0	0
Total	241,854	100	53,292	295,146	100	82

Legend: Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB
Legend: Acronyms explained in the list of abbreviations
ShITW = IDW/Total IDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

following positions are covered by ES (137 shared positions), FR (89), the NL (65), DE (25), etc. Therefore, there is a big distance between the strategic coordination efforts made by the UK and the next country and much more with the others. Notice the huge distance with DE, which has only 5% of the directors engaged by the UK. However, as we will see right below, there are two reasons why this gap should be not interpreted straightly in terms of influence power exerted on EASIN by the UK. One explanation is in the Bc centrality, which records still the UK at the first place, but with much shorter distances with the other, closely following countries. In fact, Bc centralization is considerable (0.43 and 0.42), but not so high as the eigenvector. This fact confirms the role of the UK also in accessing and intermediating strategic knowledge flowing into the network, but at the same time reduces the relative primacy respect to the other countries.

The second (and more important) reason can be found in Table 6.13 (and especially, 6.13b), which shows the share of internal links over the total links and the ranking in terms of the number of links and efforts addressed toward other countries. If we look at this data, we see that, *in line with what we have already seen in the two previous chapters, Anglo-American companies have a very high propensity to*

Table 6.10 Major 30 cross-sectoral coordination efforts

Source	Target	Weight
C	EASINT	3791
N	K	2561
C	H	1994
K	C	1914
C	M	1581
M	K	1168
C	G	1133
G	C	1133
EASINT	M	758
K	EASINT	709
C	J	650
K	J	519
H	N	511
N	M	511
H	K	491
K	H	491
N	C	418
G	K	360
N	EASINT	357
C	R	316
S	C	300
EASINT	J	297
M	L	267
C	T	266
H	EASINT	256
K	L	256
F	C	234
B	C	228
L	C	214
EASINT	G	196

Legend: Each of them is symmetric

self-reference. In terms of shared directors' positions, for the UK, it is 91%, and in this particular case, Spain, which is the second country in terms of coordination effort, reaches even 92%. The consequence is that the ranking changes significantly: FR gets the first place with 47 shared positions, then the UK with 45, followed by the NL and DE with 29 and 25, respectively. Spain, which was at the second place shifts to the fifth with 11 shared positions. Noticeably, despite its general relevance witnessed in the statistical section, IT has only 4 positions shared with other EASIN

Table 6.11 Companies' weighted propensity to coordinate by sectors

Sectors	# of countries	# of companies	# of (weighted) links per company		
			IDW	EDW	Total
A	7	29	2.48	12.07	14.55
B	6	14	5.43	30.00	35.43
C	34	1825	117.83	7.32	125.15
D	6	29	2.34	12.45	14.79
E	3	6	0.33	10.67	11.00
EASINT	23	747	1.19	9.27	10.46
F	15	74	1.49	10.18	11.66
G	25	181	9.67	14.31	23.98
H	22	158	12.54	24.77	37.32
I	6	19	1.47	9.26	10.74
J	22	221	22.03	9.98	32.00
K	25	445	26.69	19.17	45.85
L	17	134	1.87	11.12	12.99
M	26	398	5.10	13.00	18.10
N	18	240	11.33	20.59	31.91
O	3	7	0.00	18.14	18.14
P	9	35	0.80	6.89	7.69
Q	6	19	0.42	10.53	10.95
R	7	18	0.11	27.06	27.17
S	9	43	1.26	16.00	17.26
T	1	6	0.00	50.00	50.00
U	1	1	0.00	3.00	3.00
No Data	18	393	–	–	–
Total	46	5042	47.97	10.57	58.54

Legend: Acronyms explained in the list of abbreviations

countries. The leadership emerging from this analysis is confirmed also by looking at the identity of the countries involved into the most intensive efforts of bilateral strategic coordination (Table 6.14), which sees FR, the UK and the NL repeatedly among the first 5 relationships.

Strategic coordination propensity per country. The total average propensity per country (Table 6.15) is equal to almost 3, and it is mostly generated by the UK, which has the largest number of companies, and its individual score is very close to the general average. The highest propensity is assigned to Germany (DE), but it is probably just because there is one single company taken into consideration. Much more informative perspective will be therefore presented in the next section on the extended network.

Table 6.12 EASIN inter-country network

Index	Binary	Weighted
Size	16	
Density (norm)	0.125	
Density (abs)	30	796
DD	0.01	
Fragmentation	0.350	0.562
Av. link value	1	18.89
ADc	1.875	49.75
Dc_CE (Fre)	0.431	–
Dc_CE (Sni)	0.182	–
Bc_CE	0.431	0.421
Eig_CE	0.412	0.991
Katz_CE	0.003	0.882
GORC	0.295	0.349
Apl	2.282	8.603
GCL	0.441	5.500
SW	2.533	

EASIN + NEIGH. Even in the extended network, the number of countries involved in strategic coordination is lower than in operative coordination: 45 versus 60. There are only 258 connections, which employ 323 thousand shared directors' positions (Table 6.16), meaning that on average each connection involves 1252 positions. Still on average, each country has almost 6 partners, involving 7177 positions to share strategic knowledge coordination. However, as we have shown so far and will discuss in a dedicated section below in this chapter, most of the times average values are rather misleading in this field of people-based inter-firm coordination network, because most topological and attributive variables are distributed in a heavy-tail (HT) way. In fact, the statistics just mentioned are vitiated, especially for what concerns the weighted links—that is, the coordination effort—by the overwhelming role of the US, which have more than 226 thousand positions out of the 354 thousand (Table 6.14 in Data Appendix), thus 64% of all links. This is also the cause of the high degree and eigenvector centralization: 0.5 and 0.2 in binary terms, 0.99 for weighted eigenvector.

However, as we did for the role of the UK in the EASIN inter-country network, even the US have 90% of degree of closure, as also the UK in this extended network. Ireland too has 80% share of internal over total links. Therefore, *the very high propensity to focus on self-coordination seems to be an Anglo-American trait, further confirmed by the fact that EASIN (as a separate entity in this EASIN + NEIGH inter-country network) has a very low (0.1) degree of closure* (Table 6.17). Actually, if we look at the binary degree centrality (Table 6.14 in Data Appendix), we see that, while EASIN is necessarily connected to all other countries—precisely by definition—the

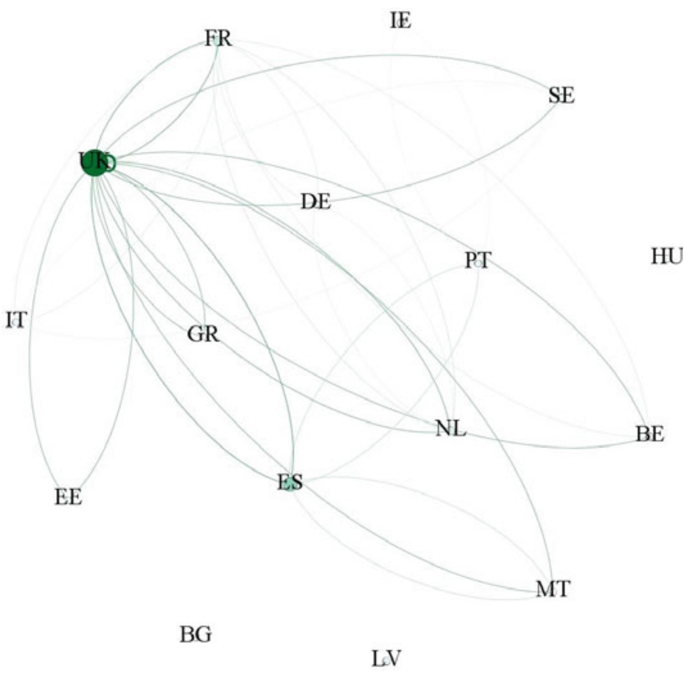

Fig. 6.5 Inter-country graph of EASIN coordination. *Legend*: the size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of board interlocks

US is connected only to 24 (besides EASIN). That is, despite the disproportionate number of binary and (even more) weighted connections of the US respect to EASIN, they do not reach all the countries. As a consequence, if we look at the countries ranking in terms of external links (EDB) or external coordination efforts (EDW)—where external means excluding self-links—then we see that, though the ranking of the earlier places indicates the same countries, which means the Anglo-North-American countries, their relative distances and the distance between this block and EASIN or continental Europe are much shorter.

To some extent, while EASIN's low degree of closure is also induced by the logic of data gathering and the definition of neighbors itself, this inducement effect does not determine as well the extremely high degree of closure of the Anglo-American block of countries. These two facts are rather independent, and it would be very interesting in a future study to reverse the approach by centering on the US and identifying its neighbors.

Further, if we look at the binary Bc, we see that the ranking changes substantially: EASIN with 412 paths, the UK with 81 (thus, one-fifth of EASIN) and the US with only 38 paths. Finally, if we look at the weighted Bc, besides the first place of

Table 6.13 **a** Share of internal (binary) links across countries, **b** Share of internal (weighted) links across countries

(**a**)

Sector	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
UK	284	58	40	324	54	88
ES	108	22	10	118	20	92
FR	40	8	23	63	11	63
NL	36	7	9	45	8	80
MT	0	0	7	7	1	0
SE	4	1	3	7	1	57
LV	6	1	0	6	1	100
BE	2	0	3	5	1	40
PT	2	0	3	5	1	40
DE	0	0	4	4	1	0
IE	2	0	2	4	1	50
IT	2	0	2	4	1	50
EE	2	0	1	3	1	67
BG	2	0	0	2	0	100
HU	2	0	0	2	0	100
GR	0	0	1	1	0	0
Total	492	100	108	600	100	82

(**b**)

Sector	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
UK	462	66	45	507	57	91
ES	126	18	11	137	15	92
FR	42	6	47	89	10	47
NL	36	5	29	65	7	55
DE	0	0	25	25	3	0
SE	12	2	5	17	2	71
MT	0	0	7	7	1	0
PT	4	1	3	7	1	57
IT	2	0	4	6	1	33
LV	6	1	0	6	1	100
BE	2	0	3	5	1	40
BG	4	1	0	4	0	100
EE	2	0	2	4	0	50
HU	4	1	0	4	0	100
IE	2	0	2	4	0	50
GR	0	0	1	1	0	0

(continued)

Table 6.13 (continued)

(**b**)						
Sector	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
Total	704	100	184	888	100	79

Legend: Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB
Legend: Acronyms explained in the list of abbreviations
ShITW = IDW/Total IDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

Table 6.14 Major 5 cross-country coordination efforts

Sector	Target	Weight
UK	FR	18
DE	FR	14
NL	FR	13
NL	DE	11
ES	UK	9

Table 6.15 Companies' weighted propensity to coordinate across EASIN countries

Country	# of companies	IDW	EDW	Total
BE	3	0.67	1.00	1.67
BG	2	2.00	0.00	2.00
DE	1	0.00	25.00	25.00
EE	3	0.67	0.67	1.33
ES	62	2.03	0.18	2.21
FR	25	1.68	1.88	3.56
GR	1	0.00	1.00	1.00
HU	2	2.00	0.00	2.00
IE	3	0.67	0.67	1.33
IT	4	0.50	1.00	1.50
LV	6	1.00	0.00	1.00
MT	2	0.00	3.50	3.50
NL	14	2.57	2.07	4.64
PT	3	1.33	1.00	2.33
SE	6	2.00	0.83	2.83
UK	168	2.75	0.27	3.02
Total	305	2.31	0.60	2.91

Legend: Acronyms explained in the list of abbreviations

Table 6.16 Inter-country network of EASIN + NEIGH

Index	Binary	Weighted
Size	45	
Density (norm)	0.130	
Density (abs)	258	354,364
Fragmentation	0.088	0.430
Av. link value	1	1252
ADc	5.73	7177
Dc_CE (Fre)	0.752	–
Dc_CE (Sni)	0.533	–
Bc_CE	0.429	0.290
Eig_CE	0.209	0.995
GORC	0.146	0.114
Apl	1.755	6.568
GCL	0.778	0.114
SW	2.482	

EASIN, the ranking radically changes: CH at the second place and CN at the third, with relatively shorter distances. Accordingly, binary Bc centralization is pretty high (0.43), while the weighted is much lower (0.29).

In terms of strategic coordination effort, the biggest connection occurs between the US and CA (12,509 shared positions) and the fourth is between the US and the UK (2376 shared positions), showing again the relevance of strategic coordination within the Anglo-North-American block. The second connection is between the US and EASIN, which shares 2890 inter-board positions, straightly followed by the connection between the UK and EASIN (2832 positions).

In short, *the Anglo-North-American and the continental EU blocks have a similar capacity either to coordinate the EASIN-induced global Aerospace coordination network or to access and orient the strategic knowledge flowing through it*. This is also apparent when considered are the most intense flows between individual pairs of countries (Table 6.18).

Strategic coordination propensity per country. Considering the propensity to strategically coordinate (Table 6.19), the largest score is assigned to the US, which has also the largest number of companies. Considering that in EASIN the country with the largest number of companies had propensity only close to the average score, this twofold underlines the importance of the US in the extended inter-country network. Country with the second propensity has fifteen times less companies, and it is CA—another North-American country—the score perfectly presenting what is shown in the section on clustering analysis. The first European country and the second on in terms of numbers of companies is the UK, whose propensity is about three times smaller than that of the first the US (Fig. 6.6).

Table 6.17 **a** Share of internal (binary) links across early 20 countries, **b** Share of internal (weighted) links across early 20 countries

(**a**)

Country	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
US	154,018	76	15,125	169,143	69	91
UK	24,596	12	5024	29,620	12	83
FR	10,798	5	1888	12,686	5	85
CA	730	0	7601	8331	3	9
EASINT	600	0	5836	6436	3	9
IE	5214	3	1172	6386	3	82
ES	1448	1	633	2081	1	70
SE	420	0	1094	1514	1	28
HK	464	0	875	1339	1	35
CY	930	0	46	976	0	95
AU	70	0	802	872	0	8
NL	332	0	308	640	0	52
FI	584	0	53	637	0	92
SG	4	0	587	591	0	1
IT	420	0	126	546	0	77
PT	270	0	85	355	0	76
DK	246	0	73	319	0	77
MA	2	0	315	317	0	1
ZA	0	0	201	201	0	0
CN	14	0	184	198	0	7
Total	201,738	100	43,006	244,744	100	82

(**b**)

Country	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
US	204,420	70	21,867	226,287	64	90
UK	56,884	20	6637	63,521	18	90
CA	1510	1	13,325	14,835	4	10
FR	11,014	4	2075	13,089	4	84
IE	8484	3	2084	10,568	3	80
EASINT	888	0	8150	9038	3	10
ES	2086	1	781	2867	1	73
HK	1208	0	1617	2825	1	43
SE	662	0	1516	2178	1	30
AU	176	0	1104	1280	0	14
CY	992	0	46	1038	0	96

(continued)

Table 6.17 (continued)

(**b**)

Country	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
FI	760	0	63	823	0	92
NL	332	0	448	780	0	43
IT	582	0	176	758	0	77
SG	20	0	724	744	0	3
PT	382	0	103	485	0	79
DK	400	0	81	481	0	83
MA	2	0	317	319	0	1
BE	36	0	215	251	0	14
IN	82	0	161	243	0	34
Total	291,564	100	62,800	354,364	100	82

Legend: Acronyms explained in the list of abbreviations
ShITB = IDB/Total IDB (vertically)
ShTB = TDB/Total TDB (vertically)
ShIB = IDB/TDB
Legend: Acronyms explained in the list of abbreviations
ShITW = IDW/Total IDW (vertically)
ShTW = TDW/Total TDW (vertically)
ShIW = IDW/TDW

6.6 Cluster Analysis

Their analysis results are casted over three clusters[2] for the first two, while the last one proved to be best explained with five clusters. Their features are further analyzed by projecting each cluster within its network, thus evidencing where they are placed, and distinguished are also their geographical and sectoral aspects.

EASIN. Due to a major coverage of economic attributes, in this cluster analysis, we could also employ them (Fig. 6.7; Tables 6.20 and 6.21), so that after some experiments, we found the following key-parameters: BDc, BCc and TURN,[3] and TURN data for clustering analysis was available for 166 out of 307 companies—that is 54%. The results are further analyzed by projecting each cluster into the network, thus evidencing where they are placed.

Cluster 1. It represents 84% of companies with TURN data that could be classified. It includes the major part of the network, where companies belong to the smaller components—therefore their long and short distance connectivity is also smallest, and they also generate the least TURN (Fig. 6.8).

Cluster 2. It represents 2% of companies with TURN data that could be classified. They are the opposite of Cluster 1, here highlighted are companies which have

[2] The methodological procedure to create the clustering analysis is explained in the Methodological Appendix.

[3] Normalized respect to highest value, decreased by one decimal place to level with other parameters.

Table 6.18 Major 30 cross-country coordination efforts

Source	Target	Weight
US	CA	12,509
US	EASINT	2890
EASINT	UK	2832
US	UK	2376
IE	HK	1365
US	FR	1151
US	SE	939
ES	EASINT	492
AU	US	458
US	SG	439
IE	EASINT	376
EASINT	FR	359
UK	AU	312
CA	EASINT	264
US	MA	254
ZA	US	170
CA	FR	163
IE	UK	161
CN	UK	145
SE	CA	143
NL	US	139
IT	EASINT	137
EASINT	NL	129
BE	US	128
US	BE	128
FR	UK	126
SE	EASINT	122
ES	UK	110
UK	ES	110

Legend: Each of them is symmetric

medium close range, direct connectivity, the smallest long-range connectivity, but are strongest in terms of economic TURN attribute. They are members of one, medium-size component (Fig. 6.9).

Cluster 3. It represents 14% of companies with TURN data that could be classified. They are companies with the highest close and long-range connectivity and represent TURN a bit larger than small companies from Cluster 1. They are members of the medium-size components (Fig. 6.10).

Table 6.19 Companies' weighted propensity to coordinate across early 20 EASIN + NEIGH countries

Country	# of companies	IDW	EDW	Total
US	1451	140.88	15.07	155.95
UK	1104	51.53	6.01	57.54
EASINT	747	1.19	10.91	12.10
ES	323	6.46	2.42	8.88
FR	294	37.46	7.06	44.52
IE	233	36.41	8.94	45.36
IT	142	4.10	1.24	5.34
CA	97	15.57	137.37	152.94
SE	74	8.95	20.49	29.43
NL	71	4.68	6.31	10.99
FI	49	15.51	1.29	16.80
PT	41	9.32	2.51	11.83
CH	40	3.20	2.78	5.98
DK	39	10.26	2.08	12.33
CY	34	29.18	1.35	30.53
AU	31	5.68	35.61	41.29
CZ	30	2.73	0.70	3.43
HK	30	40.27	53.90	94.17
EE	29	6.34	1.59	7.93
IN	27	3.04	5.96	9.00

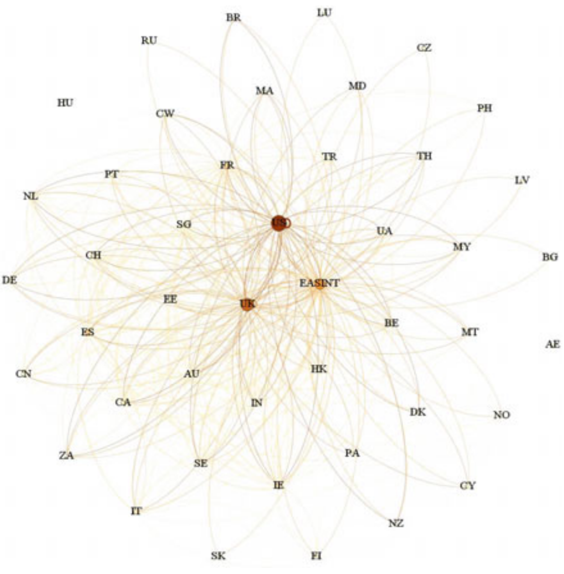

Fig. 6.6 Inter-country graph of EASIN + NEIGH coordination. *Legend*: the size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of board interlocks

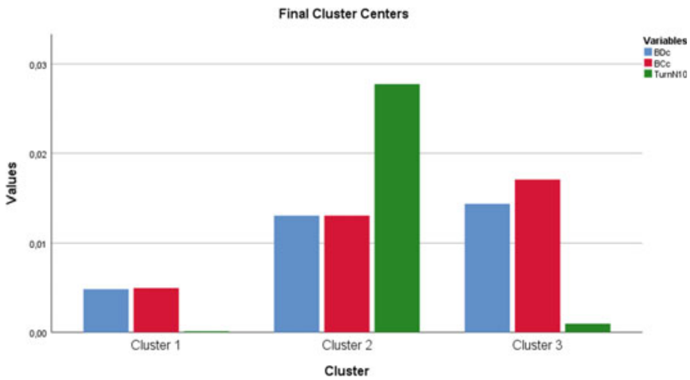

Fig. 6.7 EASIN clusters

Table 6.20 EASIN attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	166	84	1	15
TURN	270,812++	21	55	24
EM	398+	27	36	37
EC	64,920++	30	25	45
TASS	363,064++	23	56	21

Legend: +,000; ++,000,000 current US$

Table 6.21 EASIN clusters statistics

General	BDc	BCc	TURN	*C1*	BDc	BCc	TURN
Average	2	0.007	1631++	Average	1	0.005	416++
Min	1	0.003	0	Min	1	0.003	0
Max	10	0.033	79,591++	Max	4	0.021	12,751++
Median	1	0.003	21++	Median	1	0.003	19++
C2	BDc	BCc	TURN	*C3*	BDc	BCc	TURN
Average	5	0.016	7322++	Average	10	0.033	29,579++
Min	1	0.003	10+	Min	10	0.033	29,579++
Max	6	0.023	79,591++	Max	10	0.033	29,579++
Median	5	0.016	57++	Median	10	0.033	29,579++

Legend: +,000; ++,000,000 current US$

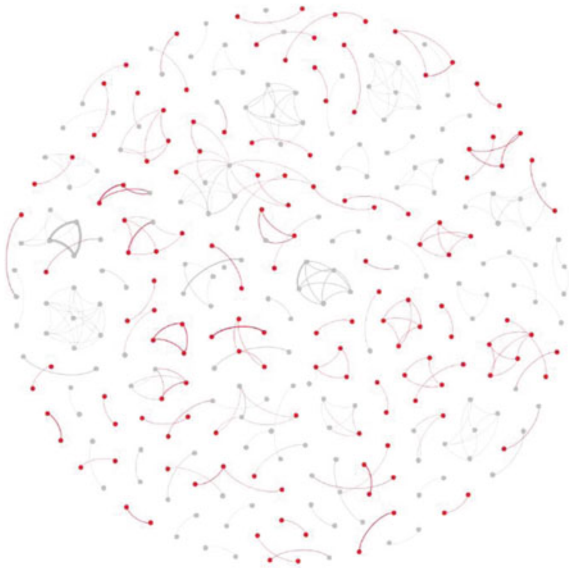

Fig. 6.8 Cluster 1 in EASIN

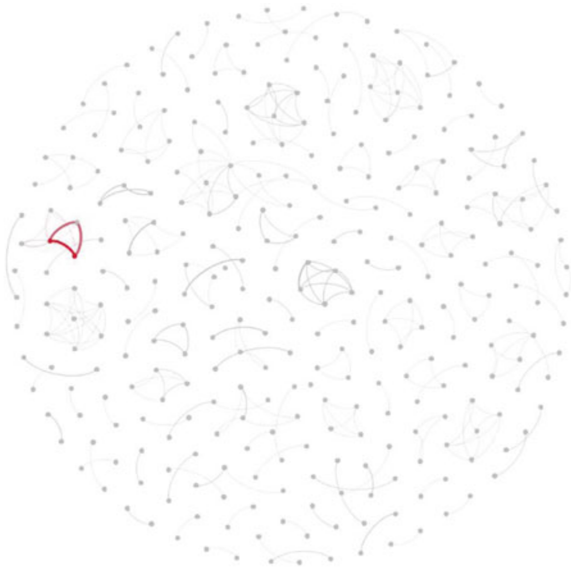

Fig. 6.9 Cluster 2 in EASIN

EASIN Integrated. Out of all EASIN companies connected in the EASIN + NEIGH network, a bit more than a half (52%) had the attributive data which allowed us to fairly sufficiently conduct the following analysis. Further, in the cluster analysis of EASIN Integrated with the use of the same parameters as in EASIN, it turned out that the same connectivity trends simply transferred to the integrated network. As

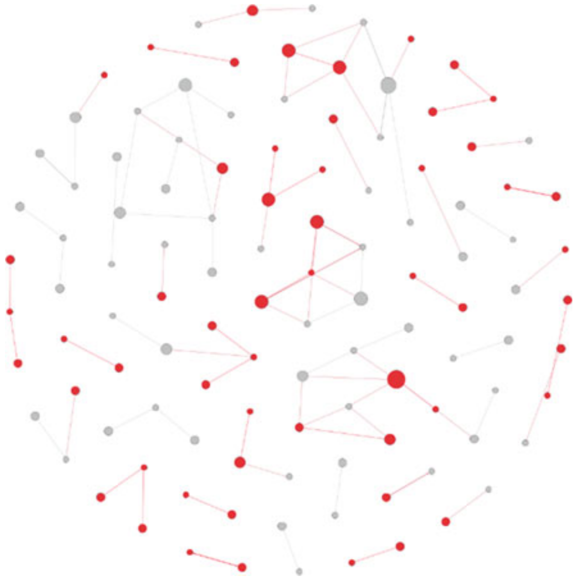

Fig. 6.10 Cluster 3 in EASIN

a result, Cluster 1, which is the most present (shift from 84 to 92% of share), has the lowest TURN—which is much smaller even than the medium cluster and clearly the lowest connectivity indexes. Cluster 2 resembles its counterpart from previous analysis, here as well 0.5% of companies possess the highest BDc—meaning they belong to the largest cliques, though their BCc is equal as that of the medium cluster—meaning companies of Clusters 2 and 3 both belong to the main component of EASIN + NEIGH network, and Cluster 3's TURN is by far the highest—being about 10 times larger than that of Cluster 3. Cluster 3 representing 7% of companies, which are medium size in terms of TURN, possess about half of cluster's 2 BDc—close distance, direct connectivity, which gives insight into potential relative size of cliques to which those companies might belong to.

Similarly to M2M, this analysis also very well resembles the heavy-tail feature of our networks, where top connectivity is reserved only for few most central companies, and the rest are at the opposite side of the connectivity and size spectrum.

The general insight stemming from this analysis is: (1) EASIN exhibits a heavy-tail distribution of its topological and size attributes; (2) it is divided into numerous components, where majority is made of small ones, usually dyads, several of them are made up of several companies, and only few of them form larger components; (3) the largest components are usually associated with companies, which exhibit also the largest economic size attributes; (4) there are only very few companies, who are both economically large and occupy an outstandingly advantageous network positions, where they are the "thick of the things" being surrounded by a fairly large immediate neighborhood and also being connected to longer chains, thus having access to further companies.

EASIN + NEIGH. The clustering analysis has identified five clusters (Fig. 6.11) by applying the same three variables that were employed for operative coordination (M2M): length and size of the associated component (NLORC), binary Dc (BDc) and binary Katz centrality (BKc). The relative weight of each variable in each cluster and in the whole set is shown in Fig. 6.11, while the basic statistics in Tables 6.22 and 6.23. Unlike the operative coordination network, where the cluster analysis had identified only three, here we found five clusters, meaning that *though it is much smaller in terms of companies and connections, strategic coordination is more differentiated than operative coordination*. The results are further analyzed by projecting each cluster into the network, thus evidencing where they are placed. Moreover, we proceed the analysis by distinguishing the countries and the industrial sectors into the topology-placed clusters.

Cluster 1. In this cluster, 18% of companies have decent connectivity with the rest of the network, but not necessarily belong to the largest cliques. They are equally spread all over the network (Fig. 6.12), being the "well-connected noise" to the biggest strategic coordination groups that float between them. In the main component, they play significant role being the connectors of the largest cliques or being members

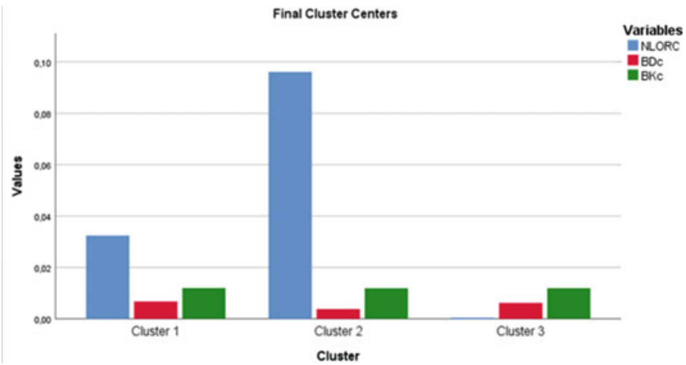

Fig. 6.11 EASIN + NEIGH clusters

Table 6.22 EASIN + NEIGH attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)	Cluster 4 (share in %)	Cluster 5 (share in %)
# of companies	5043	18	17	1	57	7
TURN	1,831,830++	11	52	1	31	5
EM	2741++	17	34	1	43	5
EC	1,106,424++	2	31	1	54	12
TASS	4,878,313++	9	27	1	57	6

Legend: +,000; ++,000,000 current US$

Table 6.23 EASIN + NEIGH clusters statistics

General	LORC	BDc	BKc	*C1*	LORC	BDc	BKc
Average	781	49	1.189	Average	2838	11	1.028
Min	1	1	1.002	Min	1	1	1.002
Max	6834	264	2.558	Max	6834	115	1.379
Median	26	14	1.034	Median	2814	6	1.014
C2	LORC	BDc	BKc	*C3*	LORC	BDc	BKc
Average	63	149	1.669	Average	2499	248	2.491
Min	1	1	1.002	Min	1	101	1.318
Max	3845	252	2.521	Max	4608	264	2.558
Median	18	132	1.462	Median	2680	252	2.521
C4	LORC	BDc	BKc	*C5*	LORC	BDc	BKc
Average	57	18	1.051	Average	2949	111	1.370
Min	1	1	1.002	Min	2	63	1.172
Max	4610	264	2.558	Max	5343	150	1.557
Median	11	8	1.019	Median	2814	115	1.379

of the medium-size ones, in fact they are usually the bridging companies, so they will be closer looked at in their own, dedicated section.

Cluster 2. The opposite of Cluster 1 is Cluster 2, which is made of 18% of companies that are strongly connected within their own groups (Fig. 6.13), but have rather weak connections to the rest of the network. They are mostly made up by tight US cliques (Fig. 6.14a) and in much smaller scale also by French, British and Canadian ones. In terms of sectors (Fig. 6.14b), they are in large majority from Manufacturing (C), which remains rather isolated and does not mix with others and also from a blend

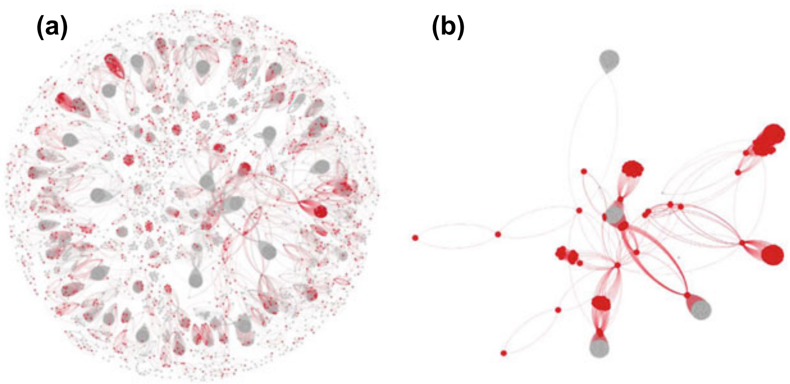

Fig. 6.12 **a**, **b** Cluster 1 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**). *Legend*: Companies belonging to this cluster are evidenced in red

of companies from Financial (K) and Administrative (N) sectors. In this graph, the "null" category has companies that did not have available NACE code information, but it is interesting to point out that missing data concern almost entirely a single, tightly connected clique from the UK. Manufacturing companies again come from the US, whereas Financial and Administrative ones come from France.

Cluster 3. Only less than 1% of companies—from Cluster 3—plays a very significant, central role in the perspective of the whole network (Fig. 6.15). They were distinguished, because they are the crucial part of the main component—which has been argued to be the most "representative" part of the network—where they are advantageously positioned. They are very heavily connected in terms of binary Dc, what in this case symbolizes the size of their own clique, being one of the biggest in the network and the main component itself and also in terms of the long-range indexes like LORC and Katz—what presents their advantageous access to long chains where they are themselves their most central parts. Below they are represented in the

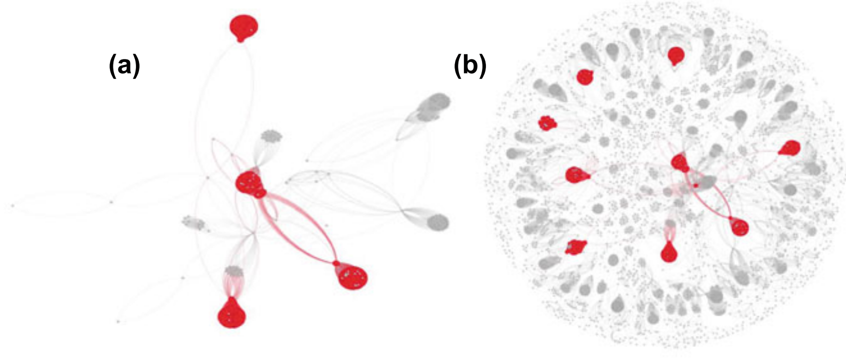

Fig. 6.13 **a**, **b** Cluster 2 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**). *Legend*: Companies belonging to this cluster are evidenced in red

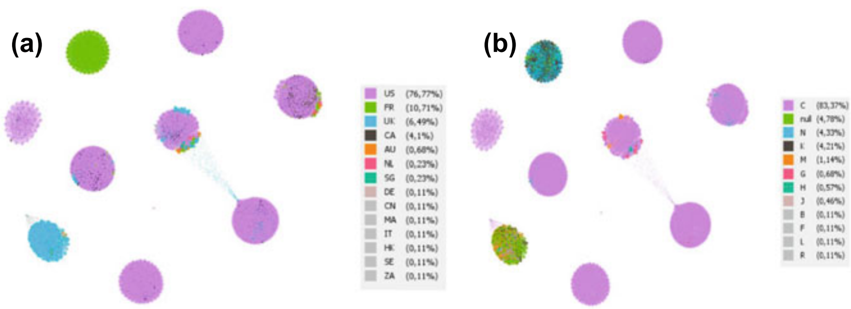

Fig. 6.14 **a**, **b** Cluster 2 by evidencing countries (**a**) and sectors (**b**). *Legend*: Symbol "null" includes companies with no data on sector

perspective of the whole network as well as only the main component. In terms of countries and sectors (Fig. 6.16), this cluster is made up mostly of the US and the UK companies. In terms of sectors, those companies are all mostly from the Manufacturing (C) and marginally from Finance (K) and others. Overall, the Manufacturing sector, except one company, comes entirely from the US, and the other sectors are located within the UK.

Cluster 4. In Cluster 4 there are the most (57%) companies, which are loosely connected both to their immediate neighbors and to the rest of the network (Fig. 6.17). Even though they may belong to the same components, they are not necessarily members of cliques, but rather surround the most central companies of their strategic coordination group. Similarly to Cluster 1, they are also the bridging companies, but with much smaller LORC, meaning they tend to be outside the main component and

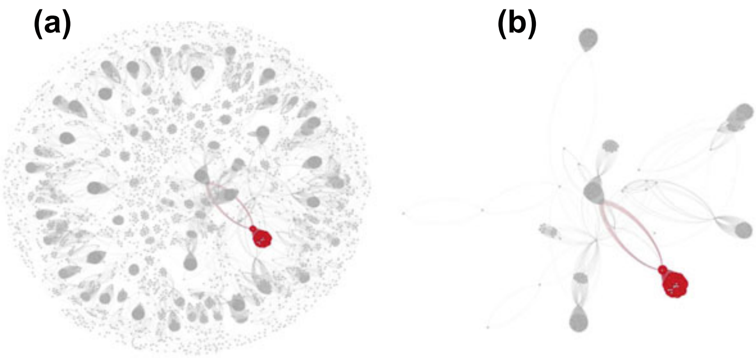

Fig. 6.15 **a**, **b** Cluster 3 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**). *Legend*: Companies belonging to this cluster are evidenced in red

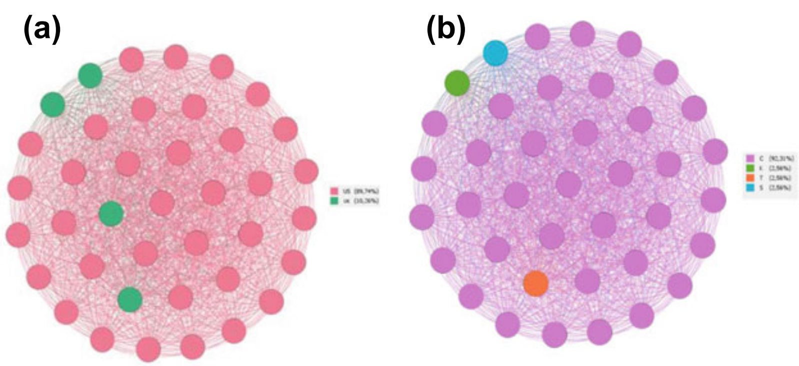

Fig. 6.16 **a**, **b** Cluster 3 by evidencing countries (**a**) and sectors (**b**)

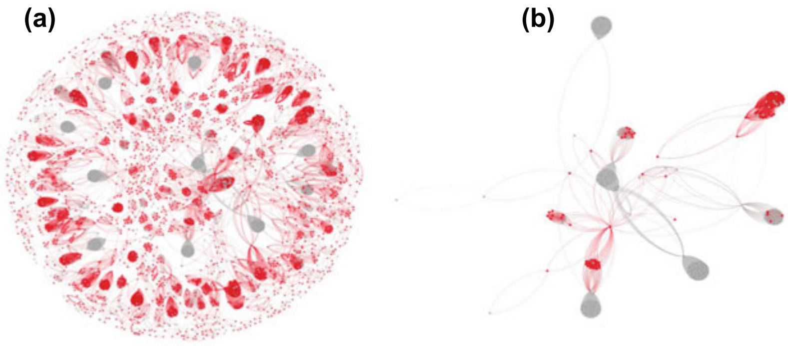

Fig. 6.17 **a**, **b** Cluster 4 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**). *Legend*: Companies belonging to this cluster are evidenced in red

connect the other, rather smaller cliques together. They also will be highlighted in the section dedicated to bridging companies.

