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Who Are the Gatekeepers of Economics? An Exploratory Network Analysis of Institutions, Scholarly Communities and Journals

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Introduction

The main aim of this thesis, in its three essays, is to update and enrich the knowledge of the composition and the characteristic of the gatekeepers of economics though the lenses of Social Network Analysis (SNA).

Since the origins of network analysis in the early 1930s with the work of Jacob Moreno, this approach has advanced and spread in an extremely wide and ever-growing range of applications (Freeman 2004). Otte and Rousseau (2002), examining network analytic articles published between 1984 and 1999, showed that, year-by-year, there has been an almost linear growth in the number of substantive areas in which the social network approach has been applied. In fact, network analysis cuts across the boundaries of traditional disciplines and has developed important applications in research on *social networks* (for example, friendship networks, informal communication networks within companies, political networks, etc.), *information networks* (like networks of citations between academic papers, preference networks), *technological networks* (e.g., networks of roads, networks of airline routes, internet), and *biological networks* (networks of chemical reactions among metabolites, protein interaction networks, real neural networks) (Newman 2003). The common analytical perspective in the network approach is to have a *structural* perspective, which means to examine the environment and links among the objects of study rather than the object themselves taken as isolated units of analysis. In social science, the structural approach that is based on the study of interaction among social actors is called *Social Network Analysis (SNA)* (Freeman 2004).

The focus of SNA is on the social relationships established between social entities rather in the social entities themselves. Therefore, the individual is not the basic social unit, but it is the structure of interpersonal ties. Social network analysts assume that interpersonal ties matter, as do ties among organizations or countries, because they transmit behaviour, attitudes, information, or goods (De Nooy et al. 2018). In fact, the main goal of this technique is to examine both the contents and patterns of relationships in social networks, in order to understand the relations among actors and the implications of these relationships. Typical social network studies address issues of centrality (which individuals are best connected to others or have most influence) and connectivity (whether and how individuals are connected to one another through the network). Recently, an impressive advance in social network studies was determined by two relevant reasons: the growing availability of large volumes of relational data, and the intuition that an individual's connections can yield richer information than his/her isolate attributes (Oliveira and Gama 2012). SNA is used widely in the social and behavioural sciences, as well as in economics, marketing, and industrial engineering.

Examples include communications among members of a group, economic transactions between corporations, and trade or treaties among nations (Wasserman and Faust 1994).

Standard economic theory did not give much credit to the role of networks until the early 1990s, but since then the study of the theory of networks has prospered. One of the reasons of this diffusion is connected to the fact that a growing body of empirical work has argued that the mainstream approach is inadequate for understanding many phenomena (for example, innovations, variations in crime, differences in trust and cooperativeness, peer effects in academic performance, the proliferation of research alliances among firms, and the extensive use of personal contacts by both employers and workers in labour markets), and this is due to the neglecting social part of behaviour of the mainstream approach (Goyal 2009). The ways individuals or social entities interact and the influence they have on one another, is then being study successfully through SNA. Examples are connected to the study of labour market, technological diffusion, and research collaboration among firms (see Goyal 2009 for a review of the literature), but also to study the diffusion of economic ideas in shaping policy responses (Helgadóttir 2016), or to analyse the gatekeepers of economics (Baccini 2009, Baccini and Barabesi, 2010). This last topic is going to be the centre of this thesis.

In fact, as already mentioned, the main aim of this thesis is to update and enrich the knowledge of the composition and the characteristic of the gatekeepers of economics. The reason that drives this research is linked to the necessity to understand if the composition of gatekeepers in economics can be one of the reasons why this discipline has a very strong closure to any type of criticism and a rigidity in changing its method of analysis and the education of economists (Ötsch and Kapeller 2010). Indeed, considering the institutional central role that gatekeepers play in the definition, evaluation and development of scientific knowledge, limiting gatekeeping to individuals with specific socio-demographic and professional characteristics can generate distorting effects to the detriment of certain categories, research fields and geographical areas, and consequently be an obstacle to the compliance of the distinctive normative ethos that was institutionalized in modern science (Merton 1942). The thesis is organized in the following way.

In Chapter 1, it is presented the first assay which is dedicated to an overview of the main contributions on the topics that the research on gatekeeping of science through SNA has focused most, highlighting the central role that gatekeepers play both in the process of social production of scientific knowledge and, more generally, in the mechanisms of social reproduction of the scientific community itself. Moreover, it is reported a general and succinct presentation of the essential definitions and techniques of SNA and how these are able to examine social networks among gatekeeping. A particular attention is given to the techniques that have being used in the subsequent essays.

Chapter 2 contains the second essay which investigates the fairness of the composition of the panels appointed to evaluate research in economics and statistics during the Italian research assessment exercises, considering its internationally relevant example. For investigating the fairness of the panels, a network analysis approach is adopted by comparing the co-authorship networks, the networks of journals in which panelists have published and the network of universities, research centres and newspapers that connect them. Three evaluation exercises are considered for the years 2004-2010, 2011-2014, 2015-2019. The first two panels were appointed directly by the member of the governmental agency for the evaluation of university and research (ANVUR); the third was instead selected randomly by a lot from among those who had applied to be panelists. This permits to consider the third panel as a control group.

Finally, the third essay, exposed in Chapter 3, analyse the national distribution of editorial boards members of economics journal, their affiliation, and their gender. It is also studied the network generated by the presence of the same person on the editorial board of more than one journal (interlocking editorship). The SNA has been used to individuate the most influential gatekeepers, from the level of the individual scholar and of journals, and to check for cohesive groups. The analysis is based on a unique database comprising all the 1.517 journals indexed in the database EconLit as of 2019, that contains more than 44.000 members from more than 6.000 institutions and 141 countries. These unique data allow to investigate the phenomenon of gatekeeping in contemporary economics on an unprecedented large scale.

CHAPTER 1

Investigation on Gatekeeping of Science through Social Network Analysis: An Overview

Abstract

≪A gatekeeper is an individual or collective actor who is in a position to control access to resources and rewards relevant in a particular social system≫ (Hoenig, 2015). The gatekeeper therefore plays a central role both in the process of social production of scientific knowledge and, more generally, in the mechanisms of social reproduction of the scientific community itself. Gatekeepers are first and foremost the scientists themselves when they exercise the role of reviewers during the peer review process, then they are the editorial boards of scientific journals, they are the members of the committees of the research funding agencies and the national and international institutions entrusted to the policy of the science. Since the first article by Merton and Zuckerman (1971), the number of articles on the issues of editorial and institutional gatekeeping has progressively grown, denoting an increasing attention by scholars to the topic. However, understanding scientific gatekeeping from the lens of social networks analysis (SNA) is a fairly young research area. Much attention was paid to the fact that limiting gatekeeping to individuals with specific socio-demographic and professional characteristics can generate distorting effects to the detriment of certain categories, research fields and geographical areas. In this paper we will summarize the main contributions by examining on which topics the research on gatekeeping has focused most. Moreover, we will report a general and succinct overview of the essential definitions and techniques of SNA and we will see how these are able to examine social networks among gatekeeping.

1.1 Introduction

The study of gatekeeping as a central role in the definition, evaluation and development of scientific knowledge has been a subject of significant interest since the 1960-70s (De Grazia 1963; Crane 1967; Zuckerman and Merton 1972). However, understanding scientific gatekeeping from the lens of social networks analysis is a fairly young research area. The spreading interest is connected, on one hand, to the growing availability of large volumes of relational data and of faster and more effective data processors, on the other hand, to the intuition that an individual's connections can yield richer information than his/her isolate attributes and that network analysis could be the correct way to detect gatekeepers and to study their characteristic.

≪A gatekeeper is an individual or collective actor who is in a position to control access to resources and rewards relevant in a particular social system. These resources might take the form of money or information, of reputation or social capital≫ (Hoenig 2015: p.618). Gatekeeping is considered as ≪basic to the system of evaluation and the allocation of roles and resources in science≫ (Merton 1973: p. 521), and gatekeepers mostly operate through panels of peers. The gatekeeper of science is anyone who regulates ≪scientific manpower and the allocation of resources for research≫ (Zuckerman and Merton 1972: note 33, p. 316) and the role of a gatekeeper typically can take two forms: ≪providing or denying access to opportunities≫ (Merton 1973: p. 522). The gatekeeper therefore plays a central role both in the process of social production of scientific knowledge and, more generally, in the mechanisms of social reproduction of the scientific community itself. Gatekeepers are first and foremost the scientists themselves when they exercise the role of reviewers during the peer review process, then they are the editorial boards of scientific journals, they are the members of the committees of the research funding agencies and the national and international institutions entrusted to the policy of the science.

The analysis of the role of gatekeeping in science has been very useful to understand the social dimensions of scientific knowledge and to study the history of science in institutional terms. In particular, it was used to check the compliance of distinctive normative ethos that was institutionalized in modern science. Merton (1942), the founding father of sociology of science, identified four salient scientific norms: 'universalism', 'communism', 'disinterestedness' and 'organized skepticism'. In particular, universalism requires that scientific contributions are evaluated according to general impersonal criteria without regard to characteristics of the contributors such as their race, religion, and nationality. Communism requires that knowledge is shared, not kept secret. Disinterestedness refers to the injunction that the procedures and products of science is not appropriated for private gain. Organized skepticism permits and encourages challenges to knowledge claims. Connected to them, we can find also the norm of 'fairness' in the evaluation of scientific knowledge (Cole 1992). Much attention was paid to the fact that limiting gatekeeping to individuals with specific socio-demographic and professional characteristics can generate distorting effects to the detriment of certain categories, research fields and geographical areas, and consequently be an obstacle to the compliance of these scientific norms.

In this paper we will summarize the main contributions by examining on which topics the research on gatekeeping of science through SNA has focused most. The organization of the article is as follows: in Section 2, traditional gatekeeping literature from various fields including psychology, information science, and communications is introduced; in Section 3, it is reported an overview on the literature that has studied if the gatekeeping implemented or not the normative ethos of universalism and fairness in academic judgments; in Section 4, there will be shown the use that has been made of network analysis to the study of gatekeeping in science; finally, it will be presented a general and succinct outline of the essential SNA definitions (in Section 5) and techniques (in Section 6), in particular it will be shown the traditional centrality measures and methods for identifying cohesive subgroups.

1.2 The importance of being gatekeeper

The father of gatekeeping theory is Kurt Lewin (1943, 1947, 1951), who firstly coined the concept of gatekeeper and looked at gatekeepers through psychological lenses (Barzilai-Nahon 2009). Born in Poland in 1890 and raised in Berlin, Lewin was a pioneer of applied psychology in the United States (DeIuliis 2015). In his studies Lewin (1943) started by investigating the food habits of five groups of Americans by tracing back various channels of buying and gardening, baking and canning food. Researching how and why the food habits and activities of families differed, he noted that, in the groups he examined, housewives controlled the decision-making process related to food habits and activities by creating behavioural barriers and incentives; Lewin referred to these housewives as gatekeepers (Barzilai-Nahon 2009; Hoenig 2015). Lewin articulated his field theory in two articles published in the journal *Human Relations* in 1947. These papers, along with several other theoretical papers, were collected in 1951 and posthumously published as *Field Theory in Social Science*. In the first paper, Lewin developed the constructs of social fields and quasi-stationary equilibria. In the second, Lewin proposed "gatekeeping" as a way to examine how objective problems, such as the movement of goods and people, are affected by subjective states and cultural values. In this famous article, Lewin shifts his focus to the social channels that connect individuals to social fields, and the ways to make change at the level of not only a work team, but also society as a whole (DeIuliis 2015).

Since Lewin's use of the gatekeeper concept, inquiries of gatekeeping have been mostly spread in communication research and in science and technology studies, then it has been explored in various fields including political science, sociology, economics, management, and law. Moreover, it has been applied to practical domains such as journalism (e.g., understanding newspaper editors as gatekeepers), health science, operations research, and technology development (e.g., understanding consultants who provide a second opinion or function as intermediaries between clients and services). Each discipline and field emphasized different components in the conceptualization of gatekeeping (see Barzilai-Nahon 2009 for a critical review). In the *International Encyclopedia of the Social & Behavioral Sciences* it has been stated that «a gatekeeper is an individual or collective actor who is in a position to control access to resources and regulate the allocation of rewards relevant in a particular social system. These resources might take the form of money or information, of reputation or social capital» (Hoenig 2015: p. 618).

In sociology of science, the study of the gatekeeping phenomenon has as precursors De Grazia (1963) and Crane (1967) who referred to editors of journals as "the" gatekeepers of science. This expression indicates the role of editors in shaping the direction of scientific knowledge, through the selection of works worthy of publication. Then Robert K. Merton, the founding father of sociology of science, defined gatekeeping as one of four roles of scientists and scholars, along with teaching, research, and scientific administration (Zuckerman and Merton 1972). Gatekeeping is considered as «basic to the system of evaluation and the allocation of roles and resources in science» (Merton 1973: p. 521), and gatekeepers mostly operate through panels of peers. The gatekeeper of science is anyone who regulates «scientific manpower and the allocation of resources for research» (Zuckerman and Merton 1972: note 33, p. 316) and the role of a gatekeeper typically can take two forms: «providing or denying access to opportunities» (Merton 1973: p. 522).

In the procedures and outcomes of scientific knowledge production, the gatekeeping role is central as it contributes to the maintenance of scientific standards, evaluation, and quality assurance; it defines what counts as 'scientific' or not; it controls and regulates legitimate access to scientific institutions. In this sense, «gatekeeping has far reaching consequences on whether a particular person is allowed to continue research, be it on a particular topic or doing research at all» (Hoenig 2015: p. 618). The gatekeeper's role in science is connected to mentoring, publishing industry, research funding, career promotion, and it can be exercised by individual actors or institutions such as peer-review panels, funding organizations, scientific journals, state ministries, administrative elites (Hoenig 2015).

1.3 Universalism and fairness of the gatekeepers of science

Considering the institutional central role that gatekeepers play in the definition, evaluation and development of scientific knowledge, many studies have focused on searching possible particularistic biases in decision making to see if gatekeeping implemented or not the normative ethos of *universalism* in academic judgments (Merton 1942). Structurally seen, the gatekeeping role is crucial for understanding the operation of intellectual authority and the reproduction of social stratification and scientific elites (Cole and Cole 1973; Zuckerman 1977; Whitley et al. 2010). This kind of analysis has been conducted at an individual level, analysing the individual characteristics of gatekeepers or their institutional affiliations (Crane 1967), and at a meso- and macrolevel, considering the role that research foundations, state ministries, administrative elites, and employers' organizations have in shaping the research policy of a country, for instance, by setting up academic evaluation systems or funding regulations operative in a national research landscape (Whitley et al. 2010).

At an individual level, according to Merton (1973), the gatekeepers are clearly structured toward an older age bias, because scientists and scholars usually act as gatekeepers in later phases of their career, when they have a reputation as researcher already established or assumed. Moreover, women and 'minorities' are much scarcer as gatekeepers of science as they structurally encounter fewer opportunities to shape research policy issues. When the gatekeepers are predominantly men, women have difficulty gaining access to desirable academic positions (Husu 2004). The mechanism of homophily is often used to explain this outcome (Van den Brink and Benschop 2014). Homophily (i.e. love of the same) is the principle that communication and relationship formation between similar people occurs at a higher rate and is easier than contact among dissimilar people (McPherson et al. 2001). A related phenomenon is homosociality (Kanter 1977) – seeking, enjoying, and/or favouring the company of one's own gender – and the 'similar-to-me-effect' (Byrne 1971). The same mechanism applies to non-Anglophone authors considering that Anglo-American scholars dominate the gatekeeping positions (Schurr et al. 2010).

At an institutional level, many studies have been conducted on institutions such as peer-review panels, funding organizations, scientific journals, and career track systems that can take a gatekeeping central function in science. Cole (1992), studying the peer review process of the National Science Foundation (NSF, Arlington, VA, USA), showed that the evaluation of new work is influenced by a complex interaction between (i) universalistic factors, such as scientific merit, and (ii) scientific and non-scientific particularistic factors, such as gender. Based on these findings, Cole (1992) assumes that there is no way to objectively evaluate new scientific work. For this reason, typically, the concern is that gatekeepers can create inefficient or inequitable levels of homophily, conferring greater benefits to those with whom they share interests and affiliations (Krieger et al. 2021). Firstly, Crane (1967) has found empirical evidence that an author's academic affiliation, doctoral origin, and professional age happened to be rather similar to the distribution of those characteristics among journal editors, and these highly affect editorial decisions in the selection of journal articles. Then, many other studies evidenced a homophilic relationship between the demographics of the gatekeepers and authors and the outcome of peer review; that is, outcomes were more favourable for male authors and those affiliated with institutions in North America and Europe, and these groups were also over-represented among gatekeepers (see Murray et al. 2019 for a review). Another source of bias is what is called cognitive particularism, whereby scholars have preferences for work and ideas similar to their own (Travis and Collins 1991). These biases are reflected not only in the selection of journal articles, but also in a national research landscape, where specific groups can capture regulatory processes of academic evaluation systems or funding (Whitley et al. 2010).

For this reason, studies on evaluation of research and connected peer reviews have focused on the *procedural fairness*, which ≪is concerned with procedures used to arrive at those outcomes≫ (Beersma and De Breu 2003, page 220). It has been showed that overlap in competences is associated with better cooperation and with open conflict between scientific experts (Langfeldt 2002), and that groups with heterogeneous members with complementary skills take better group decisions than homogenous groups (Levi 2007). Consequently, different studies indicate as the first recommendations on how to stimulate open and thorough panel discussions resulting in fair and good quality outcomes to ≪compose panels in such a way that there is heterogeneity among panelists. A heterogeneous panel can be established, for example, by appointing men and women with different disciplinary and/or methodological backgrounds, with different specializations, from various institutions≫ (Van Arensbergen et al. 2014, page 11). The concept of procedural fairness consider that distribution of reward or punishment is only the final step in an allocative process. So, while the concept of *distributive fairness* restricts the analysis of perceived justice only to this last step, in the procedural fairness it is considered that people perceive fairness not solely in terms of the distribution of reward but also in terms of the social system which generates that distribution. In fact, as it has been pointed out (Baccini and Ricciardi 2012), the role of panelists is very similar to that of the members of a popular jury in a trial. In order to have a fair judgment by a panel of judges, it is necessary to designate a fair jury and therefore presumably less inclined to partiality.