Cluster 5. The final cluster strong with indexes and fairly limited in size (7% of total) is Cluster 5. It is made up of companies that are still some of the most relevant in the network (Fig. 6.18), as they have equally outstanding reaching capacity, but they are less connected directly (meaning they are smaller cliques) and have worse Katz centrality as compared to Cluster 3. This means they can reach the other companies of the network (though clearly because of network's fragmentation not all of them) fairly easy, but they are not in the "thick of things", being less central and rather more in the mid-range.[4] Country-wise (Fig. 6.19a), those companies also belong in two-thirds to the US, in one-fifth to the UK, and the rest is marginal. The companies of the same countries, except one component, show great tendency to relate almost exclusively to one another. From the sectoral perspective (Fig. 6.19b), they are mostly from Manufacturing and almost entirely from the US, and the rest of sectors come from countries such as the UK and France.

The board interlocks network, due to its complexity in the extended network of EASIN and its neighbors, generated not three like in all other types of relations, but five clusters. Some of the features are transferred here from the EASIN analysis, some are new. In summary, the cluster analysis highlighted that: (1) the extended network is also distributed in a heavy-tail way; (2) membership in clusters is heavily dependent on participation in cliques, their size and also on a role that is played within them; (3) except for one cluster, there is no strong dependence on the main component, four clusters have members who are present either in or out of it; (4) extracts of those clusters in large majority are self-referential, meaning that their members present large tendency to relate to others of the same type—either country—or sector-wise; (5) as a consequence of point 1 and 4, the clusters show a trend, that is present

[4] Surprisingly, not all of the nodes of included cliques were selected, and this is due to overall approximations in clustering method (see the Methodological Appendix).

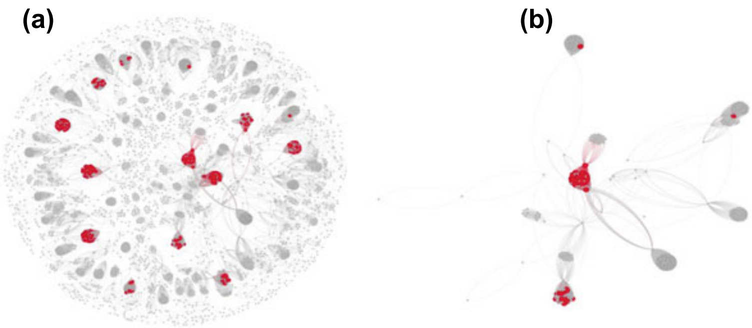

Fig. 6.18 **a**, **b** Cluster 5 in EASIN + NEIGH (**a**) and EASIN + NEIGH MC (**b**). *Legend*: Companies belonging to this cluster are evidenced in red

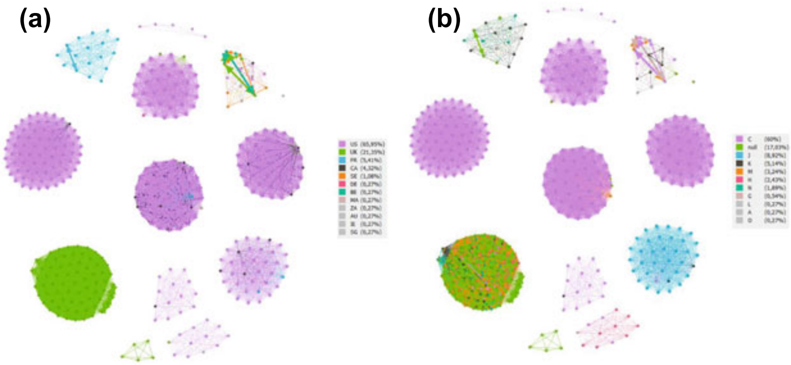

Fig. 6.19 **a**, **b** Cluster 5 by evidencing countries (**a**) and sectors (**b**). *Legend*: Symbol "null" includes companies with no data on sector

despite of the scale, all—small and large cliques, and thus clusters are all alike, the only factor that really distinguishes them is size.

6.7 Cliques Analysis

In Chap. 4, we have shown that cliques and components are distributed in a very nonlinear and heavy-tail (HT) shape in all networks, including this of inter-board coordination. Further, we have shown that clique size explains very well component size in the inter-departmental and inter-board coordination networks, as well in the ALL network, which is made almost entirely by those two networks. Here below, we deepen the analysis on the three largest cliques within this inter-board network.

The picture that comes from this analysis is fully consistent with what emerged so far: the *largest cliques are made mostly by American companies, with a residual participation of few EU companies*, which likely are subsidiaries of the American ones. Therefore, the largest groups for creating and sharing strategic knowledge are American, with an EU residual participation that likely is not actively allowing EU to access that knowledge, but rather is more in the direction of bringing that coordination in EU at the convenience of American groups. Further, *most companies are made by Manufacturing, but with a residual participation of Financial and Professional Activities companies, so to guarantee them access to strategic knowledge*.

Clique size 253. The clique (Fig. 6.20) contains mostly companies from North America (the US and Canada), few single ones come from Europe (the UK), and one comes from Asia (Singapore). Almost entirely the clique is made by Manufacturing companies, with three single occurrences from three other sectors. It belongs to the main component and includes two EASIN companies – both from BAE group.

Clique size 150. This clique (Fig. 6.21) is a bit more varied. It is also greatly dominated by the US companies, with better than before representation of the European ones—six of them are from France and the UK. There is, however, much less variety in terms of sectors, and the clique is almost entirely built by Manufacturing sector with only one occurrence of Finances. It does not belong to the main component, and there are five EASIN companies—all come from Safran group.

Clique size 133. The clique (Fig. 6.22) with 133 companies comes almost entirely from the US and in few cases from Canada. It is almost entirely a Manufacturing sector, with single appearances from several other sectors. It belongs to the main component and contains no EASIN companies.

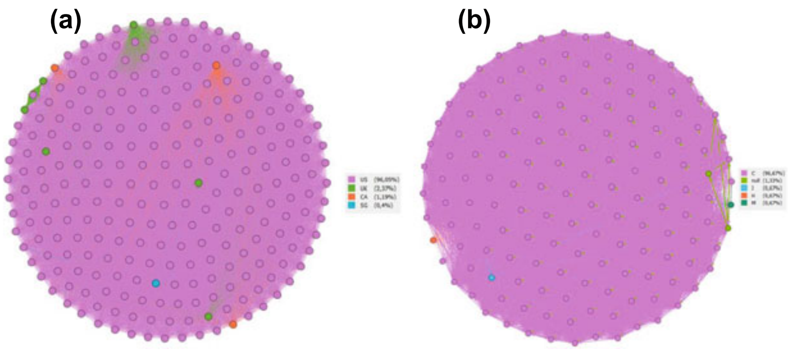

Fig. 6.20 Composition of the largest clique in terms of countries (**a**) and sectors (**b**)

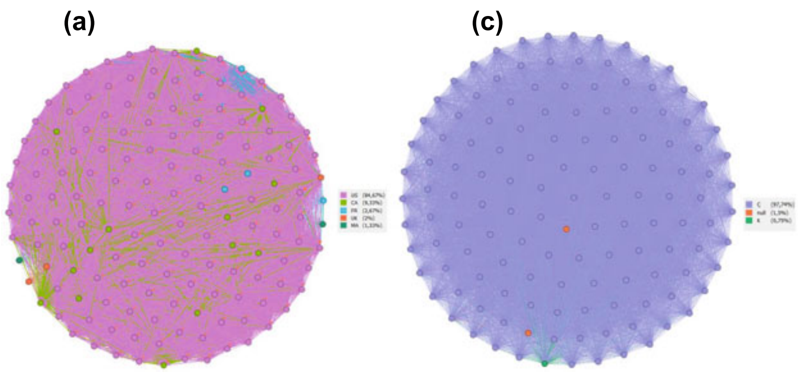

Fig. 6.21 Composition of the second largest clique in terms of countries (**a**) and sectors (**b**)

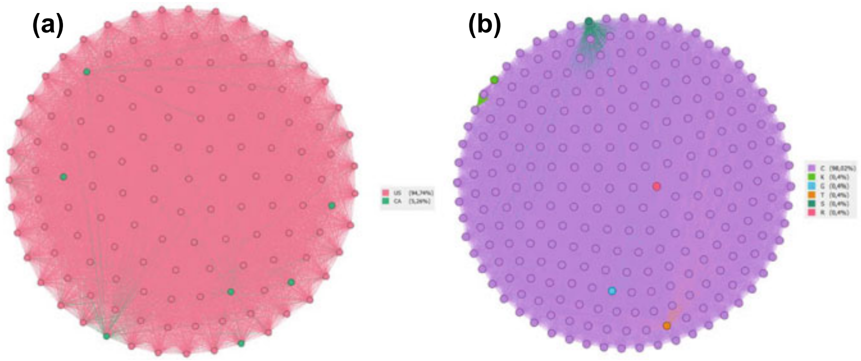

Fig. 6.22 Composition of the third largest clique in terms of countries (**a**) and sectors (**b**)

6.8 Bridging Companies as Key-Players

As concerning the strategic coordination of the extended network, *the top 88 companies that do have bridging centrality (BRc) higher than 0 are mostly located in the MC*. The following figures (Fig. 6.23) show them with the other companies present in the background for comparison, whereas the next two figures (Fig. 6.24), which are an extract of the highlighted companies with differentiation of countries and sectors, show that *the bridging companies are also well connected themselves and that some of them are not only the bridging companies, but that they actually form the "bridging cliques" together with their neighbors*. The central bridging clique is made almost entirely by companies from BP group, which come mostly from the US, the UK and few from Australia, Singapore, France, Germany and the Netherlands.

The most dominating countries in terms of creating bridges are the UK, France, the US and Ireland, and sector-wise, they are by far Manufacturing, then Finances, Professional Activities and Wholesale. Out of the 88 companies 19 are from EASIN,

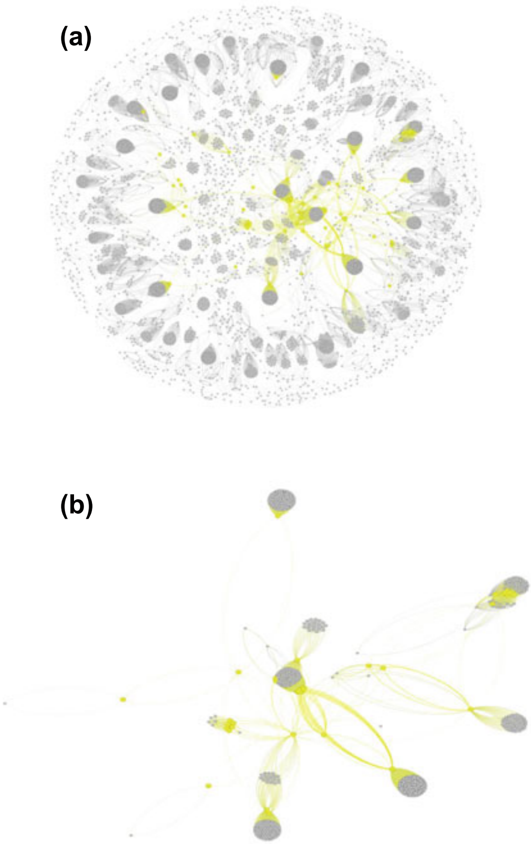

Fig. 6.23 **a**, **b** Bridging companies in EASIN + NEIGH (**a**) and in EASIN + NEIGH MC (**b**)

and among those EASIN, more than half are from the UK, and several come from France. In the figure representing countries, there are two larger same-country groups of companies sticking together from the UK and Ireland, though the biggest group in the extract is actually a mix of international companies. In terms of sectors, the extract is much more mixed up, but the two single-country groups mentioned earlier are also almost entirely single-sector forming a British M and an Irish K groups.

6.9 Heavy-Tail Scale-Free Analysis

EASIN. In the EASIN network among the economic size attributes (Figs. 6.1 to 6.5 in Data Appendix), only EC and TURN have an appreciable HT structure, while all

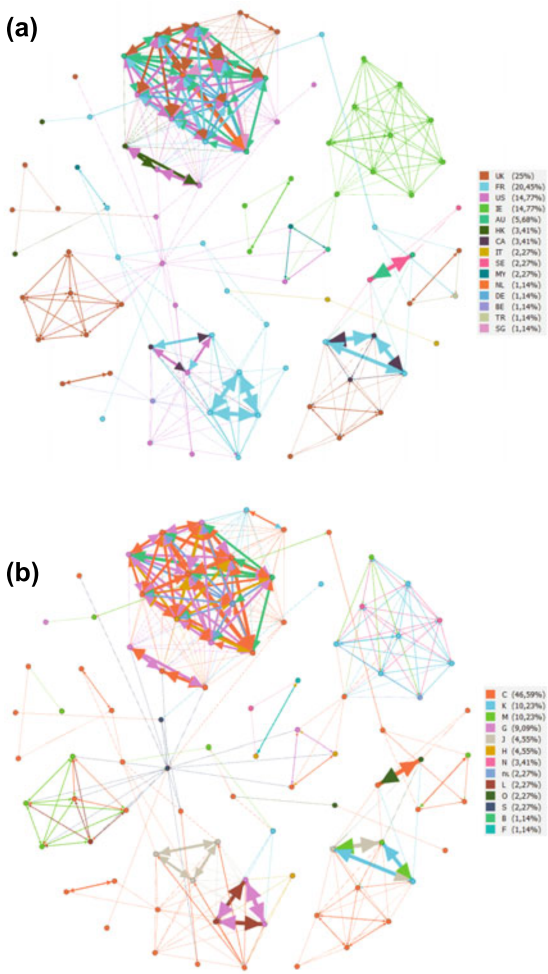

Fig. 6.24 Bridging companies in EASIN + NEIGH evidenced by countries (**a**) and sectors (**b**)

topological parameters (Figs. 6.6 to 6.10 in Data Appendix) have a very accentuated HT structure.

EASIN + *NEIGH*. Here, the distribution of economic size attributes follows a rather straight HT shape (Figs. 6.11 to 6.15 in Data Appendix), while among the topological parameters (Figs. 6.16 to 6.22 in Data Appendix) only components, cliques and Bc have an appreciable HT shape.

6.10 Assortativity

The network of inter-board coordination is perfectly assortative in the EASIN + NEIGH and in its MC and highly assortative in the EASIN-only network: 0.74 and 0.64 for the binary and weighted versions, respectively. Interestingly, it becomes moderately disassortative in the MC of EASIN: −0.34 and −0.33 for the binary and weighted versions, respectively. It means that where pure EU Aerospace strategic coordination is more important, then highly connected and large companies tend to connect with lowly connected and small companies.[5] If we jointly consider the facts that in EASIN MC there are few and disconnected small cliques and that some of them are large and highly connected companies that are the key strategic and rival players, then we discover that they tend to not share their boards, just to not share their strategic choices. Their clusters (and cliques) can enlarge in the larger aggregates of EASIN and EASIN+NEIGH, but supposedly, such enlargements tend to include companies belonging to their business groups made of ownership connections or strategic groups made of trade connections. In both cases, clusters can involve also small companies, but never involve big rivals.

6.11 Summary

The number of EASINT companies that additionally connect with neighbors grows from 307 to 748 relatively to pure EASIN network. The largest of those companies are also the highly connected ones in terms of strategic coordination, and their intermediating power of strategic knowledge flows varies with their size in terms of EC and EM. Even in the E + N MC, the SPCH is confirmed, because there is a positive (and sometimes rather high) correlation between economic size attributes and (direct and indirect) connectivity. It seems also clear that the direct and indirect capacity to influence strategic coordination of the (EASIN-induced) global Aerospace Industry network is very much associated with company size in terms of employees.

When focusing on the top 200 companies or on the Manufacturing sector or the Aerospace Industry, the coefficients grow from low to medium values, especially the intermediation and access capacity of strategic knowledge flows and, even more, the intermediation of clusters of companies. Therefore, highly connected and highly intermediating companies are mostly the large ones, which means that they are those able to create strategic coordination with their partners and, anyway, those able to access strategic knowledge which emerged from elsewhere within the global network.

The strategic coordination of the EASIN network is a very elitist phenomenon, with the power firmly concentrated in a pull of few companies. However, projected at the global level, EASIN strategic behavior is almost entirely coordinated by neighbor

[5] We have already mentioned the hypothesis supporting the association between economic large and highly connected companies and partly proofed in the correlation analysis. We will definitely discuss it in Chap. 7.

companies. This coordination occurs separately in hundreds of disconnected components (groups of companies), likely sharing other common traits or interests, like trade or ownership or technological connections. Conversely, the companies' elite residing in the MC has a very big capacity to create strategic knowledge directly with their partners, though through a minor number of efforts per each partnership. Their strategic decisions are then diffused alongside the MC through long chains of transmission.

The creation and transfer of strategic knowledge at global level are made essentially by neighbor Manufacturing companies, which are mostly Anglo-American, then (much less) by neighbor Financial companies, which are mostly European (but not only EU28) and much less by EASIN companies.

The engagement of EASIN countries into strategic coordination is about half of what occurs in operative coordination, and the UK is the leader. However, in line with what happens in operative coordination, its companies have a very high propensity (91%) to self-reference. The consequence is that, in terms of inter-country coordination, FR gets the first place with 47 shared positions, then the UK with 45, followed by the NL and DE with 29 and 25, respectively. The strategic coordination of EASIN countries is mostly a business of 5 countries, with a prominent role of the UK.

Even in the extended network, the number of countries involved in strategic coordination is much lower than in operative coordination. The Anglo-North-American and the continental EU blocks have a similar capacity either to coordinate the EASIN-induced global Aerospace coordination network or to access and orient the strategic knowledge flowing through it.

The bridging companies are also well connected themselves, and some of them are not only the bridging companies, but they actually form the "bridging cliques" together with their neighbors. BINTs are built much preferably between companies of the same capacity to build board interlock, and thus to exchange strategic knowledge. Such a preference becomes extremely high when including the neighbors, but it reverses when considering the bunch of companies into EASIN MC.

When classified into clusters, both EASIN and EASIN + NEIGH show a heavy-tail feature, where there are larger majority of lowly connected and in case of EASIN small in terms of economic attributes, companies. Members of clusters are usually self-referential, both in terms of countries and sectors. EASINT cluster analysis showed that only the binary number of connections was relevant in distinguishing companies.

The EASIN companies exerting their influence through high direct coordination tend to not share their strategic knowledge into the core, but rather they share it with their suppliers: likely, they appoint some of their directors into their boards. Conversely, EASIN highly connected companies can indirectly share their strategic knowledge through neighbors alongside relatively long chains of transmission, which largely can involve other sectors, mostly Manufacturing and Financial companies. Such chains involve American companies in several bilateral exchanges.

Chapter 7
Asymmetric Knowledge Coordination Through the Manager-Director Hybrid Role

7.1 Network Outline and Statistical Analysis

EASIN. Hybrid (asymmetric) inter-firm coordination, where there is a mismatch of positions and a director becomes a manager somewhere else, is significantly much less present when compared with BINT and DINT relationships. There are 429 EASIN companies engaged in such form of strategic alliance (Table 7.1 in Data Appendix) in the E+N network, that is 14% of the whole EASIN. Connected internally within EASIN itself are only 112 companies. In terms of number of companies, the first place belongs to the UK (Fig. 7.1a), the second one to Italy, which has only one third of companies when compared with the first country, and the rest belongs to France, Spain and Belgium. The UK composes one third of all the engaged companies, but the most significant country in terms of economic attributes is France, second one is the UK, and the rest is similarly marginal.

Neighbors. Also, the neighbors (Table 7.2a in Data Appendix) are fewer than in previous types of coordination: the network contains 3990 neighboring companies, where 54% come from the EU28 and the rest from the remaining part of the globe (Fig. 7.1b). The leader in number of companies in Europe is the UK with 33% of the European part and 18% of the global one. The global leader is the US with 38% of companies worldwide and more than twice as much as the next country—the UK. The next in the top of Europe are France, Italy, Spain and Ireland, where the UK and France are the top European countries in terms of the economic attributes and the US, as always, is the top in the non-EU28 part.

The Financial neighbors (Table 7.2b in Data Appendix) showed a shift in the leadership, where France overtook the UK at the first place in Europe—it composes 28% of the European part and 22% of the whole. It is also in the top in terms of the economic attributes, but it is Financial companies of Sweden that are the largest in terms of economic resources, even though they make up only 2% of the European part. Overall, European Financial neighbors stand at almost 80% of economic attributes of all neighbors, considering that the HINT is the best representation of power imbalance between network actors, and it seems European Financial institutions in particular

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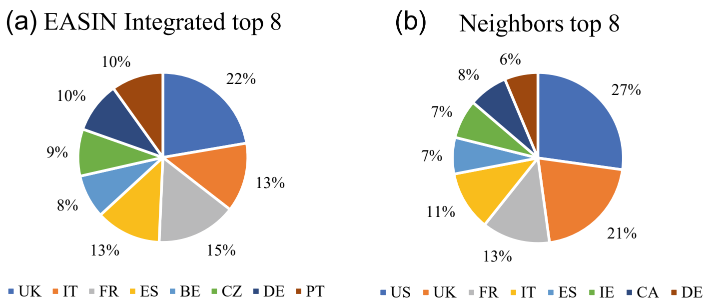

Fig. 7.1 **a**, **b** Share of top 8 countries in terms of number of companies in EASIN without isolates (**a**) and neighbors (**b**). *Legend* The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables, and "the others", which are included in Tables 7.1a and 7.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 8

are the key-players in the power-imbalance creation. In the non-EU28 part, the US leads with 12% of network share, and it also controls a significant proportion of the economic attributes. The most resourceful country in terms of EC and TURN is, however, Singapore where the two indexes stand at more than one third of the whole network. Even though the data availability is much scarcer in the non-EU28 part, the two leading countries they are in fact dominating the entire network with those two attributes. This shows that although the European Financial institutions may be more active and present, they are not necessarily the biggest players that are out there.

EASIN + NEIGH. By far, the most present (Table 7.3 in Data Appendix) is the US (34%) followed by the UK (19%) and France (8%). Europe covers 58% of the network and on average owns about two-thirds of the economic attributes. The following pie charts highlight the situation in more aggregated form showing the relative position of EASIN as compared to its neighbors, represented as the percent share of the total per each economic attribute. The neighbors are presented through a cross section of sectors (Fig. 7.2) with particular attention given to those most prominent ones, and the economic capabilities of the whole EU28 compared to the rest of the world are already provided in tables which can be found in the Data Appendix so it will not be duplicated here. Although EASIN is not a sector, but rather just an industry within a particular geographical context, it is added to the analysis because it is after all the focal point of the entire book. It is apparent that EASIN is always present in the top 3 along with, usually, Financial and Manufacturing sector. Companies that participate in M2D E+N represent on average more than 90% of resources of the ALL E+N network (Fig. 7.3). Although there is less of them than in M2D or D2D, they still hold high numbers in terms of economic attributes, which shows that overall it is rather the larger companies who engage in HINTs.

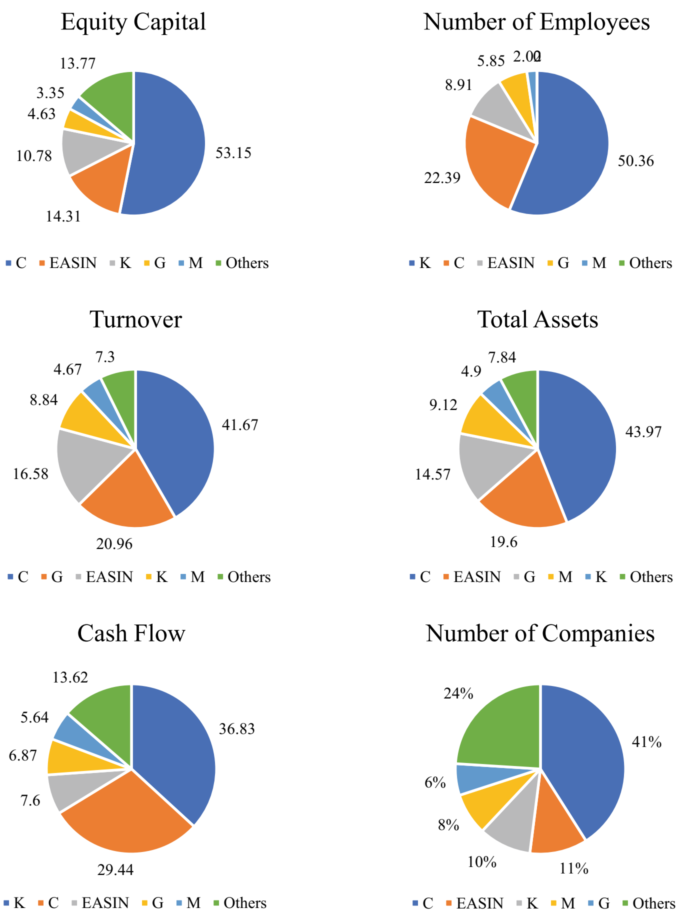

Fig. 7.2 a–f Economic attributes of EASIN compared with all its neighbors, which are grouped into their respective sectors. *Legend* The percent scores represent proportion of the total, the values in the pie charts do not sum up to 100% as for clarity variables, and "the others", which are included in Tables 7.1a and 7.2a in Data Appendix, were omitted to not dim the relevance of the smallest countries of the top 5

7.2 Correlation Analysis

EASINT. Because the formal representation of the AKE relationship orients the connection from a company where connecting person is a manager to another where s/he is a director, In_Dc refers to companies that appoint that person into their board, while Out_Dc refers to companies in which that person is a manager. Therefore, Out_Dc measures the extent to which a company acquires strategic knowledge from others giving in exchange operative knowledge, and vice versa in case of In_Dc. Due

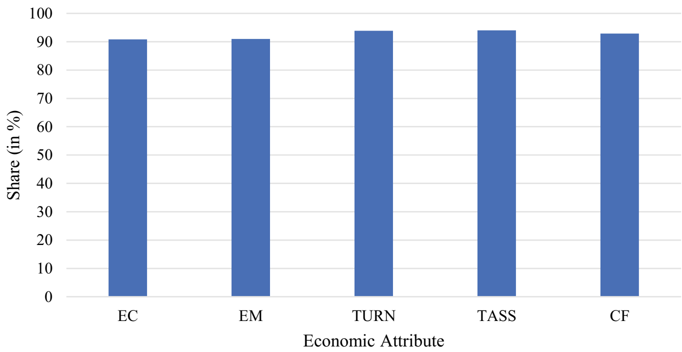

Fig. 7.3 Economic attributes of M2D E+N companies as proportion of ALL E+N companies

to this element of more complexity related to the distinction between In_ and Out_Dc, the correlations findings of EASIN and EASINT could change considerably.

Let us first analyze EASINT (Table 7.1), which is more important than EASIN (Table 7.2, Table 7.9 in Data Appendix), because it includes also EASIN companies that are connected only to NEIGH and additionally because the companies that are already connected within EASIN now regard also their connections with NEIGH.[1] This enlarged group includes now 429 companies, out of which the large majority (74%) are connected only to NEIGH.[2] There is an appreciable positive correlation between size and both types of Dc, more accentuated for In_Dc: 0.21 and 0.38 on average for binary and weighted, respectively, with values particularly high in terms of EM and CF (0.44 and 0.57, respectively). It means that larger companies are more likely to be influenced by or subjected to AKE. However, if we consider a company's relevance to exploit or be exploited by AKE connectivity at the whole network level, then the correlation holds significant and positive only between size and exploiting capacity. That is, likely and quite reasonably, only large companies are able to get advantages through AKE. If we combine the two aspects, it comes that *companies with large size tend to be associated with the capacity to exploit not only their direct neighbors, but also (through them) the rest of the network*. Conversely, the large companies that are exploited by AKE suffer it only from their direct neighbors.[3] These results are also confirmed by the fact that company size is also significantly positively associated with capacity to access knowledge flowing through the AKE chains: average binary and weighted Bc are 0.45 and 0.42, respectively, with much higher values occurring when size is measured in terms of EC and CF—0.53 and 0.49 in the former case and 0.61 and 0.57 in the latter case.

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[1] It means that the Dcs of EASIN companies do change, because now considered are also the connections with their neighbors.

[2] The number of valid observations for the correlations analyzed here varies from 248 to 429, and in most cases, significance is rather high (see Sect. 7.2 in Data Appendix).

[3] We can see these facts by looking at in- and out-eigenvector and Katz centrality indexes.

Table 7.1 Correlations in EASIN integrated

	EC	EM	TURN	TASS	CF	Average
LORC	– 0.03	– 0.02	– 0.03	– 0.02	– 0.02	–
BIDc	0.18**	0.26**	0.14*	0.17**	0.29**	0.21
BODc	0.24**	0.11	0.13*	0.14**	0.23**	0.17
WIDc	0.39**	0.44**	0.23**	0.28**	0.57**	0.38
WODc	0.32**	0.19**	0.16**	0.18**	0.34**	0.24
BBc	0.53**	0.48**	0.32**	0.30**	0.61**	0.45
WBc	0.49**	0.45**	0.30**	0.28**	0.57**	0.42
BICc	0.18**	0.24**	0.14*	0.16**	0.28**	0.20
BOCc	0.31**	0.13*	0.21**	0.20**	0.27**	0.22
BIEc	– 0.13*	0.18**	0.11	0.16**	– 0.02	0.06
BOEc	0.41**	0.05	0.61**	0.43**	0.02	0.30
WIEc	– 0.13*	0.18**	0.11	0.16**	– 0.02	0.06
WOEc	0.41**	0.05	0.61**	0.43**	0.02	0.30
BIKc	– 0.05	0.20**	0.13*	0.17**	0.05	0.10
BOKc	0.50**	0.19**	0.41**	0.33**	0.36**	0.36
WIKc	0.01	0.21**	0.13*	0.16**	0.11	0.12
WOKC	0.54**	0.24**	0.42**	0.35**	0.41**	0.39
BRc	0.03	0.03	0.04	0.02	0.05	–

Legend Statistical significance: $*P \leq 0.05$, $**P \leq 0.01$

In EASIN, there are only 112 companies, and even less of the sample with valid data, which range from 78 to 93 (see Data Appendix). There is a remarkably high positive correlation (0.58) with binary and even higher (0.62) with weighted Out_Dc, meaning that the bigger a company is the more likely it can obtain a knowledge advantage from its neighbors through its managers. This capacity to exploit AKE is even higher when considering the whole network through the neighbors' neighbors, especially when size is measured in terms of TURN and TASS: about 0.86 and 0.76, respectively. In both the EASIN versions, there is no any significant correlation of any measure of size with the number of influenced companies (LORC) or with the bridging capacity (BRc).

EASIN + NEIGH MC (1641 companies) and EASIN + NEIGH (4423 companies). Things change dramatically in the extended network (Tables 7.6, 7.7 and 7.10 in Data Appendix), where any correlation dissolves, likely also due to the lack of attributive data,[4] with the exception of a very mild positive association with LORC in the MC: 0.12 and 0.17 for EC and TURN, respectively. Therefore, it seems that outside the

[4] The number of valid cases drops down to between 300 and 550 in MC and between 990 and 2200 in E+N (see Data Appendix).

Table 7.2 Correlations in EASIN

	EC	EM	TURN	TASS	Average
LORC	0.09	0.02	– 0.01	– 0.04	–
BIDc	– 0.16*	– 0.09	– 0.11	– 0.14	– 0.13
BODc	0.59**	0.43**	0.67**	0.64	0.58**
WIDc	– 0.15	– 0.09	– 0.12	– 0.14	–
WODc	0.65**	0.53**	0.66**	0.66	0.63**
BBc	0.03	0.13	0.10	0.06	–
WBc	0.03	0.13	0.10	0.06	–
BICc	– 0.15	– 0.09	– 0.11	– 0.14	– 0.12
BOCc	0.60**	0.43**	0.70**	0.66**	0.60
BIEc	0.02	0.05	0.05	0.02	–
BOEc	0.43**	0.06	0.86**	0.76**	0.53
WIEc	0.02	0.05	0.05	0.02	–
WOEc	0.43**	0.06	0.86**	0.76**	0.53
BIKc	– 0.13	– 0.06	– 0.08	– 0.11	–
BOKc	0.64**	0.38**	0.81**	0.76**	0.65
WIKc	– 0.13	– 0.07	– 0.08	– 0.11	–
WOKc	0.70**	0.48**	0.81**	0.78**	0.69
BRc	0.02	0.13	0.08	0.05	–

Legend Statistical significance: $^{*}P \leq 0.05$, $^{**}P \leq 0.01$

European Aerospace Industry, inter-firm coordination through this type of asymmetric links has no association with company size, excepted for those that are at the top of long and wide chains of influenced companies.

Top 200. If ordered in terms of TASS, TURN, EC or EM (see Tables 7.8 and 7.12 in Data Appendix), in EASIN + NEIGH there is no correlation between any kind of Dc, Bc and BRc indexes and any kind of economic attributes.

Sectoral and industrial correlations. The specification of correlations for sectors and Aerospace Industry (see Tables 7.13–7.15 in Data Appendix) shows results very different from the two previous forms of coordination networks: (i) with few interesting exceptions, focusing on specific sectors does not provide a substantial gain in terms of growth of correlation; (ii) the focus on the sole Aerospace Industry does not produce higher correlations; and (iii) correlations with direct and indirect (Dc and Bc) centrality are very different. The most interesting exception is the remarkable association (> 0.5) between Out_Dc and EM in the Professional Activities sector (Table 7.13c in Data Appendix), which suggests that large companies of that particular sector generate high influence by appointing their managers into the board of others. A similar result holds also when considering TURN instead of EM as size variable.

In the Manufacturing sector (Table 7.13a in Data Appendix), the positive association of Out_Dc with employees' size is much weaker (0.18), but it occurs much stronger than with Bc, meaning that large companies are usually those more able to intermediate HINTs. A final remark should be done on the not irrelevant (0.26) positive correlation between binary In_Dc and EM in the Financial sector (Table 7.13b), which suggests that they receive an asymmetric control from other companies that appoint their managers into the boards of Financial companies. It could be supposed that this fact is a sort of reciprocal control made by companies that get equity or loan capital from Financial companies. Moreover, a milder coefficient (0.18) between the same variables—In_Dc and EM—occurs also into the Manufacturing sector (Table 7.13a), meaning that also between this type of companies held this same asymmetric coordination mechanism.

7.3 Network Analysis

EASIN. The crucial network traits of both the EASIN (Table 7.3a) and the extended version (Table 7.3b) of the asymmetric coordination are the almost total fragmentation degree[5] and the perfect hierarchical degree.[6] These two topological properties have a lot of implications: a very low (about 0.06) global clustering coefficient (GCL), lack of betweenness centralization (Bc_CE), an almost irrelevant degree centralization (in both Freeman's and Snijders' measures) and, at least within the EASIN network, a very short diameter (2) and a very short (1.04) average distance (Apl).

As we have already seen in the previous section, the EASIN network is rather small (112 companies) grouped into 37 components, none of which is strongly connected, out of which a very small MC (10 companies). The diffusion of this form of hybrid coordination is rather limited: only 87 shared positions, which lowers to 12 in the MC. In short, this network is made of a number of (many disconnected) out-trees in the form of stars and a series of dyads. This can be confirmed by the components analysis made in Sect. 4.3 of Chap. 4, deepened also in Sect. 7.6 of this chapter dedicated to cluster analysis, which is supported by a visual representation. However, the weights of links in some component, and the length and size of some chains of AKE, which reside into the MC, make out-eigenvector centralization almost complete.[7]

EASIN + NEIGH. The network size grows enormously to 4414 when including the neighbors (Table 7.3b), with the remarkable use of about 17 thousand shared positions, largely occurring (63%) in the main component, which however contains only 37% of companies. Therefore, the average number of links is almost 4 and grows

[5] The lower value of distance weighted fragmentation shows that links weights of peripheral nodes and small components are smaller than those in the MC.

[6] This latter is represented by the zero value of reciprocity and geo(desic) reciprocity degree.

[7] Here, we do not apply Katz centralization, because when it is applied to a directed network like this with many nodes having only out- or only in-edges, Katz centrality lacks validity: see Newman (2010) and our Methodological Appendix.

Table 7.3a M2D EASIN: main indexes of network analysis

Index	EASIN [b]	EASIN MC [b]	EASIN [w]	EASIN MC [w]
Size	112	10	112	10
Density (norm)	0.007	0.133	0.007	0.133
Density (abs)	87	12	95	12
Fragmentation	0.993	0.833	0.042	0.167
Av. link value	1	1	1.092	1.0
ADc	0.777	1.2	0.848	1.2
Out_Dc_CE (Fre)	0.038	0.469	–	–
In_Dc_CE (Fre)	0.029	0.222	–	–
Out_Dc_CE (Sni)	0.002	0.141	–	–
In_Dc_CE (Sni)	0.001	0.030	–	–
Bc_CE	0.000	0.011	0.000	0.011
RWB_CE	–	0.573	–	0.375
Out_Eig_CE	0.999	0.999	0.999	0.999
In_Eig_CE	0.999	0.999	0.999	0.999
Reciprocity	0.000	0.000	0.000	0.000
Geo-reciprocity	0.000	0.000	0.000	0.000
GORC	0.056	0.444	0.005	0.444
GIRC	0.029	–	0.005	–
Diameter	2	2	2	2
Apl	1.044	1.200	1.066	1.200
GCL	0.064	0.174	0.064	0.174
SW	27	24	–	–

Legend b = binary links, MC = main component, w = valued links; ADc = average degree centrality; Dc_CE = degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; RWB_CE = random walk betweenness centralization; Eig_CE = eigenvector centralization; Geo-reciprocity = hierarchical degree according to Krackhardt's approach; GORC = hierarchical degree according to the reaching capacity; Apl = average path length; GCL = global clustering coefficient; SW = small-worldliness index

to 6.5 in the main component. Due to the 40 times size increase, the diameter grows too from 2 to 6. Similarly to the EASIN-only network, this one too is fragmented into a lot of components: 328, none of which is strongly connected. Thus, *the topology of this network is very similar to that of the EASIN only: it is made by a huge number of out-trees in a star-like form whose links are oriented mostly toward the central node (in-star) or from it to the neighbors (out-star).* The largest among them, where the neighbors appoint managers to their neighbors' boards—or vice versa, but more seldom, arrive through neighbors to the central "knowledge-exploited" company—become true (centrifugally or centripetally oriented) pyramids. There are no reciprocal connections (also due to methodology, consider the Methodological Appendix), that is, no cases where company A appoints a manager into the board

Table 7.3b M2D EASIN + NEIGH: main indexes of network analysis

Index	EASIN + NEIGH b	EASIN + NEIGH MC b	EASIN + NEIGH w	EASIN + NEIGH MC w
Size	4423	1641	4423	1641
Density (norm)	0.001	0.004	0.001	0.004
Density (abs)	17,024	10,715	20,966	13,496
Fragmentation	0.999	0.995	0.233	0.275
Av. link value	1	1	1.232	1.260
ADc	3.857	6.530	4.750	8.224
Out_Dc_CE (Fre)	0.025	0.066	–	–
In_Dc_CE (Fre)	0.046	0.124	–	–
Out_Dc_CE (Sni)	0.004	0.014	–	–
In_Dc_CE (Sni)	0.004	0.017	–	–
Bc_CE	0.000	0.000	0.000	0.000
RWB_CE	–	0.465	–	0.279
Out_Eig_CE	0.704	0.705	0.704	0.705
In_Eig_CE	0.986	0.994	0.981	0.992
Reciprocity	0.000	0.000	0.000	0.000
Geo-reciprocity	0.000	0.000	0.000	0.000
GORC	0.034	0.009	0.000	0
GIRC	0.049	0.129	0	0
Diameter	6	6	12	12
Apl	1.304	1.379	–	–
GCL	0.060	0.083	0.060	0.083
SW	158	35	–	–

Legend b = binary links, MC = main component, w = valued links; ADc = average degree centrality; Dc_CE = degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; RWB_CE = random walk betweenness centralization; Eig_CE = eigenvector centralization; Geo-reciprocity = hierarchical degree according to Krackhardt's approach; GORC = hierarchical degree according to the reaching capacity; Apl = average path length; GCL = global clustering coefficient; SW = small-worldliness index

of company B and vice versa, but there are many cases of transitive triads, where company A appoints one or more managers into the boards of company B and C, and one of these two does the same with the other. In conclusion, *the companies that acquire a competitive advantage through AKE do it in a one-way direction, because none of the companies sharing their board has any direct (reciprocal) or even indirect (through a path) M2D flowing in the opposite direction.* Seldom (13% of cases in EASIN and 16% in E+N), they can have also an inter-board connection, and in 58% and 51% of cases (respectively), they have also a DINT connection.

EASIN + NEIGH MC. However, none of the two types of coordination reinforcements occurs in the MC of E+N, which actually is the core structure. *All this configures a strongly hierarchical relationship behind the AKE, which indeed appears as the clue of a more general subordination of the company that shares its board*. Actually, as we will see below in Sect. 7.8, in EASIN the distribution of In_ and Out_Dc is heavy-tail, where the largest majority of companies receive only one manager into their board and only one company receives 4 in-edges, and only one company sends 5 out-edges into other companies' boards. The same heavy-tail structure holds in the extended network, but with very extreme values: 10 companies have more than 100 HINT connections from the "subordinate side", that is, incoming links, out of which one has more than 209. As we explain in the Methodological Appendix, it does not mean that in that company there are 209 directors, who are managers in 209 companies. In fact, as it happens also for the M2M or D2D networks, many companies can share the same person—be s/he a manager or a director—and so the number of persons corresponding to those links is very small: it could reduce to 4–5 people, and at the extreme cases also to just one. Actually, in Sect. 3.3 (subsection *People and Positions*) of Chap. 3 we have shown that some directors and some managers connect a huge number of companies.

The main difference between M2D and the other two forms is that *the structures of "coordination by knowledge exploitation" (AKE clusters) are made essentially by open or transitive triples, while in M2M and D2D they are mostly made by cliques*. In fact, in M2D there are no strong cliques and only relatively few small groups of 3 and very rarely 4 companies. Further, as we will show more deeply in Sect. 7.9 of this chapter while discussing the heavy-tail distribution form of direct links, the companies that have the highest In_Dc usually do not have high Out_Dc, and often no Out_Dc at all, and vice versa. In other words, *a knowledge exploiter is not exploited on its own, and vice versa. The companies able to acquire AKE advantages have a truly competitive advantage, and vice versa.*

7.4 Inter-sectoral Network

In the AKE perspective, inter-sectoral network tells us to what extent sectors use this coordination mechanism to interact and whether some sector is in a particularly advantageous position with respect to others. If compared to other economic or trade inter-firm networks (i.e., Bojanowski et al., 2012; Cepeda et al., 2017; Daisuke et al., 2017), the M2D inter-sectoral network is very dense (0.54), meaning that *AKE clusters tend to be very inter-sectoral*. However, if compared with the other managers or directors' inter-sectoral networks, which score 0.87 and 0.81 normalized density, this network is much sparser (Table 7.4). This sounds rather reasonable, because AKE is a true form of exploitation that is hard to obtain with respect to symmetric (of equal relevance) forms of knowledge sharing. Likely, it is more difficult to realize it between companies of different sectors.

Table 7.4 Inter-sectoral network of the M2D network

Index	Binary	Weighted
Size	22	
Density (norm)	0.580	0.580
Density (abs)	266	16,049
Fragmentation	0.045	0.303
Av. link value	1	60.34
ADc	12	729.5
Out_Dc_CE (Fre)	0.395	–
In_Dc_CE (Fre)	0.444	–
Out_Dc_CE (Sni)	0.371	–
In_Dc_CE (Sni)	0.473	–
Bc_CE	0.104	0.122
RWB_CE	0.073	0.505
Out_Eig_CE	0.102	0.939
In_Eig_CE	0.109	0.484
Out_Katz_CE	0.001	0.220
In_Katz_CE	0.001	0.075
Reciprocity	0.729	0.987
Geo-reciprocity	0.048	0.119
GORC	0.048	0.002
GIRC	0.048	0.006
Apl	1.435	–
GCL	0.754	78.7
SW	1.45	

Legend b = binary links, MC = main component, w = valued links; ADc = average degree centrality; Dc_CE = degree centralization: (Fre) is according to Freeman, while (Sni) is according to Snijders; Bc_CE = betweenness centralization; RWB_CE = random walk betweenness centralization; Eig_CE = eigenvector centralization; Geo-reciprocity = hierarchical degree according to Krackhardt's approach; GORC = hierarchical degree according to the reaching capacity; Apl = average path length; GCL = global clustering coefficient; SW = small-worldliness index

If we compare this with the ALL network—which, by virtue, are both directed networks—we see that it has a higher degree centralization, but a much lower betweenness and eigenvector centralization. This could suggest that the main sector—that in both cases is Manufacturing—has less centrality relevance (see Table 7.16 in Data Appendix). However, if we consider weights of links and distinguish Out_Dc from In_Dc, that is exploiters from exploited sectors, we see that ranking does considerably change: with 8791 shared positions, the Manufacturing sector is far more able to get AKE advantages, followed by the Financial sector with 1889 shared positions, then by the Wholesale sector (1065), the Professional Activities sector (884) and then EASINT (EASIN Integrated)[8] with 420 shared positions. Hence, despite the Financial sector and EASINT have almost the same number of companies (409 and 429, respectively) employing this type of coordination, *the Financial sector activates it more than 4 times intensively than EASINT companies*. This appears as a clear sign of weakness of EASINT, because being on the exploiting side of AKE indicates influence power. In this perspective, Table 7.5 is even more informative: while the Manufacturing sector is a "net exploiter" for 43% of its shared positions, EASINT is a "net exploited" for 78% of its links. Because most (54%) of Manufacturing companies are Anglo-American even in this type of coordination form, here we see the *subordination of EASINT with respect to that geographical block—the inflow is 25 times higher than the outflow*. Among the main sectors, even the Financial, the Professional Activities and the ICT sectors result to be net exploited for, respectively, 23, 37 and 45% of its shared positions, while the Wholesale confirms to be a strong sector with 43% of favorable AKE.

Though not much centralized in terms of geodesic Bc (0.10 and 0.12 for the binary and weighted version, respectively), this network is very much centralized in terms of weighted RWBc (0.5), which is a much more effective and informative measure. The Manufacturing sector is again the leader in accessing this indirect form of AKE (see Table 7.16 in Data Appendix), followed by the Professional Activities and the Financial sectors with half capacity, and then by EASINT with a little bit less capacity. It means that *though the Professional Activities sector, the Financial sector and EASINT are AKE exploited more than exploiters, they have anyway a high capacity to access strategic knowledge produced by other sectors with AKE forms*. In this sense, it is noticeable that the Wholesale sector, which is a strong net exploiter in direct relationships, has a weaker capacity to access AKE advantages by accessing flows circulating between other sectors.

There is also a lower binary reciprocity, which is here 0.78, while in the ALL network is complete, but indeed, when considering links' weights, even in this network reciprocity is almost full, meaning that, when considering the intensity of knowledge flow, there is no any particular sector more exploited than others. Interestingly, both these networks are weakly shaped in a small-world way, though the GCL of both networks is rather high, especially in the ALL network. This is due to the extremely high fragmentation and directionality of scarce flows, and its economic meaning is that *AKE advantages are not transferred across AKE clusters: by keeping them "entrapped" in each cluster, "exploiters companies" are very attentive to not share such competitive advantages with others.*

As we can see (Tables 7.6a and 7.6b), unlikely of M2M and D2D coordination forms, only 16% of links are internal to each sector: the largest majority is cross-sectoral. Such percentage almost doubles in the Financial (K) sector, and it raises up to 24% in the Manufacturing (C) sector, while it is very small in EASINT (4%). Hence,

[8] We remind that the integrated version of EASIN includes also the companies that in EASIN are isolated, but become connected when considering also its neighbors. In M2D EASINT is made of 429 companies, 342 more than EASIN.

Table 7.5 Cross-sectoral power gap in M2D

Sector	EXT-INT weighted links	EXT-INT share on TOT links (%)
C	5324	43
G	637	43
L	155	18
H	132	14
A	86	29
F	59	16
I	21	18
U	10	100
T	9	69
E	4	25
R	− 2	− 4
D	− 7	− 4
Q	− 10	− 17
B	− 32	− 43
O	− 48	− 73
S	− 55	− 20
P	− 73	− 46
N	− 286	− 19
J	− 862	− 45
M	− 1027	− 37
K	− 1109	− 23
EASINT	− 2926	− 78

it seems that *the Financial sector employs this asymmetric way of coordination within itself much more intensively than it would happen between companies of other sectors.*

Because the largest majority of AKE is cross-sectoral, it is therefore important to deepen this aspect, so to discover who is more significantly exploiting/influencing whom. Now, if we look at the inter-sectoral out-flows (Table 7.17 in Data Appendix, Table 7.7 and Fig. 7.3), we see that *the Manufacturing sector exploits AKE advantages of the other sectors with the following shares: 71% of EASINT, 74% of Information sector, 49% of the Professional Activities sector and 43% of the Financial sector*. Therefore, the Manufacturing sector managers can substantially acquire the other sectors' strategic knowledge. Quite interestingly, besides itself (with the 24% of share), *the Financial sector is particularly influential (43%) on the Administrative and Institutional sector*. In an industry such as the Aerospace, characterized by the essential role of public institutions as both customers and regulators, that relative majority share is *a clear sign of the strategic choice of banks and other financial operators to access the very crucial information residing into the board of the most*

Table 7.6a Share of internal (binary) links across sectors

Sector	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
C	1460	54	1131	6040	35	24
EASINT	87	3	2354	2441	14	4
K	698	26	1565	2263	13	31
M	160	6	1380	1540	9	10
J	82	3	1140	1222	7	7
G	26	1	349	879	5	3
N	52	2	771	823	5	6
L	15	1	246	499	3	3
H	48	2	317	487	3	10
F	21	1	110	168	1	13
A	29	1	41	157	1	18
S	1	0	153	154	1	1
P	4	0	109	113	1	4
I	6	0	43	69	0	9
O	0	0	57	57	0	0
D	18	1	37	55	0	33
B	2	0	47	49	0	4
Q	0	0	34	34	0	0
R	0	0	29	29	0	0
T	0	0	2	11	0	0
U	0	0	0	10	0	0
E	0	0	4	8	0	0
Total	2709	100	9919	17,108	100	16

Legend Acronyms explained in the list of abbreviations
ShITB = IDB/total IDB (vertically)
ShTB = TDB/total TDB (vertically)
ShIB = IDB/TDB

important institutions giving in exchange only operative knowledge (or maybe just nothing else).

Conversely, from the perspective of sectors chosen as targets for employing a sector's effort of AKE exploitation, the largest part of the Manufacturing managers appointed as directors are placed into EASINT (27%), itself (24%), 15% the Financial sector, 12% the Information sector and 11% into the Professional Activities sector. EASINT's main efforts to access strategic information through hybrid connections go to itself (23%), to the Manufacturing sector (20%), the Financial (14%) and the Professional Activities sector (13%). As for the Financial sector, the largest part goes to itself (39%), then the Manufacturing sector (12%) and to EASINT with only 8%, thus showing a *relatively scarce interest to employ this way to acquire*

Table 7.6b Share of internal (weighted) links of sectors

Sector	IDW	ShITW (%)	EDW	TDW	ShTW (%)	ShIW (%)
C	2150	60	1317	8791	39	24
EASINT	95	3	3251	3346	15	3
K	740	21	2258	2998	13	25
M	173	5	1738	1911	8	9
J	107	3	1277	1384	6	8
G	31	1	397	1065	5	3
N	55	2	857	912	4	6
H	48	1	355	535	2	9
L	15	0	333	503	2	3
F	25	1	126	210	1	12
A	54	2	51	191	1	28
S	2	0	162	164	1	1
P	4	0	111	115	1	3
D	47	1	39	86	0	55
I	6	0	43	70	0	9
O	0	0	57	57	0	0
B	4	0	49	53	0	8
Q	0	0	35	35	0	0
R	0	0	29	29	0	0
T	0	0	2	11	0	0
E	0	0	6	10	0	0
U	0	0	0	10	0	0
Total	3556	100	12,493	20,966	100	16

Legend Acronyms explained in the list of abbreviations
ShITW = IDW/total IDW (vertically)
ShTW = TDW/total TDW (vertically)
ShIW = IDW/TDW

strategic knowledge. The Professional Activities sector addresses its hybrid connections mostly to the Manufacturing sector (25%), itself (20%), EASINT (16%) and the Financial sector (12%). Such flows tell us that EASINT and the most important sectors are very intertwined not only with the symmetric links of BINT and DINT, but also even through HINT. However, they also disclose that EASINT exploits AKE more from itself than from the other sectors: 95 shared positions, followed by 83 from the Manufacturing, 58 from the Financial, 54 from the Professional Activities, etc. Vice versa, EASINT is exploited far more by the others than by itself: 3251 shared positions appointed by other sectors, out of which 2373 are with the Manufacturing sector, that is, coming from the Anglo-American companies. This means that *horizontal HINTs are much less diffused than vertical HINTs when EASINT*

Table 7.7 Major 30 cross-sectoral coordination efforts

Source	Target	Weight
C	EASINT	2373
C	K	1298
C	J	1030
C	M	945
K	N	395
G	C	343
N	K	251
C	G	246
G	M	230
M	C	224
K	C	222
C	N	205
L	K	186
C	H	182
G	EASINT	164
C	L	161
K	EASINT	147
M	EASINT	137
J	C	132
G	K	125
H	EASINT	123
K	M	116
M	K	109
H	M	108
J	J	107
G	N	91
N	M	86
EASINT	C	83
H	K	79
J	M	78

is the "victim of exploitation", while they are only a little bit more diffused when EASINT is the exploiter.

If we look at bilateral AKE (Table 7.7), we see that the four highest bilateral AKEs occur between the Manufacturing sector on the exploiting side and EASINT, the Financial, the ICT and the Professional Activities sectors on the exploited side, with the former having almost double (2373) shared positions than the second one (1298). Indeed, in the list of the early 30 partnerships, while the Financial sector appears already at the fifth rank—and with a remarkable number of shared positions (395), to see EASINT on the side of exploiters, we must scroll almost the whole list, and with a rather small number (83) of shared positions appointed into the Manufacturing sector. This is another way to look at the AKE between the Manufacturing (and thus the Anglo-American) companies and EASINT, which favors the former against the latter.

Companies' propensity for adopting hybrid coordination. Average propensity of EASIN companies to (actively or passively) adopt shared positions in the form of hybrid manager-director coordination is 0.85, which corresponds to the average link value showed in Table 7.3a if we consider that it resembles the connected part—and there are also the isolates what makes the index go below 1. For the whole extended network (Table 7.8), that propensity is much higher (4.8 shared positions per company), and for EASINT, it is even higher (7.8). Interestingly, with respect to the five main sectors (C, G, J, K and M), that propensity reaches the highest value, and it is mostly due to the coordination with external companies. More specifically, when distinguishing between the exploiter versus exploited role, the Financial (K), the ICT (J) and the Professional Activities (M) sectors show a much higher propensity to be exploited (EIDW) than exploiting (EODW). Conversely, the Manufacturing (C) and Wholesale (G) companies seem to have the opposite propensity (Fig. 7.4).

7.5 Inter-country Network

EASIN. Only 15 EU28 countries are involved in this type of hybrid coordination (Table 7.9), and its links are much less dense than the inter-sectoral network, which is also bigger than this one (22): normalized density is 0.167 versus 0.58, corresponding to 35 links in binary and 95 in weighted terms. Conversely, it is very similar to the inter-country network of D2D, which has about the same number of countries (16) and links (30), but it has actually a much higher intensity of shared positions, confirming that this hybrid type of coordination is used in a more parsimonious way, likely due to the difficulty to be accepted by the "exploited party". In both networks, there are 9 the same missing countries, out of which the larger ones in terms of size are Austria, Poland or Czech Republic. The difference is much bigger with the M2M inter-country network, which involves almost all EU28 countries and has an intensity of connections 16 times stronger than it, showing the strength of such coordination also at inter-country level. Consequently, the average number of shared positions per each link between countries is much lower: 2.7 for M2D, 18.9 for D2D and 14.6 for M2M. Each country has 2.3 average connections, channeling 6.3 shared positions, which become about 50 for D2D and 61 for M2M.

Further, this M2D network is rather fragmented: 0.605 versus 0.547 of M2M and 0.35 of D2D. This is due to the fact that this is a directed network, while the other two are undirected, and thus, even after aggregating companies into countries, many countries do not have reciprocal connections: reciprocity is only 0.17 and 0.56, in binary and weighted terms, respectively. Even georeciprocity is rather high (0.49

Table 7.8 Companies' weighted propensity to coordinate across sectors

Sectors	# of companies	# of (weighted) links per company			
		IDW	EODW	EIDW	Total
A	35	1.54	3.91	1.46	5.46
B	12	0.33	1.42	4.08	4.42
C	1657	1.30	4.01	0.79	5.31
D	25	1.88	1.28	1.56	3.44
E	6	0.00	1.67	1.00	1.67
EASINT	429	0.22	0.76	7.58	7.80
F	76	0.33	2.43	1.66	2.76
G	251	0.12	4.12	1.58	4.24
H	127	0.38	3.83	2.80	4.21
I	26	0.23	2.46	1.65	2.69
J	199	0.54	2.09	6.42	6.95
K	409	1.81	2.81	5.52	7.33
L	144	0.10	3.39	2.31	3.49
M	328	0.53	2.17	5.30	5.83
N	198	0.28	2.88	4.33	4.61
O	5	0.00	1.80	11.40	11.40
P	31	0.13	1.23	3.58	3.71
Q	16	0.00	1.56	2.19	2.19
R	16	0.00	1.69	1.81	1.81
S	39	0.05	2.74	4.15	4.21
T	4	0.00	2.75	0.50	2.75
U	1	0.00	10.00	0.00	10.00
No data	380	–	–	–	–
Total	4414	0.44	2.77	3.26	4.83

Legend Acronyms explained in the list of abbreviations

and 0.54, in binary and weighted terms, respectively), meaning that AKE remains unequal even indirectly, that is, moving alongside paths.

If measured in binary terms, no any country has particularly better capacity to exploit the others, as witnessed by the two indexes of Out_Dc centralization (particularly low for the Snijders' index), but if we consider the intensity of this hybrid coordination, four countries (and especially France) have a significantly better capacity (Table 7.18 in Data Appendix). Conversely, In_Dc centralization is rather high in both binary and weighted terms, showing that the UK is often the major target of direct exploitation, as it can be seen also in Fig. 7.5. If we look at the indirect capacity to exploit other countries, we see that, especially when considering the intensity of exploitation, this power is very much centralized, as it is witnessed by weighted

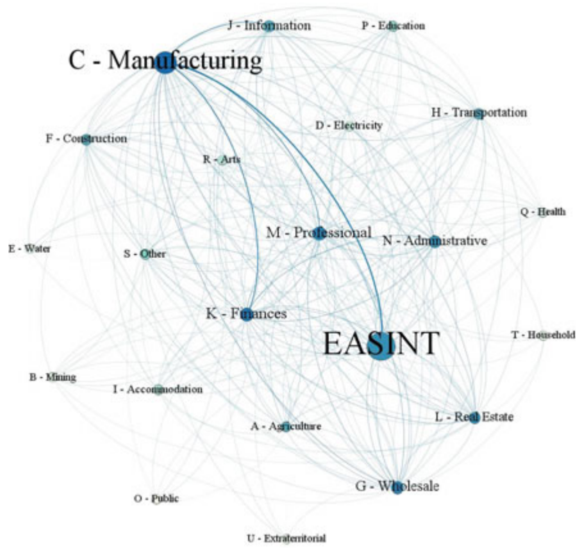


Fig. 7.4 The inter-sectoral graph of EASIN + NEIGH coordination. *Legend* The size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of the hybrid department-board relations

out-eigenvector and Katz centralization (Table 7.9), and concentrated in the hands of France and the UK (Table 7.18 in Data Appendix). The same holds for the side of exploited countries, where the UK appears to be the preferred target.

Because of high fragmentation, intermediation power and the variance of exploitation components size are both relatively low, as shown by Bc_CE and GORC. However, *especially when considering weighted values, France and the UK appear to be the key countries also in accessing strategic knowledge flowing through this coordination mechanism* (Table 7.11). Finally, this network is shaped in a lowly SW way, indicating the reluctance of AKE to be transferred across clusters of countries (Tables 7.10a and 7.10b).

The degree of geographical closure is strictly less than 30% (Tables 7.10a and 7.10b), thus *showing a clear preference for inter-country relationships*, in evident contrast with what occurs for inter-board and inter-departmental connections, which round about 82–79% and 72–77%, respectively (in binary and weighted terms).

Hybrid coordination propensity per company. Within EASIN, companies' propensity to employ hybrid coordination is generally very low, with the three remarkable exceptions of the Netherlands (3.67), entirely due to the capacity to exploit other countries' companies, followed by Belgium (1.83), mostly in the role of exploited by other countries' companies, and then Denmark and France (1.47), more in the active exploitation role (Table 7.12).

EASIN + NEIGH. Unlike EASIN, in the extended network HINT involves almost all countries (61) through 392 inter-country connections (Table 7.13), not far from the analogous M2M inter-country network, which involves as well 61 countries through 560 connections (Table 5.15). However, as we have seen in the previous chapter, through the existence of huge cliques and the extremely high coordination

Table 7.9 Inter-country network of EASIN

Index	Binary	Weighted
Size	15	
Density (norm)	0.167	
Density (abs)	35	95
DD	0.01	
Fragmentation	0.605	0.528
Av. link value	1	2.714
ADc	2.33	6.33
Out_Dc_CE (Fre)	0.204	–
In_Dc_CE (Fre)	0.587	–
Out_Dc_CE (Sni)	0.033	–
In_Dc_CE (Sni)	0.184	–
Bc_CE	0.184	0.161
Out_Eig_CE	0.422	0.556
In_Eig_CE	0.554	0.919
Out_Katz_CE	0.057	0.503
In_Katz_CE	0.129	0.864
Reciprocity	0.171	0.558
Geo-reciprocity	0.506	0.456
GORC	0.256	0.021
GIRC	0.342	0.017
Apl	2.120	4.205
GCL	0.347	0.869
SW	5.261	

propensity, this inter-departmental coordination at inter-country level is implemented by almost 2.8 shared positions, while here there are only 21 thousand hybrid shared positions. Conversely, inter-board coordination at inter-country level of the extended network involves only 45 countries through 258 connections, which however are implemented with 354 thousand shared directors (Table 5.16). Therefore, *AKE is very diffused across EASINT neighbors, but it is used in a very selective and specific way, which means it is restricted to very small weak (and mostly transitive) cliques or relatively large out-components*. Indeed, the large majority (83%) of links and shared positions are implemented in neighbor-to-neighbor coordination, a share that is very high, but actually less than what characterizes BINT and DINT coordination. Conversely, in terms of number of companies, the share of neighbors is superior to that corresponding to M2M and D2D: 83 and 85%, respectively. Consequently to this much smaller intensity of coordination, the average number of shared positions per each pair of companies is only 53, while for D2D is 1252 and M2M is 2586.

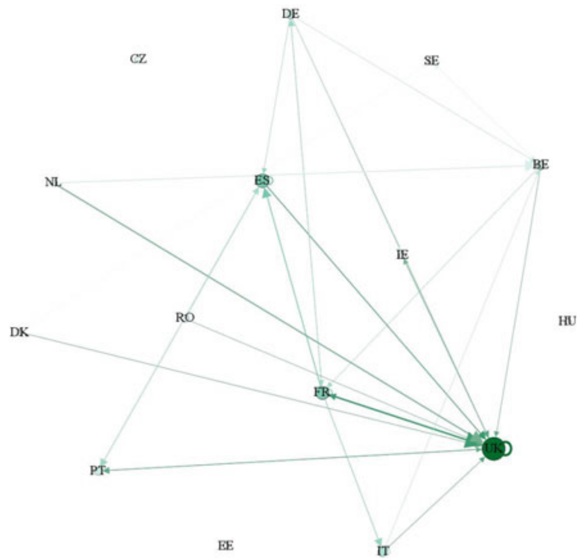


Fig. 7.5 The inter-country graph of EASIN coordination. *Legend* The size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of the hybrid department-board relations

Table 7.10a Share of internal (binary) links of countries

Countries	IDB	ShITB (%)	EDB	TDB	ShTB (%)	ShIB (%)
UK	12	35	23	35	30	34
FR	5	15	4	20	17	25
ES	6	18	7	13	11	46
NL	0	0	0	9	8	0
DE	0	0	2	7	6	0
BE	0	0	6	6	5	0
IT	4	12	2	6	5	67
PT	1	3	5	6	5	17
RO	2	6	0	5	4	40
CZ	2	6	0	2	2	100
DK	0	0	0	2	2	0
IE	0	0	2	2	2	0
SE	0	0	2	2	2	0
EE	1	3	0	1	1	100
HU	1	3	0	1	1	100
Total	34	100	53	117	100	29

Legend Total links per country are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations
ShITB = IDB/total IDB (vertically)
ShTB = TDB/total TDB (vertically)
ShIB = IDB/TDB

Table 7.10b Share of internal (weighted) links across countries

Countries	IDW	ShITW (%)	EODW	EIDW	TDW (%)	ShTW (%)
UK	13	36	26	39	30	33
FR	5	14	4	23	18	22
ES	6	17	7	13	10	46
NL	0	0	0	11	8	0
BE	0	0	8	8	6	0
DE	0	0	2	7	5	0
IT	4	11	3	7	5	57
PT	2	6	5	7	5	29
RO	2	6	0	5	4	40
DK	0	0	0	3	2	0
CZ	2	6	0	2	2	100
IE	0	0	2	2	2	0
SE	0	0	2	2	2	0
EE	1	3	0	1	1	100
HU	1	3	0	1	1	100
Total	36	100	59	131	100	27

Legend Total links per country are a sum of internal and the larger of external links. Acronyms explained in the list of abbreviations
ShITW = IDW/total TDW (vertically)
ShTW = TDW/total TDW (vertically)
ShIW = IDW/TDW

Table 7.11 Major 5 cross-country coordination efforts

Source	Target	Weight
FR	UK	9
NL	UK	6
NL	BE	5
FR	ES	4
ES	UK	3

Consistently, the average number of shared positions is much higher in these latter two types of coordination.

Binary reciprocity has an intermediate level (0.43), which about doubles when considering links weights, meaning that most intensive links are reciprocal. However, what is rather surprising is that geodesic reciprocity has an intermediate value for both binary and weighted measures: 0.5 and 0.46, respectively. Further, there are small size differences among out-components for both binary and weighted measures, as witnessed by GORC: 0.21 and 0.09, respectively. All this explains the absence of strong cliques, the smallness of weak cliques and the medium value of (binary)

Table 7.12 Companies' weighted propensity to coordinate across EASIN countries

Country	# of companies	IDW	EODW	EIDW	Total
BE	6	0.00	0.50	1.33	1.83
CZ	3	0.67	0.00	0.00	0.00
DE	7	0.00	1.00	0.29	1.29
DK	2	0.00	1.50	0.00	1.50
EE	2	0.50	0.00	0.00	0.00
ES	16	0.38	0.38	0.44	0.81
FR	15	0.33	1.20	0.27	1.47
HU	2	0.50	0.00	0.00	0.00
IE	2	0.00	0.00	1.00	1.00
IT	9	0.44	0.22	0.33	0.56
NL	3	0.00	3.67	0.00	3.67
PT	6	0.33	0.17	0.83	1.00
RO	4	0.50	0.75	0.00	0.75
SE	2	0.00	0.00	1.00	1.00
UK	33	0.39	0.15	0.79	0.94
Total	112	0.64	0.42	1.05	0.27

Legend Acronyms explained in the list of abbreviations

fragmentation, much higher than in the analogous extended inter-country D2D and M2M networks: 0.42 versus 0.09 and 0.03, respectively. However (and interestingly), despite such traits and a consequent not high value of global clustering (0.57), the small-world structure of this network is 5.4 (Table 7.13), which indeed is small, but anyway double than that of the two analogous inter-country coordination networks and triple of all inter-sectoral networks. This means that *the strategic knowledge obtained through this type of coordination flows more easily across clusters of countries than across sectors and more easily than across clusters of countries of the other two types of coordination.*

Like the EASIN + NEIGH inter-country network, the centralization degree of exploiting countries is lower than that of exploited countries: Out_Dc_CE (Sni) is 0.17, and In_Dc_CE (Sni) is 0.22. If we look at the former group of countries (Table 7.19 in Data Appendix), the US is by far the most important country with almost 11 thousand positions of managers appointed as directors in some other country (see also Fig. 7.6). Very distantly, the UK (2903) and France (1707) do follow, with EASINT placed only at the 7th rank. Such a dominant position is confirmed also by the extremely high score of weighted out-eigenvector centralization (0.93) and the high Out_Katz centralization (0.59), meaning that *the US and the UK exert their exploitation power also indirectly throughout the network*. If we turn the view to the exploited countries, in binary terms EASINT is the number one, followed by the UK, IT and the US. In weighted terms, the UK is the first one, followed by EASINT,

Table 7.13 Inter-country network of EASIN + NEIGH

Index	Binary	Weighted
Size	61	
Density (norm)	0.107	
Density (abs)	392	20,966
Fragmentation	0.421	0.511
Av. link value	1	53.49
ADc	6.43	343.7
Out_Dc_CE (Fre)	0.433	–
In_Dc_CE (Fre)	0.552	–
Out_Dc_CE (Sni)	0.176	–
In_Dc_CE (Sni)	0.220	–
Bc_CE	0.240	0.197
RWB_CE	0.283	0.617
Out_Eig_CE	0.242	0.929
In_Eig_CE	0.263	0.902
Out_Katz_CE	0.001	0.585
In_Katz_CE	0.001	0.482
Reciprocity	0.434	0.889
Georeciprocity	0.502	0.460
GORC	0.157	0.002
GIRC	0.259	0.008
Apl	2.045	5.225
GCL	0.574	78.03
SW	5.354	

the US, France and Italy. The values of weighted In_Eig and In_Katz centralization are aligned with those of out-edges, and here, the *UK is the most indirectly exploited country, followed by the US and EASINT, both presenting one third of the UK's score.*

Very interesting is the fact that, despite its weak position in terms of direct AKE, EASINT has the first rank in terms of weighted Bc, thus showing to have the best capacity to access strategic knowledge by intercepting its flow across the whole network. The second place is covered by Canada, followed by the US, Spain and France, while the UK, which is so strong in direct AKE, is positioned only at the 8th place. However, the distances between these main countries regarding this capacity are small, and in fact, the corresponding centralization index is rather low (0.197). Conversely, if we turn to the more sophisticated measure of intermediating capacity, as expressed by RWBc, the US covers the first place, closely followed by Italy at short distance, then followed by EASINT and the UK, which have a similar score, corresponding to one third of the US. Hence, despite exploited in direct AKE relationships, EASINT is in the group of five countries that can better access strategic

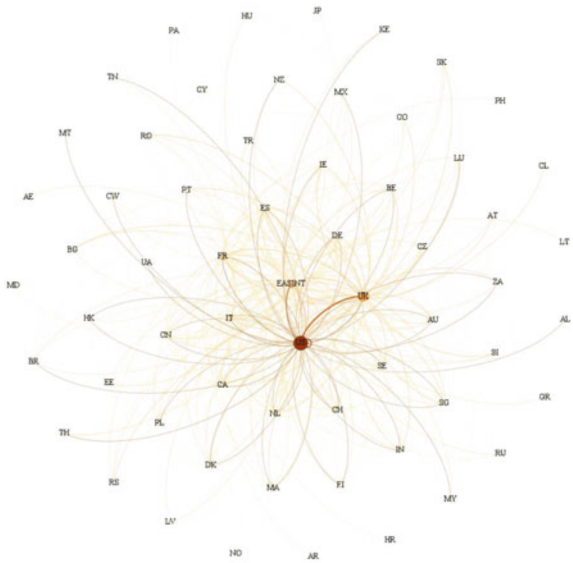


Fig. 7.6 The inter-country graph of EASIN + NEIGH coordination. *Legend* The size of nodes varies accordingly to the number of companies, while the size of links varies with its weight, that is, the number of coordination agreements under the form of the hybrid department-board relations

knowledge through this type of coordination mechanism, a group composed by the US, the UK, Canada and Italy.

EASINT turns out to interact almost entirely with its neighbors (Table 7.14), rather than among itself. The country with the largest number of links in M2D is the US, which is more inclined to work with the outside, rather than with their own country peers. The UK on the other hand is oriented toward the opposite. The degree of country closure of this type of coordination mechanism is even smaller than that of EASINT countries (Tables 7.15a and 7.15b)—0.28 in binary and 0.24 in weighted terms— and much smaller than in the analogous M2M and D2D networks, to reverse the picture. A possible explanation is that this type of coordination is more selective and specifically targeted, therefore less influenced by geographical criteria.