In particular, it has been shown that juries that reflect the full range of community perspectives are in a position to incorporate these diverse views into their fact finding. Compared to homogeneous juries, diverse juries engage in more robust and vigorous deliberation (Sommers and Ellsworth 2003). The best-known and best-documented examples concern the need to balance popular juries from the point of view of ethnic groups because it is believed that a jury composed mainly of members of the same ethnic group tends to be favourable towards a defendant of the same group, and unfavourable to a defendant from a different ethnic group. For example, Sommers and Ellsworth (2003) in a mock jury experiment, comparing the deliberations of all-white and racially mixed juries, discovered that diverse jury deliberations were more accurate, more expansive, and longer. It was not simply that the minority jurors contributed new and different information, the white jurors acted differently in all-white versus mixed-race juries: they made fewer factual mistakes, and raised more issues and evidence, during the deliberation. Moreover, representative juries are more likely to be seen as legitimate decision makers, which in turn contributes to public confidence in the justice system. For all these reasons, ≪courts should ensure that jury selection procedures serve the goal of maximizing the representativeness of jury pools and civil juries≫ (Hans 2021, p.8). For the same reasons, in order to encourage the emergence of a fair judgment by the panelist, the designation of a balanced panel of evaluators is necessary (for a review of the literature see Chapter 2 of the thesis).

The fact that gatekeepers unevenly favour work and ideas, or reputation and reward is known as the 'Matthew effect' (Merton, 1968), whereby scholars accrue accumulative advantages via a priori status privileges, irrespectively of their actual achievements. Studying and limiting this effect is fundamental to respect the norm of 'Universalism' and 'Fairness' that are 'good' ways to ≪distribute rewards because they fit our general value system≫ (Cole, 1992: p. 203), and are required to have an evaluation of scientific achievements independent of individual attributes of any scientist (Merton, 1942). To investigate gatekeeping in science, Cole (1992) firstly suggested to analyse the informal network ties that can produce significant outcomes interpretable as 'Matthew effect' applying network analysis.

1.4 Network analysis applied to gatekeeping of science

The study of networks, in the form of mathematical graph theory, is one of the fundamental pillars of discrete mathematics. Euler's celebrated 1735 solution of the Konigsberg bridge problem is often cited as the first true proof in the theory of networks, and during the twentieth century graph theory has developed into a substantial body of knowledge (Newman 2003). Recent years, however, have witnessed a substantial new movement in network research, with the focus shifting away from the analysis of single small graphs and the properties of individual vertices or edges within such graphs to consideration of large-scale statistical properties of graphs (Newman 2003). This new approach has been driven largely by the availability of computers and communication networks that allow us to gather and analyse data on a scale far larger than previously possible.

Network analysis can be applied to different types of real-world networks that can be classified as: social networks, information networks, technological networks, and biological networks (Newman 2003). *Social networks* are the ones that arise as a result of human and social interactions, like for example friendship networks, informal communication networks within companies, collaboration networks. *Information networks* (also sometimes called 'knowledge networks') are based upon the exchange of information among entities usually aiming to enhance knowledge diffusion, business, or social aims, and they are for example networks of citations between academic papers, preference networks, the World Wide Web. *Technological networks* are man-made networks designed for distribution of some commodity or resource (e.g., electricity, information). Some examples are networks of roads and railways, networks of airline routes, and networks of physical connections between computers (Internet). *Biological networks* are those that arise from biological processes, such as networks of chemical reactions among metabolites, protein interaction networks, genetic regulatory networks, real neural networks.

Lately, network analysis has been considered crucial for the study of gatekeeping, both theoretically and empirically. Theoretically, in order to conceptualize the networked nature of information in the digital era, Barzilai-Nahon (2008) proposed a new framework: the Network Gatekeeping Theory (NGT). Her theory mainly focuses on networks created by technology (e.g., the Internet); however, the theory applies to other types of networks as well, such as social networks and information networks. Through NGT she had enlarged the traditional communication literature on gatekeeping that treats the process of gatekeeping predominantly as a selection mechanism that controls the information that can pass through a gate (Shoemaker 1991). Instead, Barzilai-Nahon (2009) developed the concept of network gatekeeping as a theoretical framework that emphasizes four perspectives: first, gatekeeping as an information control process not necessarily limited to one specific type of control (e.g., selection); second, networks as a crucial dimension in conceptualizing gatekeeping; third, identifying gatekeepers and gated, the entity subjected to a gatekeeping process, through their interactions with each other; and fourth, analysing the dynamism of gatekeepers and both the gated's status and position. In this way, she added complexity and dynamism to the concept of gatekeeping and to the relation between gated and gatekeepers, giving a central role to the study of gatekeeping through network analysis (Erzikova 2018).

Empirically, in the study of the gatekeeping of science, Newman (2001) used social network analysis (SNA) to investigate the macro and micro characteristics of large *co-authorship networks*. In its simplest form, a co-authorship network is formed if two authors (node) co-author an article together (edge), and this is considered a reliable proxy of the scientific collaboration network. Barabási et al. (2002) followed up Newman's work investigated the dynamics and evolution of co-authorship networks. Co-authorship networks have since been studied extensively in various ways uncovering certain aspects of the network, such as how fragmented or cohesive the knowledge community is or who are the best connected authors in that network (see Kumar 2015 for a review). Baccini (2009), instead, used SNA to study the structural properties of the network generated by the editorial activities. In particular, he studied the networks generated by *interlocking editorship*, in which the nodes of the network are the journals and a link (edge) between a pair of journals is generated by the presence of a common editor on the board. The number of editorial board members that two journals share can be viewed as an indicator of journal similarity, and the interlocking editorship approach measures journal proximity based on common editorial board membership. Since then, editorial boards have been highly explored with SNA techniques revealing insights in networks of journal clusters within a given field or research area and in the structure of editorial gatekeeping as well (Baccini et al. 2009; Cronin 2009; Baccini and Barabesi 2010; Ni and Ding 2010) (for a review of the literature see Chapter 3 of the thesis).

Considering the growing interest in SNA and its ability to analyse the gatekeeping phenomenon (and many others), we provide in the following paragraph a general and succinct overview of the essential SNA definitions and techniques.

1.5 Essential definitions of Social Network Analysis (SNA)

Social network analysis (SNA) origin can be traced back to Moreno (1934), a psychiatrist who developed the sociometric approach as a way to conceptualize the structure of the social relations established among small groups of individuals (Freeman 2004). As Moreno (1934: p. 10–11) described it, sociometry was based on an ≪experimental technique [..] obtained by application of quantitative methods [..] which inquire into the evolution and organization of groups and the position of individuals within them≫. The focus of SNA is on the relationships established between social entities rather in the social entities themselves. Therefore, the individual is not the basic social unit, but it is the structure of interpersonal ties. Social network analysts assume that interpersonal ties matter, as do ties among organizations or countries, because they transmit behaviour, attitudes, information, or goods (De Nooy et al. 2018). In fact, the main goal of this technique is to examine both the contents and patterns of relationships in social networks, in order to understand the relations among actors and the implications of these relationships (Oliveira and Gama 2012).

Typical social network studies address issues of centrality (which individuals are best connected to others or have most influence) and connectivity (whether and how individuals are connected to one another through the network). Recently, an impressive advance in social network studies was determined by two relevant reasons: the growing availability of large volumes of relational data, and the intuition that an individual's connections can yield richer information than his/her isolate attributes (Oliveira and Gama 2012). Common tasks of today SNA involve the identification of the most influential, prestigious, or central actors, using statistical measures; the identification of hubs and authorities, using link analysis algorithms, and the discovery of communities, using community detection techniques (Oliveira and Gama 2012). At the heart of SNA there are some key concepts of network analysis that are fundamental to the discussion, we will report below the principal.

In its simplest definition, ≪a *network* is a set of items, which we will call vertices or sometimes nodes, with connections between them, called edges≫ (Newman 2003: p.168). Vertices represent a wide variety of individual entities (e.g., people, organizations, countries, papers, products, plants, and animals) according to the application field. An edge is the line that connects two vertices and, analogously, it can represent numerous kinds of relationships between individual entities (e.g., communication, cooperation, friendship, kinship, acquaintances, and trade). The structure of such networks is usually represented by graphs (Figure 1.1). Therefore, networks are often regarded as equivalent to graphs.

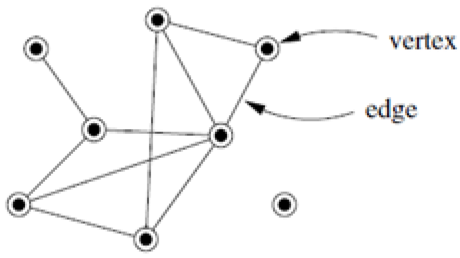


Figure 1.1 A small example network with eight vertices and ten edges (Newman 2003)

Formally, a graph G consists of a nonempty set $V(G)$ of vertices and a set $E(G)$ of edges, being define as $G = (V(G), E(G))$. According to Diestel (2005), the *order* of a graph G is given by the total number of vertices n or, mathematically, $|V(G)| = n$. Analogously, the *size* of a graph G is the total number of edges $|E(G)| = m$.

Two main types of graph-theoretic data structures are referred to represent graphs: the first one are *list structures* and the second are *matrix structures*. List structures are incidence lists and adjacency lists. Matrix structures can be incidence matrices, adjacency matrices or sociomatrices, Laplacian matrices or distance matrices (Oliveira and Gama 2012).

There are many ways in which networks may be more complex (Figure 1.2). For instance, there may be more than one different type of vertex in a network, or more than one different type of edge. Vertices or edges may have a variety of properties, numerical or otherwise, associated with them. They can carry weights, or an edge can connect a vertex to itself (namely a *loop*), it can also be directed, pointing in only one direction.

Networks can thus be classified in different ways. Firstly, they can be classified according to the direction of their links which leads to the differentiation between *undirected* and *directed* graphs (or networks). A graph is directed if all of its edges are directed. Directed edges, which are sometimes called *arcs*, have an orientation assigned, so the order of the vertices they link matters. Undirected networks are graphs whose edges connect unordered pairs of vertices.

Regarding the values assigned to edges, we can make a distinction between *unweighted* and *weighted* graphs. Unweighted graphs are binary since edges are either present or absent. On the other hand, weighted graphs are richer graphs because each edge has associated a weight providing the user with more information about, for instance, the strength of the connection of the pair of vertices it joins, describing typically a measure of the 'intensity' of the interaction (Oliveira and Gama 2012).

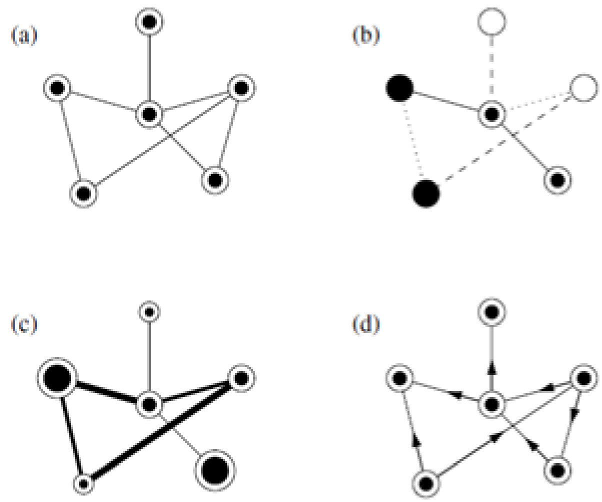
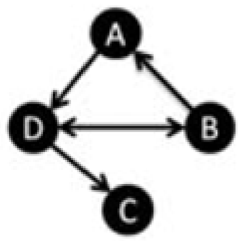


Figure 1.2 Examples of various types of networks: (a) an undirected network with only a single type of vertex and a single type of edge; (b) a network with a number of discrete vertex and edge types; (c) a network with varying vertex and edge weights; (d) a directed network in which each edge has a direction. (Newman 2003)

For undirected and unweighted graphs, adjacency matrices are binary (as a consequence of being unweighted) and symmetric (as a consequence of being undirected, meaning that $a_{\mathrm{ij}} = a_{\mathrm{ji}}$, with $a_{\mathrm{ij}} = 1$ representing the presence of an edge between vertices i and j, and $a_{\mathrm{ji}} = 0$ representing the absence of an edge between vertex pair (i, j)). For directed and weighted graphs, the entries of such matrices take values from interval $[0,\ max(w)]$ and are nonsymmetric. For undirected and weighted graphs, matrices take values from interval $[0,\ max(w)]$ and symmetric. For directed and unweighted graphs, matrices are binary and are nonsymmetric. In any case, we deal with nonnegative matrices. In Figure 1.3, it is represented an example of how a graph can be represented by an edge list and by an adjacency matrix.

Vertex	A	B	C	D
A	-	0	0	1
B	1	-	0	1
C	0	0	-	0
D	0	1	1	-



Vertex	Vertex
A	D
B	A
B	D
D	B
D	C

Figure 1.3 An example of directed graph represented by means of an adjacency matrix (left-hand side of the figure) and an adjacency list (right-hand side of the figure) (Oliveira and Gama 2012).

Moreover, we can classify networks considering the number of modes in the network. The mode of a network is the number of sets of entities on which structural variables are measured (Wasserman and Faust 1994). Commonly, there are two sets, which are called *actors* and *events*, for example, scholars (actors) and publications (events), thus we have that *one-mode networks* study just a single set of actors, while *two-mode networks* focus on two sets of actors, or one set of actors and one set of events. In other words, in a one-mode network, each vertex is part of the same set and can be related to every other vertex. In a two-mode network, vertices are divided into two sets and vertices can be related only to vertices in the other set (De Nooy et al. 2018). Two-mode networks can be analysed as two-mode networks or projected to one-mode networks. In the example below (Figure 1.4), the two-mode collaboration network can be transformed into a network of relationships between people (based on co-authoring one or more papers, shown in the upper right of the figure), or a network of relationships between the papers they wrote (based on common authors, shown in the lower right of the figure).

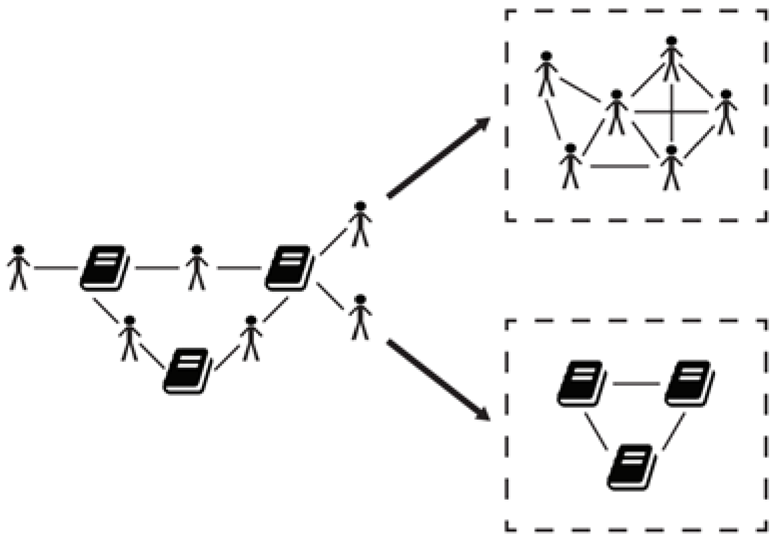


Figure 1.4 Transformation of a two-mode network (left) to a one-mode co-authorship network of people (upper right) and of papers (lower right) (Sheble et al. 2016).

1.6 Some techniques of Social Network Analysis (SNA)

SNA is not only focused on the graphical representation of social networks but uses different techniques to get insights about the structure of the network, to identify the most influential, prestigious, or central actors, and to detect communities. We report here some of these useful techniques, especially those used in the analysis of gatekeeping and those that have been used in the following Chapters of the thesis.

Often the first step is to study the network as a whole. *Density* is an important network-level measure, which is able to explain the general level of connectedness in a network. It is given by the proportion of edges in the network relative to the maximum possible number of edges, as defined in Eq.(1). Density is a quantity that goes from a minimum of 0, when a network has no edges at all, to a maximum of 1, when the network is perfectly connected (also called complete graph or clique). Therefore, high values of density are associated to dense networks, and low values of density are associated to sparse networks:

$$\rho(G) = \frac{m(G)}{m_{max}(G)}, \qquad 0 < \rho < 1 \tag{1}$$

where m is the number of edges in the network and $m_{\max}$ denotes the number of possible edges (Oliveira and Gama 2012). For undirected networks, the number of possible edges is $\binom{n}{2} = \frac{n(n-1)}{2}$, thus the density is given in Eq.(2):

$$\rho(G) = \frac{m}{\binom{n}{2}} = \frac{2m}{n(n-1)}. \tag{2}$$

1.6.1 Centrality and centralization measures

One of the primary uses of SNA is the identification of the 'most important' or 'central' actors in a social network (Wasserman and Faust 1994). As far back as Moreno (1934), researchers have attempted to quantify the notions of sociometric 'stars' and 'isolates'. The reason behind is quite forward: central actors, also called 'focal points', are associated to powerful actors in the network because their central position offers them several advantages, such as easier and quicker access to other actors in the network (useful for accessing resources such as information) and ability of exerting control over the flow between the other actors (Oliveira and Gama 2012). The most common statistical measures of centrality are degree, betweenness and closeness proposed by Freeman (1979), then there is also eigenvector centrality proposed by Bonacich (1987). These measures can be applied to measure the *centrality* of individual vertices or the *centralization* of networks, and they will give us different information.