Consistently with what we have discussed above about the US dominance and the weak position of EASINT, we see that, among the twelve main bilateral AKE, the US covers the first three positions and appears eight times, the UK twice and France and Canada once. Those eight AKEs with the US in the role of exploiters cover the 75% of the shared positions activated by the early 30 bilateral AKE (Table 7.16). Among them, EASINT is only once on the exploiters' side and six on the exploited side.

Hybrid coordination propensity per country. While the average propensity of the whole extended network to adopt this coordination form is 5.2 shared positions per company (Table 7.17), most main countries have a much higher propensity: the UK 10.2, EASINT 8.2, DE 7.4, the US 7.3, the NL 6.8 and FR 6.2. At a closer view, it is further confirmed that the UK and EASINT are mostly providers of strategic knowledge: 7.2 and 8 shared positions per company, respectively. Conversely, the

Table 7.14 Cross-country power gap in M2D

Country	EXT-INT weighted links	EXT-INT share on TOT links (in %)
US	8067	67
EASINT	3683	95
UK	3656	46
IT	754	59
CA	707	90
DE	596	99
NL	432	68
SE	255	96
AU	250	98
ES	220	55
CH	195	80
MY	165	100
BE	160	49
TH	147	100
SG	143	100
CZ	71	31
PT	− 98	− 37
SK	− 114	− 55
FR	− 247	− 10
IE	− 334	− 43

Legend The top 20 countries are selected according to the total WDc

US and DE are rather operative knowledge providers: 6 and 7.3, respectively. The NL has the interesting role of intensively balancing the two sides of operative and strategic knowledge asymmetric exchanges.

7.6 Cluster Analysis

As for the previous chapters, we run cluster analysis over three clusters[9] (Tables 7.18, 7.19 and Fig. 7.7), whose features are further analyzed by projecting each cluster within its network, thus evidencing where they are placed, and distinguished are also their geographical and sectoral aspects.

[9] The methodological procedure to create the clustering analysis is explained in the Methodological Appendix.

Table 7.15a Share of internal (binary) links across early 20 countries

Countries	IDB	ShIB	EODB	EIDB	TDB	ShTB
US	1592	0.24	970	7847	0.33	0.20
UK	1968	0.30	3285	5253	0.22	0.37
EASINT	87	0.01	2497	2584	0.11	0.03
FR	1291	0.19	608	1899	0.08	0.68
IT	256	0.04	820	1076	0.05	0.24
IE	555	0.08	138	693	0.03	0.80
DE	2	0.00	31	512	0.02	0.00
CA	20	0.00	218	386	0.02	0.05
NL	102	0.02	269	371	0.02	0.27
ES	91	0.01	179	270	0.01	0.34
BE	71	0.01	29	266	0.01	0.27
SE	5	0.00	233	238	0.01	0.02
PT	160	0.02	38	200	0.01	0.80
CZ	75	0.01	23	199	0.01	0.38
SK	129	0.02	0	176	0.01	0.73
CH	19	0.00	146	165	0.01	0.12
TH	0	0.00	147	147	0.01	0.00
AU	3	0.00	89	139	0.01	0.02
MY	0	0.00	130	130	0.01	0.00
SG	0	0.00	126	126	0.01	0.00
Total	6655	1.00	10,369	23,856	1.00	0.28

Legend Total links per country are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations
ShITB = IDB/total IDB (vertically)
ShTB = TDB/total TDB (vertically)
ShIB = IDB/TDB

EASIN. In cluster analysis of EASIN, just like in previous chapters, additionally was used normalized TURN, lowered by one decimal point to match scale of network indexes.

Cluster 1. This cluster is in fact only 1 company—Airbus from France, which has very high relative direct and indirect connectivity—as it is a member of the largest component in the network, and also, it has the largest TURN (Fig. 7.8).

Cluster 2. It includes exactly half of companies; they have more TURN than companies in Cluster 3, much more out-going direct and indirect relationships and almost no incoming relationships (Fig. 7.9).

Table 7.15b Share of internal (weighted) links across early 20 countries

Countries	IDW	ShITW	EODW	EIDW	TDW	ShTW
US	1962	0.27	998	10,993	0.36	0.18
UK	2158	0.29	5069	7227	0.23	0.30
EASINT	95	0.01	3414	3509	0.11	0.03
FR	1310	0.18	666	1976	0.06	0.66
IT	265	0.04	946	1211	0.04	0.22
IE	555	0.08	153	708	0.02	0.78
DE	4	0.00	31	573	0.02	0.01
CA	39	0.01	240	545	0.02	0.07
NL	102	0.01	269	371	0.01	0.27
ES	91	0.01	255	346	0.01	0.26
BE	84	0.01	40	288	0.01	0.29
SE	5	0.00	246	251	0.01	0.02
PT	181	0.02	42	223	0.01	0.81
SK	161	0.02	0	208	0.01	0.77
CZ	80	0.01	26	205	0.01	0.39
CH	25	0.00	163	188	0.01	0.13
MY	0	0.00	165	165	0.01	0.00
TH	0	0.00	147	147	0.00	0.00
AU	3	0.00	117	139	0.00	0.02
SG	0	0.00	130	130	0.00	0.00
Total	7353	1.00	13,613	30,810	1.00	0.24

Legend Total links per country are a sum of internal and the larger of external links. Acronyms explained in the list of abbreviations
ShITW = IDW/total TDW (vertically)
ShTW = TDW/total TDW (vertically)
ShIW = IDW/TDW

Cluster 3. It includes almost half of companies; they have very little TURN when compared with other companies of the network, and they also have almost only incoming relationships (Fig. 7.10).

EASIN Integrated. When considering EASINT, the three clusters are distinguished basically by the different level of In_Dc, because in all of them Out_Dc and Out_Cc are low. The biggest cluster—the third one—includes the largest majority of companies, which have a low degree of all the three variables, while *the first and the second cluster identifies the elective "preys" of knowledge exploitation made by some EASIN companies, but mostly by neighbors*. In fact, the cluster analysis of the extended network has just shown that in the first cluster there is a significant number of exploiting companies, and the following cluster analysis of EASIN also shows that there is a small number of exploiting companies too (Tables 7.20 and 7.21; Fig. 7.11).

Table 7.16 Major 30 cross-country coordination efforts

Source	Target	Weight
US	UK	4250
US	EASINT	2452
US	IT	544
UK	US	478
US	FR	462
UK	EASINT	202
FR	US	188
CA	EASINT	184
US	CA	166
US	SE	165
US	MY	141
US	TH	141
NL	UK	139
DE	US	136
DE	UK	127
BE	NL	120
CA	UK	118
US	SG	100
EASINT	UK	99
CZ	UK	98
AU	US	97
ES	ES	91
LU	UK	91
US	AU	87
DE	EASINT	85
US	CH	84
US	CN	78
FR	EASINT	75
RO	ES	72
NL	EASINT	67

EASIN + NEIGH. By employing binary In_ and Out_Dc and Out_Cc, cluster analysis has discovered three clusters (Tables 7.22, 7.23 and Fig. 7.12): the former two have a marked value of some variable, while the third cluster, which is by far the biggest one (Table 7.22), is made by companies that have indistinctively low values of all the three variables used in this analysis. This clusterization outcome is confirmed also by the analysis of degree centrality done in the next chapter, enriched by the information provided by closeness centrality (Table 7.23).

Table 7.17 Companies' weighted propensity to coordinate across early 20 EASIN + NEIGH countries

Country	# of companies	IDW	EODW	EIDW	Total
US	1515	1.30	5.96	0.66	7.26
UK	712	3.03	1.05	7.12	10.15
EASINT	429	0.22	0.85	7.96	8.18
FR	317	4.13	1.25	2.10	6.23
IT	227	1.17	0.32	4.17	5.33
ES	117	0.78	0.48	2.18	2.96
IE	113	4.91	0.60	1.35	6.27
CA	102	0.38	4.96	2.35	5.34
DE	78	0.05	7.29	0.40	7.35
BE	75	1.12	2.72	0.53	3.84
PT	74	2.45	0.55	0.57	3.01
CZ	73	1.10	1.71	0.36	2.81
DK	63	0.98	0.98	0.13	1.97
NL	55	1.85	4.82	4.89	6.75
CH	40	0.63	1.43	4.08	4.70
FI	39	1.54	0.56	0.85	2.38
SK	39	4.13	1.21	0.00	5.33
SE	33	0.15	0.42	7.45	7.61
CY	26	0.92	0.00	0.15	1.08
CN	24	0.58	2.21	3.96	4.54
Total	2636	1.57	1.97	2.56	5.15

Legend Total links per country are a sum of internal and the larger value of external links. Acronyms explained in the list of abbreviations
ShITW = IDW/total TDW (vertically)
ShTW = TDW/total TDW (vertically)
ShIW = IDW/TDW

Table 7.18 EASIN attributes by clusters

Attribute	General (abs.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	78	1	11	88
TURN	191,465[b]	39	30	31
EM	266[a]	4	63	33
EC	52,897[b]	18	62	20
TASS	231,880[b]	31	42	27

Legend [a],000; [b],000,000 current US$

Table 7.19 EASIN clusters statistics

General	BODc	BIDc	BOCc	TURN	C1	BODc	BIDc	BOCc	TURN
Average	0.777	0.777	0.007	2455[b]	Average	5	0	0.049	70,624[b]
Min	0	0	0	0	Min	5	0	0.049	70,624[b]
Max	5	4	0.049	70,624[b]	Max	5	0	0.049	70,624[b]
Median	1	1	0.009	34[b]	Median	5	0	0.049	70,624[b]
C2	BODc	BIDc	BOCc	TURN	C3	BODc	BIDc	BOCc	TURN
Average	2.375	0	0.021	3129[b]	Average	0.435	0.913	0.003	1937[b]
Min	2	0	0.018	0	Min	0	0	0	0
Max	4	0	0.036	70,624[b]	Max	1	3	0.009	29,579[b]
Median	2	0	0.018	15[b]	Median	0	1	0	63[b]

Legend [a],000; [b],000,000 current US$

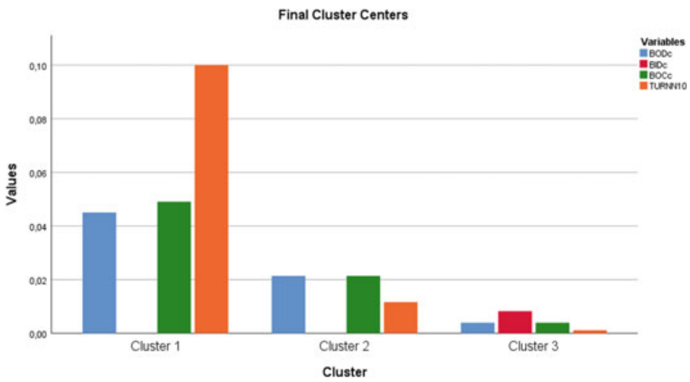


Fig. 7.7 EASIN clusters

Cluster 1. Including 2% of companies, this cluster represents those with the largest Out_Dc, barely any In_Dc, and the largest Out_Cc (out-closeness centrality). Therefore, they are the centers of the star structures, the so-called authorities, which exploit others by giving operating knowledge in exchange for strategic knowledge and, at the same time, the ones which can more easily access other, further strategic knowledge because they are closer to them. They are highlighted in Figs. 7.13 and 7.14, where it is visible that at times they mix up with each other as well.

The most central companies come mostly from the US, the UK and France, showing that *the Anglo-American companies are particularly effective in exploiting others' strategic knowledge by giving in exchange operative knowledge*. Particularly interesting is the fact that *the strategic knowledge acquisition made by American companies through AKE is markedly oriented to acquire it from other countries instead within the US*. In fact, unlike for M2M and D2D, the share of weighted

Fig. 7.8 Cluster 1 in EASIN

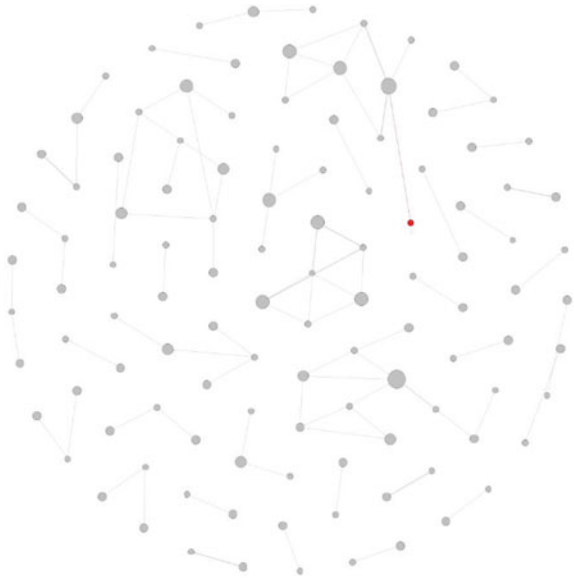
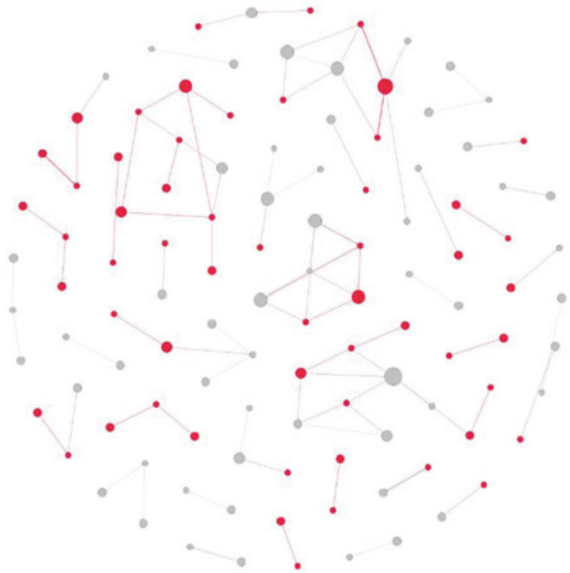


Fig. 7.9 Cluster 2 in EASIN



internal links on total links is, for M2D, only 18% (see Table 7.15b). Sector-wise, these intensive predators are mostly in the Manufacturing (C) and Finance (K) sectors.

Cluster 2. This cluster is made up of less than 1% of companies and has close to none Out-Dc and Out_Cc, but has exceptionally high In_Dc. They are the pure victims of

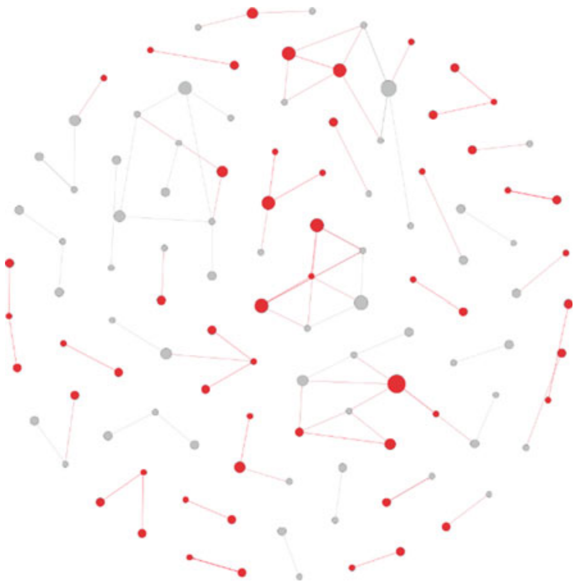


Fig. 7.10 Cluster 3 in EASIN

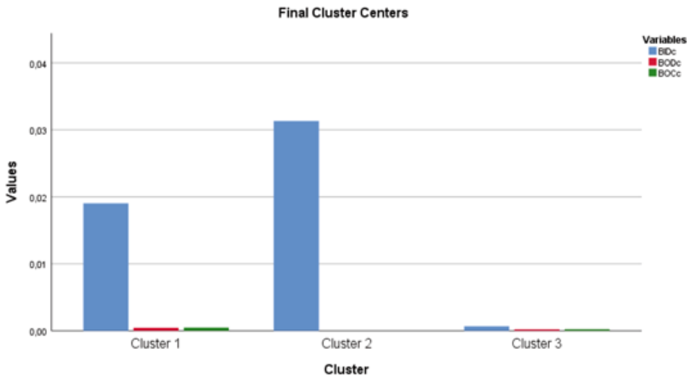


Fig. 7.11 EASIN integrated clusters

Table 7.20 EASIN integrated attributes by clusters

Attribute	General (abs. val.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# of companies	287	2	1	97
TURN	351,677[b]	30	43	28
EM	604[a]	37	24	39
EC	87,161[b]	58	19	23
TASS	505,272[b]	31	40	29

Legend [a],000; [b],000,000 current US$

Table 7.21 EASIN Integrated clusters statistics

General	BIDc	BODc	BOCc	TURN	C1	BIDc	BODc	BOCc	TURN
Average	7	1	0.0003	1225[b]	Average	3	1	0.0003	382[b]
Min	0	0	0.0000	0	Min	0	0	0.0000	0
Max	162	14	0.0032	79,591[b]	Max	52	14	0.0032	16,918[b]
Median	1	0	0.0000	9[b]	Median	1	0	0.0000	7[b]
C2	BIDc	BODc	BOCc	TURN	C3	BIDc	BODc	BOCc	TURN
Average	3	4	0.0012	75,107[b]	Average	98	1	0.0003	7512[b]
Min	1	0	0.0000	70,624[b]	Min	31	0	0.0000	2[b]
Max	4	7	0.0025	79,591[b]	Max	162	9	0.0022	29,579[b]
Median	3	4	0.0012	75,107[b]	Median	95	0	0.0000	825[b]

Legend [a],000; [b],000,000 current US$

Table 7.22 EASIN + NEIGH attributes by clusters

Attribute	General (abs. val.)	Cluster 1 (share in %)	Cluster 2 (share in %)	Cluster 3 (share in %)
# companies	1562	2	1	97
TURN	2,121,718[b]	4	3	93
EM	3093[a]	6	9	85
EC	1,162,116[b]	6	5	89
TASS	5,688,506[b]	20	3	77

Table 7.23 EASIN + NEIGH clusters statistics

General	BIDc	BODc	BOCc	C1	BIDc	BODc	BOCc
Average	4	4	0.001	Average	1	63	0.016
Min	0	0	0.000	Min	0	6	0.008
Max	209	114	0.025	Max	13	114	0.025
Median	0	1	0.000	Median	0	69	0.016
C2	BIDc	BODc	BOCc	C3	BIDc	BODc	BOCc
Average	104	1	0.000	Average	3	3	0.001
Min	57	0	0.000	Min	0	0	0.000
Max	209	9	0.002	Max	53	34	0.011
Median	95	0	0.000	Median	0	1	0.000

strategic knowledge exploitation through AKE and mostly lie at the periphery of the network: the so-called sinks. The most present countries here are the UK, Italy and France, thus showing that *about 50 EU companies are the biggest preys of strategic knowledge exploitation of (mostly American) predator companies through M2D at*

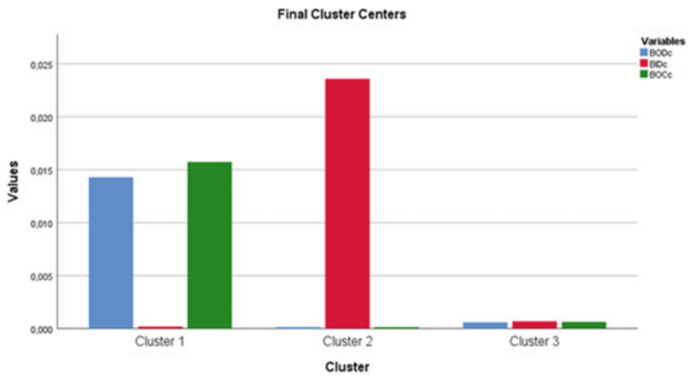
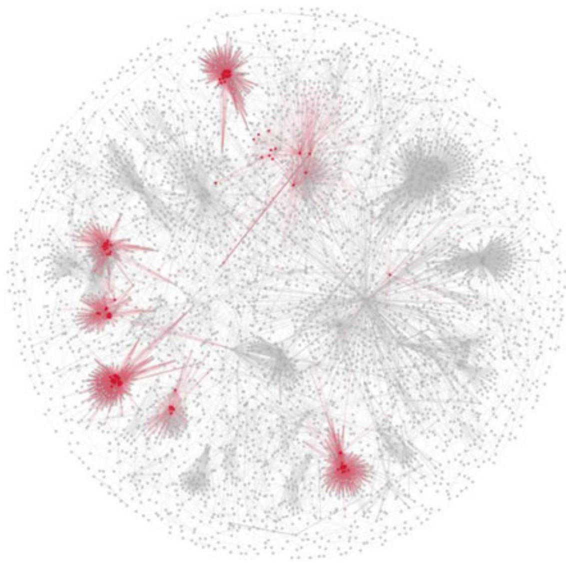


Fig. 7.12 EASIN + NEIGH clusters

Fig. 7.13 Cluster 1 in EASIN + NEIGH



global level. Sector-wise, they are Manufacturing (C), Professional Activities (M) and Finance (K) (Figs. 7.15 and 7.16).

Cluster 3. This cluster includes all the other 97% of companies, those that have some close and long-distance relationships, both in and out, but are not standing out with them enough to differentiate themselves in any way. They are the large majority of companies, because most companies are weak exploited or exploiters (see next section too). On the graph, they would be the complement to the other two, previous pictures.

In summary, the cluster analysis highlighted that: (1) the extended network is also distributed in a heavy-tail way; (2) membership in clusters is, contrarily to other

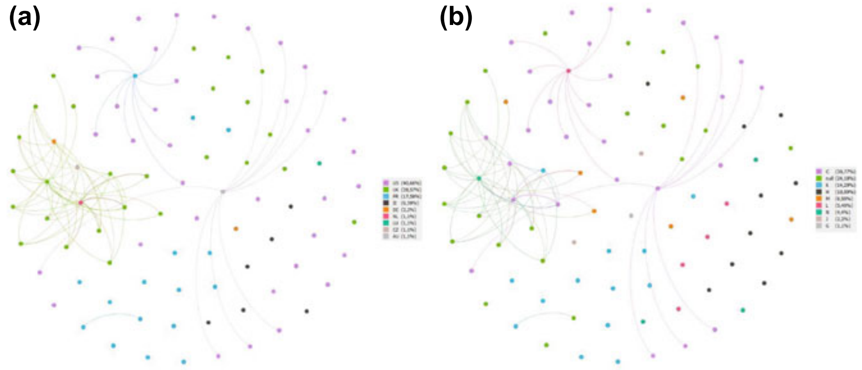
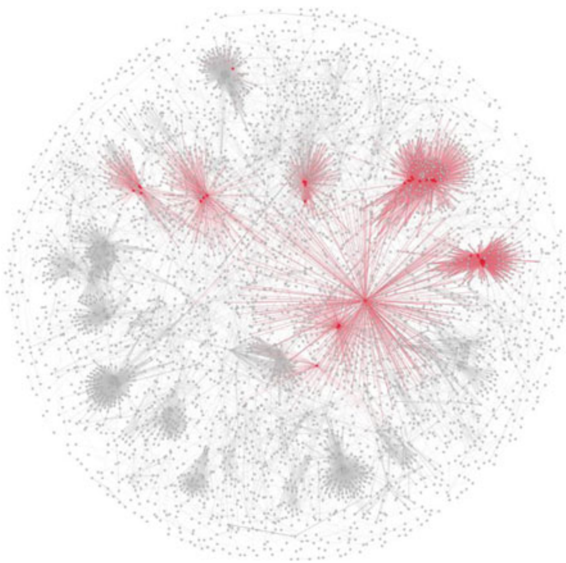


Fig. 7.14 **a**, **b** Cluster 1 in EASIN + NEIGH by evidencing countries (**a**) and sectors (**b**)

Fig. 7.15 Cluster 2 in EASIN + NEIGH



chapters, not dependent on participation in cliques, but rather on their position in star-like structures; (3) there is no strong dependence on the main component, and all clusters have members who are present either in or out of it; (4) extracts of those clusters in large majority are self-referential, meaning that their members present large tendency to relate to others of the same type—either country- or sector-wise, though it happens less than in other types of networks (M2M or D2D); and (5) the main factor that really distinguishes the clusters is their position within stars and direction of their links, combined with TURN size in EASIN.

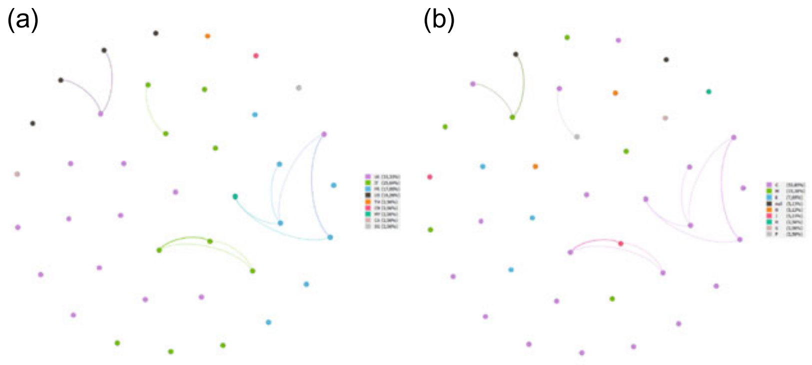
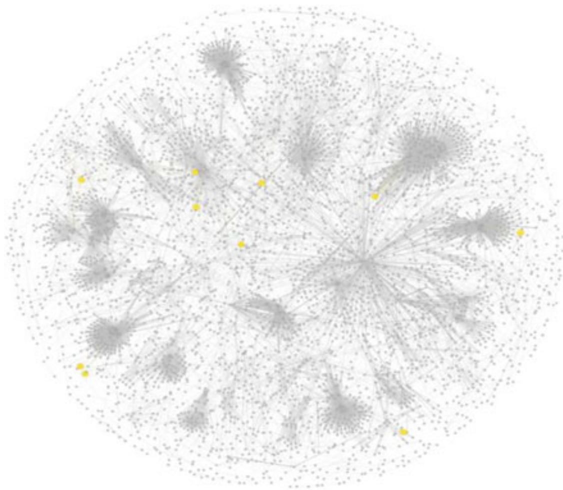


Fig. 7.16 **a**, **b** Cluster 2 in EASIN + NEIGH by evidencing countries (**a**) and sectors (**b**)

Fig. 7.17 Bridging companies in EASIN + NEIGH



7.7 Bridging Companies as Key-Players

There are only ten companies that in the extended network have a bridging centrality index major then zero,[10] because only 55 have a Bc > 0. This is due to the almost total fragmentation of the extended network, which in turn is due to its largely prevalent composition based on dyads and transitive triads, two “motifs” in which all nodes have Bc = 0. The ten bridging companies come from the US, the UK, Italy and Finland (Fig. 7.17). Sector-wise (Fig. 7.18), they are from Manufacturing (C), Finance (K) and Wholesale (G).

[10] In EASIN, they are only 4.

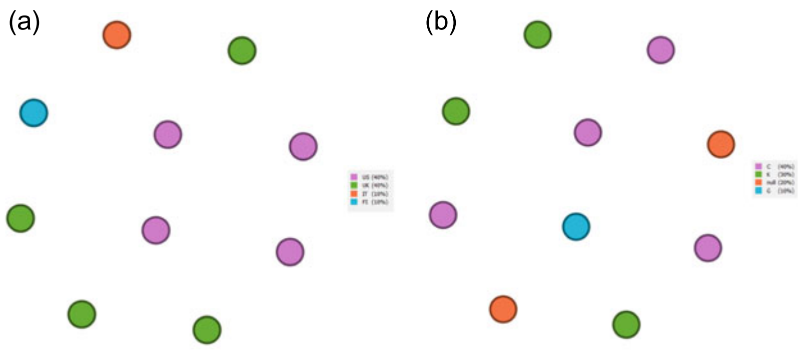


Fig. 7.18 **a**, **b** Bridging companies in EASIN + NEIGH evidenced by countries (**a**) and sectors (**b**)

7.8 Heavy-Tail Scale-Free Analysis

EASIN. Here, the economic variables have very mild heavy-tail (HT) shape (see Figs. 7.1 to 7.13 in Data Appendix), meaning that, though rather heterogeneous, companies do not differ in size so much as it happens for BINTs or DINTs. Conversely, with the exception of components and cliques, all topological parameters are highly shaped as HT. Hence, it holds the same tripartite categorization of the extended network: few intensive "predators" or "preys", and most low-intensive ones.

EASINT. When focusing on the 429 EASINT companies, the feature of being only exploiter or exploited still holds, because only about 5% of companies plays both role, while most (60%) companies are exploited and the minority (35%) only exploiters (see Table 7.24). Consistently, the net amount of AKE is 2175 HINTs in which a manager is placed into EASINT companies' boards, thus representing 73% of all connections. In weighted terms, this unbalance appears even bigger, because out of the about 4000 shared positions, 88% corresponds to strategic AKE. Though part of it occurs within EASINT, most of it is due to NEIGHs, as will be shown in Sect. 8.2 of Chap. 8. Therefore, *EASINT is an exploited land*.

EASIN + NEIGH. In the extended network, all economic variables are distributed in a remarkable HT shape (see Sect. 7.4 in Data Appendix, Figs. 7.14 to 7.30), which is even higher for the topological parameters, especially clique distribution and, interestingly because it rarely happens in the other coordination networks, also for LORC and LIRC distributions. It means that *few companies are directly or indirectly able to acquire large amounts of strategic knowledge from many others through the AKE mechanism*. Out of top 10 country-wise, they come mostly from France, then the US and the UK; sector-wise, they are mostly from the Manufacturing and then Professional Activities. The same happens on the side of exploited companies, some of which are particularly "plundered". The top 10 country-wise come also from the US, the UK and few other European countries; sector-wise, they all come

Table 7.24 Binary and weighted In_Dc and Out_Dc of early 20 companies in EASIN

Ordered according to WIDc abs				Ordered according to WODc abs			
BIDc	BODc	WIDc	WODc	BIDc	BODc	WIDc	WODc
82	9	404	16	82	9	404	16
162	0	258	0	0	14	0	14
141	0	228	0	0	13	0	13
80	0	146	0	0	11	0	11
52	1	132	1	0	11	0	11
129	0	129	0	0	11	0	11
121	0	122	0	0	10	0	10
102	0	103	0	0	3	0	10
101	1	101	2	0	9	0	9
95	4	95	6	0	8	0	9
94	4	94	4	0	8	0	8
84	0	84	0	0	8	0	8
82	0	82	0	0	8	0	8
34	6	80	6	4	7	8	7
29	0	79	0	0	5	0	7
25	0	71	0	0	7	0	7
68	0	68	0	95	4	95	6
23	1	46	1	34	6	80	6
10	0	40	0	0	6	0	6
35	3	35	3	0	5	0	6

from Manufacturing, out of which 4 companies are from EASIN. Therefore, the extended network is particularly polarized between few powerful companies with a high LORC value and a few exploited companies with high LIRC value, and in the middle, *most companies adopt this coordination form only in triadic or dyadic structures*, as it is confirmed also by the clique analysis done in Chap. 4 and cluster analyses done in the previous section.

Because AKE is the peculiar trait of this form of coordination and it occurs in a dyadic relationship, we now deepen the analysis of Dc of the extended network. The following findings appear particularly interesting:

- In the whole network, only 8% of the 4414 companies are both exploiters and exploited, showing that *the large majority has a marked identity as exploiter or exploited*, namely 53% of companies are only exploiters and 39% only exploited. Therefore, *the roles are very marked, showing a clear strategic intent and an asymmetric "exploitation power"*;
- If we take both groups as blocks, we see that they are two large groups, but that of exploiters is significantly bigger. This fact suggests that *it is much harder to*

exploit than to be exploited: it is possible to exploit only few, while it is relatively easy to be exploited by many[11];

- Moreover, if we rank in decreasing order the companies connected in terms of Out_Dc or In_Dc, regardless of the presence of links pointing at the opposite direction (Table 7.25), we see that: (1) *the largest exploiters have a number of directors' shared positions obtained with their managers that is much lower (about one third) than the number of directors' shared positions issued by the 20 most exploited companies*; (2) the early 20 largest stars ordered by weighted In_Dc (left part of the tab), only 3 shared positions are out-edges, with respect to hundreds in-edges. In other words, those 20 are almost purely exploited companies, which at best will have some shared managers or directors with their own exploiters or with others. Very analogously, though not so purely and extremely, it happens for the early 20 exploiters;
- Though the 372 companies that are at the same time exploiters and exploited are divided about 50% between who is more exploiting and who is more exploited, the total net value of shared positions is negative (− 731), meaning that *the number of shared positions as board members overcome that of managers appointed to that aim*. Therefore, *the companies playing the double role are more exploited than exploiters*, suggesting that they are subordinate actors of large exploitation clusters and confirming what argued right before.

7.9 Assortativity

The extended (E+N) network is moderately disassortative (− 0.36) for the OUT-IN association, because a company with a given out-degree tends not to be connected to a company with a similar level of in-degree. In fact, as we have seen in previous sections, there are more exploiters than exploited and most companies play only one of the two roles. Therefore, most exploiters are connected with only exploited. This association lowers a bit to − 0.29 when considering also the weights of links (see Sect. 8.2 in Chap. 8). Noteworthy, the value of such correlations is higher when focusing only the MC, where actually occurs 90% of coordination and where the most important companies reside, meaning that *when the most important Aerospace- and geographically related companies are involved, the most powerful companies in exploiting the AKE coordination employ it with companies not delivering the same amount of knowledge, albeit of the strategic type*. This effect also means that *large exploiters drain strategic knowledge from many source companies*. Interestingly, the other three combinations are substantially uncorrelated, including the IN–OUT,

[11] The big numbers should not surprise too much because, as said in other parts of the book and especially in the Methodological Appendix, few people can coordinate many companies and a given "target" company can be connected with them. The result is that in the target company there are not, of course, let say 625 directors, but rather a few of people can embody/implement a large number of shared positions. Put differently, one single person can be appointed by dozens of companies into the same target company.

Table 7.25 Binary and weighted In_Dc and Out_Dc of early 20 companies in EASIN + NEIGH

Ordered according to BIDc abs				Ordered according to BODc abs			
BIDc	BODc	WIDc	WODc	BIDc	BODc	WIDc	WODc
209	0	392	0	9	114	9	114
209	0	625	0	0	105	0	111
188	0	334	0	0	102	0	102
162	0	258	0	7	96	8	96
145	0	211	0	0	96	0	97
141	0	228	0	0	96	0	97
137	0	189	0	0	96	0	96
132	0	132	0	0	95	0	95
130	0	130	0	0	94	0	94
129	0	129	0	3	88	3	88
121	0	122	0	3	88	4	90
119	1	236	1	1	88	1	89
117	0	153	0	1	88	2	88
102	0	103	0	3	86	3	86
101	1	101	2	3	85	3	85
100	0	101	0	0	85	0	85
100	0	100	0	5	84	5	84
99	0	99	0	0	84	0	89
97	0	97	0	0	83	0	84
95	4	95	6	0	83	0	83

meaning that *exploited companies are engaged by companies with any kind of out-degree centrality*.

Moving the attention to EASIN only, we find a rather different picture: the disassortative (binary and weighted) OUT-IN correlations here become assortative (positive), but with lower values with respect to the extended network: 0.22 and 0.29, respectively. Therefore, *the AKE mechanisms of coordination are employed, to some extent, among the same companies.*[12] What also differ here is the existence of a low but non-irrelevant positive OUT-OUT correlation, meaning that, *to some extent, companies form chains of hybrid coordination*. In fact, above we already noticed that there are no reciprocal connections of this type because the degree of reciprocity is zero (Table 8.3 in Chap. 8), and indeed, a reciprocal AKE would be rather strange. Otherwise, why employing this defensive-offensive and advantageous coordination if we left it available also to our partner? A shared director, eventually doubled with

[12] We should remind that the size of EASIN is very small: 112 versus 4414 of the extended network. We notice also that the detailed analysis of out- and in-degree centrality done in Sect. 7.9 was concerning EASINT, not EASIN, which has 429 companies. Being composed by only 10 companies, the MC of EASIN is not so relevant and we skip the corresponding comment.

a shared manager if also operative knowledge had to be exchanged, would be much more effective than a double bind through an AKE. In Sect. 8.3 of Chap. 8, we will see a confirmation of this argument when discussing the results of the overlapped types of coordination, because while many links are overlapped between D2D and M2M, and also between M2D and M2M, only a few are overlapped between D2D and M2D. Actually, a company appointing its manager as a director in the other company could accept to reinforce operative coordination by sharing another manager, but will hardly accept to share a director, if not for reinforcing its control over the other's board.

7.10 Summary

In Europe, the most important countries in this kind of strategic coordination are the UK, Italy, then France, Spain and Belgium. Although the most companies come from the UK, it is France that has the largest ones of them in terms of the economic attributes. In EASINT, the number of companies grows from 112 to 429. Once again among neighbors, the most companies in Europe come from the UK and within the rest of the world from the US. In terms of Financial sector companies, the most of them come actually from France. In general, the European Financial neighbors make up 80% of the economic attributes of that entire group.

Companies with large size tend to be associated with the capacity to exploit not only their direct neighbors, but also (through them) the rest of the network. Conversely, the large companies that are exploited by AKE suffer it only from their direct neighbors. With some sporadic exception, such correlations hold only for EASIN and not for the neighbors.

The structure of both EASIN and EASIN + NEIGH M2D networks is made by a huge number of AKE clusters, the largest among whom are true (centrifugally or centripetally oriented) pyramids. Seldom, they can have also an inter-board connection, while more often add also an inter-department connection. All this configures a strongly asymmetric relationship behind the AKE, which indeed appears as the clue of a more general subordination of the company that shares its board. AKE clusters are made essentially by open or transitive triples, where a "knowledge exploiter" is not exploited on its own, and vice versa, thus acquiring an AKE advantage that is supposed to generate a truly competitive advantage.

AKE clusters tend to be very inter-sectoral. The Manufacturing sector is the leader, and the Financial sector activates this form of coordination more than 4 times intensively than EASINT companies. Further, horizontal are much less diffused than vertical hybrid interlocks when EASINT is the "victim of exploitation", while they are only a little bit more diffused when EASINT is the exploiter. There is a clear subordination of EASINT with respect to the Anglo-American geographical block. Though the Professional Activities sector, the Financial sector and EASIN are AKE exploited more than exploiters, they have anyway a high capacity to access strategic knowledge produced by other sectors with AKE forms. AKE advantages are not transferred across AKE clusters: by keeping them "entrapped" into each cluster, "exploiters companies" are very attentive to not share such competitive advantages with others.

There is a clear sign of the strategic choice of banks and other Financial operators to access the very crucial information residing into the board of the most important institutions giving in exchange only operative knowledge (or maybe just nothing else). The Financial sector is relatively lowly interested to employ this coordination form to access EASINT's strategic knowledge, at least through direct relationships.

Only about 50% of EU28 countries are involved in this type of coordination mechanism, and especially when considering weighted values, France and the UK appear to be the key countries in both direct and indirect access to the strategic knowledge flowing through it, which actually does not circulate easy, because of a remarkable reluctance of countries' companies to transfer AKE across their countries' clusters.

Through the AKE mechanism, in both EASIN and EASIN + NEIGH networks, few companies are directly or indirectly able to acquire large amounts of strategic knowledge from many others and few are heavily plundered by releasing their knowledge to many others, while most companies can implement it only in triadic or dyadic structures. The large majority of companies has a very marked role as exploiter or exploited, thus showing a clear strategic intent and an asymmetric "exploitation power". The group of exploiters is significantly bigger than the other, thus suggesting that it is much harder to exploit than to be exploited: it is possible to exploit only few, while it is relatively easy to be exploited by many. This holds also when concerning the companies that are exploiters and exploited at the same time: they too are more exploited than exploiters. The top 100 exploiters in direct AKE are mostly American companies, which are also the nearest to all others, thus in the best position to acquire knowledge from all companies. Conversely, the group of top 50 heavily exploited companies are mostly European and located at the periphery of the M2D extended network. As well peripheral are those 97% of companies that are weak exploiters or weakly exploited.

The prey role played by EASIN (indeed, EASINT) is confirmed by both network and cluster analysis. In fact, EASINT companies show an impressive 88% of prevalent outflow of strategic knowledge due to AKE in "compensation" of as well inflow of operative knowledge.

In the extended network, and especially when the most important companies are involved, the most powerful companies in exploiting the AKE coordination employ it with companies not delivering the same amount of knowledge, albeit of the strategic type. This effect also means that large exploiters drain strategic knowledge from many source companies, while it does not happen in the reverse direction, meaning that exploited companies are engaged by companies with any kind of exploiting capability. Conversely, in EASIN, the AKE mechanisms of coordination are employed, to some extent, among the same companies, which can also form chains of hybrid coordination.

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Chapter 8
Comparing the Three Coordination Forms and Hypotheses Testing

8.1 Bridging Companies and their Coordination Propensity

As we have seen, HINT coordination is very different from the other two types of interlock coordination under most statistical and topological respects. Here, we underline that the asymmetric relationships established by bridging companies in EASIN + NEIGH are much more frequent than in the whole set of links (Table 8.1a): in binary terms, 11.6% respect to 3%, while in weighted terms 5% respect to 0.7%.[1] Further, when a hybrid coordination is employed, about one third of times it happens for a bridging company (Table 8.2), while in the other two forms of coordination, bridging companies are involved only about 12% of times for both binary and weighted BINT, while for DINT with 13% of bridging companies in binary and only 7% in weighted coordination. Therefore, the difference is striking: symmetric coordination does not work well for bridging strategic or operative coordination, while the asymmetric one is better suited. Hence, the picture that is appearing is that *some companies (not necessarily the largest ones) try to coordinate companies' clusters (often cliques) by appointing one of their managers into board of some company that plays the role of bridge to access strategic or operative knowledge created within the cluster*.

The picture is even more interesting when considered is just EASIN (Table 8.1b). In fact, while the proportion of asymmetric coordination here too is higher between bridging companies than in the whole network, what really hits is the 60% share of asymmetric links that are connected to bridging companies (Table 8.2), both in binary and weighted terms, out of the total number of M2D links. On the contrary, in D2D and M2M that share rounds to about 30%, with a higher share of 39% for weighted M2M. It means that *in the pure EU28 Aerospace Industry, asymmetric interlock coordination is used, in majority of cases, to access knowledge from clusters*

[1] The same Tables 8.1a and 8.1b shows another interesting difference concerning the share of strategic links: in binary terms, it lowers from 43 to 38%, while in weighted terms, it grows from 11 to 18%.

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Table 8.1a Distribution of links established by bridging companies in the ALL EASIN + NEIGH network

	D2D b	D2D w	M2M b	M2M w	M2D ib	M2D ob	M2D iw	M2D ow	Sum bin	Sum wei
Absolute value	28.455	44.277	38.399	198.147	5.418	3.349	7.545	3.833	75.621	250.090
Weighted share (%)	–	18	–	79	–	–	3	2	–	–
Binary share (%)	38	–	51	–	7	4	–	–	–	–

Legend b = binary, w = weighted, i = in, o = out

Table 8.1b Distribution of links established by bridging companies in the ALL EASIN network

	D2D b	D2D w	M2M b	M2M w	M2D ib	M2D ob	M2D iw	M2D ow	Sum bin	Sum wei
Absolute value	164	258	281	612	44	53	49	57	542	984
Weighted share (%)	–	26	–	62	–	–	5	6	–	–
Binary share (%)	30	–	52	–	8	10	–	–	–	–

Table 8.2 Share of bridging companies per type of coordination (in %)

	EASIN + NEIGH			EASIN		
	D2D	M2M	M2D	D2D	M2M	M2D
Binary	12	13	32	27	31	60
Weighted	12	7	36	29	39	60

of companies in a proportion that is almost double of that related to the extended network.

8.2 Assortativity

As discussed in a large part of specialized literature (Gabbai, 2005; Giuri et al., 2007; Hickie, 2006; Niosi & Zhegu, 2005; Prencipe, 2011)[2], Aerospace Industry is made of large (and mostly highly connected) companies that play the roles of main contractors and system integrators. Such roles require to coordinate a number of suppliers with them and between suppliers themselves (Rose-Anderssen et al., 2008, 2009). This coordination occurs in various ways and for different purposes, likely employing either contractual or informal means. The three interlock coordinations complement

[2] For a relatively recent and extensive review, see Biggiero & Angelini (2015).

those forms in high-tech industries, like the Aerospace, where strategic and operative knowledge is so complex and influential on a company's competitiveness.

Because knowledge is so crucial, main contractors or system integrators tend to avoid direct relationships, in order to prevent risk of inadvertently giving away some precious chunk of technological, market or managerial knowledge. Therefore, with few exceptions, strategic and operative connections will not occur so frequently between those types of companies, which are almost always also the large and highly connected ones, though some of these latter are just large suppliers.

This whole argument is very peculiar of EASIN and, even more accentuated, of its MC, which is the locus where its features are more precise. The coming of neighbors into play is supposed to change the picture in two converging directions: firstly, the push of technological and market features of Aerospace on the two interlock coordination "devices" (directors and managers) is supposed to remarkably decline, because a number of other industries enter the scene; secondly, large neighbors—especially Financial companies, Public administrations, non-EU28 Aerospace companies and Manufacturing companies—are strongly required for (and thus, connected with) large EASIN companies and are also strongly connected among themselves.

In light of this reasoning, we can read the rows of Table 8.3 on assortativity coefficients from left to right indicating two aspects:

- A progressive increase of inter-industry homogeneity of the four networks: E + N is the most heterogeneous, because it comprises all sectors and countries and any kind of size; E + N MC has a minor degree of heterogeneity, because some countries and some sectors are not there, and company size distribution has a lower variance; and EASIN is homogeneous from an industrial point of view and has only one third of all E + N countries;
- A progressive increase of heterogeneity of intra-industry connectivity, relatively to the network size, because the industry structure is made of horizontal and

Table 8.3 Coefficients of assortativity in all networks

Networks		EASIN + NEIGH		EASIN + NEIGH MC		EASIN	
		Binary	Weighted	Binary	Weighted	Binary	Weighted
ALL	IN-IN	0.95	0.93	0.94	0.92	0.51	0.4
	IN–OUT	0.95	0.93	0.94	0.92	0.50	0.39
	OUT-IN	0.96	0.93	0.94	0.92	0.50	0.39
	OUT-OUT	0.95	0.93	0.94	0.92	0.49	0.38
D2D	–	1	0.92	1	0.99	0.74	0.64
M2M	–	0.96	0.96	0.95	0.96	0.5	0.44
M2D	IN-IN	−0.02	−0.01	−0.05	−0.02	0.14	0.13
	IN–OUT	0	0	−0.01	0	0.02	0.02
	OUT-IN	−0.36	−0.29	−0.57	−0.48	0.22	0.29
	OUT-OUT	0.09	0.08	0.08	0.07	0.27	0.19

vertical segments: the former addresses to different companies specialized into parts of the same production stage, while the latter addresses to companies engaged into different stages of the whole filiere. Therefore, in EASIN, large companies are mostly main contractors and/or system integrators that design the general architecture of the final product and then coordinate the production of horizontal and vertical suppliers.

Now, to interpret findings of this section on assortativity and of many other findings discussed in this chapter, we will use this perspective, also supported by the results derived from testing the sixth hypothesis, that concerning an association between size attributes and interlock coordination propensity. In fact, as we will see below in Sect. 8.10, there is a general positive association between company size and coordination propensity, especially in EASIN and its main component, and especially for the strategic knowledge coordination. Therefore, here we will run our interpretations assuming that the largest are also the most connected companies.

With few exceptions in the M2D network, all the extended networks (including their MC) are almost fully assortative[3]: more than 0.92 and in some cases almost 1 (Table 8.3). Therefore, *strategic and operative coordination tends to occur almost exclusively between companies with the same degree of involvement in this kind of coordination.* This result is indeed strongly influenced by the presence of many huge cliques, because each member of such cliques is, ipso facto, highly assortative with all other members. In fact, the anomaly of the M2D network is explained by the fact that, as we have seen in Chap. 4 (Table 4.11) and in Chap. 7 (Sect. 7.3), in that network there are only relatively small (weak) cliques and no any strong clique.

In the EASIN core of M2M networks, assortativity more than halves in the weighted version and is about 10 points higher in the binary version, meaning that in DINTs, highly connected companies tend still to prefer coordination among themselves, but such preference is substantially lower than what happens when neighbors are involved. This could mean that, *in the pure European Aerospace Industry, operative knowledge diffusion does not always require the same level of capacity to coordinate in this way, especially in terms of effort intensity*. EASIN assortativity of strategic knowledge coordination is much higher (0.74 in the binary and 0.64 in the weighted version) than that of operative knowledge, meaning that *effective sharing of strategic knowledge among European Aerospace companies requires that they are at a similar level of coordination capacity.*

Let us now analyze hybrid coordination, which is articulated in four combinations, because it deals with asymmetric connections. In running this analysis, we gain from that done in Chap. 7, in particular in the fifth section, which deepened the distribution of in- and out-degree centrality. There, we have seen that, in the extended network, the large majority has a marked identity as exploiter or exploited, that is, have only out- or in-edges, that is, are providing only managers or only "hosting" them in their boards. Moreover, the 372 companies that are at the same time exploiters and exploited

[3] We remind that assortativity measures the correlation of node connectivity: a network is assortative when highly and lowly connected nodes tend to connect among themselves. See the Methodological Appendix and investigate deeper with Newman (2010).

are divided about 50% between who is more exploiting and who is more exploited. These findings explain why the extended networks are significantly disassortative, especially in the MC: −0.57 and −0.48, in binary and weighted terms, respectively. Correlations of the three combinations of connectivity—IN-IN, OUT-IN and OUT-OUT—turn mildly positive in EASIN, meaning that some companies tend to connect regardless of their role of exploiters or exploited.[4]

We can conclude that, at global level, where the specificity of the Aerospace production and commercialization is diluted into many other types of economic activities—represented by various sectors—all the networks except M2D are extremely assortative, which means that large and highly connected companies tend to coordinate their activities with other large and highly connected companies, and the same happens for small and lowly connected ones. Conversely, when focusing on the only EASIN network of ALL and M2M networks, assortativity more than halves, while keeps very high for D2D, which means that strategic coordination occurs mostly between companies of the same connectivity level, while operative coordination can happen, to some extent, also between companies of a different level of connectivity. In sum, we can say that: (i) *the more industrially homogeneous is the network, the less assortative it is*; (ii) *networks of hybrid coordination are very different from the others, due to the logic driving formation of directed networks made of asymmetric relationships.*

8.3 Topological Similarity between Companies within Networks

To understand the extent to which companies have similar coordination patterns, we have analyzed the degree of structural equivalence (SE) in terms of the Jaccard Method between companies in each network.[5] We have distinguished between SE in

[4] Notice that EASIN is rather different than EASINT, which actually is a more significant entity because, especially in this type of coordination, it includes also connections with the neighbors. Moreover, EASIN is made by only 112 companies, thus statistically not very significant. The analysis of EASINT run in Sect. 7.5 of Chap. 7 shows that it does not differ much from E + N, thus changing very much the traits of EASIN. As for EASIN MC, we chose to skip these results for all the types of links, because the corresponding MCs are not statistically significant, either because they do not include connections with neighbors or are made by only about 10 companies.

[5] To run this analysis, as well for that of SE between the networks (see the next section), we used a dedicated software, because all current commercial generalist software cannot afford this type of calculation for networks of this size. As well, with existing software it was impossible to run the analysis of regular equivalence. One of us developed a software, called NEDDI, able to calculate inter- and intra-network SE with algorithms of Euclidean Distance, Simple Matching and Jaccard Matching. This software, which can be freely downloaded from www.luciobiggiero.com, can distinguish directed and undirected and binary and weighted networks. To know how we operationalized it, see Methodological Appendix and the standard handbooks on network analysis, such as Wasserman & Faust (1994), Hanneman & Riddle (2005), Newman (2010) and Alhajj & Rokne (2014).

purely structural (binary) and in weighted terms, thus allowing to understand whether the intensity of coordination is higher or lower than the pure structural value. As we did for assortativity in the previous section, we comment here SE of all the four networks, so that we can also compare them. This is necessary also because, being this the first study on the SE of interlocking coordination forms, and even more the only one on interlocking departments, the only comparisons we can do is across our own networks.

Quite interestingly, average SE of the ALL network is moderate but not irrelevant, except for the EASIN MC in weighted terms, where it is very small (about 0.1), but with a high coefficient of variation in each of the four versions of the ALL network, which indicates that the average is scarcely representative and that, likely, SE of individual nodes is distributed in a HT way. This sounds consistent with the presence of huge cliques, a feature that influences also SE, because most companies of the same clique will have the same score of SE. Thus, *there are groups of super-connected and super-similarly-patterned companies, which correspond to those belonging to the largest cliques, and a plethora of poorly connected companies, which have extremely different patterns of connection.*

Quite obviously, the SE of the ALL network is similar to that of the M2M network, which in fact accounts for the 88% of its connections: namely, a bit lower than that of M2M, because the presence of D2D connections increases its differentiation, and thus, it lowers the similarity across companies' patterns of coordination. Quite interestingly, D2D networks have a very high average SE,[6] which is even not too differentiated across companies, despite the existence of some huge cliques, meaning that *strategic coordination patterns are more homogeneous than operative coordination patterns.* The significantly lower similarity of companies in MCs of all the four extended networks depends on relatively smaller size and rarity of cliques, what seems to be due to a search for efficiency in coordination. Actually, as is argued in the literature on inter-firm networks addressed in Chap. 2, a coordination relationship consumes a lot of resources and requires specialized competencies to select partners, and then designing, evaluating, keeping and developing the corresponding relationship. In this sharp difference between the hundreds of minor components and the main component, it seems to see also *a big difference between the Anglo-American on one side and the continental EU managerial culture, when the former is much more oriented to invest resources in interlocked coordination than the latter*.

In fact, in Sect. 4.8 (Chap. 4) we showed precisely that MC has a very different geographical and sectoral composition with respect to the rest of the network, namely all the minor components. We found that the block of about 4000 MC companies is made by 66% of Anglo- and North-American and 30% by EU continental companies—with the US covering 43 and the UK 17%, while in the minor components, the former share lowers to 23%—with 21% covered by the UK and

[6] This happens with the exception of EASIN MC, which indeed is almost irrelevant, due to its very small size. As we noticed in the previous section, the same irrelevance holds for the EASIN MC of all networks.

Table 8.4 Degree of intra-network overlapping according to Jaccard Matching

Network		EASIN + NEIGH		EASIN + NEIGH MC		EASIN		EASIN MC	
		Binary	Weighted	Binary	Weighted	Binary	Weighted	Binary	Weighted
ALL	Average	0.398	0.231	0.375	0.211	0.463	0.267	0.283	0.097
	co. var	1.148	1.563	1.208	1.662	0.751	1.180	0.821	1.589
D2D	Average	0.871	0.753	0.856	0.797	0.809	0.683	0.321	0.227
	co. var	0.369	0.498	0.398	0.479	0.382	0.543	0.589	0.779
M2M	Average	0.415	0.278	0.377	0.239	0.560	0.359	0.394	0.168
	co. var	1.137	1.452	1.227	1.598	0.638	1.002	0.775	1.589
M2D	Average	0.648	0.538	0.537	0.371	0.574	0.500	0.279	0.279
	co. var	0.550	0.707	0.657	0.881	0.556	0.629	0.359	0.359

neither 1% by the US—and continental EU about 73%. Hence, the two partitions of the ALL EASIN + NEIGH network have the inverse relevance of the two cultural-institutional-managerial blocks: the Anglo- and North-American versus the continental EU.

Even more interestingly is the fact that, despite the absence of large cliques, *in the hybrid coordination network, average SE (and also the coefficient of variation) is intermediate between that of M2M and D2D*. Actually, as we have seen in the previous chapter, the M2D network has no large and no strong clique at all. Conversely, as we have seen in Chap. 7, its topological *motif* is thousands of stars of size 3, 4 and 5, and a few dozens of > 5 stars. They are archetypical hierarchical structures (Biggiero & Mastrogiorgio, 2016) in the form of out-tree graphs. Therefore, *the M2D similarity of structural patterns is due to such thousands of similar elementary structures, which are also mostly disconnected from one another, and it is just their disconnectedness that makes them structurally similar. Interestingly, this strong peculiarity of the M2D network is diluted in the extended network, because the other two types of links tend to connect many of the disconnected stars, to enlarge and transform them into different subnetworks, often cliques* (Table 8.4).

8.4 Topological Similarity between Networks

Through a modified version of the Jaccard Matching method (see the Methodological Appendix), we have measured SE across the three networks (Table 8.5). Before commenting the results, let us clarify the interpretive perspective that we have taken here, though aware that there could be some other[7]: when two of the three types of links overlap, it could be supposed that they are complementary, because they are both necessary to run a good (effective) coordination, while when the degree of overlap is

[7] More on the matter in the Methodological Appendix.

Table 8.5 Degree of inter-network overlapping according to a modified Jaccard Matching

	M2D-M2M	M2M-D2D	M2D-D2D	Average
EASIIN + NEIGH	0.51	0.75	0.16	0.47
EASIN + NEIGH MC	0.00	0.38	0.00	0.13
EASIN	0.58	0.57	0.13	0.43
Average	0.36	0.57	0.10	0.36

low, it means that the types of coordination are substitutes instead of complements. So, this analysis focuses on a fundamental topic—though just at the beginning of investigation—of inter-firm networks and strategic alliances: which coordination means can be employed as complements or substitutes. Perhaps, a criticism to the interpretive perspective adopted here is that it is too rational and intentional, because BINT, DINT and HINT could be issued for reasons else than reinforcing inter-firm coordination. Likely, this rationale concerns more BINTs and HINTs than DINTs, because the latter is supposed to be more "anchored" to operative work and, thus, more measurable and concrete than strategic aspects. We are aware of this criticism, but we argue that when a dataset is so big as our network—especially the E + N—it is reasonable to think that some basic "force" is at stake. Further, even the rationale of pure elite power evoked by the studies of Carroll & Fennema (2002), Carroll et al. (2011) and others (see Sect. 2.3 of Chap. 2) is, at the very end, a means of inter-firm coordination.

The lowest average degree of overlap (0.1) is recorded between M2D and D2D across the three networks,[8] which means that once a company appoints one of its managers into the board of another company, then likely it has no longer need to reinforce coordination with an inter-board connection. This is due to the fact that for the company A in which the shared person is appointed as manager there is already an acquisition of strategic knowledge from the company B, where that person is appointed as director. Therefore, company A does not need a further reinforcement of strategic knowledge acquisition. It becomes useless to double the effort of strategic coordination. Further, as we discussed widely, because a HINT hides an AKE, that is, a power unbalance between the two companies, the exploiting company has weak interest to further reinforce it, especially if with a symmetric (balanced) knowledge exchange, as it would be with a BINT or DINT. At the same time, the exploited company is supposed to be such, because it is the weak side of the two, and thus, it would be hardly able to "push" the strong part establishing a symmetric knowledge exchange, especially if concerned is the strategic knowledge. Hence, *none of the two parts has a strong motivation to reinforce a HINT with a BINT in the whole extended network*. Therefore, the fact that the lowest degree of overlap is recorded between M2D and D2D seems to be perfectly reasonable. Due to the huge size (3200 companies) of the intersection of the M2D and D2D E + N networks, the result of only 0.16 degree of overlap sounds rather solid and extendible to all sectors, not only

[8] We omitted the comparison across EASIN MC, because the very small size of some EASIN MC suggests that it would be statistically not significant.

the Aerospace, because those two networks include all sectors (see the inter-sectoral networks of Chaps. 6 and 7).

Actually, moving to the more important and less heterogeneous networks E + N MC (see the previous discussion about assortativity), the above reasoning is reinforced and brought to the extreme consequence, because, quite incredibly, *there is zero overlap in the MC of the extended network between M2D on one side and M2M or D2D on the other*. Properties of the E + N MC network (see Sect. 4.8) allow to accompany the previous interpretation with the following: *when companies' coordination is more focused on the Aerospace Industry and much more intensive in terms of shared positions, no any symmetric (equal) relationship needs to be complemented by an asymmetric one.*[9] The singularity of HINT is confirmed by the fact that, on the contrary, DINT-BINT relationships overlap a lot, even in the MC (0.38). At global E + N level, the degree of overlap is huge (0.75), while for EASIN is 0.57. This means that the existence of a strategic coordination (BINT) does not guarantee a good operative coordination (DINT), and vice versa. Therefore, *whenever it is evaluated that both types of knowledge should be shared and provided that the two partners have the required capacities to establish these types of partnerships, both types of coordination are issued*.

Indeed, this result questions the idea that the type and amount of coordination requirements between European Aerospace companies themselves are much superior to that required between them and their neighbors on one side and between their neighbors themselves. That idea says that the high coordination needs—which can double one type of link with another one or even with two others—depend on the technological peculiarities of the Aerospace Industry, where the need to guarantee high quality standards, common codes, precise timing, etc., requires an extremely high coordination that cannot be done only by a contract, but rather requires a strategic or operational coordination and often both types of coordination. Our finding suggests that even the relationships between EASIN and non-EASIN Aerospace companies and those between the Aerospace and non-Aerospace manufacturing or engineering companies concern complex products and services, so that they too require very intensive and multiple (strategic-operative) interlock coordination efforts.

Indeed, the remarkable difference of the degree of overlapping in EASIN and E + N suggests that *neighbors need both types of coordination more often than EASIN companies*. This fact could have many different explanations, which would need specific hypotheses testing. One of them could be related to possible major persistence and consolidation of partnerships among EASIN companies, which could save part of coordination efforts. Another possible explanation addresses to neighbors' industrial heterogeneity, which would make, on average, coordination efforts and knowledge sharing more difficult than between more industrially homogeneous companies. We will develop this issue below in this chapter, when dealing

[9] This fact has a remarkable topological implication, which in turn has also the following remarkable conceptual implication: companies that have the power to issue an asymmetric strategic coordination influence others companies coordination by coordinating (connecting to) one of the members of cliques or a bridging company, not by directly entering a clique.

with sectoral/technological proximity. A third hypothesis would concern again the managerial culture, because we know that neighbors are largely dominated by Anglo-American companies, which are supposed to be more able (skilled) and oriented to build partnerships. We have seen that this hypothesis is supported by the very different composition between EASIN and E + N and between the E + N MC and the minor components: the former is very different from the latter.

In sum, *when companies' coordination is more focused on the Aerospace Industry and much more intensive in terms of shared positions, no any symmetric (equal) relationship needs to be complemented by an asymmetric one. Conversely, whenever it is evaluated that both strategic and operative knowledge should be shared and provided that the two partners have the required capacities to establish these types of partnerships, both types of coordination are issued*.

8.5 Does Interlock Coordination Enhance a Better Economic Performance?

One of the central tenets of SNA (see Sect. 2.4 of Chap. 2) applied to economic or business networks is that covering a central position in a network, let say knowledge flow or trade exchange, gives a competitive advantage, because those companies can better access knowledge or products, respectively. Likely, most time holds also the vice versa: being more competitive increases the probability to be selected as a partner by many or strategically important companies, and thus, this will bring to a more central position. Indeed, due to self-reinforcing processes, this is a typical case of circular causality (Biggiero, 2001, 2011, 2016a, b, 2022; Leydesdorff, 2021). According to this view, centrality indexes are expected to be positively associated with some kind of economic or financial performance indexes. We can call it the Centrality/Performance Advantage Hypothesis (CPAH).

In the case of our research, it implies that higher BINT connectivity is associated with better performance, thus implicitly assuming that getting a higher BINT connectivity would be an advantage. Therefore, we should expect that higher centrality indexes are correlated with better performance indexes. Findings of this test add to those discussed in Sect. 2.7 of Chap. 2, which presented controversial results accumulated during many decades of studies. Our results contribute also to the debate on BINT and market efficiency that we have outlined in Sect. 2.8 of Chap. 2, because a negative correlation would suggest that high BINT connectivity is a company's negative feature. Taken from this perspective, we can address it with the Low Performance Hypothesis (LPH), that we will treat in next section by deepening the analysis under the supposition that the relation between BINT connectivity and performance be nonlinear. Hence, CPAH is tested here supposing a linear association, while LPH is tested in next section supposing a nonlinear association.

Likely, results of tests on these complex issues (and its interpretations) depend significantly on the type of centrality and performance index: direct or indirect centrality and economic or financial performance. Further, the time dimension matters, because reaching central positions may take time to produce its good effects on performance, and vice versa. Moreover, market contingencies could harm such relationships. Hence, it would be important to run the test through a time series of five or more years. Of course, they substantially depend also on the type of sample. Unfortunately, we do not have longitudinal data, but we thought it is worth anyway to test that relationship, because of three reasons: (i) we have a dataset with enough data; (ii) many centrality indexes with whom checking the correlation; (iii) a huge number of other findings with whom interpreting the results of correlations; and (iv) the opportunity to run the test also on DINT and HINT types of interlock. So, though our test is flawed by the lack of a time series, at least it is interesting for the sample size. A further good point of our test is the richness of centrality indexes with which we have run the test: they are 15. Now, even considering that some of them are highly correlated with one another, let say that we still have at least 5–6 genuinely different analytical perspectives. Further, as we have extensively discussed in Chap. 2, our sample is built on a single industry (Aerospace) within a large region (EU28), so it benefits from a high degree of homogeneity, at least for the EASIN network, and an acceptable degree of heterogeneity for the E + N, because the neighbors are related to EASIN. Moreover, we have considered all limited liability companies, not only the largest/public/listed ones, thus giving a high informative content to the findings.

Indeed, after running the calculation, only few results revealed to be statistically significant (Table 8.6), and only with binary or weighted Dc indexes.[10] In the ALL EASIN network, no any result is significant, while in the E + N network, the coefficient of ROE (before taxes) with BIDc and BODc is mildly negative (−0.06) and highly significant: P-value is 0.0009 and 0.001, respectively. In D2D EASIN, the same two centrality indexes have a positive 0.18 coefficient of correlation with ROCE, but it is not highly significant. In D2D E + N and M2M EASIN and E + N, there is a low negative correlation with ROE and a good P-value. No result was significant in M2D EASIN and E + N networks. Hence, *the only significant results are mostly negatively (but with very low values of the coefficient) correlated, especially for the extended network and for DINTs.* A mild (0.18) positive association with ROCE occurs however for BINTs in EASIN, meaning that *the creation and sharing of strategic knowledge with many partners are correlated with better economic performance.* Actually, this strategic coordination into the EU28 core Aerospace Industry has shown different characteristics from the operative coordination also under other topological and statistical respects. It means that these two types of coordination refer to two genuinely different types of knowledge—strategic versus operative—and, likely, that such differences are firmly dependent on the technological and market features of this industry.

In sum, *we can say that, when concerning operative knowledge coordination or the neighbors companies, the CPAH is not confirmed or maybe should be even reversed, while it can be confirmed in reference to the EASIN strategic knowledge coordination.*

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[10] The number of cases of significant coefficients rounds from a minimum of 115 for D2D EASIN up to 2798 for ALL E + N. See Data Appendix for more details.

Table 8.6 Significant correlations between binary Dc and financial performance indexes

	ALL	D2D		M2M	
	EASIN + NEIGH	EASIN	EASIN + NEIGH	EASIN	EASIN + NEIGH
ROE	−0.06	–	−0.07	−0.07	−0.07
ROCE	–	0.18	–	–	–

Therefore, with respect to the debate on the relation BINT/performance, we can say that at industry level, that is considering a not irrelevant number of companies (305) that are not restricted only to largest ones and not so heterogeneous, like in the typical cross-sectoral samples characterizing all the studies done so far, the presence of BINTs is positively associated with performance. Lowering the degree of companies' homogeneity by including also the cross-sectoral neighbors determines an inversion of the sign of correlation, though keeping it on very small values. This finding strengthens the KBV of BINTs that we have adopted in our study. However, the exchange of operative knowledge through DINTs is negatively associated with a company's performance of any kind, regardless of its degree of homogeneity.

We will see in next section from which types of companies this result comes from. Further, we will see that the three profitability indexes—PM (profit margin), ROE (return on equity) and ROCE (return on capital employed[11])—move in very different ways depending on the type of coordination and on the degree of direct connectivity. It means that the form of coordination produces different effects on economic-financial performance and that those three indexes provide truly different information.

8.6 Could the Connectivity-Performance Relation Be Nonlinear?

In this section, we focus on the idea, mostly supported by standard economics, of a negative influence of BINT on performance: it is the LPH, which in the previous section revealed to be moderately true for the extended network and moderately false for EASIN. Actually, as we have seen in Chaps. 4–7, EASIN and, even more, its extended networks are characterized by a huge number of cliques, which actually are the strongest form of alliance, because their members connect everyone with everyone. Therefore, the effects predicted by the LPH should be particularly strong. Further, we know that there are also some huge-size cliques (with more than 100 members), where the predicted effects of lower competitiveness are supposed to be even stronger, because the "degree of protection" from the selective market forces driving to efficiency would be even higher. Now, we deepen its testing by checking for possible nonlinear effects.

[11] It can be called also ROA (Return on Assets) or Return on Investments.

More specifically, we guessed that these relations could be nonlinear with Dc. Therefore, we have identified four groups of companies[12]: (i) isolated companies, which are only in EASIN, because the neighbors are by definition necessarily connected; (ii) lowly connected companies ($TDc <= 10$); (iii) remarkably connected companies ($TDc > 10 < 100$); and (iv) very highly connected companies ($TDc > 100$).

As performance parameters, we used again PM, ROE and ROCE, as we did to test the previous hypothesis too. Analogously, we distinguished D2D, for which that theory (and the corresponding hypothesis) was specifically formulated, from M2M and M2D coordination, because there is no any necessary strong connection between them. To refine the analysis, we have considered three aggregates: EASIN, EASIN + NEIGH and NEIGH, so to distinguish the different degree of heterogeneity, growing from EASIN to NEIGH.

The analysis of results in the D2D EASIN (Table 8.1a in Data Appendix) shows a clear confirmation of the LPH only for ROE, which actually, starting from the isolated companies group, declines in the lowly connected group and then becomes heavily negative in the two highly connected groups. Conversely, PM and ROCE move differently: the lowly connected group has about the same values of the isolated, and then, they significantly grow up (noteworthy for ROCE) in the remarkably connected group, to decline sharply (especially ROCE) in the fourth (highly connected) group. Hence, results are rather contradictory, but if we observe that the first two groups are statistically more significant in terms of sample size—2396 and 649 companies, respectively—and that the group of the most highly connected is very small (16 companies), we can say that, considering BINT in EASIN *in PM and ROCE terms, LPH should be rejected, while in terms of ROE it can be accepted*. In the E + N and neighbors' networks (Table 8.1a and d in Data Appendix), ROE and ROCE results do not give a clear trend for a confirmation or rejection, while PM of the three connected groups is always superior (and for the second and third groups, growing) to that of the isolated companies. In short, it could be said that *for the strategic knowledge coordination through BINT in EASIN and its neighbors, LPH can be rejected in terms of PM and is unclear for the other two performance indexes.*

When looking at M2M EASIN (Table 8.1b in Data Appendix), we see that the hypothesis is confirmed for ROCE, with the exception of the fourth group, in which the performance sharply increases becoming 50% higher than that of the first group. Conversely, for the PM and ROE the LPH must be rejected and inversed, meaning that, in EASIN, *a company's degree of operative knowledge coordination through DINTs influences positively and substantially its economic-financial performance.* If we look at the corresponding extended and the only neighbors' networks (Table 8.1b and d in Data Appendix), results show that, in terms of PM, *LPH must be as well rejected and inversed: the more connected through operative coordination forms, the more profitable is a company*. However, *the LPH is confirmed for ROE and ROCE*, though in this case PM seems a better index, because its coefficient of variation is much smaller than that of the other two indexes. If we separate neighbors, then

[12] More information on the main characteristics of each group can be found in this chapter in Data Appendix.

Table 8.7 Summary of results of LPH tests by grouping companies

		D2D	M2M	M2D
PM	EASIN	No	No/rev	?
	NEIGHBORS	No	No/rev	No
ROE	EASIN	Yes	No/rev	?
	NEIGHBORS	?	Yes	Yes
ROCE	EASIN	?	Yes	?
	NEIGHBORS	?	Yes	Yes

we see that PM grows with connectivity, while ROE and ROCE have an oscillating movement. Therefore, LPH should be fully rejected for PM and partially rejected for ROE and ROCE.

In the M2D network, there are not so big cliques or highly connected companies as in the other two networks (see the previous chapter), and so we have only two groups of connected companies: $< = 10$ TDc and > 10 TDc. In the EASIN network, there is no any clear indication, because for all the three indexes the group of low connectivity scores lower values than the isolated, but then in the group with high connectivity, such values overcome those of the isolated companies. *Turning to the* $E + N$ *networks, LPH should be rejected for PM, because it grows with TDc until almost the double of the isolated companies. Conversely, it is well confirmed in terms of ROE and ROCE, which crash down to very negative values.*

The following Table 8.7 helps us to summarize these not univocal results across the indexes, the three forms of coordination and the two aggregates. The only strong indication concerns PM: the LPH should be rejected, because profitability does not decrease with connectivity and for the operative coordination it should be even reversed (REV), because profitability grows with connectivity. Conversely, results are rather contradictory or unclear for the other two indexes (ROE and ROCE), with a weak favor for LPH confirmation, especially for the neighbors companies, which however are those with the lower share of data.[13]

These findings are of special relevance, because they show that, in terms of PM, the simple linear relation between interlock connectivity and business performance does not work, being it nonlinear in terms of connectivity. Further, it resolves a problem that was raised by the test in the previous section, namely that DINT seemed to not generate any kind of performance advantage in a high-tech industry like the Aerospace. It sounded rather strange, because operative knowledge is supposed to be very important in such types of industries, but this deeper analysis demonstrates that that supposition was true for both the EU28 Aerospace companies and their neighbors. Indeed, this deeper analysis shows that *DINT connections provide even more performance advantages than BINTs*. Further, this analysis confirms that BINTs

[13] Indeed, let us remind that, especially in some categories, the sample size is very small, due to the lacking coverage of financial performance indexes, as it can be seen in the Table 8.1 in Data Appendix.

give a performance advantage to Aerospace companies and its partners through strategic knowledge interlock out of EU28 and/or the Aerospace Industry.