Degree centrality is based on the idea that central actors must be the ones that have the most ties to other actors in the network. Thus, degree centrality of a vertex is its degree. The degree of a vector is computed as the number of edges incident on a given node, for undirected networks:

$$\kappa_i = \sum_{j=1}^{n} a_{ij}, \qquad 0 < \kappa_i < n \tag{3}$$

where a_{ij} is the entry of the ith row and jth column of the adjacency matrix **A** (Oliveira and Gama 2012). *Degree centralization* of a network is the variation in the degrees of vertices divided by the maximum degree variation that is possible in a network of the same size (De Nooy et al.2018). This index reaches its maximum value of 1 when one actor is connected to all other actors, and the other actors interact only with this one, central actor. This is exactly the situation in a star graph (Figure 1.5). The index attains its minimum value of 0 when all degrees are equal. This is exactly the situation realized in the circle graph (Figure 1.5). Graphs that are intermediate to these two have indices between 0 and 1, indicating varying amounts degree centralization (Wasserman and Faust 1994).

Betweenness centrality lies on the consideration that interactions between two non-adjacent actors might depend on other actors who lies on the paths between the two. This 'actor in the middle', the one between the others, has some control over the interactions between the two nonadjacent actors. This means that the centrality of a person depends on the extent to which he or she is needed as a link within the network (Wasserman and Faust 1994). The betweenness of a node measures the extent to which a node lies between other nodes in the network and can be computed using the formula presented in Eq.(4):

$$b_\nu = \sum_{s,t \in V(G) \setminus \nu} \frac{\sigma_{st}(\nu)}{\sigma_{st}}, \tag{4}$$

where σ_{st} denotes the number of shortest paths (namely called *geodesics*) between vertices s and t (usually $= 1$) and $\sigma_{\mathrm{st}}(\nu)$ expresses the number of shortest paths passing through node ν (Oliveira and Gama 2012). By definition, a *path* is a sequence of nodes in which consecutive pairs of nonrepeating nodes are linked by an edge. The *geodesic* distance, or *shortest path*, between nodes i and j, denoted as $d(i, j)$ can be defined as the length of the shortest path, or the minimal path, between nodes i and j (Oliveira and Gama 2012). *Betweenness centralization* is the variation in the betweenness centrality of vertices divided by the maximum variation in betweenness centrality scores possible in a network of the same size (De Nooy et al. 2018). The centre of a star-network (node n_1 in a, Figure 1.4) has maximum betweenness centrality and all other vertices have minimum betweenness centrality (0) because they are not located between other vertices. The centrality scores of vertices in a star graph have maximum variation, so the betweenness centralization of the star is maximal (1), because removing its central node all connections are destroyed. In the line graph (c in Figure 1.5), removal of a vertex may also break the flow of information, but parts of the chain remain intact. Therefore, centrality indices vary less than in the star-network, and betweenness centralization is lower (De Nooy et al. 2018).

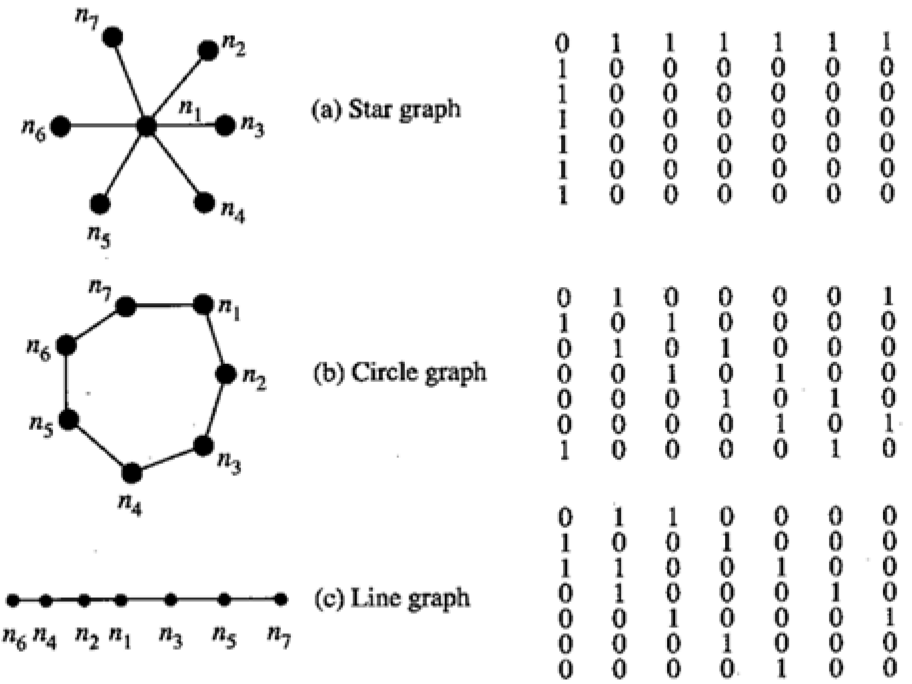


Figure 1.5 Three illustrative networks for the study of centrality (Wasserman and Faust 1994).

Closeness centrality focuses on how close a node is to all the other node in the set of nodes. The idea is that an actor is central if it can quickly interact with all others. Centrality is therefore inversely related to distance and central nodes in a network have 'minimum steps' when relating to all other nodes (Wasserman and Faust 1994). Formally, it is the mean length of all shortest paths from one node to all other nodes in the network and this measure is computed using the formula presented in Eq.(5) (Oliveira and Gama 2012):

$$Cl_\nu = \frac{n-1}{\sum_{u \in V(G)\setminus\nu} d(u,\nu)}. \tag{5}$$

Closeness centralization is the variation in the closeness centrality of vertices divided by the maximum variation in closeness centrality scores possible in a network of the same size (De Nooy et al. 2018). In star-network (node n_1 in a, Figure 1.4), vertex n_1 has maximum closeness centrality because it is directly linked to all other vertices (1). The other vertices of network a have a closeness centrality score that is considerably lower (0.545). For the circle graph, the actor indices are all equal to 0.5. For the line graph, the indices vary from 0.50 to a low of 0.286. Because the variation of closeness centrality scores in network b is less than in network a and c, network b is less centralized and network a is more centralized (Wasserman and Faust 1994). Note if an undirected network is not connected, there are no paths between all vertices, so it is impossible to compute the distances between some vertices, so we cannot use closeness measures.

Eigenvector Centrality is a relative measure that assumes that not all connections have the same importance by taking into account not only the quantity, but especially the quality of these connections. The idea is that a person is more central if he or she has more contacts that are more central. It therefore measures how well a given actor is connected to other well-connected actors. This score is given by the first eigenvector of the adjacency matrix we can say that the centrality of a given node i is proportional to the sum of the centralities of i's neighbors. This is the assumption behind the eigenvector centrality formula, which is as follows in Eq.(6):

$$x_i \frac{1}{\lambda} \sum_{j=1}^{n} a_{ij} x_j, \tag{6}$$

where $x_i \setminus x_j$ denotes the centrality of node $i \setminus j$, a_{ij} represents an entry of the adjacency matrix $\mathbf{A}$ ($a_{\mathrm{ij}} = 1$ if nodes i and j are connected by an edge and $a_{\mathrm{ij}} = 0$ otherwise) and λ denotes the largest eigenvalue of $\mathbf{A}$. *Eigenvector centralization* is the variation in the eigenvector centrality of vertices divided by the maximum variation in eigenvector centrality scores possible in a network of the same size.

1.6.2 Cohesive subgroups detection

Another major concern of SNA is the identification of cohesive subgroups of actors within a network. *Cohesive subgroups* are subsets of actors among whom there are relatively strong, direct, intense, frequent or positive ties (Wasserman and Faust 1994). These methods attempt to formalize the intuitive and theoretical notion of *social group* and to study the emergence of consensus among members of a group. It is expected that similar people interact a lot, at least more often than with dissimilar people, so people who interact intensively are likely to consider themselves a social group. Consequently, according to this idea, one expects greater *homogeneity* among persons who have relatively frequent face-to-face contact or who are connected through intermediaries, and less homogeneity among persons who have less frequent contact (Friedkin 1984). Cohesive subgroups can be formalized by looking at many different properties of the ties among subsets of actors. In this paragraph we discuss some methods for finding cohesive subgroups within a social network based on the ways in which vertices are interconnected. This property usually arises as a consequence of both global and local heterogeneity of edges distribution in a graph. Thus, we often find high concentrations of edges within certain regions of the graph, called *communities* or *modules* or *clusters*, and low concentration of edges between those regions. These techniques are useful also to detect *central actors* among subgroup members and *intermediate actors* between communities.

The first consideration to do is that sometimes the network is not entirely connected, but it can be cut up in pieces. Isolated sections of the network may be regarded as cohesive subgroups because the vertices within a section are connected, whereas vertices in different sections are not (De Nooy et al. 2018). Intuitively, a graph is connected if there is a path between every pair of nodes in the graph. The connected subgraphs in a graph are called components, so if there is only one component in a graph, the graph is connected, while if there is more than one component, the graph is disconnected. Formally, a *component* of a graph is a maximal connected subgraph. In an undirected network, there is only one type of connectedness and one type of component. In a directed network, we can have strong connection and strong components, if you can travel from each vertex to any other vertex obeying the direction of the arcs (so called *path*), or weak connection and weak components, which is equivalent to connectedness in undirected networks, if we can walk from each vertex to all other vertices if we neglect the direction of the arcs (so called *semipath*). In Figure 1.6, we have two simple networks: the one in Figure 1.6a is connected, since there is a path between each pair of nodes; the other one in Figure 1.6b is not connected, since there is no path between n_1 and n_2. In Figure 1.6b, the nodes can be partitioned into subsets $N_1 = \{n_1 , n_6 , n_5\}$ and $N_2 = \{n_2 , n_3, n_4\}$. The subnetworks generated by the different sets, N_1, and N_2 are the components of the network, so the network in Figure 1.6b has two components.

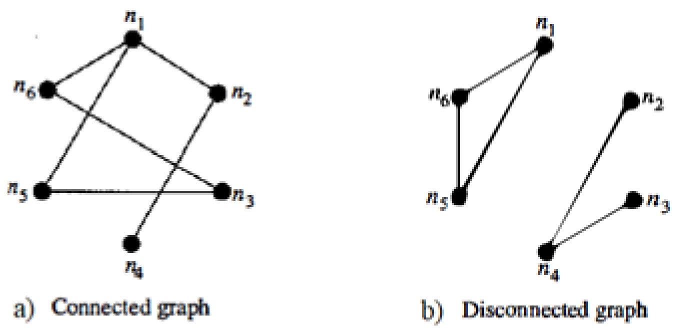


Figure 1.6 A connected graph and a unconnected graph with two components (Wasserman and Faust 1994).

Sometimes, when we analyse components, we get rather dense subnetworks that can be broken down into smaller communities, as we can see in Figure 1.7. In order to do so, different techniques use *line multiplicity*: multiple lines are considered important because the larger the number of interlocks between two actors, the stronger or more cohesive their tie, the more similar or interdependent they are (De Nooy et al. 2018).

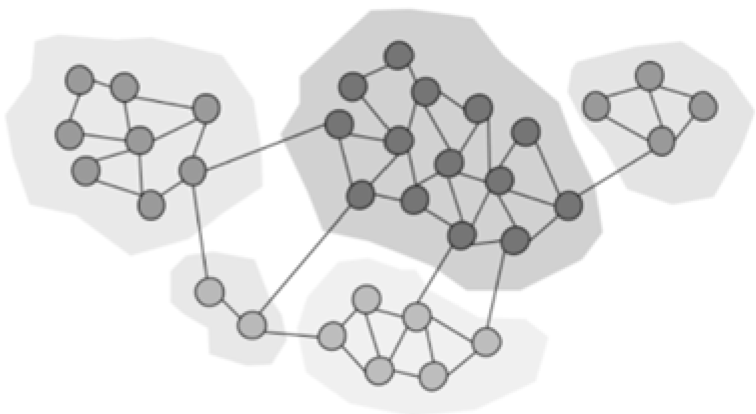


Figure 1.7 Five different communities in a network (Jayawickrama 2021).

One of these techniques is *island*, a subnetwork defined by the multiplicity or value of lines. An island is a maximal subnetwork of vertices connected directly or indirectly by lines with a value greater than the lines to vertices outside the subnetwork. An island can be thought of as a local summit in the network if we use the highest value of the lines incident with this vertex as its height (De Nooy et al. 2018). Another community detection technique, conceptually very different, is the *Louvain Method*, that searches for the partition of vertices into communities with the highest value of modularity.

Modularity is a measure that compares the density of lines and their line values inside and outside clusters, considering that the density of lines inside clusters is larger than the density of lines between clusters. The main difference of these two methods is that, in islands, it is actually used an edge-cut technique: an island is a set of nodes joined by lines with a defined minimum value and several vertices are not assigned to islands (they are in cluster 0 of the islands partition). While, through modularity, vertices are always assigned to a community with relatively dense connections (De Nooy et al. 2018).

It is also possible to compare the partitions that result from different methods for searching communities through statistical indices of association that can tell us how strong the association is. Indices range from 0 to 1, and as a rule of thumb we may say that values between 0 and 0,05 mean that there is no association, values between 0,05 and 0,25 indicate a weak association, values from 0,25 to 0,60 indicate a moderate association, and values higher than 0,60 indicate a strong association. For example, there are Cramer's V, Rajski's information index, and Adjusted Rand Index. *Cramer's V* measures the statistical dependence between two classifications. It is not very reliable if the cross-tabulation contains many cells that are (nearly) empty. *Rajski's indices* measure the degree to which the information in one classification is preserved in the other classification. The *Adjusted Rand Index* (ARI) is another index of the similarity between two partitions. Its values range from a minimum of 0 (independent partitions - no association) to maximum of 1 (identical partitions - maximum association) (De Nooy et al. 2018).

1.7 Concluding remarks

The growing availability of large volumes of relational data and of faster and more effective data processors, connected to the intuition that an individual's connections can yield richer information than his/her isolate attributes has increased in general the popularity of SNA. Moreover, SNA has been considered a correct way to detect gatekeepers of science and to study those characteristics that can produce significant outcomes interpretable as 'Matthew effect' (e.g., the fact that there is unevenly favour of work and ideas, or reputation and reward) (Cole 1992).

In this paper we have summarized the main contributions by examining on which topics the research on gatekeeping of science through SNA has focused most. As we have seen, also thanks to the technological advances and consequent impact in the availability of networked data, new discoveries have been done in the topic both theoretically and empirically. Moreover, since there is a lot of interest in SNA, we have provided a general and succinct outline of the essential SNA definitions and techniques that can be useful to anyone who is interested in applying network analysis in professional or academic problems.

The current trends arising on the investigation on gatekeeping of science through SNA lead to test the results we have briefly reported here into large-scale social networks and to study the dynamics and evolution of social networks detecting and understanding temporal and spatial changes in these networks.

CHAPTER 2

Is the panel fair? A network analysis of the composition of the Economics panels in the Italian research assessment exercises

Abstract

One of the pillars of the national research assessment exercises is the fairness of the composition of panels charged to evaluate submitted research products. If the composition of panels is unfair, there is the risk of a lack of diversified points of view. This may introduce biases in favour of some research programmes, methodological approaches or groups of scholars. The question of fairness is particularly delicate in discipline such as economics, characterized by the coexistence of many schools of thought with different approaches, methodologies and policy recipes. This paper investigates the fairness of the composition of the panels appointed to evaluate research in economics and statistics during the Italian research assessment exercises, considering its internationally relevant example. The panels of three evaluation exercises are considered for the years 2004-2010, 2011-2014, 2015-2019. The first two panels were appointed directly by the member of the governmental agency for the evaluation of university and research (ANVUR); the third was instead selected randomly by a lot from among those who had applied to be panelists. This permits to consider the third panel as a control group. For investigating the fairness of the panels, a network analysis approach is adopted by comparing the co-authorship networks, the networks of journals in which panelists have published and the network of universities, research centres and newspapers that connect them. The results show that the members of the first two panels had connections in terms of co-authorship, affiliation, and cultural approaches much higher than the members of the control group. We conclude that the fairness of composition of panels was not guaranteed for the first two panels, that a particular group connected to the Bocconi University was over-represented, and hence that the results of the Italian research assessments in Economics from 2004 to 2014 should be considered as possibly unfair.

2.1 Introduction

One of the central themes on university and research policies is the question of evaluation. In fact, since 1980s we have seen the emergence and spread of evaluations of research programmes, research institutions and research fields/disciplines in most OECD countries (Langfeldt 2004). Evaluation has become a major aspect of the scientific knowledge-making process, so much that it has taken ≪the function of gatekeeping, filtering, and legitimating≫ it (Lamont and Huutoniemi 2011, p.209). In particular, for gatekeeper it is meant ≪an individual or collective actor who is in a position to control access to resources and regulate the allocation of rewards relevant in a particular social system. These resources might take the form of money or information, of reputation or social capital≫ (Hoenig 2015: p.618). Thus, the notion of *gatekeeper of science* includes not only the editors of journals (De Grazia 1963, Crane 1967), but anyone who regulates ≪scientific manpower and the allocation of resources for research≫ (Merton 1972, note 33, p.316). Among these gatekeepers of science, we can also find research foundations, state ministries, administrative elites, and employers' organizations that can shape the research policy of a country, for instance, by setting up academic evaluation systems or funding regulations operative in a national research landscape (Whitley et al. 2010).

Considering the risk that specific groups can capture regulatory processes of scientific evaluation systems which are usually conducted through the practices of peer review panels (Whitley et al. 2010), many scholars focused on the fact that non-scientific characteristics, like sex, age, and affiliation of the author, may affect evaluation practices. A particular attention has been given to the *ex-ante research evaluation,* which is referred to the evaluation of journals and to funds distribution process (Cole 1992; Cole and Cole 1981; Cole, Rubin, and Cole 1979; Lamont and Huutoniemi 2011), while fewer studies have been done on the *ex-post research evaluation,* which is referred to national research assessments such us the ones applied in United Kingdom and Italy (Harley and Lee 1997; Lee 2006; Lee et al. 2013; Baccini 2011, 2013, 2014, 2016; Baccini and Ricciardi 2012; Corsi et al. 2010, 2011).