8.7 Proximity and Interlock Coordination

The debate on the role of proximity in inter-firm networks evidenced various forms of proximity enhancing the propensity to build a connection or to make an innovation performance (Boschma, 2005; Huggins & Johnston, 2010; Knoben & Oerlemans, 2006; Torre, 2014; Wu et al., 2020). Here, we deal with three of them, the first one being the most classical, geographical proximity, then followed by sectoral proximity, which can be taken as a proxy of technological proximity, and finally organizational proximity, expressed in terms of company size. Some authors (Nooteboom, 2004; Nooteboom et al., 2007) advanced the idea that companies tend to establish connections when their similarity (proximity) is at an intermediate level, because, if too similar, they can match easily but have little interest to collaborate, while if too dissimilar, they have a potential big interest to collaborate but strong differences make the collaboration difficult to be established and maintained. Others (Broekel & Boschma, 2012) claimed the existence of a proximity paradox: too much proximity can be harmful for innovation capacity. Very interestingly, Broekel & Boschma found empirical evidence of this situation just in the knowledge network of Dutch Aviation Industry, which is part of the Aerospace Industry, thus very near our object of study. In our work, we followed this idea, which we call the Optimal Proximity Hypothesis (OPH), and tested it against our data.

For all the three forms of proximity, we will measure a company's effort of collaboration with *coordination propensity*, that is, the average number of collaborations (coordination partners) per company (Table 8.2 in Data Appendix for sectors[14]). That is, we have a scalar to measure it, varying also according to the type of coordination.[15] If OPH were true, we should expect values near 1 (which is the minimum) in self-referential coordination, for example, Italian with Italian companies, or with very different companies, for example, Italian with Singapore companies, while there must be a high intensity of coordination between Italian and German or French companies. Analogously, when dealing with sectoral coordination, Manufacturing horizontal (intra-sector) links are expected to be near the minimum, because they are self-referential, while very high for technologically near sectors, like Manufacturing and Professional Activities (M), and again very low when technological diversity is high, like between the Wholesale (G) and the Art (R) sectors.

Before showing and commenting the results, let us warn that this analysis is approximate, because it had to be done at industry (and not sector) level and with a geographical and technological accurate categorization, driven from the extensive literature concerning technological or knowledge relatedness. We are aware of these

[14] The inter-country matrix was too big to be inserted.

[15] However, here we have tested the two proximity hypotheses only against the ALL network.

flaws, but we thought that, especially focusing on the most striking results, it is worth and fruitful running our approximate analysis, due to the very large dataset of many thousands of companies, compared with the few dozens of Broekel & Boschma (2012) and Sammarra & Biggiero (2008). Future works on this data will allow to improve and deepen the analysis.

We can address to the traditional (non-paradoxical) hypothesis that considers coordination efforts as *proportional to proximity*, according to which firms look for the easiest way to build inter-firm relationships, because the risks to waste too much resources in unproductive or unsuccessful or volatile partnerships are too high. We believe that this alternative hypothesis, that we can call the PPH (Proportional Proximity Hypothesis[16]) is sensitive to an industry's technological or market complexity, because it works well when at least one of those two forms of complexity is high, due to the high required efforts of coordination and at the same time also the corresponding risks. As we know, this is precisely and strongly the case of the Aerospace Industry, because both forms of complexity hold. Hence, in our comments we will take into account also this PPH.

Geographical proximity. We have chosen the average coordination intensity per single company as a measure of the average effort of a company in a given country to coordinate with a company in its same country or in another country. According to OPH, we should expect propensity be minimum within a same country or between very different/distant countries and much higher between moderately different/distant countries. Now, out of our 61 countries in the ALL network, we can say that non-EASIN but EU countries are precisely in the set of these latter, because they are geographically and culturally close, so that we should expect the highest average propensity. Then, relations between EASIN and the US or CA are geographically but not culturally or institutionally distant, so that there can be a propensity near that of EASIN. EASIN countries are geographically and institutionally very close, so that we should expect a rather low propensity to coordinate. Finally, non-EU and non-North-American countries are supposed to be among the most geographically and institutionally/culturally distant with respect to EASIN and North America, so that we should expect again a low coordination effort. Of course, two companies from Singapore and South Korea, respectively, can be supposed to be rather proximate, but in our coarse grain analysis we focus mostly on the EU and North-American companies, because it is from there that 90% of our companies come from. Moreover, the sample itself is somehow biased, because neighbors have been selected according to EASIN companies, and thus, it does not represent all the Aerospace-related companies worldwide, and even less the cross-country coordination efforts in the whole Manufacturing sector.

[16] To be precise, we are not arguing that there is a linear proportionality. On the contrary, it is likely that the positive coefficient of proportionality does change according to some proximity value. However, all this is matter for future research agenda.

Table 8.8 Main statistical parameters of average coordination propensity

	Countries			Sectors		
	Average	Std. Dev	Covar	Average	Std. Dev	Covar
ALL	1.68	2.52	1.50	1.72	1.45	0.84
M2M	1.55	2.15	1.39	1.47	1.48	1.01
D2D	1.72	1.88	1.09	1.20	0.38	0.32
M2D	1.15	0.53	0.46	1.12	0.26	0.24

Legend Std. Dev. = standard deviation, Covar. = covariance

In Table 8.10, it is shown the average coordination intensity per single company across or within countries concerning the seven main countries.[17] Before starting comments, let us specify that these matrixes have different degrees of heterogeneity (variance) (Table 8.8): the coefficient of variation is systematically higher by countries than by sectors, and across the three coordination forms, the lowest coefficient is that of M2D, then followed by D2D and M2M. This ranking is indeed also a consequence of the corresponding network density that we have already seen in this chapter concerning SE and in Chaps. 3 and 4: the denser the network, the higher its heterogeneity.

We have designed four categories (Table 8.9) in order of decreasing proximity degree, which are colored differently, so to allow easy understanding: orange marks very high degree (the case of self-reference), then followed by yellow (high), red (medium) and green (low). According OPH, in the top positions we had to see mostly red colors, but this is not the case (Table 8.10): out of the four out-layers (> = 30), two are (rightly) characterizing medium proximity, while the other two low proximity. To find another couple of medium proximity, we should scroll down 10 positions, while in the middle there are mostly 8 low, 2 high and 3 very high proximity cases. The results of these high values continue showing a mix of colors, where the red one is the far minority. Therefore, *it seems that both the OPH and PPH should be rejected for the case of interlock coordination efforts occurring in the ALL network*. According to this data, *it seems more credited the opposite view of OPH, which could be represented by a U-shaped curve in which the more intensive coordination effort is made preferably with the lowest and highest proximity, though for very different reasons*. We will go back to this conclusion after commenting also on results for technological and organizational proximity.

Sectoral/technological proximity. The test of sectoral/technological proximity follows the same approach: after categorizing sectoral pairs (Table 8.11), we look at the colors characterizing the early major positions (Table 8.12). Here, the contradiction with OPH is really striking: the first medium (red color) proximity is only at the 13th place, while the early 5 are in the maximum (same sector) and the second group is in the minimum proximity. Therefore, *OPH should be rejected, while the*

[17] Unfortunately, the whole matrix was too large to be inserted in the Data Appendix, but it may be given on request.

Table 8.9 A simple categorization of geographical proximity

VERY HIGH	HIGH	MEDIUM	LOW
SELF	EASIN	EU-EASIN	ALL OTHERS
-	US-CA	EU-US	-
-	US-UK	EU-CA	-
-	UK-CA	-	-
-	CA-AU	-	-

Table 8.10 Average ALL network coordination efforts per company at country level

Source	Target	Weight	Source	Target	Weight	Source	Target	Weight
UA	IE	39	DE	FI	9	AU	DE	5
IE	UA	38	FI	DE	9	DE	ZA	5
CA	CW	30	UA	FI	9	GR	EASIN	5
CW	CA	30	CW	US	8.57	CA	AU	4.9
SG	SG	17.50	FI	UA	8	DE	SG	4.8
AU	SG	17	SG	DE	7.67	DE	AU	4.72
SG	AU	17	AU	FR	6.39	AU	AU	4.5
SG	NL	14.33	SE	IE	6.31	SE	DE	4.5
NL	SG	13.67	IE	SE	6.25	US	EASIN	4.43
CA	US	13.35	SE	UA	6.25	EASIN	US	4.39
US	CA	13.24	UA	SE	6.19	EASIN	CA	4.35
US	US	13.23	CW	UK	6	CA	EASIN	4.31
AU	NL	13.13	UK	CW	6	AT	DK	4
CA	CA	12.28	FR	ZA	5.75	DK	AT	4
NL	AU	12	ZA	FR	5.75	US	UA	3.87
NL	CW	12	FR	AU	5.57	DE	SE	3.63
CW	NL	11.33	UK	UA	5.25	AU	NZ	3.5
DE	UA	10	UA	UK	5.25	NZ	AU	3.5
UA	DE	10	AU	CA	5.23	AU	US	3.45
US	CW	9.57	AL	US	5	SG	UK	3.38

Legend Only the (60) values double of the mean are listed in decreasing order.

PPH perfectly fits with data. Noteworthy, here too becomes clear that, especially in the high relevance of self-reference, operative coordination follows a different logic in the relationship between proximity and coordination efforts, respect with the other two forms of coordination (Tables 8.13a, 8.13b and 8.14).

Table 8.11 A simple categorization of sector proximity

VERY HIGH	HIGH	MEDIUM	LOW
SELF	C-M	C-K	ALL OTHERS
-	C-G	C-E	-
-	C-D	C-P	-
-	C-B	C-O	-
-	-	C-F	-

Table 8.12 Average ALL coordination efforts per company at sectoral level

Source	Target	Weight
C	C	14.627
B	B	14.455
G	G	14.419
J	J	13.771
H	H	9.668
B	C	6.358
C	B	6.353
M	B	5.652
B	M	5.522
B	H	4.545
H	B	4.545
K	K	4.488
C	K	4.251
C	EASIN	4.201
EASIN	C	4.180
B	G	4.118
K	C	3.979
G	B	3.895

Legend Only the (19) values double of the mean are listed in decreasing order

Organizational proximity. We measure this dimension of proximity with company size in terms of EM, TURN or its joint conditions over the four EC-defined categories: large, medium, small and micro.[18] In this view, very high proximity is when a

[18] Source: European Commission (2003).

Table 8.13a Propensity to (weighted) coordination across company size in ALL EASIN

Source	Target	Confirmation of standard theory
Large	Large	Yes
Large	Medium	Yes/yes
Large	Micro	Yes/no
Large	Small	Yes/no
Medium	Medium	Yes
Medium	Micro	No/yes
Medium	Small	Yes/no
Small	Micro	No/no
Small	Small	No
Micro	Micro	Yes

Legend There are double evaluations because most combinations involve two categories

Table 8.13b Average values of propensity

Source	Target	Weighted
Large	Large	5.611
Medium	Medium	0.988
Small	Small	8.077
Micro	Micro	0.852
	Average	3.305
Large	Medium	6.492
Medium	Small	6.093
Small	Micro	0.541
	Average	4.375
Large	Micro	4.852
Large	Small	7.058
Medium	Micro	4.601
	Average	5.503

Table 8.14 Mixing assortativity coefficients for organizational, geographical and sectoral proximity

	EM	TURN	EM and TURN	Geographical
All EASIN	0.188	0.286	0.195	0.674

connection ties companies in the same size category, like large-large, while maximum proximity is at the opposite extreme of the scale, like large-micro. We have calculated either the propensity to coordinate of each company or the correlation of the connectivity between these categories within the whole network.[19] This is a form of mixing assortativity, which we have measured in a categorical and numerical way.[20] Mixing assortativity is a sophisticated method that combines the topological and attributive dimensions, so to tell whether connectivity between nodes (companies, in our case) with the same attributes is high or low: assortative in the former case and disassortative in the latter.[21]

In order to better synthesize these results, we have done two further things, which can help testing the hypotheses concerning the proximity theory of inter-firm networks. Firstly, we have put an evaluation YES or NO in the right column of Table 8.13a, depending on the confirmation or rejection of the OPH. As it can be seen, confirmations prevail. Secondly, in the part b of those tabs, we have indicated the average values of propensity to coordination of all the four maximal and three middle and minimal combinations of proximity. Well, according to the OPH, we should find that the average value of propensity of highest and lowest proximity should be the lowest. This happens not so clearly for the EASIN network, where the average propensity grows from the highest to the lowest propensity. In sum, *so far the OPH did not receive a confirmation in terms of geographical and sectoral dimensions, while the alternative PPH did it, at least to some extent. Conversely, in terms of organizational proximity, the OPH has had a confirmation, though not fully and distinctively.*

Then, we decided to employ an analysis based on mixing assortative coefficients: our attributes correspond to those used to measure the three types of proximity: countries for the geographical, sectors for the technological and size for the organizational.[22] Before commenting the results of this analysis, it should be underlined that OPH requires that our networks be neutral or mildly disassortative, because the size attributes are distributed in a HT shape, as we showed in Chaps. 4–7. In fact, the highest coordination efforts are expected to be between near (but different) categories and the lowest between the same or very distant categories. Bearing this in mind, we can see that *in terms of geographical proximity, the OPH should be rejected, because EASIN is remarkably (0.6) assortative: that is, companies tend to coordinate preferably within their same country. This result confirms what we have obtained with the other method discussed above, which showed the high self-referential coordination especially of the US and the UK.*

The same conclusion can be drawn from the sectoral mixing assortativity coefficient (0.37), which is still positive, albeit moderately. This result too confirms the marked propensity of Manufacturing companies to coordinate among themselves, likely due to their US residence. As concerning organizational proximity too, mixing

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[19] As we have already warned in Chap. 4 about the correlations between economic size and centrality indexes, unfortunately we have relatively few data on neighbors' economic size, and those in our possession dramatically lower the role of large companies.

[20] See the section on assortativity in the Methodological Appendix.

[21] See (Newman, 2010) and the Methodological Appendix for more indications.

[22] In the following tab, we distinguished companies' size in terms of EM, TURN and joint criteria.

assortativity analysis leads to a rejection of OPH, though moderately, especially with respect to the geographical and sectoral proximity.

In sum, we can say that *the OPH, which represents the proximity paradox, should be rejected for EASIN, when proximity is considered in geographical, sectoral and organizational terms. It is rather inconclusive also when we include the neighbors. Moreover, in various cases, the alternative PPH seems to match data rather satisfactorily.*

8.8 Bank Centrality: Do Banks Play a Pivotal Role in Interlock Networks?

The literature review summarized in Chap. 2 evidenced that the idea that banks do play a central position in BINTs is widely shared. Actually, the majority of companies are dependent on external funding (Pye et al. 2014), especially when, like in the Aerospace Industry, investments can be huge for large and considerable also for medium-size companies. In these cases, banks can ask debtors to share a director or to appoint one of their own manager into the company's board, thus generating HINTs, the hybrid interlock form. Consistently, many studies on BINTs found an apparent dominance of banks and financial institutions, evidenced by their central positions in interlock networks (Allen, 1974; Scott, 1984; Farina, 2008; Musacchio, 2006; Caroll & Sapinski, 2011; and many more). In his study on 456 of Fortune 500 manufacturing firms in 1981, Mizruchi & Stearns (1993) discovered that "more than 70% of firms had at least one officer who sat on the board of financial institution". Such interlocks improve access to finance and lower its cost (Kroszner & Strahan, 2001; Mizruchi & Stearns, 1994; Richardson, 1987; Santos & Rumble, 2006). Additionally, representatives of financial institutions that do not provide funds may also bring expertise and certification, which may appeal especially useful to companies in distress (Booth & Deli, 1999; Byrd & Mizruchi, 2005). Further, important financial operators have a powerful relational capital with other financial operators or manufacturing or other types of companies, not to mention regulatory institutions or international/national/local government agencies. Therefore, being interlocked with the boards of financial operators allows to solve a lot of problems and access precious knowledge about "who knows what" or "who does what", because financial operators play the role of gatekeepers to strategic or operative resources, knowledge firstly. This relational capital is even more important in an industry like the Aerospace, which is globalized and strongly regulated by international institutions that are difficult to approach even for large companies and beyond any possibility for medium-small ones.

Close relations with banks may, however, backfire as financial institutions could abuse the control and subordinate the interests of the company to their own interests (Kroszner & Strahan, 2001; Richardson, 1987). Additionally, central banks often create indirect connections (Abdelbadie & Salama, 2019), that allow them to put additional impact on financial stability. Overall, this feature of interlock networks where banks and financial institutions are their focal points is best explained by Scott (1984), who interpreted it as "a common move towards bank hegemony of a loosely structured kind", which is in line with bank-control and bank-hegemony theories (Mariolis, 1975; Mintz & Schwartz, 1983, 1985).

Very peculiarly, sometimes the situation may also reverse, such as evidenced in Okhmatovskiy's (2005) study of Russian interlock network. In the aftermath of the 1998 financial crisis, Russian banks—previous leaders in converting public assets into capital—were unable to access foreign capital or even to aggregate the savings of wary householders. They yielded their centrality to giant industrial firms whose resource exports generated deep pools of capital, on which the banks themselves came to depend (Carroll & Sapinski, 2011). This is an extreme case, but still worth mentioning, to show that industrial production and its relation to finances may at times also largely depend on the political system and more local circumstances creating different forms of their inter-dependency.

Therefore, we decided to test against our data what could be called the Pivotal Finance Hypothesis (PFH), because, as discussed in previous sections and confirmed in this too, that conviction has been based on studies methodologically very different from ours: public or largest or listed companies crossing all sectors of a single or multiple countries. As we have extensively discussed in Chap. 2, these two differences can produce very different results, as it actually is the case for the LPH discussed in Sects. 8.5 and 8.6 of this chapter. Therefore, we are going to test this hypothesis in various ways by distinguishing the three different types of interlock and the bridging from the other companies, and also from two different perspectives: by focusing on the Financial sector as a whole, as well as on the single financial company's level.

The former way to measure the relevance of the Financial (K) sector is then looking at its centrality into the inter-sector network, discussed in Chap. 4. As we have seen, that network is a quasi-clique, where sectors have almost the same relevance. The K sector, however, appears to be the second most important after the Manufacturing, which prevails on all the others, because of its majority share of companies and large majority of weighted links. Moreover, we can see (Table 4.6 in Data Appendix) that the K sector has the second rank in terms of RWBc (BRWc and WRWc), that is, in terms of the capacity to intermediate *all* the flows of coordination knowledge. The same happens for BINTs and DINTs (department interlocks): the K is in the second rank.[23] So, we can give a first *weakly positive answer to the hypothesis of centrality of banks and other financial operators in the multi-layer network and in the strategic and operative knowledge coordination networks*. More specifically, though it is not the pivotal sector, it is the second one. Most likely, this shift from the first to the second position is just due to the presence of small-medium companies, which need less financial support than large ones, due to the bigger investments done by these latter.

By looking at the number and propensity to coordinate bridging companies (Table 8.15), we can measure the relevance of the K sector in a different way, which

[23] In some cases after skipping EASINT, otherwise it would be in the third place.

evidences more precisely the strength of individual (unitary) financial companies in this special group: even in this perspective, the Financial sector covers the second position. Therefore, the Financial sector is strategic also among those crucial companies that play the key-role of bridging clusters of companies: that is, *banks and other financial operators put themselves as the second type of companies in terms of capacity to connect large clusters of companies*. Noticeable, these companies are not necessarily big.

The third way to test the PFH is even the most significant, because it refers to HINTs that, as we have seen at the beginning of this chapter and in the previous chapter, play also a fundamental role into the bridging relationships. We found (Table 8.16) that *the companies of the K sector have the highest propensity to employ asymmetric coordination to appoint their managers into the board of other companies, that is to access their strategic knowledge in exchange of operative knowledge. This result evidences that actually the financial companies are mostly influential in the network of all the three forms of coordination*. The same table shows another interesting aspect: financial companies are also those that employ more intensively this asymmetric form of coordination among themselves.

In sum, *we can fully confirm the hypothesis that assigns a massive and strategic role to financial companies for the formation of a huge international network based*

Table 8.15 Number of bridging companies per sector and its propensity to coordinate in the ALL network

Sector	# of bridging companies	Propensity to coordinate
C	449	49.02
K	103	11.24
M	92	10.04
H	54	5.9
J	48	5.24
N	38	4.15
G	37	4.04
L	23	2.51
F	16	1.75
S	15	1.64
P	9	0.98
I	6	0.66
B	5	0.55
O	5	0.55
O	5	0.55
R	3	0.33
A	3	0.33
D	3	0.33
T	1	0.11
Q	1	0.11

Table 8.16 Propensity to asymmetric coordination (M2D) by sector

Sector	# of companies	Share (%)	BODcA	Prop.	WODcA	Prop.	BIDcA	Prop.	WIDcA	Prop.	IDB	Prop.	IDC	Prop.
A	35	0.79	15	0.429	191	5.457	7	0.200	105	3.000	29	0.829	54	1.543
B	12	0.27	6	0.500	21	1.750	8	0.667	53	4.417	2	0.167	4	0.333
C	2086	47.26	20	0.010	8791	4.214	21	0.010	3467	1.662	1460	0.700	2150	1.031
D	25	0.57	8	0.320	79	3.160	14	0.560	86	3.440	18	0.720	47	1.880
E	6	0.14	5	0.833	10	1.667	20	3.333	6	25.167	0	0.000	0	0.000
F	76	1.72	15	0.197	210	2.763	16	0.211	151	5.632	21	0.276	25	0.329
G	251	5.69	18	0.072	1065	4.243	16	0.064	428	1.606	26	0.104	31	0.124
H	127	2.88	15	0.118	535	4.213	13	0.102	403	0.386	48	0.378	48	0.378
I	26	0.59	10	0.385	70	2.692	9	0.346	49	53.231	6	0.231	6	0.231
J	199	4.51	15	0.075	522	2.623	16	0.080	1384	15.065	82	0.412	107	0.538
K	409	9.27	19	0.046	1889	4.619	19	0.046	2998	7.330	698	1.707	740	1.809
L	144	3.26	17	0.118	503	3.493	17	0.118	348	2.417	15	0.104	15	0.104
M	328	7.43	18	0.055	884	2.695	20	0.061	1911	5.826	160	0.488	173	0.527
N	198	4.49	17	0.086	626	3.162	17	0.086	912	4.606	52	0.263	55	0.278
O	5	0.11	4	0.800	9	1.800	3	0.600	57	11.400	0	0.000	0	0.000
P	31	0.70	11	0.355	42	1.355	12	0.387	115	3.710	4	0.129	4	0.129
Q	16	0.36	6	0.375	25	1.563	11	0.688	35	2.188	0	0.000	0	0.000
R	16	0.36	8	0.500	27	1.688	9	0.563	29	1.813	0	0.000	0	0.000

(continued)

Table 8.16 (continued)

Sector	# of companies	Share (%)	BODcA	Prop.	WODcA	Prop.	BIDcA	Prop.	WIDcA	Prop.	IDB	Prop.	IDC	Prop.
S	39	0.88	12	0.308	109	2.795	13	0.333	164	4.205	1	0.026	2	0.051
T	4	0.09	5	1.250	11	2.750	2	0.500	2	0.500	0	0.000	0	0.000
U	1	0.02	5	5.000	10	10.000	0	0.000	0	0.000	0	0.000	0	0.000
n.a	380	8.61												
Total	4414	100.00												

Legend prop. = propensity; A = absolute *on interlock coordination forms*. At least, this is what happens into the global coordination network activated by the EU28 Aerospace Industry.

8.9 Do Continental EU Countries Have Stronger Connection with the Financial Sector?

Some authors found that in some continental EU (CONEU) countries, namely DE and FR, companies have a BINT connectivity with banks and other financial operators much intensive than Anglo-American companies. In particular, taking seven sample years of BINT networks in Germany from 1896 to 2010, Windolf (2014) found that the average number of shared positions (weighted Dc links in our work) from banks to non-financial firms declined from 8 to 0.5 from 1928 (the peak year) to 2010. In those same years, network (normalized) density decreased from 16.2 to 1.2%, but it should be noticed that the samples were concerning only top 250–350 largest firms and banks. He concludes that, by 2010, the German corporate network is effectively dismantled, with little discernable difference between Germany and the US. This last finding seems very consistent with our findings, and, perhaps, our study suggests that, between those two countries, the relevance of the banking system within the BINT network reversed over time, showing a big transformation of the corresponding capitalistic development. A phenomenon that, according to our data, in France maybe did not occur or occurred to a much milder extent, because its Financial sector covers a relatively stronger position.

In a study of the top 300 European firms in 2005 and 2010, Heemskerk and colleagues (2013) found that "geography still plays an important role: there exist clear communities and they have a distinct national character". This is fully confirmed by our analysis, which shows that internal (self-link) propensity to BINT formation at country level is very high and often higher than that to external connectivity (see the inter-country network of EASIN in Sect. 6.5 of Chap. 6). They also provide many interesting analyses and findings, but, as we have noticed repeatedly for all the other studies, their comparison with ours is not worthwhile, because objects of investigation are too much different, for example, in this case, 300 largest cross-sector companies versus 3143 all-sizes companies of a single industry. There is not any reason why most findings should be consistent.[24]

In this perspective, DE and the US are taken as the paradigmatic types of cooperative and bank-driven capitalism in the former case versus the competitive capitalism in the latter. We tested this hypothesis in our dataset distinguishing BINT from DINT and HINT and as usual distinguishing binary and weighted connections. Due to the huge size difference between countries, we have run the test after normalizing the

[24] A further methodological problem comes from the criterion adopted to identify the top (usually 300, who knowns why not 200 or 500 or 1000 …) companies: some researchers chose capitalization index, some other equity capital, some other turnover, etc. So, especially when mixing sectors, the ranking and the sample's composition can vary a lot and makes results incomparable.

country size, so to get *the company propensity to connect*. Further, we articulated the test distinguishing the dataset with the sectors from another one obtained by selecting only the Manufacturing companies. Here, we summarize the main results,[25] while in Data Appendix we place the ranking of the early largest binary connections between countries and the K (Tables 8.3–8.7 in Data Appendix).

Let us start with BINT through binary (Table 8.3 in Data Appendix) or weighted connections. In terms of the number of connections, the K sector is in the third place in both rankings, but what is interesting is that these are K-K connections, that is, BINT established within the K itself: about 7000 links, activating 11,900 shared positions. In terms of propensity, the corresponding ranks lower to the 11th and 10th position: about 16 links and 27 shared positions. The first country with the highest financial BINT appears at the ninth place, and it is FR with 2637 binary links, followed by the UK with 2460 and the US with 1302. In weighted terms, FR and the UK invert their primacy: the UK is at the 6th place, while FR at the 13th. The IE and the US follow in both binary and weighted rankings, and DE does not appear among the early 100 pairs. If we turn to the calculation normalized per the number of companies in each country, the situation does not change significantly. Therefore, in BINTs between all the types of companies, the highest exchanges in which the K sector is involved are within itself. Then, there is FR as a continental EU (CONEU) country, but immediately followed by Anglo-American countries, and there is no DE between the early 50 exchanges. Hence, though with the remarkable exception of FR, *the hypothesis that there is a privileged BINT with K is not confirmed, while it could be argued just the opposite*. These results hold for both the binary and weighted versions and both in absolute and normalized versions. Because we are dealing with a sample of about 8000 companies—more than 20 times the size of previous studies—these results seem rather strong.

If we limit the test to only the Manufacturing sector, the results are even more unbalanced toward the Anglo-American countries, especially in binary and proximity terms, with the exception of a high rank of SE in terms of proximity. Therefore, *we can reject the idea that K-BINT connections are prevalent in the CONEU, while much less in the Anglo-American block*. This hypothesis could even be reversed. There could be three possible—and perhaps—overlapping explanations. The first one is what the other researchers found, that it was picturing the situation of many years ago and that in the meanwhile the strategies and structures of the industry network changed. The second explanation refers to a fact that we have underlined many times in this book: what happens at the top of the iceberg of listed companies can be definitely not representative of what happens in the middle-bottom part of the economy. The third one addresses once more to the biased samples of listed companies, that are typically cross-sectoral: it could be that an industry-specific sample leads to very different results.

We have extended the test also to DINT and HINT relationships. As for DINT (Table 8.4 in Data Appendix), there is a marked propensity of the US in weighted

[25] Notice that we have skipped the distinction between EASIN and neighbor companies, considering just countries and the K sector.

terms when considering either all types of companies or only Manufacturing. All in all, *the Anglo-American block tends to have stronger K-DINT links and, in any case, the CONEU does not prevail*, meaning that the ranking is mixed between the presence of the two blocks and other countries. Further, DE does not ever appear among the early 100 top connections and never among the top counterpart of the K sector. So, we should reject the original hypothesis.

The analysis is much more complicated for HINTs (Table 8.5 in Data Appendix), because here we should add also specification of direction of the coordination, then checking whether K sector is the exploiting or the exploited part. If we focus on binary absolute values, the highest exchange (773 links) goes from the US to the K sector, followed by the K sector exploiting FR (594 links), then IE exploiting the K sector (423 links) and at the fourth rank the K sector exploiting the UK. Then, with about half connections, do follow the US, the UK, FR and IT in various roles, and then other EU countries. If we turn the analysis to propensity, the first rank is made by IE (5.88), followed by SL, FR, BE and other EU and Anglo-American countries. Because in this type of coordination the weighted version is very similar to the binary,[26] nothing very much changes when considered is the weighted version. If we restrict the analysis to Manufacturing companies, the mix relevance of the two blocks is confirmed. Hence, even in this type of coordination, we cannot confirm the hypothesis of a major involvement of CONEU, though we cannot reverse it.

In general, from this whole analysis, we can underline that, between the most important countries of CONEU and even normalizing per the number of companies, FR is far more connected to the K sector than all the others, and DE is not among the strongest connected. In sum, *the supposed stronger BINT connectivity with the Financial sector found for largest (mostly listed) companies in many studies does not hold for the European Aerospace Industry and its neighbors, because Anglo- or North-American countries seem to be more intensively connected than the EU continental ones.* This result is consistent with the major propensity to employ interlock coordination with the 3–4 main sectors showed by the Anglo- or North-American countries, as we evidenced in the previous analysis concerning pattern similarity and the degree of complementarity between BINT and DINT coordination (Sects. 8.3 and 8.4, respectively).

8.10 Is There an Association Between a Company's Size and Interlock Coordination Propensity?

The literature on inter-firm collaboration and partner selection is vast and fast growing. It shows that there is a number of different criteria followed by managers to search for the alternatives and to make a choice of a fit partner. However, though some recent papers (Castaner & Oliveira, 2020; Fuertes et al., 2020) seem to support

[26] In fact, no one dyad is reciprocal and a company appoints only one or very few managers into the same other's board (to dig deeper, see Chap. 7).

the hypothesis that there is a statistical association between a company's size and its number of partners, this topic has not been explicitly investigated into MOS (Management and Organization Science). Actually, despite a partner's size might not be an intentional criterion, it could be that it results to be statistically significant, as it is underlined by Bishop (2003) in a study on the UK defense industry, which is particularly important for our study, because that industry is part of the Aerospace Industry and the UK is part of our dataset. On a sample of 356 companies, he found that size has a positive impact on the propensity to collaborate, especially for international collaboration. Unfortunately, Bishop does not specify what kind of collaboration was at stake, so we do not know whether interlock coordination forms have been considered part of it. Besides the lack of specific studies on this topic, it is clear that it is very important either for managerial practice or for the theory of inter-firm relationships, and even more for a deep understanding of interlock coordination.

In Chap. 4, we introduced this hypothesis calling it SPCH (Size Proportional Connectivity Hypothesis) discussing the correlation between company size and centrality indexes. Here, we summarize those results and integrate them with further methods. The rationale to test this hypothesis for our networks would be that building BINT or DINT requires a number of high managerial skills to select the right partners and then design, manage and evaluate those partnerships. Further, a partners' portfolio requires slack resources, advanced managerial culture and knowledge and likely also a good experience. Now, all these aspects are typical of large, or at least medium-size enterprises, thus suggesting that small or micro-companies can lack them and have only few passive relationships, likely as subcontractors of large companies. This idea seems to adapt also to the Aerospace Industry, with perhaps the warning that, due to its high-tech feature, it is possible to have also a significant number of small companies that can have a remarkable number of partners thanks to a very high level of technological specialization. Therefore, we expect that coordination propensity of small size companies is not very small, at least for DINT, where technical are supposed to be much more important than the strategic aspects.

The size attribute has been measured in terms of all the main economic variables: EM, EC, TURN and TASS. Coordination propensity is measured in terms of Dc, possibly accompanied with some other centrality index, so to have a wider view. However, we have to warn that, as we have already said in the section concerning organizational proximity, such results are harmed by the paucity of data about the size attribute, especially about neighbors and, between them, especially about American companies.

We can provide a first confirmation of the SPCH through the correlations between company size and centrality indexes discussed in previous chapters: *there are high positive coefficients with all most important (direct and indirect) indexes both in the EASIN and E + N networks, but especially in EASINT. Thus, we can answer positively to this hypothesis as concerning these two ALL networks*. The same positive answer into the same network is confirmed also by the following Tables 8.17a and 8.17b, which shows the company average propensity to coordination in each size class. It is apparent that, in EASIN of the ALL network, propensity declines with size, regardless of binary or weighted links, that is, regardless focusing only on

Table 8.17a Propensity to (binary) coordination by company size in ALL EASIN

Category	Links	# of companies	Propensity
Large	271	113	2.398
Medium	160	86	1.860
Small	106	85	1.247
Micro	150	122	1.229
All	687	406	1.692
Missing	149	464	–

Table 8.17b Propensity to (weighted) coordination by company size in ALL EASIN

Category	Links	# of companies	Propensity
Large	792	113	7.009
Medium	302	86	3.512
Small	166	85	1.953
Micro	224	122	1.836
All	1484	406	3.655
Missing	1035	149	–

each peer of companies or considering also the effort (intensity) of the coordination. Therefore, we can say that, *considering jointly all the three forms of coordination in the pure EU28 Aerospace Industry, the propensity to employ some form of interlock coordination varies with company size, precisely it grows with it.*

Moreover, if we distinguish the three forms of coordination, *the correlation between size and centrality for DINTs* (see the analogous correlations in Chap. 5) *has too a significant and positive coefficient for EASINT* but not for E + N, though nevertheless it is confirmed in the main component of the E + N network or if we consider the top 200 companies or only the Manufacturing or only the Aerospace companies, with a growing value of the coefficient. *For BINTs, correlations (see the analogous tabs. in* Chap. 6) *are moderately or even remarkably positive between almost all indexes and almost all size measures*[27] *in all kinds of networks*: EASIN, EASINT, E + N, E + N MC, top 200 companies and sectoral or industrial sets.

The relationship between size and coordination propensity is confirmed also for HINTs, because it shows positive coefficient for some combinations of size measure and centrality index, varying in relation to the type of aggregation. In synthesis, the most important combinations for this type of coordination form, namely those involving binary or weighted Out_Dc, are very positively correlated in EASIN with all size measures. Conversely, with the exception of Bc, no any combination between the two sets of parameters (centrality indexes and size measures) is correlated in E + N and in its MC, nor when selecting only the top 200 companies. There is some positive correlation in some combinations (especially with EM) in some (C, M,

[27] For all cases, we have measured size in terms of all the main economic attributes: EC, EM, TURN, TASS and sometimes also CF.

K) sector-based selection, and (rather strangely) not even when selecting only the Aerospace Industry companies. All other combination results are lowly negatively correlated.

In sum, *we can say that the SPCH is supported by our results for all the three types of interlock, especially concerning EASINT. For the extended network, instead, the confirmation is limited to some type of parameter and some aggregate.*

8.11 Is Companies' Interlocking Propensity Country/Size-Specific?

Considering that different countries do possess different legal and business regimes, it is reasonable to expect that they will also differ in their approach toward interlock coordination, especially in reference to the CONEU versus the Anglo-American block, and more precisely the UK.[28] Therefore, we tested also this hypothesis, which is confirmed, because *a company's propensity to coordinate is not only country-specific, but also size-specific across countries.* The results for this part of test (Tables 8.18a and 8.18b) show that companies' interlock propensity varies across countries in each type of interlock. In fact, the coefficient of variation is moderately high for EASIN countries, extremely high for the ALL, M2M and D2D extended networks[29] and moderately high for M2D for the extended network. Indeed, as it can be seen from the section of the inter-country networks in Chaps. 4–7, on this variance the primary influence comes from the US companies into the Manufacturing sector. If we cut the US, the coefficient of variation would be moderately high also for the extended network, aligned with that of EASIN.

The second part (Table 8.19) of this test concerns a further specification of the previous question, by investigating if there are also differences across countries in the companies' propensity related to their size and in the mix among the three types of interlock. Because we have few data on neighbors' size, we limited this analysis to only EASIN countries. Further, to shorten the analysis, let us focus only on few countries and coordination efforts (weighted propensity), which actually is more important than the binary propensity.

The main difference is between DE and the other three countries in terms of average propensity in the "Large company" category: that of DE is more than double of FR, four times of the UK and ten times of IT. Another sharp difference is still between DE and the other three countries concerning the type of coordination: its company's propensity to strategic coordination is 24, while in the others varies from 1.5 of IT to 3.16 of the UK. Further, this result is obtained by DE due to the presence of only large companies engaged into this type of coordination. *It seems, therefore, that German companies are committed to BINTs much more than the other three*

[28] We remind that, because of too few and distorted sample data, we cannot run this analysis also on the US.

[29] Indeed, it is even higher, because here we have calculated it only on the early 20 countries.

Table 8.18a Statistical parameters on countries' propensity to coordinate

		EASIN			EASIN + NEIGH		
		# of (weighted) links per company			# of (weighted) links per company		
		Internal links	External out-going	Total links	Internal links	External out-going	Total links
ALL	Average	2.12	1.42	3.62	104.32	74.24	179.16
	Std. Dev	1.94	1.76	2.93	357.83	226.54	436.96
	Coef. of Var	0.92	1.24	0.81	3.43	3.05	2.44
M2M	Average	8.29	2.49	10.78	87.48	55.76	143.23
	Std. Dev	18.65	5.25	22.51	332.72	199.61	400.63
	Coef. of Var	2.25	2.11	2.09	3.80	3.58	2.80
D2D	Average	1.24	2.44	3.68	22.62	16.72	39.33
	Std. Dev	0.92	6.08	5.78	32.41	32.26	46.60
	Coef. of Var	0.74	2.49	1.57	1.43	1.93	1.18

Legend Std. Dev. = standard deviation, Coef. of Var. = coefficient of variation

Table 8.18b Statistical parameters on countries' propensity to HINT coordination

	EASIN				EASIN + NEIGH			
	# of (weighted) links per company							
	IDW	EODW	EIDW	Total	IDW	EODW	EIDW	Total
Average	0.27	0.64	0.42	1.05	1.57	1.97	2.56	5.15
Std. Dev	0.24	0.97	0.46	0.91	1.43	2.10	2.62	2.36
Coef. of Var	0.90	1.52	1.09	0.86	0.91	1.07	1.02	0.46

Legend Acronyms explained in the list of abbreviations. Std. Dev. = standard deviation, Coef. of Var. = coefficient of variation

EASIN countries, and they pursue this goal with only large companies. DINT is adopted with major propensity by French companies (5.62), followed by German companies, and in both cases, the higher effort is concentrated into large companies: a propensity of 17 for DE and 8 for FR. Therefore, *it seems that these two countries are more capable to establish and diffuse the technical and commercial standards to the whole EASIN*. Finally, French companies are the most oriented to adopt HINTs, while the British are the least oriented. All in all, it seems that, *when considering EASIN as a closed system, that is without counting the links with its neighbors, FR and DE are the most engaged into interlocking coordination efforts, with DE particularly committed to strategic and FR to operative knowledge coordination.*

Table 8.19 Company's coordination propensity in main countries

		ALL		D2D		M2M		M2D	
Country	Size	PropB	PropW	PropB	PropW	PropB	PropW	PropB	PropW
UK	Large	2.35	5.81	1.75	3.35	2.04	3.15	0.25	0.25
UK	Medium	2.45	6.05	1.85	3.50	2.45	3.05	0.50	1.00
UK	Small	1.69	3.31	1.78	2.44	1.42	1.75	0.00	0.00
UK	Micro	2.55	5.27	2.00	2.67	2.50	3.40	0.00	0.00
–	Average	2.29	5.35	1.83	3.16	2.12	2.91	0.23	0.31
FR	Large	2.65	9.22	2.38	4.00	2.28	8.00	1.44	1.78
FR	Medium	1.00	1.44	1.17	1.17	1.00	1.50	0.00	0.00
FR	Small	1.14	1.86	1.33	1.33	1.00	1.60	1.00	1.00
FR	Micro	2.50	3.00	1.00	1.00	2.50	2.50	0.00	0.00
–	Average	2.02	5.95	1.87	2.78	1.90	5.62	1.17	1.42
IT	Large	1.88	2.75	1.00	3.00	1.50	2.13	1.00	1.00
IT	Medium	1.57	3.43	1.00	1.00	1.67	3.67	0.00	0.00
IT	Small	1.44	1.78	0.00	0.00	1.44	1.56	1.00	1.00
IT	Micro	1.54	2.04	1.00	1.00	1.54	1.96	0.33	0.33
–	Average	1.58	2.29	1.00	1.50	1.53	2.12	0.63	0.63
DE	Large	2.57	20.71	3.00	24.00	2.29	17.00	1.00	1.00
DE	Medium	1.63	3.13	0.00	0.00	1.63	2.75	1.00	1.00
DE	Small	2.00	2.25	0.00	0.00	2.00	2.25	0.00	0.00
DE	Micro	1.37	1.58	0.00	0.00	1.33	1.56	1.00	1.00
–	Average	1.71	5.50	3.00	24.00	1.65	4.81	1.00	1.00

Legend PropB = binary propensity; PropW = weighted propensity

8.12 Summary

Companies with a marked bridging role use HINT coordination ten times more than the other companies, meaning that they attempt to access knowledge from strategic groups and clusters without giving in exchange knowledge of the same relevance. This happens more intensively into the pure EU28 Aerospace Industry; asymmetric coordination is used, in the majority of cases, to access knowledge from clusters of companies in a proportion that is almost double of that related to the extended network.

Due to their minor direct rivalries respect to the EU28 Aerospace Industry, interlock coordination of strategic and operative knowledge between neighbors occurs strictly between companies with the same degree of connectivity. Conversely, because less heterogeneous than their neighbors and, thus, more at risk of giving precious knowledge to close rivals, EASIN companies are more available to establish BINTs and DINTs with different degrees of involvement, especially in the latter case. Conversely, hybrid coordination in the extended network tends to occur between mostly exploiters and mostly exploited companies, thus showing a clear role, especially between companies into the main component.

In both EASIN and the extended network, there are groups of super-connected and super-similarly-patterned companies, which correspond to those belonging to the largest cliques, and a plethora of poorly connected companies, which have extremely different patterns of connection. Interlock coordination patterns of BINTs are more homogeneous than those of DINTs, while HINT patterns have an intermediate degree of similarity. This difference between the three forms of interlock coordination suggests that operative knowledge is much more firm-specific than strategic knowledge. Anglo-North-American companies are mostly influencing these high levels of similarity of interlock coordination patterns, because lower significantly in EASIN or in the main component of the extended network, where they are not very represented.

Interlock coordination between two companies occurs often by establishing both BINT and DINT, thus considering them rather complementary, while the coexistence of one of them and HINT is much less frequent, and indeed, it never happens into the very core part of the main component of the extended network. Likely, if a company appoints one of its managers into the board of another, then this effort is considered enough to access the required knowledge. Likely due to the heavy presence of Anglo- and North-American companies, which are better skilled to build partnership than continental EU companies, the coexistence of BINT and DINT coordination is much less frequent between EASIN companies.

When concerning operative knowledge coordination or the neighbors companies regardless of the type of knowledge coordination, the CPAH (Centrality/Performance Advantage Hypothesis) suggested by the SNA central tenet is not confirmed or maybe should be even reversed, while it can be confirmed in reference to the EASIN strategic knowledge coordination. At a closer sight that distinguishes companies in terms of ranges of direct connectivity, the opposite view (the LPH), according to which BINTs weaken a company's performance by lowering its motivation to be competitive and market efficiency, has received a clear evaluation only in relation to the PM index. This hypothesis should be rejected (and thus, CPAH confirmed) for both EASIN and its neighbors, because PM does *not* decrease with BINT connectivity and grows with DINT connectivity, thus suggesting that in this latter case it should be reversed. Therefore, DINT connections provide even more performance advantages than BINTs. These findings show a picture consistent with the KBV to interlock coordination that we have assumed in our work. In terms of ROE and ROCE and for HINTs, test results are contradictory, though they seem to indicate a weak confirmation of the LPH.

Our analysis of the relationship between proximity and coordination efforts provides a plenty of results, distinguished in terms of geographical, sectoral/technological and organizational proximity. For the first two types of proximity, results show a clear rejection of the OPH (Optimal Proximity Hypothesis), because the highest intensity of interlock coordination was when proximity is very high, thus confirming the alternative PPH (Proportional Proximity Hypothesis), which supposes that firms, especially in high-tech industries, tend to minimize risks of unsuccessful or inefficient efforts and therefore engage more efforts when proximity is high. As concerning the geographical proximity, it seems that interlock coordination is higher also when it is very low, thus suggesting a third (nonlinear) hypothesis of a U-shaped relation. Concerning organizational proximity, results are contradictory, depending on the type of methods employed. The more sophisticated method—the mixing assortativity—leads to moderately reject the OPH and support the PPH, while the semi-qualitative method reverts these findings.

The PFH (Pivotal Finance Hypothesis), which assigns a strategic role to financial companies for the formation of a huge international coordination network based on BINTs and DINTs, is moderately confirmed by our results. In fact, though never at the first place, financial companies are systematically at the second position in terms of direct or indirect centrality in each inter-sectoral network, and they are also those more often playing the role of bridging companies. Finally, more often than others, they employ the asymmetric coordination form, though more among themselves than with other sector companies. Hence, our work confirms what has been found by previous studies.

As concerning the supposed stronger BINT connectivity with the Financial sector of continental EU countries, and especially Germany and France, respect to the Anglo- or North-American countries, we can say that it does not hold for the European Aerospace Industry and its neighbors, because, with the exception of France, the latter block of countries seems to be more intensively connected with the Financial sector than the former. This result is consistent with the major propensity to employ interlock coordination with the 3–4 main sectors showed by the Anglo- or North-American countries, as we evidenced in the previous analysis concerning pattern similarity and the degree of complementarity between BINT and DINT coordination (Sects. 8.3 and 8.4, respectively).

Considering jointly all the three forms of coordination in both the pure EU28 Aerospace Industry and its extended neighbors' networks, the propensity to employ some form of interlock coordination varies with company size, namely it grows with it. In fact, the SPCH (Size Proportional Connectivity Hypothesis) is supported by our results for all the three types of interlock, especially concerning EASINT. For the extended network, instead, the confirmation is limited to some type of parameter and some aggregate. However, when the three forms of coordination are distinguished, the positive relationship still holds for most of the inter-departmental, all the inter-board, but only some (and limitedly to few combinations) of the asymmetric interlock coordination networks. When considering EASIN as a closed system, that is without counting the links with its neighbors, FR and DE are the most engaged into interlocking coordination efforts, with DE particularly committed to strategic and FR to operative coordination. The hypothesis of a positive relationship between company size and coordination propensity is supported by our results, especially concerning the integrated version of EASIN.

We also found that a company's propensity to coordinate is not only country-specific, but it is also type-of-coordination-specific across countries: for example, German companies are committed on strategic knowledge coordination much more than the other three EASIN countries, and they pursue this goal with only large companies. Further, FR and DE are more capable to establish and diffuse operative knowledge to the whole EASIN. More generally, when considering EASIN as a closed system, that is without counting the links with its neighbors, FR and DE are the most engaged into interlocking coordination efforts, with DE particularly committed to strategic and FR to operative coordination.

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Chapter 9
Conclusions

An unavoidably complex analysis. One can wonder if it was necessary to conduct such a complicated analysis as that realized in this book, which can be summarized as follows: (i) a statistical analysis of all the companies of the EU28 Aerospace Industry; (ii) a statistical and network analysis of four different aggregates of connected companies; and (iii) binary and weighted versions of the three types of interlock coordination (DINT, BINT and HINT), each type generating a specific network topology, plus the multi-layer network obtained by considering them all together, with its corresponding topology. The four different networks are the following: (1) the companies connected among themselves within the EU28 Aerospace Industry; (2) those connected also or only with the neighbors; (3) the entire set of the EU28 Aerospace Industry and its neighbors; and (4) the main component of the whole network. We answer that such complexity is necessary in this type of research, because there are sharp differences between characteristics of each network, further depending on the type of link (interlock) and on the pure structural (the binary version) or the weighted dimension. For example, only a very small share (between 5 and 10%) of the EU28 Aerospace Industry employs interlock coordination among themselves, but that share about doubles when considered are also interlocks with neighbors. Further, the distribution of economic relevance by countries does not keep identical between the first and the second network, and even less when including also the isolated (not connected) companies. Moreover, the inclusion of neighbors—which we have limited only to the first step neighbors—generates a true phase transition in the density of all networks and noticeable structural transformations, in each type of interlock coordination. Such changes are even more accentuated when focusing on the main component of the extended network, which actually contains most of the largest companies and connections.

Board interlock is a very diffused form of coordination. The acknowledgment that firms—and more generally, any kind of organization—interact and coordinate their behaviors not only through prices or quantities is all but new. It is also well known that such forms of coordination include also sharing a director between two or more companies. To the previous knowledge, this book adds that board interlock is

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employed much more extensively than what had been believed so far. In 2019, out of the 3143 EU28 Aerospace companies employing about 894 thousands individuals, 307 companies have established 600 connections of this type among themselves, a number that raises to 748 when considered were also those with their neighbors (interlock partners) outside EU28 or outside the Aerospace Industry, consequently issuing 12,272 board interlocks. Moreover, those 5043 neighbors established among themselves 244,744 connections: all these are very high numbers, if compared with previous researches. Where does this difference come from? It comes from two original methodological choices we have employed, that distinguish our work from all the previous ones within this field: considering all limited liability companies of a single industry, instead of only the largest (usually listed or public) companies across all sectors. Implicitly, it means that, though the number of board interlocks varies with the size of those companies, this type of coordination is not exclusive of the largest companies.

Department interlock revealed to be by far the most diffused form. Out of the 3143 EU28 Aerospace companies, 471—much more than those employing board interlock—issued 904 connections, which became 18,670 when involved were also the neighbors established by 1181 companies of the EU28 Aerospace Industry. It could be argued that this type of coordination is peculiar of our specific object of analysis, but it is not so, because when considering only the connections among the almost 5800 neighbors, they reach the huge amount of almost 283 thousands. Therefore, the lack of department interlock coordination was a big hole in the scientific literature developed so far, and this work opens a new promising research stream that will substantially increase our understanding of inter-firm relationships. If the relevance and diffusion of inter-firm interlock coordination has been so far rather underestimated, in our study, perhaps, it is instead overestimated, likely due to the fact that it is reasonable to suppose that department interlocks are more relevant and diffused in high-tech industries, like the Aerospace. However, our findings show that the neighbors, which are distributed through all the types of sectors, have higher propensity to establish interlock coordination when compared with the EU28 Aerospace Industry. They concern, with a far larger presence of the Manufacturing (including non-EU28 Aerospace) sector, also the Professional Activities, the Financial and the ICT sectors. Future empirical researches in other industries, both low- and high-tech, will confirm or reject this conjecture.

Despite over-boarding and over-departmenting, a huge number of shared managers and shared directors is involved. The surprisingly high numbers of board and department interlocks are due partly to the role played by strategic and business groups, where a leading or a mother company appoints a director and/or a manager into a board (or a department) of its subcontractors or subsidiaries, thus multiplying the number of links and shared positions. We can see this aspect through the phenomenon of “over-boarding” and “over-departmenting”: almost 90 managers coordinate more than 110 operative positions each and 10 directors seat in more than 110 boards, out of whom one is member of 256 and another of 153 boards. Further, a share of connections and shared positions is likely due to director and manager mobility, which makes them appearing in two companies while they actually migrated from one to the other, thus not building a true interlock. We tried to consider this aspect in our dataset, but we cannot exclude some residual cases of false connections. Another way to look at the huge size of interlock coordination devices employed in our empirical case is by considering the pure number of directors and managers involved. In the extended (E + N) network combining the three distinguished networks, there are 7344 individuals, out of which 6272 are managers and 1710 are directors.

A multi-faceted heavy-tail interlock network. When considering the phenomenon of "over-boarding" and "over-departmenting", the number of connections is not more so overestimated. However, 83% of coordinators have only one or two positions, thus showing that they are distributed in a scale-free form. Indeed, almost all topological and economic variables that we treated in our study are shaped in such a way or at least in a clearly heavy-tail form. Therefore, from any of the possible angles from which we can look at this big industry and its neighbors, its topological and economic structure is shaped in an irregular way. This fact has a number of conceptual, methodological and epistemological implications that only very recently have started to be understood (Biggiero, 2016, 2022; Taleb, 2007). In practice, it means that relatively few elements keep the most mass of a phenomenon, but the large majority is all but irrelevant either statistically or structurally, thus making it rather resilient. The EU28 Aerospace Industry and its neighbors—either taking separately or jointly—fully show such a statistical and structural property.

The hybrid board—department interlock. The relevance of the hybrid form of interlock, which allows a manager sitting in a board of another company, is also an interesting discovery and, though quantitatively residual, it is extremely interesting, because in our study it revealed to be characterizing crucial companies from a positional perspective. Relatively to the other two types of interlock coordination, they cover more bridging roles by connecting entire clusters of companies and involve the Financial sector more extensively. While board and department interlocks are usually treated as symmetric relationships, because they are established by people who cover the same position in both companies, the hybrid board-department interlock has an inner asymmetric nature, because it potentially exchanges strategic for operative knowledge, so that the company appointing its manager into the other company's board gains a potential advantage. The former is the knowledge exploiter and the latter the knowledge exploited company. We have shown that, actually, this case is particularly diffused among the bridging companies, those that behave as gatekeepers to convey or draw strategic knowledge flows to/from clusters of companies: bridging companies use hybrid interlock coordination 10 times more than the other companies. We have found also that, among financial companies and between them and other non-financial companies, this type of coordination is much more diffused than average. This is consistent with previous literature on board interlock, which often did not make any distinction between board and hybrid interlocks, because the position covered by a "coordinator" in a bank was overlooked. Focusing on the relationship between the EU28 Aerospace Industry and the Anglo-North-American block, we have seen that this latter plays mostly the exploiter and the former the exploited role.

The Anglo-North-American and the European block. Strictly related to this aspect is another important finding, which contrasts with previous expectations: the Anglo- or North-American companies employ interlock coordination much more and not much less than the continental Europe ones. Further, these latter, with the exception of France, establish board interlocks with the Financial sector less intensively than the former. We do not know whether these two findings are peculiar of the Aerospace Industry or of any high-tech industry or mark a discontinuity common to all industries respect to the past, but whatever is the case, they are rather remarkable. When considering the whole network of all the three forms of interlock coordination—board, department and hybrid—occurring in the EU28 Aerospace Industry and its neighbors worldwide, the Anglo- or North-American block is dominant, much more than the European block. The US appears to be very influential, but not much more than the second most influential, which quite surprisingly is Canada (30%), almost fully oriented toward the global market, then followed by the EU28 Aerospace Industry (9%), the UK (6%) and others. These shares are net of interlock coordination occurring between companies within each country, because otherwise the share of the US would be much larger. Actually, internal interlock coordination is, with few exceptions, much more intensive than that with foreign companies. Interestingly, the degree of closure is extremely variable across countries and it is positively but very lowly (if any) correlated with all the other variables, including the number of companies and the total number of internal links.

Interlock coordination forms as knowledge flows. Board interlocks are a complex phenomenon, because they have many different causes and effects, as it is witnessed by many research streams that have dealt with it for more than 100 years. Our conceptual choice was considering that, regardless of purposes and beyond intentions of people who establish them, they convey knowledge, namely strategic knowledge. Mostly in tacit form, which is more typical of relational and individual-mediated communication, but also channeling documents and other forms of explicit knowledge. We have treated in this view also the other two forms of interlock coordination: the department interlock, which conveys more operative knowledge, and the hybrid department-board interlock, which potentially allows the asymmetric exchange of operative vs. strategic knowledge. In this perspective, the 357 thousand interlocks occurring in the EU28 Aerospace Industry and its neighbors worldwide represent as well channels of strategic and (in our industry case mostly) operative knowledge creation, sharing and transfer. Our study shows that the Anglo-North-American block dominates the flow among the interlock partners (neighbors) of the EU28 Aerospace Industry for both kinds of knowledge, with a primary place within that block, namely between the US and Canada reaching an interlock coordination effort of more than 100 thousand shared positions. If considering only the direct interlock with the EU28 Aerospace Industry, that block holds more than 25,000 shared positions, a considerable number of channels for knowledge creation/sharing/transfer.

Interlock forms as substitutes or complement. We attempted to understand whether the three forms of interlock are substitutes or complement to one another, and we have found that while board and department interlocks tend to coexist in more than half partnerships, the hybrid form is mostly substitutive of one or the other. Likely, if a company appoints one of its managers into a board of another, then this effort is considered enough to access the required knowledge. The complementarity between the other two forms reduces by one third in the EU28 Aerospace Industry, likely due to a lower propensity of its companies than the North-American ones to employ interlock coordination forms. Such a sharp difference emerges in many ways throughout all the analyses, and we argue that it could significantly depend on more advanced managerial skills in implementing successful inter-firm collaboration of the North-American respect to the European companies. This would add to the previous differences between the two blocks that we have above underlined. However, this is only a conjecture that should be confirmed or rejected by future research.

Two types of neighbors in relation to the two geocultural blocks. Actually, there are two types of neighbors, depending on whether they operate within the main component or minor components, that is, the super-cluster of all connected companies or other (much) smaller clusters. The former is dominated by a major diffusion of Anglo- and North-American companies, with a minor weight of the continental EU countries, and reverse for the latter. Because we know that, into the main component, the knowledge conveyed through interlock coordination flows much easier and more extensively than into minor components, and because companies of the main component are on average bigger than the others, this difference of composition between the two blocks of the continental EU and the Anglo- or North-American assumes a crucial relevance. It also helps to formulate hypotheses that put formation of the huge cliques and the high self-reference in the propensity of coordination in relation with different institutional-organizational contexts characterizing the two blocks.

The main types of interlock partners. Let us now wonder between which companies an interlock coordination tends to be established in terms of its intensity. Well, our analysis has shown that, in the Aerospace Industry, the economic and technological structure strongly influences companies' propensities to employ this type of coordination. Besides the knowledge growth provided by the description of the various interlock networks and the outcomes of hypotheses tests, this is a central and original theoretical contribution of our work to the scientific advancement in this field. In a high-tech industry like this one, where strategic and operative knowledge is very crucial factors of competitiveness, leader companies—that is, main contractors or system integrators or technological leaders—tend to avoid direct trade or R&D relationships, to the aim of preventing risks of inadvertently giving away some precious chunks of technological, market or managerial knowledge. Therefore, with few exceptions, strategic and operative connections rather seldomly occur between those types of companies, which are almost always also the large and highly connected ones, though some of these latter are just large suppliers. Now, the key point which we have found is that such selective preference to connect holds also for the propensity to employ interlock coordination. More precisely, moving from the industrially and technologically most heterogeneous aggregate—the network including all neighbors—to the least heterogeneous aggregate—the network corresponding to the pure EU28 Aerospace Industry, leader companies tend to dramatically reduce their propensity to interlock among themselves. Moreover, their shifting toward interlock coordination with lowly connected companies, which means also smaller size companies, is even more accentuated for department interlock, thus suggesting that, where operative knowledge is so important like in the high-tech industries, department interlock tends to occur more frequently and intensively between companies that are different in terms of size and propensity to interlock.

Cohesive interlock clusters. Even considering together all the three forms of relationships, coordination is established within a huge number of separate groups, whose largest majority is made by just a few of companies, but few of them are huge. What characterizes the whole multi-layer network is an astonishing number of cliques in the extended network and also in its main component. Operative and strategic knowledge coordination through shared managers and directors occurs by means of fully cohesive groups, some of which are very big: for example, 6% (253) of companies in the main component, which contains 51% of companies and 89% of links of the whole multi-layer network, are fully reciprocally coordinated through a mix of (mostly) department and (secondarily) board interlock. They share the same strategic and operative knowledge conveyed through shared managers and directors, and supposedly, they strictly coordinate their strategic behavior. The size distribution of cliques explains the size distribution of components, thus confirming that the formation of strategic and operative groups is the fundamental process that drives the structuration of the whole industry. Companies of large cliques are not only mostly structurally equivalent, but they are also extremely homogeneous in sectoral and geographical terms, thus reinforcing the idea that they are very strong strategic and operative groups, where knowledge is created and transferred very easily, due to common languages and technological similarities.

Strategic and operative knowledge generates a different distribution of interlock clusters. By far, the largest share (46%) of the main component over the extended network occurs in department interlock, meaning that the need of operative coordination due to technological aspects generates a positive network externality in creating and transferring codes and standards through shared managers among technological departments. Conversely, the network with the lowest relative (and also absolute) size of the main component (15%) is that of board interlock, likely because sharing strategic knowledge cannot be too much extended without taking high risks of favoring your competitors. We argue that the degree of knowledge relevance matters: when it is very high, companies prefer to keep it more restricted, thus limiting the number of their interlock. Consequently, at network level, the size of the main component will be smaller and the knowledge flow fragmented into a number of small groups (disconnected components). This explains the extremely high fragmentation of both the pure EU28 Aerospace Industry network and the network extended to include its neighbors. Noticeably, the hybrid board-department interlock generates a network very different under almost all respects from the other two types of interlock. It is much more fragmented and lacks reciprocal connections, large cliques and strong cliques, suggesting that the corresponding knowledge is very important and that the specific relationship built on it is a fact between two companies, closing the access to others. These hybrid interlocks can form even considerably large clusters, but they appear to be as “hierarchical forests”, that is, sequences of asymmetric links or a collection of small stars, having at the center a strong exploiter or a heavy exploited company: predators and preys.

Interlock connectivity varies with company size. We have just above mentioned that the largest are also the most connected companies. This is also an interesting result obtained by testing the hypothesis that the degree of interlock connectivity varies with company size, expressed through the number of employees or turnover. This confirms once more that all the previous empirical studies on board interlock explored only the top of the iceberg, while they overlooked the plethora of small-medium companies that have interlock relationships not only with the large companies, but also among themselves. That neglect implies not only a dramatic underestimation of the phenomenon, but also a substantial distortion of the whole topology, and even of the subnetwork regarding the large companies, because, as it happens in our research object, they are very much indirectly connected just through the lowly (and small size) connected companies. Hence, board, department and, to a less extent, hybrid interlock is a business not limited only to large companies.

Interlock centrality is nonlinearly and positively associated with business performance. We have also found confirmation of the central tenet of Social Network Analysis, namely that topological centrality is positively associated with better business performance. However, the relation is nonlinear and very much depends on the degree and the selected index of connectivity on one side and on the selected index of performance on the other side. In our case, degree centrality and profit margin revealed to be significant, while other types of centralities and ROE or ROCE are not significant. Interestingly, this holds for both board and department interlock, especially strong for the latter type, but no any association has been found for the hybrid form. This seems to be a further clue of the high-tech feature of the industry, which makes operative knowledge a fundamental factor of competitiveness. Moreover, industry structure matters again, especially in terms of companies’ heterogeneity: the correlation is stronger when heterogeneity is lower. Likely, this relation is also very much depending on two fundamental aspects: a) focusing only on the largest (or listed) companies or, vice versa, including all limited liability companies; b) being cross-sectoral or, vice versa, industry-specific. These three aspects—nonlinearity, company size and industry specificity—could explain why the previous studies have been so far inconclusive to find precise and sound relations between board interlock connectivity and economic-financial performance. Further, the high-tech nature of the Aerospace Industry, where the creation and sharing of operative knowledge is so crucial for a firm’s competitive capacity, justifies our theoretical choice of considering knowledge flow as a fundamental aspect—albeit not necessarily always intentional—of interlock coordination. This acknowledgment suggest to reconsider the prevalent view in standard economics, according to which the collusive nature of this—and of any kind of—inter-firm agreement reduces a firm’s profitability due to a minor pressure on its competitiveness. To some extent, this positive relation between interlock connectivity and profitability questions also the rationale of the corresponding antitrust legislation, though here the issue would require further specific deepening.

Interlock coordination and proximity. We have tested also whether there is a relation between propensity to establish any kind of interlock coordination and degree of proximity between two or more companies, distinguished in terms of geographical, sectoral/technological and organizational proximity. As concerning the geographical proximity, we have found no evidence of a positive proportionality between the two or an optimal inverse U-shaped curve, which would enhance interlock coordination forms at an intermediate level, as suggested by the "proximity paradox". Conversely, we have found clues of a U-shaped curve in which the more intensive coordination effort is made preferably with the lowest and highest proximity, though for very different reasons. The sectoral/technological proximity seems to influence interlock propensity through a positive relation: the less heterogeneous the sectors, the easier it is to establish some interlock coordination, which reaches the highest level when companies operate precisely within the same sector. As it can be seen, the aspect of industrial heterogeneity still keeps very important to explain our results on interlock choices. Likely, it could be that relation is nonlinear too, but we did not deepen the matter. Finally, a similar result occurs in terms of organizational proximity, which is rather robust because, despite limited only to the pure EU28 Aerospace Industry network (due to scarcity of data for the neighbors), it has been obtained by applying different methods.

The role of the Financial sector. We have tested also whether the Financial sector would be the most important partner for building interlock connections. We found a partial confirmation of this role for board and department interlocks, because, though the Financial sector is not at the first place of the partners' list, but in the second one, and though there is a considerable distance from the primary partner, which is the Manufacturing sector, however it covers the second position also in terms of its capacity to intermediate knowledge flows across the whole network. This means that financial companies have a strong advantage in accessing strategic and operative knowledge conveyed through interlock relationships not only with direct connections, but also through intermediary power. Likely, previous studies found that the Financial sector was at the first place, because they analyzed only largest companies, which perhaps are more indebted with that sector than the small-medium companies are. Moreover, it is possible that some of those studies did not distinguish hybrid relation from the board interlock. In fact, even in our research object, the financial companies have the highest propensity to employ asymmetric knowledge coordination, that is, to access strategic knowledge in exchange of operative knowledge.

No remarkable differences of the two geocultural blocks in building interlocks with the Financial sector. Unlike a wide belief in specialized literature on board interlock and corporate governance, we did not find evidence that continental EU has a higher propensity than Anglo-American companies to build interlock connections with financial companies. In fact, with the noticeable exception of France, Anglo- or North-American companies seem to be more intensively connected than the EU continental companies. In this case, it is possible that, besides the usual factor of considering all the limited liability and not only the largest or listed companies, what could make a difference with previous studies is a change in the economic structure of the EU countries during last decades. This fact could have characterized especially the Euro Zone member countries, which indeed, with the noticeable exception of the UK, are at the same time the most important countries of the EU28 Aerospace Industry.

Country differences in companies' propensity to interlock by size and in preferring interlock forms. Companies' interlock propensity dramatically varies across countries in each type of interlock, though much less within the EU28 Aerospace Industry than within neighbors. Actually, the huge manufacturing clusters formed by the North-American companies increase very much the value of company's propensity. Deepening the analysis to the combination of "interlock mix" between the three forms and of the influence of companies' size that employ it, we had to limit it to the EU28 Aerospace Industry, because of the scarcity of attributive data of its neighbors. We found that German companies are much more oriented to build board interlock than Italian, French or British ones. Further, this result is due to the presence of only large companies engaged in this type of coordination. Conversely, department interlock is adopted with major propensity by French companies, followed by German companies, and in both cases, the higher effort is concentrated in large companies, showing that those two countries are more capable to establish and diffuse the technical and commercial standards in the whole EU28 Aerospace Industry through interlock coordination. Finally, French companies are the most oriented to adopt the hybrid form, while the British are the least oriented.

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Methodological Appendix

A.1 Data

The data for the book on interlocks of people have been collected from ORBIS Bureau van Dijk, that has been regarded as reliable data source by number of authors (Compston, 2013; Heemskerk et al., 2016; Vitali et al., 2011). It consisted of a company's attributive data, such as name, industry (NACE code), country of origin, economic attributes information (equity, capital, turnover, shareholder funds, total assets, cash flow, etc.) and also data on employees, such as name and roles and departments for each held position.

The initial search for data began with extracting companies of our focus—those belonging to aerospace industry (NACE:3030) and geographically to EU28 (as of 2019, still before Brexit). Next, each of the companies had their managers and directors assigned, along with their precise roles and occupied departments. The undertaken steps allowed us, therefore, to establish company per company links, that are created through affiliations of the people. The scope at this stage, however, was still limited only to EASIN companies, if our desire was to understand EASIN's relations with its neighbors we were still in need for the EASIN to neighbors links, but also the true volume of the neighbors' relations among themselves. To complete the former, we needed to first acquire the other affiliations of EASIN's employees, so that we could scan among them for the neighbors. The ORBIS database allows that, with the use of personal BVD contact codes we were able to find employment information of our targets. Having collected the complete list of affiliations of EASIN-related people, we were then able to find the neighbors, that is simply all non-EASIN companies that would complete our dataset. EASIN to neighbors links could be then created. In order to find the latter, the neighbor–neighbor links which were not dependent on EASIN-related people, required was further search of employees of those just-found neighbors. Having inspected all of them, we could exclude those, that belonged to EASIN, so the remaining affiliations of neighbors would allow to form additional links between the already determined neighbor companies. Hence,

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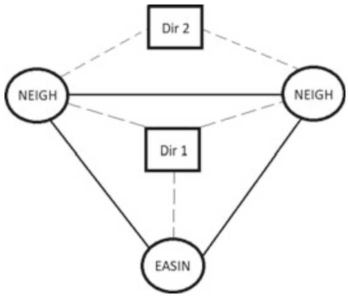

Fig. A.1 Example of connections between companies based on position of directors

using additionally the neighbors (non-EASIN) employees, it was possible to not only obtain the real weights of the already present links, but also to add new, previously undiscovered connections. Graphical explanation of the link formation process is included in Fig. A.1, where Director 1 is an EASIN-related employee and Director 2 is a non-EASIN, exclusively-neighbor employee.

The data collection process was at this stage complete. Even though ORBIS is considered one of the best data sources, it is still not ideal; it is because the attributive data is, unfortunately, not perfectly complete. The overall economic (Table 3.3a in Data Appendix), and other, attributive data availability for equity capital (EC), number of employees (EM), turnover (TURN), total assets (TASS) and cash flow (CF) was at 58.97, 37.09, 39,17, 58.64 and 30.29%, respectively. The data availability also appears to be scarcer for the non-EU companies in general (Table 3.2a in Data Appendix). The positive aspect in the unfavorable situation is that the lack of data regards mostly the less connected companies of neighbors and those from the top of the network statistics are fairly well represented. That allows us to carry out the most important parts of analysis still with a decent degree of reliability.

The data presented in this book should be taken cautiously also because of the issue of diversification, which occurs in our dataset due to two different aspects. On the one hand, variety of countries, that the analyzed companies belong to, creates a situation where variety of legal regimes meet each other and the indexes are not always interpreted in precisely the same way—for a basic example could serve TURN, that in some countries cannot be reported as a negative value (going below 0), while in others can, etc. This occurs even for the EU28 countries, which supposedly should fall into regime of the same European law, but in fact may at times interpret the indexes differently—therefore, it is recommended to take notion of that even for the first tables on European companies' only data. ORBIS database provides those variables in the most unified way it is possible to allow for cross-country analysis, and so in our analysis, we depend on its reliability. The second aspect concerning data is, that most of EASIN companies—and especially the large ones—are diversified into ICT and mechanics, but the data does not let to distinguish the pure Aerospace activities. It means that NACE:3030 is in itself category broad enough to create some distortion; there are a lot of factually different activities that in the end may fall into the same definition of "manufacture of air and spacecraft and related machinery."

However, as it is the best globally understood and unified categorization of industrial activities that we desire to study and are able to obtain, we remain with it and carry on with the analysis.

The entire set of EASIN and its neighbors consists now—after cleaning the database—of 9780 companies, 3143 of them are EASIN (NACE:3030, EU 28) and the rest—6637 are its neighbors (non-EU28 and/or non-NACE:3030). Working there are 1214 EASIN-related people and 6130 non-EASIN-related people giving a total of 7344 people. Their proper categorization and classification will be provided in respective chapters.

A.2 Links

The phenomenon of shared directors between companies is an old topic, and it has been widely studied as is shown in Chap. 2 on literature review. Typically, it has been studied by analyzing shared board of directors members between different companies forming the so-called interlocking directorates. In directors' networks (D2D) regarded were peoples' affiliations to Boards of Directors, such information is provided and clearly distinguished by the ORBIS database. In managers networks (M2M) regarded were affiliations to all other positions—mainly those of senior management, such as executives, nomination committees, audit committees and all other accounting and managerial positions—in essence everyone that did not belong to board of directors of a company, of course except all the medium and lower tiers of workers and employees. In mix networks (M2D) considered were people that fulfilled the criterion of holding at least one directorial and one managerial position. This version of networks required though an additional, special treatment of the data, considered here were only the highest positions held by a person in a company. If a person was a director and a manager in the affiliation list of a company, then the lower position was filtered out and he/she showed up only as a director. The logic behind this treatment is that two positions in one company would, first of all, create self-links that we do not include in our study as they do not provide any meaningful information in this particular context; secondly, it would complicate a person's real influence that we wish to represent. If a person was already a director and a manager in both connected companies, by including the asymmetric connections, we would have two symmetric and two asymmetric links in opposite directions—the first two symmetric ones already indicate the exchange of directorial and managerial information that is equally beneficial for both sides, addition of asymmetric links in such case would then actually include them in both directions making it in reality a symmetric link, creating a logical mistake and thus distorting our intention. In another case, where a person holds two directorial positions across two companies and only one managerial, in effect we would have one symmetric link made by directors and one asymmetric. Although it could be somehow insightful, in our consideration it was not so much, because the asymmetric links carry valuable information and their uniqueness is most apparent when a person represents purely both required positions in considered pair of companies. Of course, there are cases where in a network a company is connected by both, M2D and D2D and/or M2M, and this happens when such links are formed by different people. The version including all the links (ALL) is self-explanatory, where all of the networks are combined together. Though in order to create it, the undirected networks had to be first turned into the directed ones.