In this second case, a particular focus has been given to those discipline with contested knowledge and where there are different methodological approaches/schools of thought. One of these cases is Economics, a discipline that has also an important impact on policymaking. In particular, it has been investigated the effect of research evaluation assessments in this field, usually based on the identification of quality with citation impact, showing how it tend to create or reinforce the normative standard, reinforcing the pre-existing journals' rankings and more in general the discipline's hierarchy, harming or gradually eliminating the so-called heterodox or non-mainstream economists (see Corsi et al. 2019 for a review of the literature). Pioneering in these studies has been Frederic S. Lee, who analysed and hardly criticised the research evaluation assessments in UK, the RAE (Harley and Lee 1997; Lee 2006; Lee et al. 2013). He stated that RAE was one of the main reasons of the rapid paradigmatic homogenisation of economics that took place in the decade from 1992, the continued rise to dominance of a select group of departments, the promotion of only a single paradigmatic view and the elimination of dissenting voices. And that this process was connected to the necessity ≪to achieve a discipline-desired outcome that was (and is) compatible with the Government's pro-market ideological agenda≫ (Lee 2006, p.14). This was possible because the RAE created a panel of paradigmatic homogeneous experts ≪controlled by mainstream economists, and they have used it to support particular neoclassical research over heterodox research and promote neoclassical departments over more pluralistic ones≫ (Lee 2006, p.15).

For the Italian case, the analysis of the research evaluation assessments has been considered as an internationally relevant example on how it can disregard heterodox schools and historical methods in favour of mainstream approaches and quantitative methods (Corsi et al 2010, 2011). Even this process was indicated as connected to a cultural and political change from the Keynesian to the Ordoliberal ideology (Re 2019). It has also been highlighted the unrespect for fairness in the composition of the members selected for evaluation, which homogeneity could have probably minimized the voices of dissent with respect to the evaluation methods and rules adopted (Baccini 2011, 2013, 2014, 2016; Baccini and Ricciardi 2012).

In the present paper we are going to extend this analysis and we are going to study if it was respected or not the *procedural fairness* of the composition of the panels appointed to evaluate research in Economics during the Italian research assessment exercises. The panels of three evaluation exercises are considered for the years 2004-2010, 2011-2014, 2015-2019. As we will see later in detail, the first two panels were appointed directly by the member of the governmental agency for the evaluation of university and research (ANVUR), while the third was instead selected randomly by a lot from among those who had applied to be panelists, and this allows us to consider the third panel as a control group (Gillies 2014). For investigating the fairness of the panels, a network analysis approach is adopted by comparing the co-authorship networks, the networks of journals in which panelists have published, and the networks of universities, research centres and newspapers that connect them. The organization of the article is as follows: in Section 2, it is reported a literature review of the study on procedural fairness; in Section 3, it is described the history of VQR and of the GEVs member selection method; in Section 4, it is presented the dataset and the methodology; then there are reported the results of the analysis of co-authorship networks (in Section 5), of the networks of journals (in Section 6), and of the 'affinity' networks (in Section 7).

2.2 The definition of procedural fairness

It has been shown that some of the perverse effects of peer review, such as cronyism, the pursuit of self-interest, and cognitive particularism, may be influenced by the way panels are set up (Lamont and Huutoniemi 2011). In fact, numerous scholars have pointed out both potential and observed risks in the peer review system. It is argued that the system is conservative and suppresses innovative research. Effects such as nepotism and old-boyism in peer review are seen to hinder pioneering research (Chubin and Hackett 1990; Roy 1985), while ≪cognitive particularism≫, ≪favoritism for the familiar≫ and ≪scholarly bias≫ support the school viewpoint or research topic the reviewers themselves are conducting (see, e.g., Porter and Rossini 1985; Travis and Collins 1991; Langfeldt 2004). Another influence involves relations with panelists: Wennerås and Wold (1997) found that higher competence scores are given to applicants who are affiliated with a panelist than to applicants without such ties. Moreover, another possible group effect is groupthink, which refers to ≪a deterioration of mental efficiency, reality testing, and moral judgement that results from in-group pressures≫ (Janis, 1982, p.9). Loyalty to the group ≪requires each member to avoid raising controversial issues, questioning weak arguments, or calling a halt to soft-headed thinking≫ (Janis, 1982, p.12). Finally, according to Van den Brink (2009), in the Netherlands, more women in appointment committees led to higher numbers of women being appointed as full professor. This indicates preferences for same-sex candidates.

As a solution to these problems, some studies (Bell 1992; GAO 1994; Roy 1985) focused on the fairness of the peer review process showing that a unified and fair process of evaluating knowledge can be put in place once particularistic considerations are eliminated. Lamont and Huutoniemi (2011), instead claimed that extracognitive factors do not corrupt the evaluation process but are intrinsic to it and that the ≪fairness of the process is not undermined by nonrational features but is created through intersubjective rules that evaluators follow to distinguish between legitimate and illegitimate behavior≫. For this reason, studies on evaluation and peer reviews focused on the *procedural fairness*, which ≪is concerned with procedures used to arrive at those outcomes≫ (Beersma and De Breu 2003, p.220). In particular, it has been showed that overlap in competences is associated with better cooperation and with open conflict between scientific experts (Langfeldt 2002), and that groups with heterogeneous members with complementary skills take better group decisions than homogenous groups (Levi 2007). For this reason, different studies indicate as the first recommendations on how to stimulate open and thorough panel discussions resulting in fair and good quality outcomes to ≪compose panels in such a way that there is heterogeneity among panelists. A heterogeneous panel can be established, for example, by appointing men and women with different disciplinary and/or methodological backgrounds, with different specializations, from various institutions≫ (Van Arensbergen et al. 2014, p.11).

Thus, in order to indicate whether a valuation exercise is fair or not, great attention must be paid to the process that led to that evaluation. We are thus going to focus on procedural fairness, which should be ≪concerned with procedures used to arrive at [fair] outcomes≫ (Beersma and De Breu 2003, p.220) and not to the allocative results. This analysis is connected to the fact that it has been showed that ≪an individual evaluates not only distributions of reward, but also the mechanisms in the social system that generate those distributions. [..] The fairness of such practices is evaluated with procedural rules which dictate criteria that allocative procedures must satisfy to be fair. For example, fairness may be judged in terms of a procedure's consistency over time and across persons; its accuracy and prevention of personal bias; or its representativeness of the values, interests, and outlook of important subgroups in the population of persons affected by the allocative process≫ (Leventhal 1980, p.54). The concept of procedural fairness allows us to consider that distribution of reward or punishment is only the final step in an allocative process. So, while the concept of *distributive fairness* restricts the analysis of perceived justice only to this last step, in the *procedural fairness* it is considered that people perceive fairness not solely in terms of the distribution of reward but also in terms of the social system which generates that distribution. From all the different factors that have been indicated by Leventhal (1980) to make a distributive process fair, we are going to focus on the *fair representation* of all affected parties involved in the decision-making process.

In our study case, this means to focus on the fairness of the members selection panels called to evaluate research, which should have been selected considering not only their expertise but has also the fair representation of the diversity of the research community. In fact, as it has been pointed out (Baccini and Ricciardi 2012), the role of panelists is very similar to that of the members of a popular jury in a trial. In order to have a fair judgment by a panel of judges, it is necessary to designate a fair jury and therefore presumably less inclined to partiality. The rules of the United States *Jury Selection Service Act*, for example, state that the jury must be appointed by selecting ≪at random from a fair cross-section of the community≫. The fair composition of the popular jury aims to ensure fairness of the judgment. ≪Achieving representative cross-sections of the community in jury venires, and ensuring that our civil juries reflect the community as well, are essential components contributing to the fairness and legitimacy of our civil justice system [..] and the representativeness of juries is not merely an aspiration but a guarantee under state and federal constitutions and statutes≫ (Hans 2021, p.1).

In particular, it has been shown that juries that reflect the full range of community perspectives are in a position to incorporate these diverse views into their fact finding. Compared to homogeneous juries, diverse juries engage in more robust and vigorous deliberation (Sommers and Ellsworth 2003). The best-known and best-documented examples concern the need to balance popular juries from the point of view of ethnic groups because it is believed that a jury composed mainly of members of the same ethnic group tends to be favourable towards a defendant of the same group, and unfavourable to a defendant from a different ethnic group. For example, Sommers (2003) in a mock jury experiment, comparing the deliberations of all-white and racially mixed juries, discovered that diverse jury deliberations were more accurate, more expansive, and longer. It was not simply that the minority jurors contributed new and different information, the white jurors acted differently in all-white versus mixed-race juries: they made fewer factual mistakes, and raised more issues and evidence, during the deliberation. Moreover, representative juries are more likely to be seen as legitimate decision makers, which in turn contributes to public confidence in the justice system. For all these reasons, ≪courts should ensure that jury selection procedures serve the goal of maximizing the representativeness of jury pools and civil juries≫ (Hans 2021, p.8).

The recommendation for a fair representation of all affected parties involved in the decision-making process has been formally taken by the research evaluation assessments in UK, that is the international standard for this kind of evaluation. It was stated that the selection of panelist has to ensure that ≪the overall body of members reflects the diversity of the research community, including in terms of age, gender, ethnic origin, scope and focus of their home institution, and geographical location which represents the international reference on the subject≫ (REF 2010). Even the European Peer Review Guide of the European Science Foundation suggests that ≪the goal should be to ensure availability of diverse viewpoints, scientific perspectives and scholarly thinking≫ and that the criteria to be adopted for the selection of experts must also be the 'diversity' that is expressed in terms of ≪gender balance, scholarly thinking, background, geography, turnover≫ (ESF 2011).

As we will see in more detail in the next paragraph, in the Italian case, it was established among other things: for the GEV 2004-2010 to ≪cover all the cultural and research lines within the areas≫ and a ≪fair distribution of affiliations and geography≫; for the GEV 2010-2014 the ≪coverage of the scientific-disciplinary sectors≫, ≪a fair distribution of affiliations≫ and a ≪fair geographical distribution of Italian candidates≫; for the 2015-2019 GEV, on the other hand, no indication was given in this regard. Thus, the request for procedural fairness and in particular of a fair representation of panelists is something that was formally requested also by the Italian law. In our study we are going to see if this request was substantially respected or not.

2.3 History of VQR and of the GEVs member selection method

The Italian research evaluation assessments is something almost unique, and yet at the same time is an internationally relevant example on the effect that research evaluation has on the scientific knowledge-making process. Historically, the first university research evaluation exercise was conducted by the University Grants Committee (predecessor of the current UK Research and Innovation (UKRI)), with the aim of selectively targeting university funding in a period of economic hardship. The practice was first adopted by the British government of Margaret Thatcher who conducted the first RAE (Research Assessment Exercise) in 1986 (Benedetto 2012; Baccini 2014). Inspired by that model, Italy carried out the first three-year research evaluation exercise (VTR) 15 years later (Baccini 2013) and until now it has organized four different evaluation exercises, three of which mandatory. With Ministerial Decree (DM) 2206 of 16 December 2003, the first national exercise on a voluntary basis of the VTR, relating to the period 2001-2003, was regulated. The evaluation process was entrusted to the Steering Committee for Research Evaluation (CIVR), which started the procedures with an announcement on 18 March 2004. In March 2010, a decree of the MIUR (Ministry of education and research) initiated the 2004-2008 VQR (Five-Year Research Evaluation) assigning it to the CIVR. Pending the establishment of ANVUR (National Agency for the Evaluation of the University and Research System), this decree was not followed up. The Minister prepared a new decree in 2011 to start the VQR, extending it until 2010. Following the first evaluation exercise 2004-2010, the second one was issued for the period 2011-2014 with DM of 27 June 2015 and the third one for the period 2015-2019 with DM of 25 September 2020.

The evaluation assessment is organized by Evaluation Areas which coincide with the Areas of the National University Council (CUN). ANVUR makes use, for each Evaluation Area, of a *Group of Evaluation Experts (GEV)*, composed by highly qualified scholars, including foreign ones. The key role in the evaluation procedures is assigned to these GEVs. The GEVs, in fact, are crucial for VQR because they carry out all the activities directly connected to the research evaluation. In particular, they define the bibliometric assessment criteria, they define the procedures for deciding which works should be evaluated with bibliometrics and which with peer review, they choose the reviewers, coordinate them, summarize the review reports, evaluate in many cases directly the works submitted for evaluation (Baccini 2014).

As we have seen before, the literature on the procedural fairness suggests as the first recommendations on how to stimulate open and thorough panel discussions resulting in fair and good quality outcomes to «compose panels in such a way that there is heterogeneity among panelists» (Van Arensbergen et al. 2014, p.11). Thus, considering the central role of GEVs in the Italian research assessment evaluation, the credibility of the result of the evaluation exercise largely depends on the fair composition of GEVs. Nevertheless, the fairness of the composition of GEVs of the 2004-2010 VQR has been questioned, starting from the lack of transparency in the members appointing procedures (Baccini, 2014). Especially regarding Area-13, which is the one dedicated to Economics and Statistical Sciences, methodological and technical problems emerged in an exemplary way that distorted the results systematically. In particular, for GEV 13, elementary rules of fairness were not respected with regard to the composition of gender, with only 16.7% of women, and because members were closely linked to each other by co-authorship relationships. The absence of fairness in the composition of the panel has probably minimized the voices of dissent with respect to the evaluation methods and rules adopted by the GEVs. This is not the first time, since in the previous CIVR evaluation exercise the greatest problems occurred in this area (Baccini 2011; Re 2019).

In order to confirm or reject this consideration, we are going to analyse and compare the composition of the GEVs 13 of the three mandatory evaluation exercises (2004-2010; 2011-2014; 2015-2019). We will start by describing the method of selection of GEVs members. In particular, we are going to consider the fact that the members of the first two panels were appointed directly by ANVUR, while the members of the third panel have been randomly selected by a lot from among those who had applied to be panelists. This allows us to consider the third panel as a control group. In fact, as it has been showed, selection by random choice eliminates the systemic bias in favour of specific research programmes and connected researchers (Gillies 2014). The difference in the way the members of the third panel have been chosen is linked to a political choice made by a government supported by a different majority than the previous ones and that included the 5 Stars Movement, a 'populist' and 'anti-establishment' party. In fact, the three evaluation exercises were regulated by the following Minister for

University and Research: 2004-2010, Maria Stella Gelmini (center-right government with prime minister Silvio Berlusconi) and Francesco Profumo (technical government with prime minister Mario Monti); 2011-2014, Stefania Giannini (center-left government with prime minister Matteo Renzi); 2015-2019, Lorenzo Fioramonti and Gaetano Manfredi ('anti-establishment' and center-left government with prime minister Giuseppe Conte II).

2.3.1 GEVs 2004-2010

For the 2004-2010 GEVs, the over mentioned DM established that ANVUR Board of Directors would appoint the 450 members, divided into 14 areas, and that among those would choose the fourteen presidents. For Area 13, there were 36 members to be appointed. The GEVs selection criteria was divided in two successive phases. In the first phase, ANVUR selected a set of scholars taking into consideration their qualifications and continuity of scientific production, as well as the evaluation experience. Among those, ANVUR had to choose the members of GEVs with the aim of covering all the cultural and research lines within the areas; of having 20% of foreign teachers; of having a fair distribution of affiliations and geography; of showing attention to gender distribution. The members of the panels were chosen largely from a list prepared by the CIVR for the never realized VQR 2004-2008. A public announcement was issued to access to that list. ≪In a limited number of cases≫, but the data were never disclosed, ANVUR chose outside the list. In particular, it selected non-listed names for members of foreign universities. The procedure has been presented in this way by prof. Sergio Benedetto, member of the ANVUR Board of Directors and head of the VQR (Benedetto 2012). However, the ANVUR Board of Directors acted in disagreement with what the DM established: they appointed firstly the presidents of the GEVs (list published on 10 October 2011), and after almost two months the members of the GEVs (made public on 12 December 2011). The presidents of the GEVs were consulted during the drafting of the operating rules of the VQR (Anonymous 2011); and it is therefore likely to believe that they had a say in the choice of the other GEVs members (Baccini 2016). For Area 13 Jappelli Tullio was selected as the President of the GEV.

2.3.2 GEVs 2011-2014

For the 2011-2014 GEVs, the selection of members started from the expiry date of the invitation to submit the declaration of interest to participate in the VQR and ended with the formal approval of the composition of the GEVs and their Coordinators by the ANVUR Board of Directors in the session of 3 September 2015 (ANVUR 2015).

In selecting the 400 GEVs members, divided into 16 Areas, ANVUR started from those who had expressed their interest in participating. The GEVs selection process was based on precise quality criteria. Among the scholars who met those criteria, the further selection was made by trying to fulfil the following conditions: coverage of the scientific-disciplinary sectors (SSD) proportional to the number of expected products to be evaluated within the 16 Areas; significant percentage of members with foreign affiliation; balanced gender distribution; for Italian candidates, fair distribution of affiliations where possible. If these criteria could not be met, the search could be expanded beyond the candidate lists. The notice for the presentation of the expression of interest to cover the position of GEVs members for the 2011-2014 VQR was published on the ANVUR website on 5 May 2015, with a deadline of 5 June 2015, then extended to 15 June 2015. 2,149 candidates responded to the notice, 171 of whom for Area 13. The selection process took about two months. The appointed GEVs members received the official invitation to participate in August 2015. The positive responses were close to 99%. Subsequently, ANVUR replaced those who had not accepted the invitation, reaching the final lists. Among the 31 selected for Area 13 only 1 was chosen out of those who had shown interest, but it is not specified who, and everybody accepted. Bertocchi Gabriella has been then elected the President of the 2011-2014 GEV panel of Area 13.

2.3.3 GEVs 2015-2019

For the GEVs 2015-2019, the 600 members were randomly selected among those who applied and who respected high qualifications and international experience in research and its evaluation. The VQR was divided into 17 scientific areas and 1 interdisciplinary area for the evaluation of the activities of the 'Third Mission' (the set of activities, beyond teaching and research, with which universities have direct interaction with society). Area 13 was divided into two: 13a, ≪Economics and statistical sciences≫, composed by 22 members; and 13b, ≪Economics and business sciences≫, composed by 18 members. Where possible, each GEV was formed in compliance with the following: at least 25% must be first level professors; at least 20%, respectively, must be second level professors and researchers from Italian universities; up to a maximum of 30% can be researchers structured at Public Research Bodies (EPR); at least 5% must be researchers structured at foreign universities or research bodies; at least one member for each Recruitment Field (SC) and for each Disciplinary-scientific area (SSD) with at least 50 members; the remainder, where possible, is formed by a number of components proportional to the size of the Recruitment Field; each gender must be represented for at least one third; no more than 20% of the members may have belonged to the GEVs of VQR 2011-2014. Once members of the GEVs were appointed, the ANVUR Board of Directors identified, choosing among them, the 18 Coordinators. Application submissions were open from 5 February to 2 March 2020 (ANVUR 2020a). On 11 September 2020, ANVUR published the lists of candidates admitted to the draw (ANVUR 2020b). The draw took place on 17 September 2020, and it was possible to follow the draw procedures in streaming online (ANVUR 2020c). The results of the draw were made available on the same day, afterwards it was published the name of any substitution (ANVUR 2020d). As coordinators of the panel have been selected Marrocu Emanuela (for 13a) and Napolitano Maria Rosaria (for 13b).

2.4 Data and methodology

In order to analyse if in the selection of GEV members there was a fair representation of the diversity of the research community, we are not going to focus only on the affiliation indicated by the GEV members in the ANVUR documents. In fact, a geographical diversity would apparently seem respected, however, if we analyse the hidden connections, as we are going to do, this is not the case. Moreover, if we add to this request a more general fair respect of the diverse viewpoints, scientific perspectives and scholarly thinking heterogeneity, we get that also this request has not been respected.

To analyse and compare the procedural fairness of the panels of Area 13 it is needed a correct control group that represents as much as possible the research community and dimensions of analysis that are as much as possible able to show hidden connections among scholars. The final aim is to see if the heterogeneity that is present in the research community has been fairly represented or not, i.e., if the panels of Area 13 were procedural fair or not.

Theoretically, the best control group would have been the one randomly selected from all the Italian research community with the attention to respect the representation of minority (for disciplinary sector, gender, affiliation, geography, etc.), or a random selection from those who had apply to be panelists. However, this would have been time consuming in the first case and impossible in the second one, since the list was not editable. Luckily, as we have seen in Section 3, the GEV members for VQR 2015-2019 were randomly selected from those who have applied. Since we do not have reason to think that those who have applied in the previous research assessments are different from the last one, the only difference is that the panelists for the 2004-2010 and 2011-2014 GEVs have been directly appointed by ANVUR, while the panelist for 2015-2019 GEVs were randomly selected. Considering that selection by random choice eliminates the systemic bias in favour of specific research programmes and connected researchers (Gillies 2014), we get that the panelists of GEV 2004-2010 and of 2011-2014 are our treatment groups, while the panelists of GEV 2015-2019 is our control group. In any case, we should take in mind that the three groups are selected in different periods of time and that the decision made by the first group had probably an effect in the last one (for example reducing funds to certain schools of thought could have led to the reduction of scholars of that schools). Thus, probably the level of heterogeneity that was present in the research community in 2011 (when have been selected the panelists of GEV 2004-2010) is higher than the one in 2020 (when have been selected the panelists of GEV 2015-2019). This consideration would reinforce our results.

Once we have selected the control group, we have to choose which are the dimensions that can better represent the connections among scholars. In particular, we are interested in the links between the panelists in relation to the type of theoretical approach, personal knowledge and similar economic-political vision. Collaboration is a complex social phenomenon in research that has been systematically studied since the 1960s and one of the most tangible and well documented forms of scientific collaboration is co-authorship (for a review of the literature see Kumar 2015). Co-authorship in research articles is considered a reliable proxy of research collaborations because co-authors cannot write a paper together unless a fair degree of acquaintance exists between them. In *co-authorship network*, two scholars are considered connected if they have authored a paper together. In its simplest form, a co-authorship network is formed by two authors (node) co-authoring an article together (edge). Co-authorship networks provide a documented record of the social and professional networks of authors (Newman 2004), and their analysis could uncover certain aspects of the network, such as how fragmented or cohesive the knowledge community is or who are the best-connected authors in that network. Moreover, co-authorship network is useful to detect research communities through cluster analysis. However, co-authorship network is a moderately stringent definition, since there are many scholars who know one another or are similar to some degree but have never collaborated on the writing of a paper. For this reason, to detect hidden connections, we will look also for similar specialization, similar training, or other characteristics. In order to do so, we will not focus only on co-authorship network but also on the analysis of the networks of journal and of the 'affinity networks'. In the *network of journal* two scholars (nodes) are considered connected if they have published in the same journal (edge). The starting hypothesis is that journals represent different schools or methodology approach, so if scholars have published in the same journals, even if they have not published together, then there is a theoretical similarity. The '*affinity network*' is instead a widening definition of the affiliation network. In this last case two scholars (nodes) are considered connected if they are affiliated in the same university (edge). We consider this connection too narrow and for this reason we will analyse connections linked to similar education, affiliation, research centre and publication in the same newspapers. This consideration in based on the hypothesis that, even if scholars have not published together or in the same journals, they can have a common set of relational patterns. Even in the networks of journal and in the 'affinity networks' we will search for the most connected scholars and for communities.

The analysis and comparison of these three dimensions will be used as indicators of connections between the panelists and, by comparing the results of the first two GEVs with respect to the third one (which works as a control group), we will be able to understand if there is lack or presence of fairness within the panels. If, in fact, the first two GEVs show different results compared to the last one, then the direct selection of the panelists by ANVUR has led to an unfair representation of the diversity of the research community.

For the analysis we are going to use the softwares Pajek version 5.14 (De Nooy and Batagelj 2018), and VOSviewer version 1.6.15 to visualize the networks (Van Eck and Waltman 2020). We report below the network analysis of the GEVs divided into the three dimensions that we have analysed, specifying for each the type of study we have applied.

2.5 The co-authorship networks

The analysis of co-authorship network is the most widespread in the literature to analyse the links among scholars (for a review of the literature see Kumar 2015). In our case, we are interested in investigating whether the panelists of the GEVs 13 are co-authors with each other or have co-authors in common. The hypothesis from which we start is that if there are co-authoring ties, then probably the members of the GEVs have personal ties and theoretical similarities. We will then detect research communities through cluster analysis. If the first two panel co-authorship networks have less or larger cluster than the third one, then their composition unfairly represented the diversity of the research community, and the results of their evaluation exercise could be unfair.

To build the dataset, publications of GEVs panelists were retrieved from Scopus for 25 years from the inauguration date of the research assessment exercises. That is, for the GEV 2004-2010 the years 1987 to 2011, for the GEV 2011-2014 the years 1991 to 2015 and for the GEV 2015-2019 the years 1996 to 2020. It was not possible to find information on Scopus only for three members of the GEV 2015-2019 (i.e., Cori Enrico, De Vincentiis Paola and Pisoni Pietro Maria). After generating the co-authorship network, we have used the Pajek software to identify the clusters within it through a partition based on weak components, a technique used to identify the connected parts of a network (De Nooy et al. 2018).

2.5.1 GEV 2004-2010 of Area 13

The 2004-2010 co-authorship network is composed by 781 nodes, of which 36 are GEV members. The number of lines linking the scholars is 1801, and the density of network (i.e., the ratio of the actual number of lines to the maximum possible number of lines in the network) is 0,005. This means that only 0,5% of the possible lines are present.

Table 2.1 reports the degree distribution of the scholars, where a degree is the number of connections that a scholar has with the other scholars. The average degree is 4,61, meaning that, on average, one scholar has almost 5 co-authorship connections with other scholars. There are not isolated scholars, i.e., every GEV member has at least one co-author. Then 169 scholars (22%) have only one co-authorship connection, and 249 (32%) have two. Moreover, we can also see that there are few scholars (10, i.e., the 1,41%) that have more than 22 co-authorship connection, with the highest value that is 78 connections that is hold by Giovanni Dosi.

Table 2.1 Degree frequency distribution of the 2004-2010 co-authorship network

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
1	169	21,64	12	5	0,64	23	1	0,13
2	249	31,88	13	17	2,18	27	1	0,13
3	109	13,96	14	14	1,79	28	2	0,26
4	59	7,55	16	2	0,26	34	1	0,13
5	33	4,23	17	2	0,26	43	1	0,13
6	27	3,46	18	1	0,13	47	1	0,13
7	14	1,79	19	18	2,30	48	1	0,13
8	19	2,43	20	2	0,26	57	1	0,13
9	15	1,92	21	6	0,77	64	1	0,13
10	7	0,90	22	2	0,26	78	1	0,13

We start the analysis searching for the most central scholars by computing the betweenness centrality. In Figure 2.1 we report the distribution of these values. As we can see, there are few scholars with a higher betweenness centrality and the rest that have zero or close to zero values. In particular, 615 nodes (78,75%) have a zero betweenness centrality, 111 nodes (14,21%) have an almost zero value, and only 50 scholars (6,40%) have a value higher than 0,002. We report in Table 2.2 the name of those scholars that have a betweenness centrality higher than 0,002. As we can see, among these scholars only 28 are GEV members, while 11 are not. We also get that 9 GEV members are not part of this list.

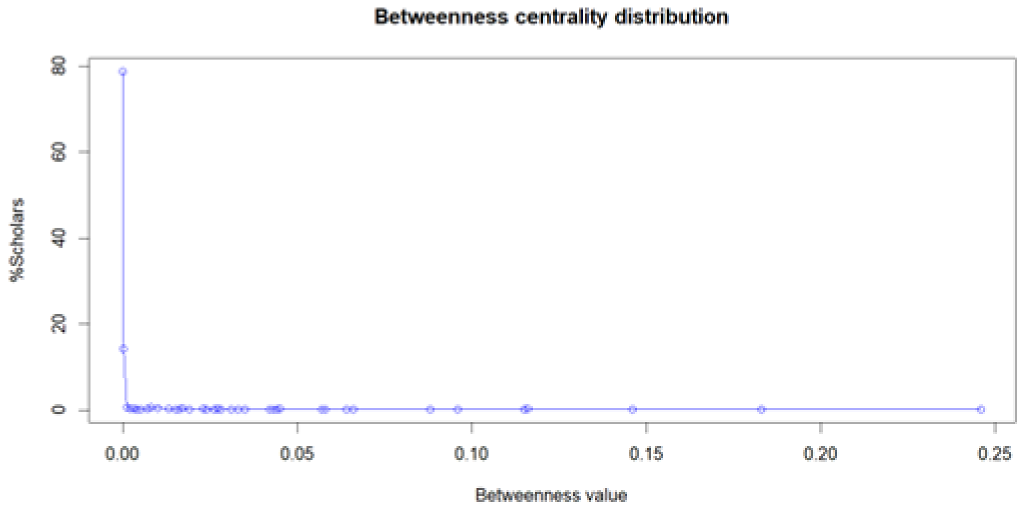


Figure 2.1 Betweenness value distribution of the 2004-2010 co-authorship network

Then, a partition based on weak components it is used to search for cohesive subgroups (De Nooy et al. 2018). We get that the 2004-2010 co-authorship network can be divided into 12 weak components, the biggest of which contains 512 nodes, which is more than 65% of the network, of which 24 (66%) are GEV members. The other 11 weak components are much smaller. In Table 2.3 we report the frequency distribution of the weak components. The graph of the co-authorship network is reported in Fig. 2.2, while in Fig. 2.3 the biggest weak component, i.e., the cluster number 1, is represented. The dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of the GEV. Fig. 2.3 shows clearly the central role that some scholars, that are not GEV members, play in the construction of the network.

Table 2.2 Betweenness centrality and rank betweenness of the GEV 2004-2010 scholars

Name	**Betweenness centrality**	**Rank Betweenness**	**GEV member**	**Name**	**Betweenness centrality**	**Rank Betweenness**	**GEV member**
Dosi G.	0,246	1	Yes	D'Aveni R.	0,023	26	No
Brunello G.	0,183	2	Yes	Marinacci M.	0,023	27	Yes
Bassanini A.	0,147	3	No	Pistaferri L.	0,019	28	No
Weber G.	0,116	4	Yes	Pagano M.	0,017	29	No
Checchi D.	0,116	5	Yes	Ichino A.	0,017	30	No
Lippi M.	0,115	6	No	Warglien M.	0,017	31	Yes
Hallin M.	0,096	7	Yes	Chiuri M.C.	0,016	32	No
Peracchi F.	0,088	8	Yes	Del Boca D.	0,015	33	Yes
Dardanoni V.	0,066	9	Yes	Ellul A.	0,013	34	Yes
Gambardella A.	0,064	10	Yes	Bertola G.	0,013	35	No
Dagnino G.B.	0,058	11	Yes	Pammolli F.	0,010	36	No
Schivardi F.	0,057	12	Yes	Bertocchi G.	0,010	37	Yes
Mariani M.	0,045	13	No	Kaniovski Y.	0,010	38	No
Fabiani S.	0,045	14	No	Terlizzese D.	0,008	39	Yes
Jappelli T.	0,044	15	Yes	Maccheroni F.	0,008	40	No
Boldrin M.	0,043	16	No	Marengo L.	0,008	41	No
Canova F.	0,042	17	Yes	Florio M.	0,008	42	No
Rustichini A.	0,035	18	No	Guthrie J.	0,007	43	Yes
Quattrone P.	0,033	19	Yes	Murgia M.	0,007	44	Yes
Felli L.	0,031	20	Yes	Panico C.	0,005	45	No
Salvadori N.	0,028	21	Yes	Magazzini L.	0,004	46	No
Bartolucci F.	0,027	22	Yes	Frino A.	0,003	47	Yes
Cornelli F.	0,027	23	Yes	Cichelli A.	0,003	48	Yes
Nesta L.	0,026	24	No	Jones L.R.	0,002	49	No
Guiso L.	0,024	25	No	Mussari R.	0,002	50	Yes

Table 2.3 Frequency distribution among weak components of the 2004-2010 co-authorship network

Cluster	**Freq**	**Freq%**	**Members Freq**	**Members Freq%**
1	512	65.5	24	66.6
2	6	0.7	1	2.7
3	71	9.0	2	5.5
4	18	2.3	1	2.7
5	49	6.2	1	2.7
6	18	2.3	1	2.7
7	48	6.1	1	2.7
8	6	0.7	1	2.7
9	8	1.0	1	2.7
10	28	3.5	1	2.7
11	8	1.0	1	2.7
12	9	1.1	1	2.7
Sum	781	100	36	100

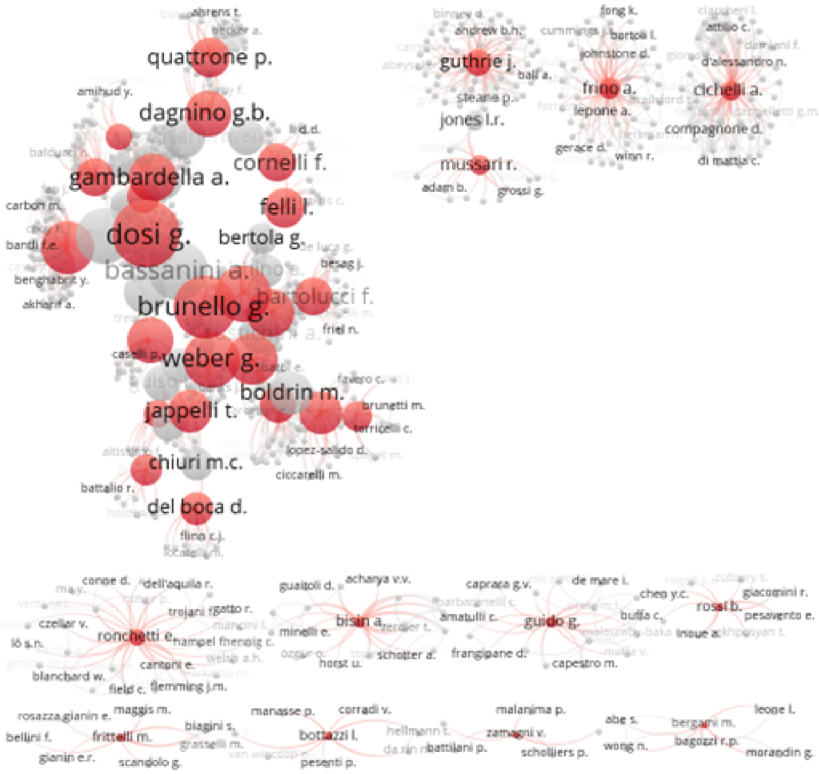


Figure 2.2 The 12 weak components of the GEV 2004-2010 co-authorship network (the dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of GEV)

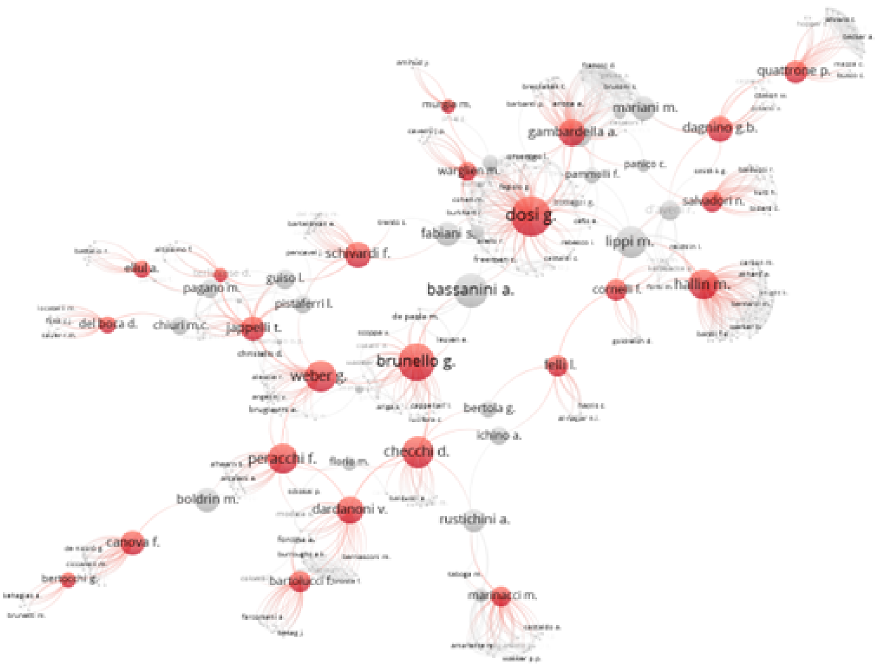


Figure 2.3 The weak component n.1 of the GEV 2004-2010 co-authorship network (the dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of GEV)

2.5.2 GEV 2011-2014 of Area 13

The 2011-2014 co-authorship network is composed by 922 nodes, of which 31 are GEV members. The number of lines linking the scholars is 2829, and the density of network is 0,006. This means that only 0,6% of the possible lines are present. 5 members of the GEV 2011-2014 were also part of the 2004-2011 panel (i.e., Bartolucci F., Bertocchi G., Gambardella A., Ronchetti E., Schivardi F.). Among these, Bertocchi Gabriella is the President of the 2011-2014 GEV panel. In addition to these 5 members in common we find 10 other scholars that were GEV member in the panel 2004-20011 and are part of the 2011-2014 co-authorship network (i.e., Canova F., Dardanoni V., Dosi G., Ellul A., Frittelli M., Jappelli T., Peracchi F., Rossi B., Weber G., Zamagni V.).