The links created between companies via shared people have inconsistent nature across different types of our networks and so require further explanation. In social networks science, the term "undirected" with respect to links serves to present that links do not have their precise origin and destination but are rather bilateral having equal impact on both of their participants. Hence, in contrast to directed (i.e. ownership) networks, an undirected network does not create any hierarchy and distinct positional relations. However, instead of calling them "undirected" (which gives them a rather neutral meaning), we prefer to label them as "symmetric." This small adjustment in semantics introduces a significant change in their perception, showing that if there was an undirected link between two companies - let us say A and B - we would merely indicate some relation between them with no particular direction and function. By labelling the link as "symmetric," we show that it is actually two links, instead of one, that simply go parallel in the opposite direction. A single, undirected link would show that there is indeed some information flow between the two companies, but that is where the interpretative potential would stop. With two, symmetric links in opposite direction we believe that now reality has better representation as it is clearer that A receives information from B and at the same time B receives information from A. Of course, some directors may be assigned at the other company to monitor what is happening in the others' board of directors; then they report on what they saw and heard back at their company of origin, but that does not mean that they will necessarily do the same for the monitored company. Hence, the reciprocity is not always granted; though due to such large scale of our study, we do this approximation. In practice, the absolute density (number of links) in our study is doubled when compared to a typical interlock study and as such should be interpreted and understood (1 undirected link AB = 2 symmetric links AB and BA). This novelty gains on importance as we proceed further with of our work. So far, the nature of symmetric interlocks created by shared managers or directors has been explained, one person holding same type of position in two different companies has ability to send between them similar type of information. The above upgrade was necessary in order to match all of the networks together, those directed and undirected ones, so that they may function within one type of network. However, in order to analyze the purely undirected networks—the M2M and D2D, we have settled for the undirected analysis, with undirected version of network indexes.

In situation where one person works for two companies, but holds different positions in both (i.e. manager in A and director in B) emerges a sort of "asymmetry." In such case where company A places its manager in company B and the A's manager becomes a B's director, company A suddenly places itself in better relative position as it sends rather less important information in exchange for more valuable type. Such situation creates in fact a heterogenous, "asymmetric" link that is directed in nature and goes from A to B. The direction from A to B comes from the fact that being in position of company A provides a sort of advantage or even control over B and so, we believe that direction from A to B is the best representation of such case. Finally, bringing it all together, forming pure directors and managers links as symmetric—usually undirected links that in fact are two directed ones in the opposite direction, and also creating the heterogenous links where if one person shares two different roles in different companies it is represented as directed relation, by giving them the unified "nature" we were able to create the ALL version of networks. The ALL version is the one with all the links put together and hence best represents the real scale of phenomenon of shared people within EASIN and also between EASIN and its neighbors. Finally, although we argue that the symmetric links are the better representation of reality of directorial and managerial interlocks, we have decided to use them in such way only in the ALL version. The analysis of department interlocks (Chap. 5) and board interlocks (Chap. 6), as they are presented in their own, separate chapters, provide an opportunity to analyze those networks also in their traditional form as undirected. The largest impact such change would create is a decrease in density. The disadvantage of symmetric links is that they may, through doubling of absolute density, artificially "inflate" some of the indexes; in order to provide a comprehensive insight into the networks, we set on providing both perspectives throughout the whole book.

The ALL version, following the symmetric logic, creates an astonishing number of 357,390 links in binary terms—that is accounted for are only links without including their weight (volume). Some of the companies may share more than one person; in such cases, the value of their interaction (if considering them for now as symmetric ones for simplicity) would be therefore equivalent to the number of shared people. In binary links that value is skipped and indicated is only the fact that such connections do exist (considering it is the ALL version the links could be made by any of the types of connections: M2M, D2D, M2D).[1] The more realistic representation of those networks is therefore provided when their values (properly called as weights) are also taken into account. In such case, the 357,390 binary links give a summary weight of 3,154,738. It would suggest that each link is made on average by 8.8 people; however, it is not quite so, our networks are heavy-tail scale-free and the situation is much more complicated than that what will be later explained in further analysis. Analysis of the other versions of networks will be carried out in their respective chapters.

A.3 Distribution of People

In order to better understand the distribution of people, who create links in our networks, it is advisable to consider first the following figure (Fig. A.2), which explains how particular relations can be formed by two types of employees—those related to EASIN and those related only to neighbors. If a person is employed by

[1] Implications, that such different reporting may cause when interpreting network indexes, are better explained in the section on network indexes and their formulas.

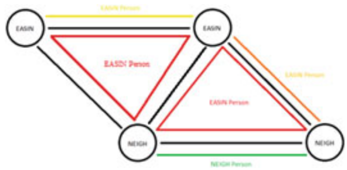

Fig. A.2 Inter-companies' relations, based on people who create them

any of the EASIN companies, he/she is automatically interpreted by us an EASIN coordinator, even when it is also hired by other NEIGH company. EASIN directors or managers can form links not only between EASIN companies (yellow color), but also between EASIN and NEIGH (orange and red color), and even NEIGH and NEIGH themselves (red color). Neighbor employees can form links only between NEIGH companies (green color).

Positions labelled as Unique (Table 3.8 and 3.9 in Data Appendix) mean, that people who fall into this category form only that particular type of links. The situation of mix positions, so people who form M2D networks, shows those employees that are employed in different positions in at least two companies. The Unique position in this case means a person who sits in only one managerial and one director position—otherwise, they would be present in the M/D sections of Man or Dir count. Such people have both positions, but still form links in that particular type of a network, i.e., when a person is a director in two companies and a manager in a third one creates one D2D and two M2D links. Because of complexity and variety of options of forming links, the difference between M/D people in Man and Dir, and Mix people could be better understood having carefully read the above section dedicated to links formation. The complexity is connected to the fact that, if a person holds a Dir and Man position in company A, and same positions in company B, he would be creating one D2D relation, one M2M relation and two M2D relations. However, as M2D links are supposed to emphasize hierarchy and asymmetry, and in the above case, they are in the end symmetric, and then in the M2D network, they are skipped and so people who create them are removed from the count, because this contradicts the idea of asymmetry. This is why the two numbers are not identical, because this may, but does not have to happen.

A.4 Multi-layer Networks

The networks built in our study, as mentioned before, could be as well interpreted individually de facto emphasizing the multi-layer aspect of the ALL network. The multi-layer aspect means that the same companies can be connected with different types of links, consequently forming a unique structure at each individual level. What is not obvious though is that not all of the neighbors from the total dataset are present in each of the independent layers, but there still may be links occurring between them. It means that EASIN's neighbors acquired i.e. by managerial links may not necessarily be present in the directors' network; yet still, the two neighbors may be related to each other with either managers, directors or through the hybrid links. Such multi- and cross-level links were hence included in our individual level networks, although going against the initial assumption where the EASIN was supposed to be the focal points of the network and each neighbor was supposed to be included only if it was connected to one of EASIN's companies. Now in each individual level, there are also neighbors who are not connected to EASIN in that particular network; yet, they are its neighbors, but in different layers. *Since links between a pair of neighbors from different layers do indeed exist, we believe they should be added to the layer of network respectively to the type of links that connects the neighbors*. It is better explained in the following Fig. A.3. Companies A and D are both EASIN, B and C are their neighbors, green links are formed by directors. and blue by managers. Although, in this example, company C is not directly connected through a director to company A (which is from EASIN), but it is still EASIN's (company D) neighbor, just one formed by a different relation; we decided to include company C into directors' network, in order to better represent all existing neighbor to neighbor relations. All of those extra relations would be showed together anyway in the ALL version, and there the expanded structures they generate would be accounted for, however, using this extra methodological step we ensured their presence also in the individual layers, thus allowing for creation of expanded cliques, components and also bridges between them and a more thorough analysis. This approach in building our networks allowed to present, according to us, more complete and as a result more realistic version of the networks.

Such multi-layer links and thus enlarged structures they may create are more holistically presented in the picture (Fig. A.4). It also very well highlights how, because of the multi-level aspect of our networks, the same companies may be connected via different types of relationships in the ALL version. The red arrow shows an example, how companies not connected in one layer do become so after casting relations from other layers. Those are the links between neighbors, that were added to the respective level, provided their link type matched the network's level type.

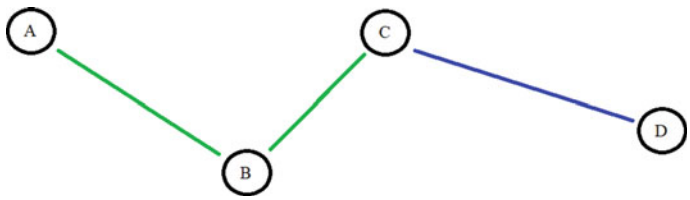

Fig. A.3 Multi-layer links

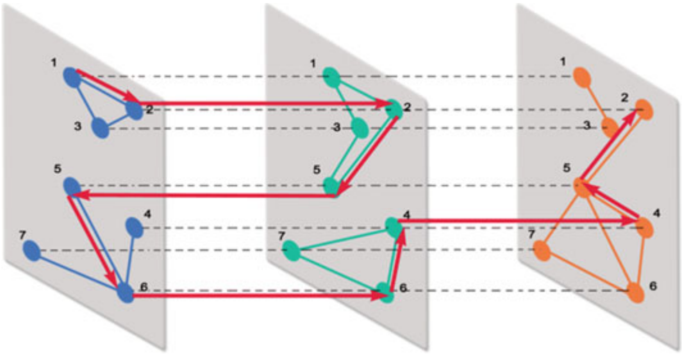

Fig. A.4 Multilayer networks. *Legend* Adapted from De Domenico et al. (2014)

A.5 Network Indexes and Their Formulas

In this book, we provide formulas for the directed indexes and send the reader to plethora of social network analysis books and textbooks to search for the undirected ones, for example in: Bonacich (1987), Borgatti et al. (2003, 2005, 2006, 2009), Hanneman and Riddle (2005), Newman (2010), Wasserman and Faust (1994), etc.

In order to carry out the network description, several social network analysis indexes are introduced. A node's (actor's) structural position in the network represents its relative power in relation to others (Bloch 2017). Freeman (1978) argued that central nodes were those "in the thick of things" or focal points. The centrality of nodes, or the identification of which nodes are more "central" than others, has been a key issue in network analysis (Freeman, 1978; Bonacich, 1987; Borgatti, 2005; Borgatti et al., 2006). There are plenty of different measures indicating different aspects of a single node's position (centrality measures), or other addressing the network as a whole (centralization measures). The focus of that book is primarily on the networks, and so centralization indexes will be of key importance here. They can be given as absolute values or normalized. The social network analysis indexes used in this research include:

(a) *Size (N)*: the number of nodes (actors) in a network.
(b) *Density (D)*: the number of links (*L*) among nodes (*N*), which becomes relative density when normalized by all the possible links.
(c) *Degree Centrality (Dc)*: The number of links adjacent to a given node in a symmetric graph is the degree of that node (Freeman, 1979). In directed networks, the index is additionally distinguished into out- and in-centrality.
(d) *Degree Centralization (Dc_CE)*: can be distinguished into In_Dc_CE and Out_Dc_CE, a measure of the dispersion of Dc indexes since it compares each actor relative (or normalized) Dc index (RDc(n_i)) with the maximum index present in the graph (RDc*)). After normalization, the relative value ranges between 0 (maximum dispersion, all nodes have the same Dc as in a *clique*)

and 1 (maximum centralization, a *star* graph):

$$\text{Dc\_ CE} = \frac{\Sigma(\text{RDc}^{*} - \text{RDc}(n_i))}{(N-1)}$$

(e) *Degree Centralization (Dc_CE_Sni) according to* Snijders[2] (1981): a measure of heterogeneity of points in a graph. Commonly used Freeman's (1977, 1978, 1979) centralization indexes focus on a single-point centered centralization in its maximum represented as a star-like graph, while Snijders proposes a way to test for presence of multi-centered structures that can be a more realistic representation of many networks, just like the ones we deal with. Centers with out-going links, so-called hubs, are represented by the large shareholders, which have a number of PCs with several descendants. The two variations of the index are J and H, both assume values between 0 and 1. J is simply normalized with respect to the maximum value, whereas H is more precise as it includes a null model, maximum value and a square root. The advantage of H is that if its value equals 0 it means its variance (J) is exactly compatible with the null model. If J is smaller than what would be expected under null model then it could even reach negative values. In case of large graphs, J and H tend to become very similar. The practical application of that index lies in its ability to distinguish, for example, between monopolistic and oligopolistic market/industry structures. In our research, we have used the H value.

(f) *Average Degree centrality (ADc)*: is referred to the whole network and is calculated as the ratio between links (both binary and valued) and nodes. ADc in undirected networks is equal to two sums of all degrees divided by the number of nodes.

$$\text{ADc} = \frac{2\sum_j n_{ij}}{N}$$

(g) *Fragmentation (Frag)*: the proportion of pairs of nodes that cannot reach each other. Distance weighted fragmentation is one minus the average reciprocal distance between all pairs of nodes. Node-level fragmentation is these values that involve the specified node. Fragmentation centrality of a node is the difference in the total score with the node and the score with the node removed. The same process is used for distance-weighted fragmentation.

$$\text{Frag} = 1 - \frac{1}{N}\sum_{i=1}^{N} n_i$$

[2] This index is not calculated by any software, but we claim that it is rather important, because our networks are all but star-like shaped. Therefore, we have implemented a software, called Analyzing Social and Economic Networks (ASEN), to calculate it and also the two indexes of hierarchical degree (see below).

(h) *Diameter*: length of the longest geodesic (geodesic is the shortest possible walk from one actor to another).

(i) *Average path length (Apl)*: the average of the shortest paths (geodesics) connecting each couple of nodes. Defining g as a geodesic function, the average path length is computed as:

$$\text{Apl} = \frac{\sum_{i \neq j} d_{ij}}{N(N-1)}$$

(j) *Reciprocity (dyadic method)*: measures the extent to which couples of nodes (dyads) are tied by symmetric relations or the extent to which to every out-going tie an in-coming tie corresponds and vice versa. When asymmetry prevails, and reciprocity is low, the network is supposed to be characterized by a certain degree of dyadic hierarchy. The index of reciprocity in the analysis that will follow is calculated according to the "dyad method" (Hanneman & Riddle, 2005): the number of dyads linked by a reciprocal or symmetric tie is divided by the number of dyads that are linked by any kind of tie. With the software ASEN (Analyzing Social and Economic Networks), we have calculated also the weighted reciprocity, which considers also the values of reciprocated and not reciprocated links;

(k) *Hierarchical degree* (H_k): quantifies the extent of asymmetry in a structure; the greater the extent of asymmetry, the more hierarchical the structure is said to be. This index has been proposed by Krackhardt (1994), according to whom hierarchy is defined as the fraction of non-null dyads in the reachability graph which are asymmetric.[3] Thus, when no directed paths are reciprocated (e.g., in an out-tree), H_k is equal to 1; when all such paths are reciprocated, by contrast (e.g., in a cycle or clique), the measure falls to 0. Defining the number of symmetric—or reciprocal—paths as "*Rp*", and the number of asymmetric paths as "max*Rp*", the formula for measuring the hierarchical degree is:

$$H_k = 1 - \frac{Rp}{\max Rp}$$

While the original index was proposed only for binary networks, with the software ASEN, here we provide it also for the valued versions. To do it, we have calculated arc reciprocity on the reachability digraph taking into account the values in monetary terms of each geodesic. We did it because for networks with such high range of links values, the calculation made only in binary terms could result misleading.

(l) *Hierarchical degree* (GORC): this index of hierarchy is very different from the previous one. It has been proposed by Mones & Vicsek (2012) and is based

[3] Concretely, we have calculated global reciprocity of the reachability digraph, which on its own corresponds to the geodesic distance matrix of the original graph. It should be said that 18 years later Krackhardt himself revised and criticized his index (Everett & Krackhardt, 2012).

on the typical logic of centralization indexes, where the highest node's value of reaching capacity is subtracted from all other nodes, then these values are summed up, and finally divided by the maximum reaching centralization, which corresponds to a star structure. With the software ASEN, we have calculated this index for both binary and valued networks. So, if we indicate with LORCmax the highest local reaching capacity, then Global Out_Reaching Capacity is given by:

$$\mathrm{GORC} = \Sigma(\mathrm{maxLORC} - \mathrm{LORC}n_i)/(n-1)^2$$

Analogously, the same method may be applied for LIRC and GIRC. As we will see, these indexes provide very different results, even though they have in common the fact that both algorithms are applied to the geodesic distance matrix. We have a preference for H_k, because it seems that it takes better into account the share of reciprocal dyads. Anyway, because they provide different analytical perspectives on the phenomenon of hierarchy, we offer to the reader both measures.

(m) *Eigenvector centrality (Eig):* a node's importance in a network is increased by having connections to other nodes that are *themselves important*. It gives each node a score proportional to the sum of the scores of its neighbors. For a node *i* in a directed network centrality is proportional to the centralities of the vertices that point to *i* (Newman, 2016). Lambda is a constant. Let A be the adjacency matrix of a network under consideration. Element A takes a value 1 if a node *i* is connected to node *j* and 0 otherwise. Thus:

$$\mathrm{Eig} = \frac{1}{\lambda}\sum_j A_{ij} n_j$$

(n) *Eigenvector Centralization (Eig_CE)*: the variation in the vertices' eigenvector centrality divided by the maximum eigenvector centrality variation which is possible in a network of the same size (Borgatti et al., 2012). REig* is a maximum index present in the graph, REig(n_i) is each actor's individual score. It can be calculated as follows:

$$\mathrm{Eig\_\ CE} = \frac{\sum\left[\mathrm{REig}^* - \mathrm{REig}(n_i)\right]}{\max \mathrm{Eig\_\ CE}}$$

(o) *Katz centrality (Katz)*: Extension of the eigenvector centrality (Katz, 1953) as it expands the "scan for influence" to the further levels of connection, it could be said that it checks for prestigious "neighborhoods"—rather than closest connections like in Eig. It computes the relative influence of a node within a network by measuring the number of the immediate neighbors (1st level nodes) and also (additionally comparing to Eig) all other nodes in the network that connect to the node under consideration through these immediate neighbors. Connections made with distant neighbors are, however, penalized by an attenuation factor α. The greater the length, the weaker the connection, how much weaker is determined by α (Hanneman & Riddle, 2005). The power of A indicates length of a path (how many other nodes need to be crossed) connecting nodes *i* and *j*. Mathematical formulation is:

$$\mathrm{Katz}(n_i) = \sum_{k=1}^{\infty} \sum_{j=1}^{n} \alpha^k \left(A^k\right)_{ji}$$

(p) *Betweenness centrality (Bc)*: aims to measure nodes' intermediation capacity—or brokerage—and is defined as the fraction of paths passing for one node over all possible paths in the graph (Freeman, 1977, 1979). It is formally expressed as the sum of the probabilities that all the geodesics (shortest paths) between all possible couples of actors (G_{ik}) in a graph will pass for a specific node (n_i) (Biggiero & Angelini, 2016):

$$\mathrm{Bc}(n_i) = \sum_{j<k} \frac{G_{jk}(n_i)}{G_{jk}}$$

(q) *Betweenness Centralization (Bc_CE)*: an index of centralization based on Bc (Freeman, 1977) will be calculated according to the same logic followed for the degree centralization index (hereafter Bc_CE), where RBc* is a maximum index present in the graph, RBc(n_i) is each actor's individual score. It can be calculated as follows:

$$\mathrm{Bc\_\ CE} = \frac{\sum\left[\mathrm{RBc}^* - \mathrm{RBc}(n_i)\right]}{(N-1)}$$

(r) *Random-Walk Betweenness centrality (RWBc)*: checks how often a given node will fall on a random walk between another pair of nodes. By counting only shortest paths, the conventional Bc implicitly assumes that information spreads only along those shortest paths. RWBC measure relaxes this assumption, including contributions from essentially all paths between nodes, not just the shortest, although it still gives more weight to short paths. (Newman, 2003).

(s) *Bridging centrality (BRc)*: a popular measure that combines the betweenness centrality and bridging coefficient metrics to characterize nodes acting as a bridge among clusters. Companies with high BRc are usually members of cliques or dense components, who connect those groups of nodes with the reachable outside parts of their network. For more information, check Pereira et al. (2021).

(t) *Closeness centrality (Cc)*: measures the distance of an actor to all others in the network. As Eig and Katz focus on power of neighbors (those intermediate and further) that influence a considered node's own power, Cc focuses on *distances* between nodes that establish its position in a network. A node with a high closeness centrality would mean it has close relationships (Metcalf & Casey, 2016) with many nodes and may be usually located around the centre of a network. It can be calculated as follows:

$$\mathrm{Cc}(n_i) = \left(\frac{(N-1)}{\sum_{j=1}^{N}(n_i, n_j)}\right)$$

(u) *Closeness Centralization (Cc_CE)*: As Cc, it can be distinguished according to the in-edge or out-edge direction for directed networks. Analogously to Bc_CE, it refers only to geodesics, where RCc* is a maximum index present in the graph, RCc(n_i) is each actor's individual score. It can be calculated as follows:

$$\mathrm{Cc\_CE} = \frac{\sum\left[\mathrm{RCc}^* - \mathrm{RCc}(n_i)\right]}{\max \mathrm{Cc\_CE}}$$

(v) *Global Clustering Coefficient (GCL)*: the fraction of paths of length two in the network that are closed (Wasserman & Faust, 1994).

$$\mathrm{GCL} = 3 \times \frac{\text{number of triangles}}{\text{number of connected triples}}$$

Also, it is used to measure the extent to which a network displays clustering defined as the presence of many local neighborhoods structured like a *clique* (Watts & Strogatz, 1998). Thus, for each node is calculated its local clustering, i.e., the density of its neighborhood; this value will range between 0—when all the neighbors are not connected among them and the focal node is the center of a *star*—and 1 if the focal node is embedded in a *clique*. Global coefficient is the average of local clustering (CL)

(w) *Small Worldliness (SW)*: graphs possess both short average node to node distances and "clustering" of acquaintances (friends of my friends tend to also be my own friends), where the large size nodes are easily reachable through various paths, due to random connections available. The higher the SW score, the more a random node (or a whole cluster) would be reachable for others, even if they are distant, thanks to the random paths.

It is important to understand how to interpret results of those indexes, because considering their plurality and complexity, it may not be the most obvious task. A primary and most basic example is presented in the figure (Fig. A.5), where peculiarities of degree centrality are explained.

This example focuses on company A, where it has two neighbors—companies B and C. With both companies, it has a connection; therefore, if we count its binary degree centrality—the number of actual relations with other companies—it will be equal to 2, as represented by its BDc index. However, when measuring links' intensity,

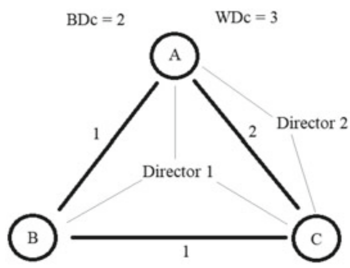

Fig. A.5 Degree centrality example

the important factor affecting their weight is the number of directors who create such inter-company links. In case of relation with company B, the link AB has weight 1, but since there is one more director connecting A with C, the AC link's weight is equal to 2. Since weighted degree centrality is simply a sum of all such links per given node, the company A's WDc is equal to 3. Therefore, *the binary degree centrality does not represent simply the number of directors shared, but rather the number of links with other companies.* The number of directors exchanged is better given with the weighted degree centrality, though it does not necessarily mean it is equal to it (imagine if companies ABC all shared two same directors—two people creating WDc = 4 for each company, because AB = 2, AC = 2 and BC = 2; hence, their individual WDc is in this case 2 + 2 each).

As a case study, which might be more demanding, it is worth bringing up here the example occurring in the extended version of the M2D network. Two of the companies there have BIDc equal to 209; in essence, they have 209 links pointing at them. It means that there are 209 asymmetric relations, where even one person could be assigned as a manager in those 209 companies from where the links come from, and in that focal company he would be a director. It could mean as well, that there are 209 different directors exchanged in the asymmetric way, in general in such networks each case is complicated and therefore should be analyzed individually.

A.6 Analysis

(a) Difference between EASIN and EASIN Integrated

Having closely studied the process of generating networks from people's affiliations, it is now advisable to understand differences between the two variants of EASIN network. EASIN is a network, that has been extracted from EASIN + NEIGH and includes only companies, that have links to other EASIN companies. The EASIN Integrated, on the other hand, has also links with the neighbors. This means that EASIN Integrated includes same companies as EASIN and additionally other that were of EU28 and NACE:3030 origin, but were not previously connected to others of that group; it is simply an expansion of the node set. The major consequence this enlargement introduces is that now EASIN companies are considered with respect

Table A.1 Financial weight (%) of companies with no sectoral data

Type	Equity capital	Number of employees	Turnover	Total assets	Cash flow
No data	5.41	0.72	3.13	6.42	6.03

to all of their links, not only those limited to EASIN. In practice, when measuring centralities, the links generated by relations with neighbors are also added to EASIN companies' centrality scores, but the neighbors themselves are not included in the node set, considered are only *relations* with them.

(b) Inter-group analysis

The analysis of aggregated sectors and countries has been carried out by aggregating the nodes belonging to a particular type and collapsing them into one node. A product of such method is a network of the aggregated groups, where each of them has assigned all links of all of the individual companies from that particular group. The links coming out from a group, if pointed at the same target, are combined and their weights are summed up. A network of such collapsed group nodes is then analyzed with the regular indexes used earlier in the main, company-level analysis. The nodes, that did not have any NACE information, available are omitted together with their links; they were 648 (6.6%) companies out of 9780, and their financial proportion of the total is presented in the Table A.1. The inter-country network includes all companies, since data concerning origin of each company were entirely available.

(c) External—Internal (the E-I analysis)

The analysis of internal and external ties of groups has been carried out first by collapsing the nodes of the same type (be it countries, sectors or industries) and treating them as one node along with all their internal (horizontal) and external (vertical) relations. This analysis has been adapted from the original Hanneman's (2005) E-I analysis, which was computed in the UCINET software, however that version worked well only for undirected networks. The drawback was that it did not differentiate between the out-going and in-coming external links per each group. To overcome this shortcoming we aggregated all the links with the same 'source', summing up 'weights' that went to the same 'targets' and simply extracted the nodes' aggregated edges and total Degree centralities. This allowed to check direct relationships with other sectors and nodes' balance of internal to external connections.

(d) Cluster analysis

Cluster analysis has been carried out with the IBM SPSS Statistics v. 26 software. The idea behind the test was to find groups of companies based on a mix of attributive and/or topological indexes, for which we selected the *K*-means analysis. In order to conduct it, a number of issues with variables selection had to be initially dealt with.

First was the scaling problem, should the analysis contain absolute or normalized scores. After a series of tests and experiments it was concluded that absolute variables, even if rescaled, pose problems and are hard to put together; therefore, the scores used were represented with normalized scores. Second is the matching of the topological and financial attributes. Although such analysis would help to answer some of the questions posed by the literature, because of the scarcity of economic attributes and (even more) of economic performance parameters, like ROA or EBITDA, with data availability at the average level of 50%, it could turn out that it would be misleading, as it is not entirely clear what kind of companies really provide data and how do they position themselves among the whole rest. Hence, we decided to stay only within the group of topological attributes in the EASIN + NEIGH analysis, as only they had complete sets of variables. Next, we decided to rely entirely on normalized scores as they were already put on the 0–1 continuous scale and were thus comparable with each other. Among them, then, we ran various experiments driving us to select those three, because the others do not identify discriminating clusters: LORC, which indicates the weighted length of the reachability out-component corresponding to each company; BODc, which is the binary out-degree centrality; and BOKc, which measures the influence power calculated in binary terms. forced us to choose only topological parameters for the EASIN + NEIGH network.

For clustering analysis on EASIN only network, it turned out more informative to include both direct in- and out-degree centrality (in directed networks) and one chain-based index such as the out-closeness. In EASIN analysis, because of smaller variance and slightly larger data availability, we have also added TURN, which was normalized over the highest score available in that dataset and then additionally reduced by one decimal point to level TURN with other variables. The last parameter would serve as proxy for performance, in order to respond to the debate from the literature review. The following analysis though should be considered with regards to the lack of financial attributive data. Although 40% of TURN data is missing, we still conducted our analysis, because companies with the highest topological attributes mostly do have it and so they will be represented adequately. Considering what we will show soon after, that the networks are shaped with the heavy-tail scale-free characteristic, it is safe to assume that companies with no data will belong to the smallest ones with presumptuously little and insignificant TURN, just like other companies which are evidently weak both topologically and economically.

Clustering analysis and graphics of the networks were prepared in Gephi (see Sect. A.7). The clusters generated by SPSS have been highlighted accordingly in the ALL version and their general overview graphics were prepared. For the other variants of networks, the clusters were first extracted from the whole network and later their layouts were adjusted with the Fruchterman Reingold algorithm to obtain an optimal positioning respectively to each other. Each company had their country and sector of origin assigned. In this way, the generated figures represent networks of companies, from particular countries or sectors, and their relations to closest partners. It is worth reminding that each of the companies has also a number of other relations, which were omitted after the extraction, and that in the original network most of those grouped companies were initially highly dispersed.

(e) Clique analysis

Formally, a clique is the maximum number of actors who have all possible ties present among themselves. A “Maximal complete sub-graph” is such a grouping, expanded to include as many actors as possible. In our work, cliques of different sizes have been first identified with UCINET and later, having a list of affiliations of companies to those particular cliques, we were able to identify and extract them from networks using Gephi attribute partition.

(f) Bridging analysis

Bridging centrality was also selected as our representative index for key players. It is because it gives importance to companies of the largest cliques, that are also intermediating the information flow with the outside of the world. Those with the largest index were therefore those who joined largest groups together and brokered the information flow between them. It was also a matter of elimination, as other parameters were highly dependent on size of cliques and essentially highlighted all their members, those of large and also small size and relevance, and they were the leaders of rankings of all other indexes we have experimented with. Bridging centrality was therefore the most pragmatic choice, as it returned the most important companies from different sections of an entire network, not just the largest clique.

(g) Scale-free and heavy-tail (log–log plots)

Many natural, artificial and socioeconomic networks show the property of being scale-free in the distribution of its links. This has a lot of implications widely discussed by Barabasi (2002) and Caldarelli (2007), among many. Biggiero & Angelini (2015) do a review of the empirical findings of the scale-free property in many economic networks and in particular in various aspects of the research project networks in the EU Aerospace Area, funded by various Framework Programmes. Biggiero & Magnuszewski (2021) show that most topological variables of the EU28 ownership network of the aerospace industry are distributed too in a scale-free shape. In both such studies, the conceptual meaning and the method to detect the scale-free property has been extended from the degree to the betweenness centrality and beyond to non-centrality non-connectivity parameters. The same intent has been followed in this book.

However, the precise attribute of scale-free property requires a method not limited to calculate the fitness value of the straightline interpolating the log–log plot of the given parameter, because there can be cut-off points that could need a specific evaluation of each case. Now, what really matters for our analytical purposes is not really the scale-free property, but rather the heavy-tail (HT) distribution, which shows that a specific parameter is very unevenly distributed and polarized. To this aim, the fitness value for the interpolating line of log–log plot is enough. Therefore, we have applied this test to various topological and attributive variables.

(h) Assortativity

A network is assortatively mixing if the nodes in the network that have many connections tend to be connected to other nodes with many connections (Newman, 2002). That is, people with many friends are connected to others who also have many friends. This gives rise to degree–degree correlations in the network, implying that degrees of two adjacent nodes are not independent. In edge-weighted networks, weighted average nearest neighbor degrees are also used to characterize strength correlations. It was found that in a typical social communication network, the degrees of two adjacent nodes are strongly correlated, while the strengths of two adjacent nodes in most cases are not (Onnela et al., 2007).

(i) Structural equivalence

An important question in SNA concerns the degree of (dis)similarity of nodes in terms of its patterns of connections, not just its degree of centrality or clustering or some other measures. There are two main measures to calculate the degree of (dis)similarity of connection patterns: structural equivalence and regular equivalence (Wasserman & Faust, 1994; Hanneman & Riddle, 2005; Newman, 2010). The former is much more restrictive than the latter, because it requires to be measured through direct connections, while the other consider also indirect connections, thus focusing more on the *role* similarity. It would have been a very interesting analysis, but unfortunately we could find no software able to run that calculation on networks of the size we have dealt with.

Indeed, also for Structural Equivalence (SE), there is no software able to compute our networks size, but to overcome this problem, one of us has developed a software (STREQ, see below) able to do it. Among the main methods to measure SE, we have chosen Jaccard Matching (Hanneman & Riddle, 2005), which is a restrictive version of simple matching, because it excludes the similarity due to missing links. In its normalized version for inter-network comparison, we have further modified it by normalizing per the minimum absolute density of the network with the smaller value of density. In fact, if there are large differences in density, then even if the smaller network was perfectly matched with the larger one, the surplus of links of the larger network will work disadvantageously to the final result, because the larger the gap the larger de facto the number of mismatched links.

In order to understand the consequences of this choice, it is worth comparing the results of the inter-network overlapping obtained with the modified Jaccard matching with those that could be obtained with the standard Jaccard matching, evidenced in the following Table A.2. The degree of overlapping is here very much lower than that of the modified index, except for EASIN M2M-D2D, where the difference is just 0.225, still considerable but much less than in the other cases. Because the three networks have a huge difference in absolute density, we thought that using the standard measure of Jaccard matching could have not allowed to distinguish the factor due to that huge difference and the factor due to the true possible overlapping. Therefore, the two indexes differ in the normalizer, which in our modified version

Table A.2 Degree of inter-network overlapping according to standard Jaccard matching

	M2D-M2M	M2M-D2D	M2D-D2D
E + N	0.004	0.099	0.01
E + N MC	0	0.064	0
EASIN	0.034	0.345	0.012

correspond to the weighted absolute density of the network with the smaller value between the compared two.

(j) Intersections (Jaccard Coefficient)

In order to check overlap between two networks an analysis of positive matches (Jaccard coefficient) can be calculated for a set of two identical networks with same sets of nodes. The method becomes more useful the more similar are densities of the two extracted sets of nodes; if they are exactly the same, then the measure represents their true similarity. If, however, there are large differences in density then even if the smaller network was perfectly matched with the larger one, the surplus of links of the larger network will work disadvantageously to the final result, because the larger the gap the larger de facto the number of mismatched links.

The preparation stage to check similarity required first finding and then extracting the nodes that were shared in two compared versions of the network, along with their links.

(k) HHI index

Herfindahl–Hirschman index (HHI) is the most diffused measure of the concentration degree of a market sales or industry production, like in the case of our work, widely used by antitrust institutions. Calculated by summing the squares of the single companies shares multiplied per 100, it varies between 0 and 10,000. Conventionally, it is assumed that:

- HHI < 100 indicates an ideal fully competitive context,
- 100 < HHI < 1500 indicates a non-concentrated context,
- 1500 < HHI < 2500 indicates a moderate concentration,
- > 2500 indicates a high concentration.

Alternatively, for a more immediate and approximate understanding, it is possible to normalize it with the following formula

$$(\mathrm{HHI} * (1/N))/(1 - (1/N))$$

where N is the number of companies.

A.7 Software

- Graph Converter: efficiently transforms one of the following four formats in one another: Edgelist, DLL, Matrix, and NetworkX Graph object.
- Gephi 0.9.2 201,709,241,107: Used for generating all network graphics in the book and also for calculating the bridging centrality index, because it was the only software that had it at the moment of our work.
- IBM SPSS Statistics v. 26: Used for calculating *K*-means clustering and generating groups of nodes for the cluster analysis in all chapters.
- Analyzing Social and Economic Networks (ASEN) is a software made in Python that puts together some algorithm implemented by Network-X and some other implemented by one of the authors. The algorithms taken from Network-X are the following: binary and weighted In and Out Dc; binary and weighted Bc; binary and weighted In and Out Katz; binary and weighted arc reciprocity; shortest paths; assortativity. The algorithms implemented by ASEN creator are the following: all kinds of binary and weighted centralizations (In and Out Dc, Bc, In and Out Katz); Snijders' In and Out Dc centralization (see above for a short description); hierarchical degree in terms of reaching capacity (LIRC, LORC, GIRC, and GORC) (see above for a short description); hierarchical degree in terms of arc reciprocity of the geodesic matrix (see above for a short description); Average Dc (ADc); weighted geodesic and non-geodesic matrix; binary and weighted fragmentation; normalized density. This software and STREQ can be downloaded from www.luciobiggiero.com.
- Structural Equivalence Calculation (STREQ) is a software made in Python by one of the authors to calculate absolute and normalized Euclidean Distance of weighted intra- (between nodes in a network) and inter-network (between networks). Actually, the normalization of weighted Euclidean distance is anything but simple, and it is not "light" in computational terms. In the current version, it has been implemented also the calculation of intra- and inter-network absolute and normalized simple matching and Jaccard matching for binary and weighted networks. This software can be freely downloaded from this website: www.luciobiggiero.com.
- R software 4.2.0: Used for calculating correlations and their P-values with package "Hmisc."
- UCINET 6.733: Used for calculating some of the network indexes, such as clustering and small world; also for generating clique memberships, which were later visualized in Gephi; creating aggregates of nodes and links for the inter-sector and inter-country networks; conducting the E-I analysis.

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