Table 2.4 reports the degree distribution of the scholars, where a degree is the number of connections that a scholar has with the other scholars. The average degree is 6,14, meaning that, on average, one scholar has more than 6 co-authorship connections with other scholars. There are not isolated scholars, i.e., every GEV member has at least one co-author. Then 136 scholars (15%) have only one co-authorship connection, and 242 (26%) have two. Moreover, we can also see that the 60% of scholars have 3 or less co-authorship connection. The 4,37% of scholars have more than 22 co-authorship connections with the highest value that is 128 connections that is hold by Alfò Marco.

Table 2.4 Degree frequency distribution of the 2011-2014 co-authorship network

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
1	136	14,75	16	6	0,65	33	4	0,43
2	242	26,25	17	10	1,08	34	2	0,22
3	168	18,22	18	8	0,87	35	2	0,22
4	79	8,57	19	15	1,63	37	1	0,11
5	44	4,77	20	16	1,74	38	1	0,11
6	38	4,12	21	8	0,87	39	2	0,22
7	22	2,39	22	5	0,54	40	2	0,22
8	24	2,60	23	4	0,43	44	1	0,11
9	6	0,65	24	1	0,11	50	1	0,11
10	20	2,17	25	2	0,22	51	1	0,11
11	12	1,30	26	9	0,98	57	1	0,11
12	16	1,74	27	1	0,11	58	1	0,11
13	3	0,33	30	1	0,11	78	1	0,11
14	4	0,43	32	1	0,11	128	1	0,11

Even in this case, we search for the most central scholars by computing the betweenness centrality. In Figure 2.4 we report the distribution of these values. As we can see, there are few scholars with a higher betweenness centrality and the rest that have zero or close to zero values. In particular, 707 nodes (76,68%) have a zero betweenness centrality, 173 nodes (18,76%) have an almost zero value, and only 31 scholars (3,36%)

have a value higher than 0,002. In Table 2.5 there are reported the names of those scholars that have a betweenness centrality higher than 0,002. Among these scholars only 18 are GEV members, while 13 are not. We also get that 13 GEV members are not part of this list. Moreover, there are 10 scholars that in both co-authorship networks have a value higher than 0,002, and they are: Bartolucci F., Bertocchi G., Dosi G., Gambardella A., Guiso L., Jappelli T., Lippi M., Pagano M., Peracchi F., Schivardi F.

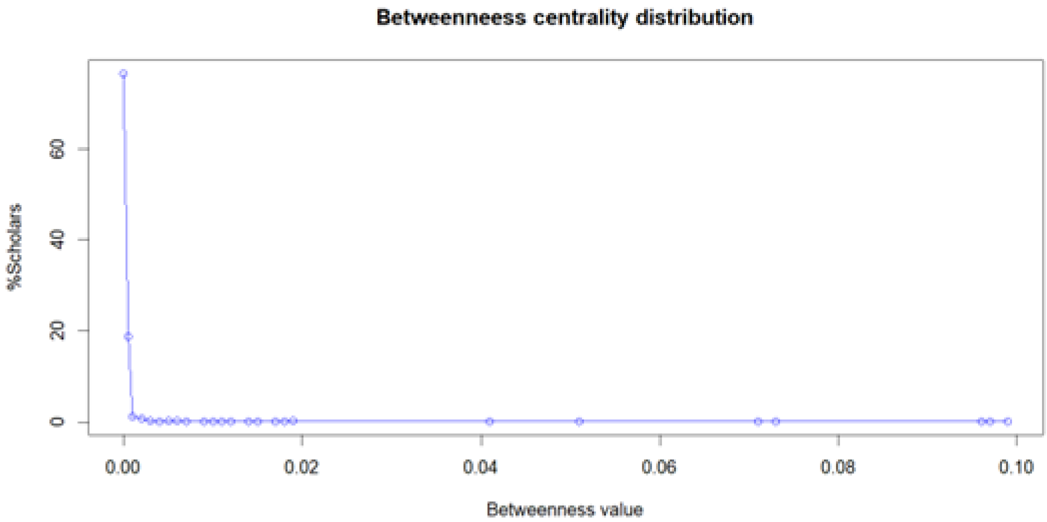


Figure 2.4 Betweenness value distribution of the 2011-2014 co-authorship network

Table 2.5 Betweenness centrality and rank betweenness of the GEV 2011-2014 scholars

Name	**Betweenness centrality**	**Rank Betweenness**	**GEV member**	**Name**	**Betweenness centrality**	**Rank Betweenness**	**GEV member**
Bartolucci F.	0,099	1	Yes	Bertocchi G.	0,009	17	Yes
Alfò M.	0,097	2	Yes	Torrisi S.	0,007	18	Yes
Peracchi F.	0,096	3	No	Vivarelli M.	0,006	19	Yes
Jappelli T.	0,073	4	No	Greco S.	0,006	20	Yes
Gambardella A.	0,071	5	No	Padula M.	0,005	21	No
Guiso L.	0,051	6	No	Paiella M.	0,005	22	Yes
Pagano M.	0,041	7	Yes	De Fraja G.	0,004	23	Yes
Brugiavini A.	0,019	8	Yes	Piga C.	0,003	24	No
Schivardi F.	0,019	9	Yes	Sarno L.	0,003	25	Yes
Prencipe A.	0,018	10	Yes	Frey M.	0,002	26	No
Bandiera O.	0,017	11	Yes	De Paola M.	0,002	27	Yes
Panunzi F.	0,015	12	No	Panetta F.	0,002	28	No
Brusco S.	0,014	13	Yes	Kretschmer T.	0,002	29	Yes
Brusoni S.	0,012	14	No	Zechner J.	0,002	30	No
Dosi G.	0,011	15	No	Giuri P.	0,002	31	No
Lippi F.	0,010	16	Yes				

To search for cohesive subgroups, it is used again a partition based on weak components (De Nooy et al. 2018). We get that the 2011-2014 co-authorship network can be divided into 17 weak components, the biggest of which contains 403 nodes, which is more than 43% of the network, of which 13 (42%) are GEV members. The other 18 weak components are much smaller. In Table 2.6 we report the frequency distribution of the weak components. The graph of the co-authorship network is reported in Fig. 2.5, while in Fig. 2.6 the biggest weak component, i.e., the cluster number 3, is represented. The dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of the GEV. Even in this case, Fig. 2.6 shows clearly the central role that some scholars, that are not GEV members, play in the construction of the network.

Table 2.6 Frequency distribution of cluster values of GEV 2011-2014 co-authorship network

Cluster	Freq	Freq%	Members Freq	Members Freq%
1	79	8.5	1	3.2
2	52	5.6	1	3.2
3	403	43.7	13	41.9
4	34	3.6	1	3.2
5	7	0.7	1	3.2
6	58	6.2	1	3.2
7	25	2.7	1	3.2
8	20	2.1	1	3.2
9	22	2.3	1	3.2
10	17	1.8	1	3.2
11	22	2.3	1	3.2
12	79	8.5	3	9.6
13	36	3.9	1	3.2
14	12	1.3	1	3.2
15	39	4.2	1	3.2
16	9	0.9	1	3.2
17	8	0.8	1	3.2
Sum	922	100	31	100

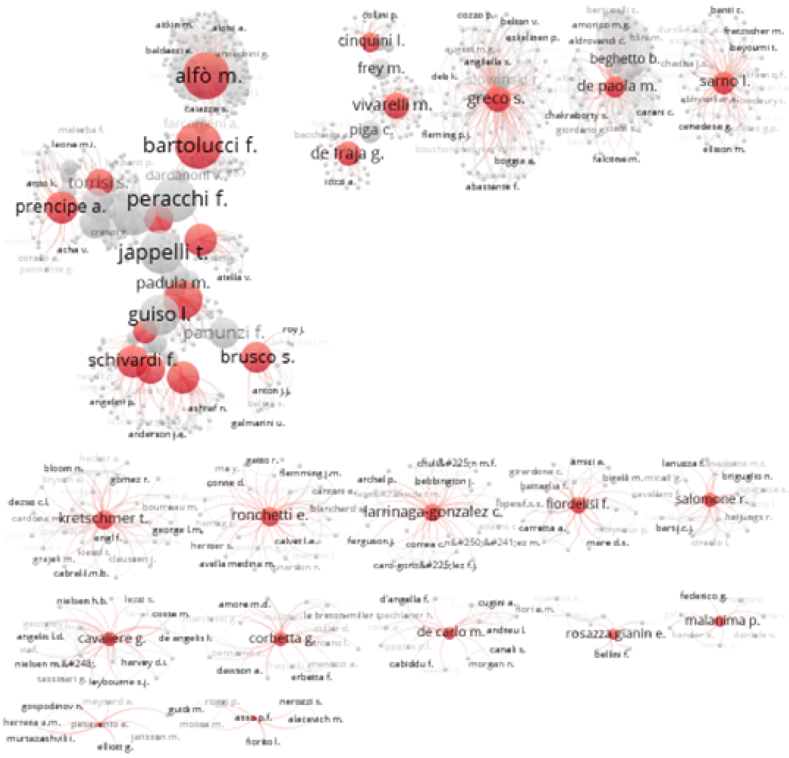


Figure 2.5 The 17 weak components of the GEV 2011-2014 co-authorship network (the dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of GEV)

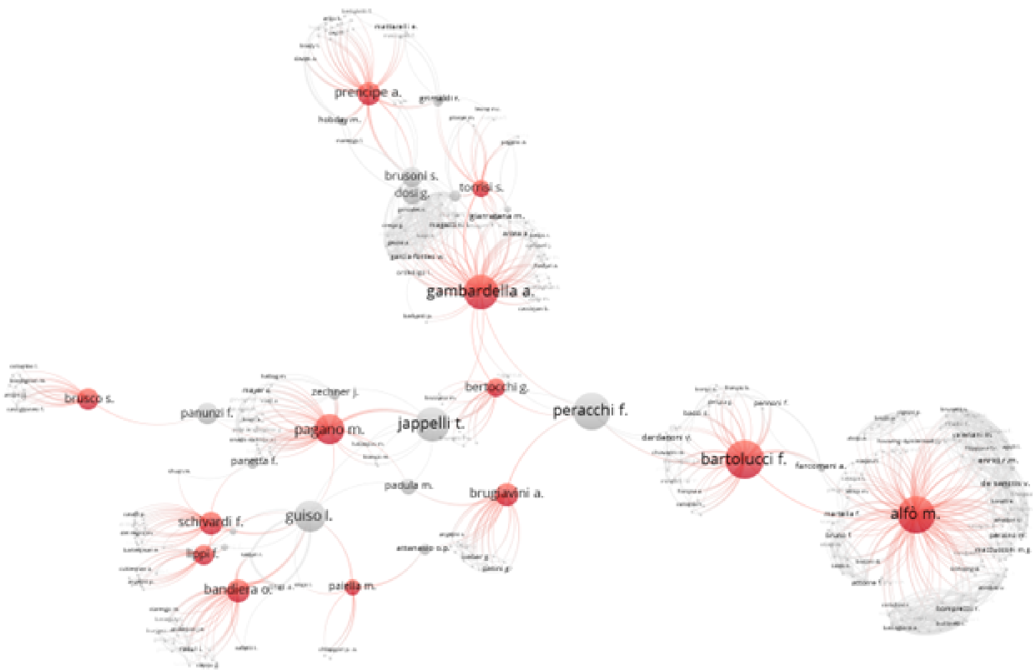


Figure 2.6 The weak component n.3 of the GEV 2011-2014 co-authorship network (the dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of GEV)

2.5.3 GEV 2015-2019 of Area 13

Lastly, we analyse the 2015-2019 co-authorship network, that is our control group. The network is composed by 1271 nodes, of which 40 are GEV members. The number of lines linking the scholars is 5678, and the density of network is 0,007. There is only 1 member of the GEV 2015-2019 who was also part of the 2011-2014 panel (i.e., Pagano M.), none was also part of the 2004-2010 panel. However, three 2015-2019 members were part of the 2011-2014 co-authorship network (Michetti E., Mosca M., Piva M.). Two 2004-2010 GEV members are part of the 2015-2019 co-authorship network (Ellul A., Jappelli T.), as well as Schivardi F., who was member of both the previous panels. Finally, only one 2011-2014 GEV member is part of the 2015-2019 co-authorship network (Vivarelli M.).

Table 2.7 reports the degree distribution of the scholars, where a degree is the number of connections that a scholar has with the other scholars. The average degree is 9, meaning that, on average, one scholar has 9 co-authorship connections with other scholars. There are not isolated scholars, i.e., every GEV member has at least one co-author. Then 219 scholars (17%) have only one co-authorship connection, and 196 (15%) have two. Moreover, we can also see that 50% of scholars have 4 or less co-authorship connection. The 11,64% of scholars have more than 22 co-authorship connection, with the highest value that is 259 connections that is hold by Stingo Francesco.

Table 2.7 Degree frequency distribution of the 2015-2019 co-authorship network

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
1	67	5,27	17	7	0,55	34	1	0,08
2	219	17,23	18	36	2,83	35	1	0,08
3	196	15,42	19	2	0,16	36	1	0,08
4	136	10,70	20	3	0,24	37	1	0,08
5	80	6,29	21	3	0,24	38	3	0,24
6	69	5,43	22	2	0,16	39	5	0,39
7	61	4,80	23	27	2,12	41	2	0,16
8	34	2,68	24	22	1,73	42	2	0,16
9	44	3,46	25	3	0,24	44	2	0,16
10	15	1,18	27	29	2,28	46	1	0,08
11	55	4,33	28	1	0,08	49	1	0,08
12	14	1,10	29	4	0,31	59	2	0,16
13	37	2,91	30	3	0,24	61	2	0,16
14	23	1,81	31	3	0,24	84	1	0,08
15	5	0,39	32	28	2,20	151	1	0,08
16	15	1,18	33	1	0,08	259	1	0,08

In Figure 2.7 we report the betweenness centrality distribution of the 2015-2019 network. As we can see, scholars do not have a particular high betweenness centrality, with the maximum value that is 0,045. The majority has zero or close to zero values. In particular, 971 nodes (76,39%) have a zero betweenness centrality, 280 nodes (22%) have an almost zero value, and only 16 scholars (1,26%) have a value higher than 0,002. In Table 2.8 there are reported the names of those scholars that have a betweenness centrality higher than 0,002. Among these scholars only 4 are not GEV members, while 12 are. We also get that 28 GEV members are not part of this list. Moreover, there is only 1 scholar that also in the 2011-2014 co-authorship networks has a value higher than 0,002, Pagano Marco, who also in the 2004-2019 co-authorship networks has a value higher than 0,002.

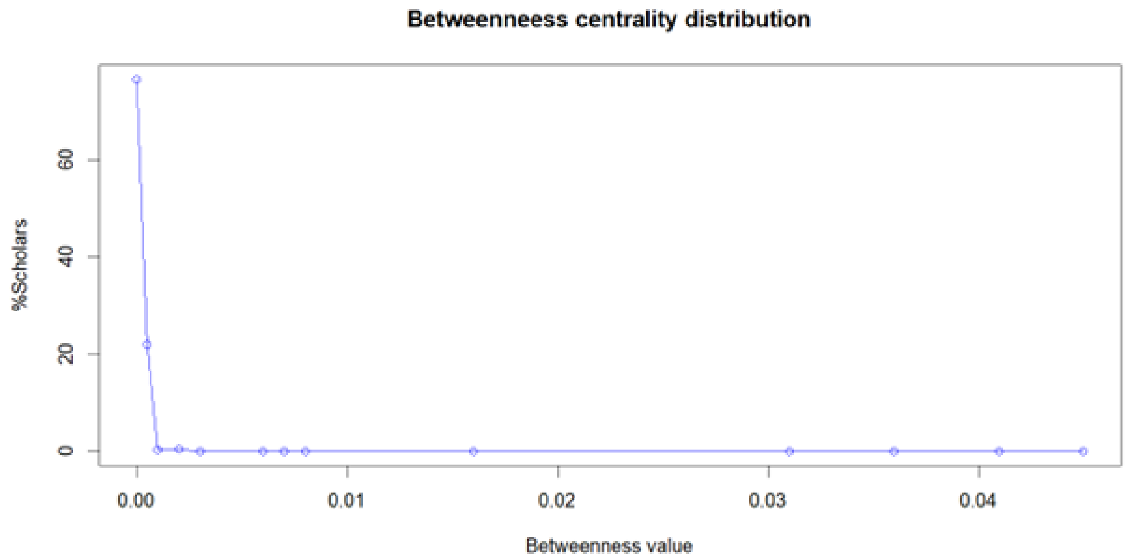


Figure 2.7 Betweenness value distribution of the 2015-2019 co-authorship network

Table 2.8 Betweenness centrality and rank betweenness of the GEV 2015-2019 scholars

Name	Betweenness centrality	Rank Betweenness	GEV member	Name	Betweenness centrality	Rank Betweenness	GEV member
Ruggeri F.	0,045	1	Yes	Meliciani V.	0,003	9	Yes
Nicolis O.	0,041	2	No	Mencarini L.	0,002	10	Yes
Stingo F.	0,036	3	Yes	Pagano M.	0,002	11	Yes
Fassò A.	0,031	4	Yes	Castellani D.	0,002	12	No
Chiodi M.	0,016	5	Yes	Piva M.	0,002	13	Yes
Adelfio G.	0,008	6	Yes	Notarnicola B.	0,002	14	Yes
Bevilacqua M.	0,007	7	No	Savona M.	0,002	15	No
Perna A.	0,006	8	Yes	Antonioli D.	0,002	16	Yes

Then, we again search for cohesive subgroups using a partition based on weak components (De Nooy et al. 2018). We have a completely different situation than the ones seen before: the 2015-2019 co-authorship network is divisible in 25 weak components, the largest of which contains only 324 nodes (the 25% of the network) and 5 panelists (13%). The other 24 weak components are quite similar one to another. There is another big component that contains 260 nodes (20,4%), but only 1 member, Stingo F., who has an exceptional number of co-authorship connections (259). In Table 2.9 we report the frequency distribution of the weak components. The graph of the co-authorship network is reported in Fig. 2.8. The dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of the GEV. Fig. 2.8 shows clearly a fragmented network.

Table 2.9 Frequency distribution of cluster values of GEV 2015-2019 co-authorship network

Cluster	Freq	Freq%	Members Freq	Members Freq%
1	68	5.3	2	5.4
2	324	25.4	5	13.5
3	64	5.0	2	5.4
4	42	3.3	1	2.7
5	18	1.4	1	2.7
6	260	20.4	1	2.7
7	16	1.2	1	2.7
8	11	0.8	1	2.7
9	44	3.4	3	8.1
10	39	3.0	1	2.7
11	88	6.9	3	8.1
12	60	4.7	1	2.7
13	27	2.1	2	5.4
14	13	1.0	1	2.7
15	2	0.1	1	2.7
16	18	1.4	1	2.7
17	42	3.3	1	2.7
18	26	2.0	1	2.7
19	18	1.4	1	2.7
20	14	1.1	1	2.7
21	17	1.3	1	2.7
22	15	1.1	2	5.4
23	12	0.9	1	2.7
24	21	1.6	1	2.7
25	12	0.9	1	2.7
Sum	1271	100	37	100

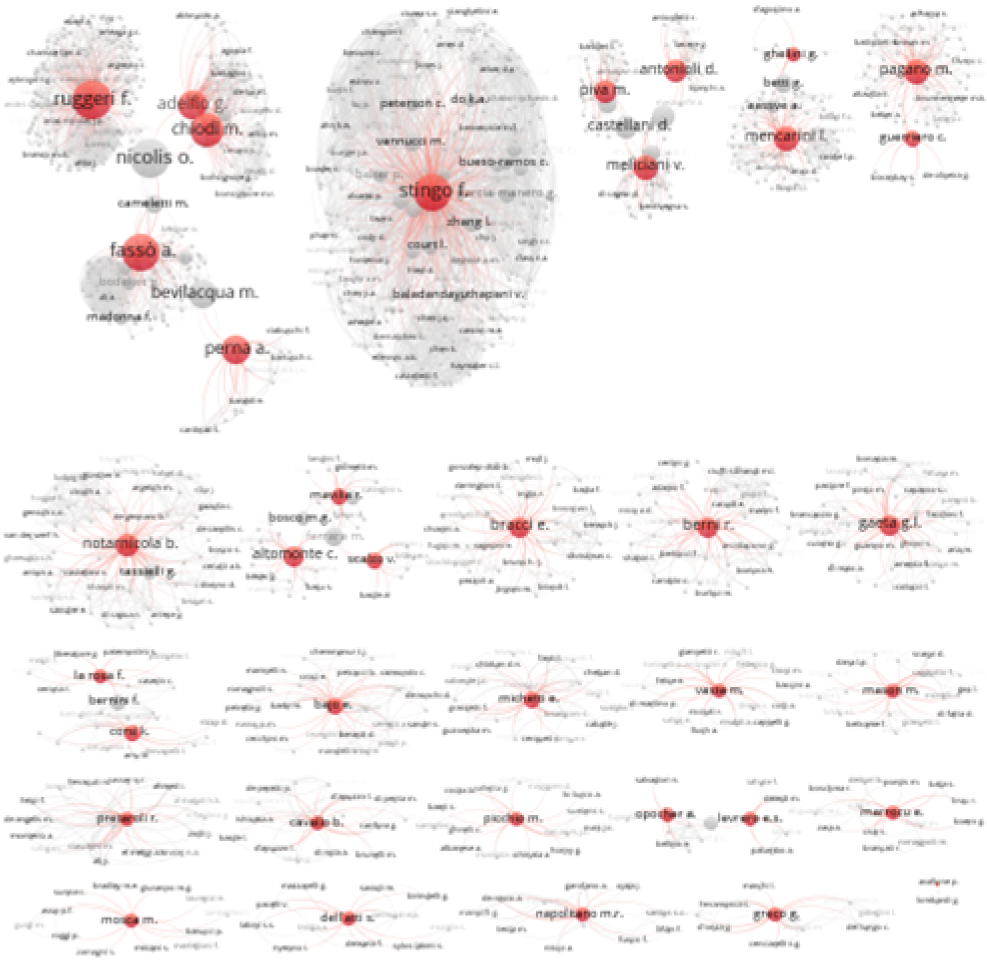


Figure 2.8 The 25 weak components of the GEV 2015-2019 co-authorship network (the dimension of vertices is proportional to betweenness centrality and the vertices in red are the members of GEV)

2.5.4 Comparison of the co-authorship networks

Finally, we focus on a comparison among the co-authorship networks, keeping in mind that the third panel is our control group. In Table 2.10 there are reported the basic statistics of the three networks and in Table 2.11 the basic statistics of the largest weak component of each network.

As we can see, the three networks have similar dimension. The third one is in fact slightly larger and has more connections among scholars, but this is connected to the presence of only one panelist, Stingo Francesco, that has 259 co-authors and 2246 links that enlarge the network dimension. Thus, the three networks are comparable.

Table 2.10 Basic statistics of the co-authorship networks

	GEV 2004-2010	GEV 2011-2014	GEV 2015-2019
N. of GEV members	36	31	40
N. of authors	781	922	1271
N. of papers	1190	1188	1079
Number of weak components	12	17	25
Number of links between authors	1801	2829	5678
Lowest value of line	1	1	1
Highest value of line	47	142	31
Number of links with value =1	1315	2178	4304
Number of links with value =2	251	337	880
Number of links with value >2	235	314	494
Density	0.005	0.006	0.007
Average Degree	4.612	6.136	8.934
All Degree Centralization	0.094	0.132	0.197
Betweenness Centralization	0.243	0.097	0.044

Table 2.11 Basic statistics of the largest weak component of each co-authorship networks

	GEV 2004-2010	GEV 2011-2014	GEV 2015-2019
GEV members	22 (66.6%)	13 (41.9%)	5 (13.5%)
N. of authors	512 (65.5%)	403 (43.7%)	324 (25.4%)
Number of links between authors	1257	1452	1631
Lowest value of line	1	1	1
Highest value of line	47	19	23
Number of links with value =1	963	1221	1156
Number of links with value =2	169	140	404
Number of links with value >2	125	91	71
Density	0.009	0.017	0.031
Average Degree	4.910	7.205	10.067
All Degree Centralization	0.143	0.301	0.439
Betweenness Centralization	0.565	0.510	0.686
All Closeness Centralization	0.191	0.247	0.367

From Table 2.10 we can see that Density is similar among the three networks and it is a value very close to zero, denoting a general low level of connectedness in the networks. The Average Degree is higher for the third network, meaning that on average in the third network there are more ties to a single node than in the first two networks, which is something that is confirmed by the All Degree Centralizations. However, the All Degree Centralizations are 0.1, a rather small value, indicating that in any case the difference between the largest and smallest actor-level indices is not very great. The Betweenness Centralizations show that the first network has much higher values of actor centrality with respect to the others. This was evident also in the previous analysis: the higher value of betweenness centrality goes from 0,25 in the first panel, to 0,1 in the second panel, to 0,05 in the last one. As well, those scholars who have a betweenness centrality higher than 0,002 are 50, 31 and 16 respectively. As demonstrated by Freeman (1979), the betweenness indices best capture the essence of the important actors in the graphs, and this let us say that three networks are similar, but the first one has more central actors (there are few vertices that are needed to create the network because they connect other vertices to each other), then, there are lesser in the second one, while the last one has nodes with similar values of centrality. Moreover, we have seen, comparing Table 2.2 with Table 2.5, that these central actors are similar among the first and the second network, while are totally different with the third ones.

Considering the cohesive subgroups of each network, we can see in Table 2.11 how the number of weak components is larger in the third GEV where we get 25 'research communities', compared to the 17 of the second GEV, and 12 of the first one. The percentage of the size of the largest component drops from 65% in the first GEV, to 43% in the second, to 25 % in the third. If we look at the largest number of GEV members in the same component, the percentage is even more different: we go from 13% in the third GEV, 41% in the second GEV, 66% in the first GEV. The statistics in Table 2.11 shows no bigger difference in the characteristics of the largest weak component except for the fact that the last one is more cohesive and centralized (and this is connected to the fact that it contains less GEV members).

This first comparison, that takes into account the co-authorship network of the GEV members, shows that the first two panels are significantly different with respect to the third one. Especially in the first one we have few central actors that are connected one to another in one single large cluster (e.g. research community) that contains more than half of the network and members panelist. The second network has similar characteristic of the first one and shares with it similar central nodes. Instead, in the third GEV there are few common members to the other two panels, there are not nodes that hold particular high centrality values, there are more clusters (e.g. research communities) and these groups are much smaller and centralized.

2.6 The networks of journals

For the networks of journals our aim is to investigate whether the members of the GEVs 13 have published in the same or in different journals. The starting hypothesis is that journals represent different theoretical approaches or methodologies, if the members have published in the same journals, then there is a theoretical similarity among them. As before, we will detect central actors and research communities through SNA. If the first two panel co-authorship networks have differences than the third one, then their composition unfairly represented the diversity of the research community, and the results of their evaluation exercise could reflect this unfairness.

The dataset is the same used for the co-authorship network, but we have isolated the members of the GEVs. After generating the network of journals, we have searched for central nodes and we used the Pajek software to identify the clusters within it through a partition based on line multiplicity: islands. This technique is based on the consideration that the larger the number of interlocks between two authors, the stronger their tie, the more similar or interdependent they are (De Nooy et al. 2018). Since the networks have different sizes, we have normalized parameters searching for islands of minimum size 1 and maximum size 3/5 of the number of GEV members rounded down (therefore 21 for the first GEV, 18 for the second GEV and 22 for the third GEV).

2.6.1 GEV 2004-2010 of Area 13

The 2004-2010 network of journal is composed by 36 nodes, who are the are GEV members. The number of lines linking the scholars is 148, and the density of network is 0,22. This means that the 22% of the possible lines are present. Table 2.12 reports the degree distribution of the scholars, where a degree is the number of journal connections that a scholar has with the other scholars.

Table 2.12 Degree frequency distribution of the 2004-2010 network of journals

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
0	2	5,56	6	4	11,11	14	1	2,78
1	1	2,78	7	2	5,56	15	1	2,78
2	2	5,56	9	2	5,56	16	4	11,11
3	3	8,33	11	2	5,56	17	2	5,56
4	2	5,56	12	3	8,33			
5	4	11,11	13	1	2,78			

The average degree is 8,22, meaning that, on average, one scholar has 8 journal connections with other scholars. There are two isolated scholars, i.e., two GEV members have never published in a journal where another GEV member has published. The others have at least one connection, with the highest value that is 17 connections hold by Jappelli Tullio.

If we search for cohesive subgroups using the Pajek algorithm island, we get three different islands: the biggest one contains 21 scholars (the 58% of the GEV members); then there are two islands composed by 3 scholars (the 8%); the remaining 9 scholar are no part of any island (in this last group there are also the 2 disconnected scholars, who are Cichelli A. and Bergami M.). In Table 2.13 we report the name of the scholars, the belonging island and the betweenness values with the connected ranking. In Fig. 2.9 the 2004-2010 network of journals is represented, in which each island has a different colour, and the dimension of vertices is proportional to betweenness centrality.

Table 2.13 Betweenness centrality and rank betweenness of the GEV 2004-2010 scholars

Name	Betweenness centrality	Rank Betweenness	Island Number	Name	Betweenness centrality	Rank Betweenness	Island Number
Dosi G.	0,138	1	3	Ellul A.	0,018	19	2
Frino A.	0,125	2	0	Bottazzi L.	0,015	20	2
Guthrie J.	0,081	3	1	Frittelli M.	0,010	21	0
Bisin A.	0,079	4	2	Marinacci M.	0,010	22	2
Jappelli T.	0,058	5	2	Hallin M.	0,006	23	2
Schivardi F.	0,051	6	2	Checchi D.	0,006	24	2
Brunello G.	0,050	7	2	Quattrone P.	0,005	25	1
Peracchi F.	0,050	8	2	Bartolucci F.	0,004	26	2
Gambardella A.	0,048	9	3	Salvadori N.	0,001	27	0
Weber G.	0,042	10	2	Cornelli F.	0,001	28	2
Dagnino G.B.	0,041	11	0	Del Boca D.	0,001	29	2
Bertocchi G.	0,031	12	2	Bergami M.	0,000	30	0
Rossi B.	0,031	13	2	Cichelli A.	0,000	31	0
Warglien M.	0,028	14	3	Guido G.	0,000	32	0
Canova F.	0,025	15	2	Murgia M.	0,000	33	0
Dardanoni V.	0,022	16	2	Mussari R.	0,000	34	1
Felli L.	0,020	17	2	Terlizzese D.	0,000	36	2
Ronchetti E.	0,020	18	2	Zamagni V.	0,000	35	0

We get that Dosi G. is the scholar with the highest betweenness centrality in absolute and in Island N.3 with the value of 0,138. Then, Guthrie J. has the highest betweenness centrality for Island N1, while Bisin A. for Island N.2 (which is the largest island and contains nodes with the higher values). 10 scholars, that represents the 28% of GEV members, have betweenness centrality lower than 0,002. Thus, few GEV members have higher centrality, while the majority has almost zero betweenness centrality. The focus on the connection through journals have unveiled a different centrality ranking and communities detection. In particular, Ronchetti E., Bisin A., Bottazzi L., Rossi B., who in the co-authorship network where isolated, are now part of the Island N.1 with other 17 scholars. Bisin A. is even the most central of this island. Instead, the big component of the co-authorship network seems to be divided in a group composed by Dosi G., Gambardella A., and Warglien M. (Island N.3), and others scholar who are no part of any island (Dagnino G.B., Salvadori N., Murgia M.), the remaining are part of the Island N.1. The only exception is Quattrone P. who was part of the big component, and now is part of the Island N.3 with Guthrie J. and Mussari R., who were also previously connected by co-authorship connections.

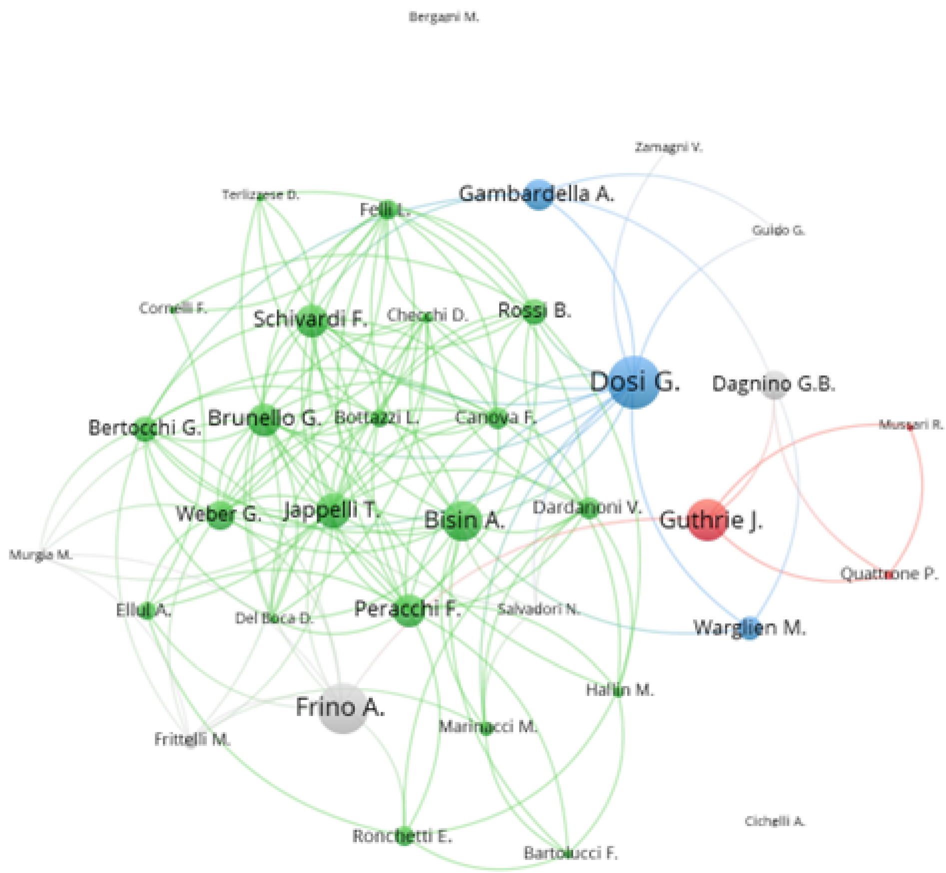


Figure 2.9 The 3 islands of the GEV 2004-2010 network of journals (each island has a different colour, and the dimension of vertices is proportional to betweenness centrality)

2.6.2 GEV 2011-2014 of Area 13

The 2011-2014 network of journal is composed by 31 nodes, the number of lines linking the scholars is 137, and the density of network is 0,28. This means that the 28% of the possible lines are present. Table 2.14 reports the degree distribution of the scholars, where a degree is the number of journal connections that a scholar has with the other scholars. The average degree is 8,84, meaning that, on average, one scholar has more than 8 journal connections with other scholars. There are three isolated scholars, i.e., three GEV members have never published in a journal where another GEV member has published. The others have at least one connection, with the highest value that is 19 connections hold by Sarno Lucio, followed by the 17 connections of Bertocchi Gabriella.

Table 2.14 Degree frequency distribution of the 2011-2014 network of journals

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
0	3	9,68	6	2	6,45	14	5	16,13
1	2	6,45	7	1	3,23	15	1	3,23
2	2	6,45	8	2	6,45	17	2	6,45
3	1	3,23	10	2	6,45	19	1	3,23
4	1	3,23	12	2	6,45			
5	1	3,23	13	3	9,68			

If we search for cohesive subgroups using the Pajek algorithm island, we get two different islands: the biggest one contains 17 scholars (the 55% of the GEV members); then there is an island with 3 scholars (10%); the remaining 11 scholar are no part of any island (in this last group there are also the 3 disconnected scholars, who are Asso P.F., De Carlo M., and Malanima P.). In Table 2.15 we report the name of the scholars, the belonging island and the betweenness values with the connected ranking. In Fig. 2.10 the 2011-2014 network of journals is represented, in which each island has a different colour, and the dimension of vertices is proportional to betweenness centrality.

Table 2.15 Betweenness centrality and rank betweenness of the GEV 2011-2014 scholars

Name	Betweenness centrality	Rank Betweenness	Island Number	Name	Betweenness centrality	Rank Betweenness	Island Number
Gambardella A.	0,130	1	1	Alfò M.	0,009	18	2
Cinquini L.	0,115	2	0	Paiella M.	0,008	19	1
Sarno L.	0,100	3	1	Corbetta G.	0,008	20	0
Fiordelisi F.	0,076	4	0	Brugiavini A.	0,006	21	1
Vivarelli M.	0,060	5	1	Ronchetti E.	0,003	22	2
Larrinaga-G. C.	0,060	6	0	Bartolucci F.	0,003	23	2
Bertocchi G.	0,052	7	1	Torrisi S.	0,002	24	1
Prencipe A.	0,043	8	1	Asso P.F.	0,002	25	0
Schivardi F.	0,040	9	1	De Carlo M.	0,000	26	0
Bandiera O.	0,027	10	1	De Paola M.	0,000	27	0
Pagano M.	0,025	11	1	Greco S.	0,000	28	0
Cavaliere G.	0,023	12	1	Malanima P.	0,000	29	0
De Fraja G.	0,023	13	1	Rosazza G. E.	0,000	30	0
Kretschmer T.	0,021	14	1	Salomone R.	0,000	31	0
Pesavento E.	0,016	15	1				
Lippi F.	0,011	16	1				

We get that Gambardella A. is the scholar with the highest betweenness centrality in absolute and in Island N.1 with the value of 0,13. Followed by Cinquini L. with a value of 0,115, the highest value among those who are no part of any island. 7 scholars, that represents the 23% of GEV members, have betweenness centrality lower than 0,002. Thus, even in this case, few GEV members have high centrality, while the majority has almost zero betweenness centrality.

The analysis of the connections through journals shows us some difference than the co-authorship connection analysis but does not change a lot. In particular, the big component of the 2011-2014 co-authorship network is now part of the Island N.1, except for Alfò M. and Bartolucci F. that are part of the Island N.2 together with Ronchetti E. (who was isolated in the co-authorship network). Moreover, are also part of the Island N.1: Sarno L., Vivarelli M., Cavaliere G., De Fraja G., Kretschmer T., Pesavento E., who were not part of the big component in in the co-authorship network.

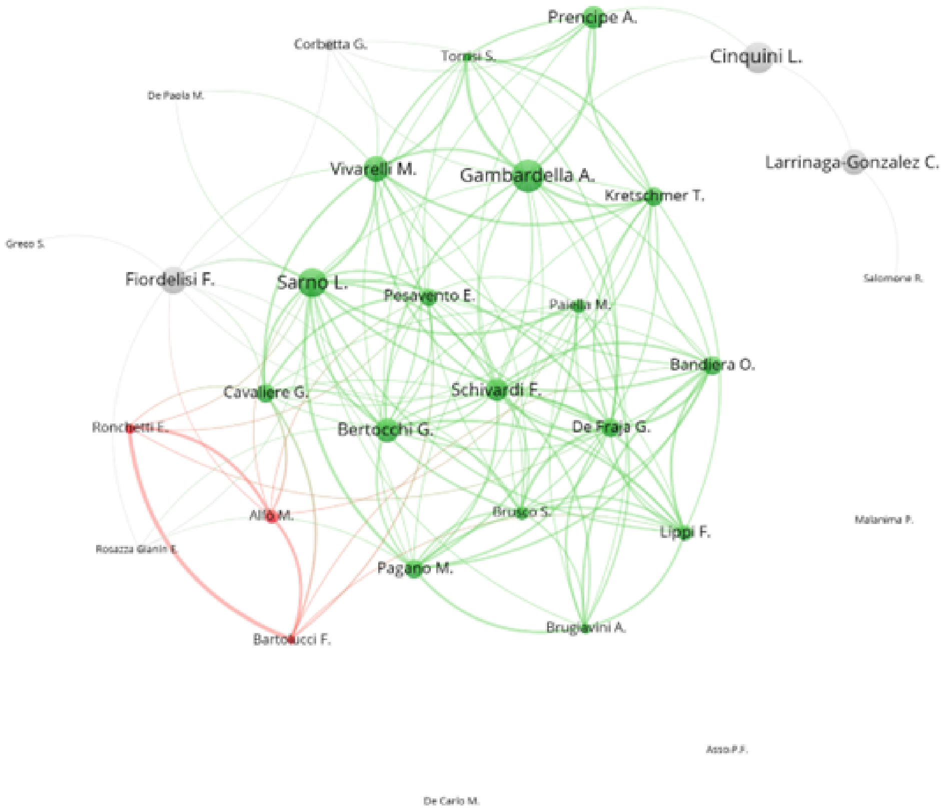


Figure 2.10 The 2 islands of the GEV 2011-2014 network of journals (each island has a different colour, and the dimension of vertices is proportional to betweenness centrality)

2.6.3 GEV 2015-2019 of Area 13

Finally, we analyse the 2015-2019 co-authorship network, that is our control group. The network is composed by 37 nodes. The number of lines linking the scholars is 137, and the density of network is 0,2 (the 20% of the possible lines are present). Table 2.16 reports the degree distribution of the scholars, where a degree is the number of journal connections that a scholar has with the other scholars. The average degree is 7,4, thus, on average, one scholar has almost 8 journal connections with other scholars. There are not isolated scholars, i.e., all the GEV members have published at least once in a journal where another GEV member has published. The highest value is 22 connections hold by Piva Mariacristina.

Table 2.16 Degree frequency distribution of the 2015-2019 network of journals

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
1	3	8,11	9	1	2,70
3	3	8,11	10	3	8,11
4	2	5,41	11	2	5,41
5	5	13,51	12	1	2,70
6	3	8,11	13	2	5,41
7	4	10,81	14	1	2,70
8	6	16,22	22	1	2,70

If we search for cohesive subgroups using the Pajek algorithm island, we get three different islands: two islands contain 6 scholars (the 16% of the GEV members); then there is an island with 3 scholars (8%); the remaining 22 scholar (60%) are no part of any island (the 60%). In Table 2.17 we report the name of the scholars, the belonging island and the betweenness values with the connected ranking. In Fig. 2.11 the 2011-2014 network of journals is represented, in which each island has a different colour, and the dimension of vertices is proportional to betweenness centrality.

Table 2.17 Betweenness centrality and rank betweenness of the GEV 2015-2019 scholars

Name	Betweenness centrality	Rank Betweenness	Island Number	Name	Betweenness centrality	Rank Betweenness	Island Number
Piva M.	0,272	1	2	Cavallo B.	0,016	20	0
Michetti E.	0,063	2	0	Adelfio G.	0,010	21	3
Marrocu E.	0,061	3	2	La Rosa F.	0,009	22	1
Pretaroli R.	0,059	4	0	Bracci E.	0,008	23	1
Berni R.	0,059	5	3	Corsi K.	0,008	24	1
Ruggeri F.	0,059	6	3	Antonioli D.	0,007	25	2
Pagano M.	0,056	7	0	Fassò A.	0,006	26	3
Opocher A.	0,056	8	0	Mavilia R.	0,004	27	2
Vasta M.	0,056	9	0	Stingo F.	0,004	28	3
Bajo E.	0,054	10	0	Chiodi M.	0,004	29	3
Picchio M.	0,047	11	0	Levrero E.S.	0,004	30	0
Gaeta G.L.	0,046	12	0	Scalzo V.	0,003	31	0
Meliciani V.	0,041	13	2	Avallone P.	0,000	32	0
Perna A.	0,038	14	0	Dell'Atti S.	0,000	33	0
Napolitano M.R.	0,034	15	0	Ghellini G.	0,000	34	0
Altomonte C.	0,034	16	2	Guerriero C.	0,000	35	0
Mencarini L.	0,027	17	0	Mason M.	0,000	36	0
Greco G.	0,020	18	0	Mosca M.	0,000	37	0
Notarnicola B.	0,019	19	0				

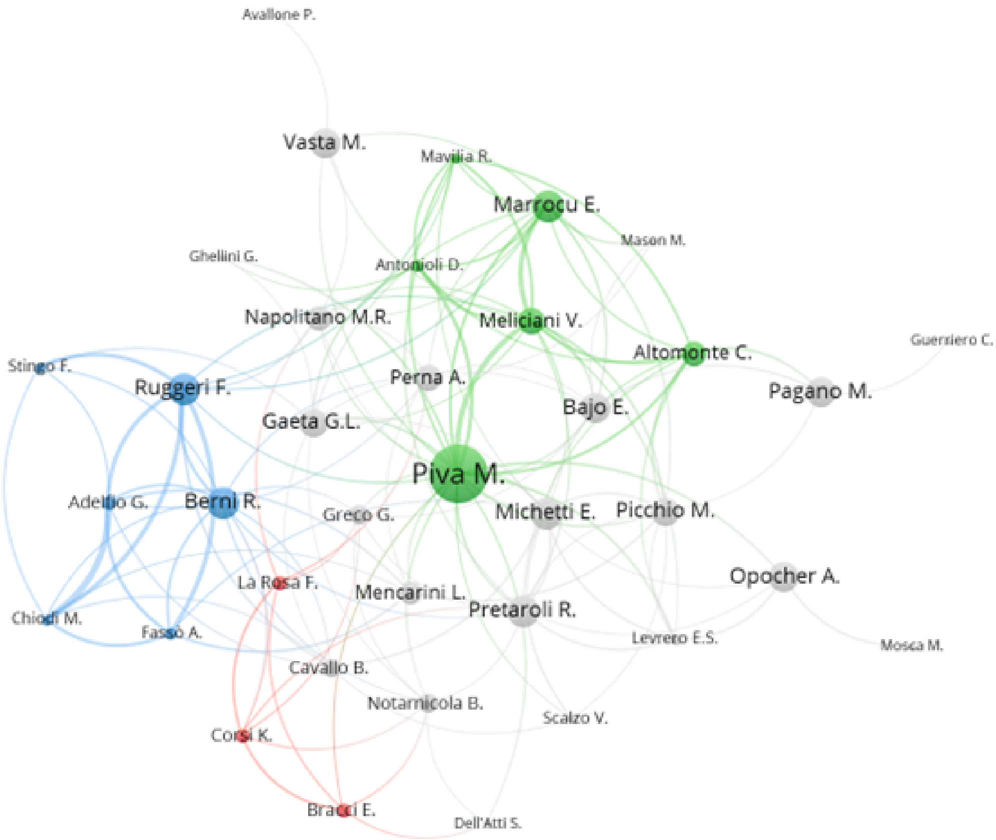


Figure 2.11 The 3 islands of the GEV 2015-2019 network of journals (each island has a different colour, and the dimension of vertices is proportional to betweenness centrality)

We get that Piva M. is the scholar with the highest betweenness centrality in absolute and in Island N.2 with the value of 0,27. Followed by Michetti E. with a value of 0,06, the highest value among those who are no part of any island. Berni R. is the scholar with the highest betweenness centrality in Island N.3 with the value of 0,06, while La Rosa F. in Island N.1 with the value of 0,01. Only 6 scholars, that represents the 16% of GEV members, have betweenness centrality lower than 0,002. Thus, in this case, it seems that the level of centrality is more distributed. Moreover, it is interesting to notice that the majority of the nodes are no part of any island.

The analysis of the connections through journals shows us few differences than the co-authorship connection analysis but does not change a lot. In particular, Island N.1 is composed by La Rosa F. and Corsi K. who were part of the same weak component in the co-authorship network, together with Bracci E. who was in a different one. Island N.2 contains Piva M., Meliciani V. and Antonioli D. who are also part of the same weak component, plus Marrocu E., Altomonte C. and Mavilia R. (these last two scholars were part of one component together with Scalzo V. who is now part of any island). Finally, Island N.3 is mainly composed by the same scholars of the 2015-2019 co-authorship network biggest component (except for Perna A. who is now in any island), together with Berni R. and Stingo F. that were before isolated.

2.6.4 Comparison of the networks of journals

To get a comparison among the networks of journals we report in Table 2.18 the basic statistics of the three networks and in Table 2.19 of the basic statistics of the largest island of each network.

Table 2.18 Basic statistics of the networks of journals

	GEV 2004-2010	GEV 2011-2014	GEV 2015-2019
N. of journals	360	467	566
N. of members	36	31	37
Isolated members	2 (6.4%)	3 (9.6%)	0 (0.0%)
Number of links between members	148	137	137
Lowest value of line	1	1	1
Highest value of line	8	13	14
Number of links with value =1	86	59	86
Number of links with value =2	32	18	35
Number of links with value >2	30	60	16
Density	0.228	0.285	0.200
Average Degree	8.222	8.838	7.405
All Degree Centralization	0.265	0.362	0.428
Betweenness Centralization	0.113	0.105	0.246
Number of islands	3	2	3

Table 2.19 Basic statistics of the largest island of each network of journals

	GEV 2004-2010	GEV 2011-2014	GEV 2015-2019
GEV members	21 (58.3%)	17 (54.8%)	6 (16.2%)
Number of links between authors	58	25	8
Lowest value of line	2	5	3
Highest value of line	7	10	14
Number of links with value =1	0	0	0
Number of links with value =2	30	0	0
Number of links with value >2	28	25	8
Density1 [loops allowed]	0.263	0.173	0.444
Average Degree	5.523	2.941	2.666
All Degree Centralization	0.413	0.358	0.700
Betweenness Centralization	0.168	0.602	0.700
All Closeness Centralization	0.396	0.486	0.785

From Table 2.18 we can see that the three networks of journals are similar and thus comparable. The basic statistics show us very few difference in terms of cohesion: Density and Average Degree are quite similar, but the third network is less cohesive.

Moreover, the third network is more centralized (All Degree and Betweenness Centralization are higher), which means that there is more difference between the largest and smallest actor-level centrality indices. In fact, the higher value of betweenness centrality is 0,13 in the first panel and in the second panel, while it is 0,27 in the last one. This is due to the presence of one member, Piva Mariacristina, that has a particular higher level of journals connections (22) with respect to the other members.

However, for our analysis we have to focus on the number and dimensions of the clusters (e.g., research communities). As we can see, the number of islands is similar but the dimension of them is very different. In fact, in the third one, we have that the majority of members are not part of any island (i.e., 22 members, 59,4%) and that in the largest island there are 6 members, which is 16,2% of the total number of members. In the first GEV, on the other hand, we have that more than half of the members are part of an island, i.e., 21 members, representing 58,3%. In the second GEV this percentage drops slightly to 54,8%, that is 17 members. In Table 2.19 we can see that the largest island of the first GEV is more cohesive, while the largest island of the last GEV is more centralized.

Therefore, also the analysis on journal connections shows that in the first two GEVs there is an unfair representation of the research community. In fact, we have that the number of clusters (e.g., research communities) are quite similar among the three panels, but in the first one and in the second one the dimension of the biggest cluster contains more than half of the panelists, while in the third one, that is our control group, only one sixth.

2.7 The affinity networks

For the affinity networks, the starting hypothesis is that not all economics departments and research centres carry out the same theoretical vision, and this diversity is also reflected in the newspapers in which scholars write. So, if the members have studied or are affiliated with the same research centres and universities, or published in the same newspapers, then the members probably have personal connections and theoretical similarities. Once we have constructed this 'affinity network' we will then detect central scholars and research communities through cluster analysis. If the first two panel affinity networks have less or larger cluster than the third one, then their composition unfairly represented the diversity of the research community, and the results of their evaluation exercise could be unfair.

Before building the dataset, we have isolated in each co-authorship network the nodes that are more central, i.e., those that have a betweenness centrality value larger than 0,002 (these names are reported in Table 2.2, Table 2.5, and Table 2.8). To these scholars, we added any GEV members who were not included in this partition. We made this choice because we decided to pay attention to the ties between member co-authors. In fact, in general, a person who is connected to people who are themselves not directly connected has opportunities to mediate between them and profit from his or her mediation. Ties bridge the connection between others, and people and organizations that bridge between others have more control and perform better (De Nooy et al. 2018). In our case, the bridges not only could have played a role in connecting panelists, but also this connection could represent an additional unfairness. In fact, if the bridges come from the same universities or research centres or publish in the same newspapers, they would spread the same theoretical vision. Thus, studying also the bridges is useful to detect further connections and possibilities of a minor representation of diversified points of view.

Once individuated the most central nodes in the co-authorship networks, we have reconstructed (manually processed) their curriculum vitae based on: maximum two places where they graduated; maximum two places where they did MSc/MA and PhD; maximum two institutes to which they have been affiliated; maximum five research centres to which they have been affiliated; maximum five newspapers in which they wrote. From this two-mode network, that connects scholars through (a broad definition of) affiliations, we then isolated the 'important vertices' using the Pajek algorithm, which is based on an eigenvector centrality approach, a two-mode variant of Kleinberg's hubs and authorities (Batagelj, 2015). Eigenvector centrality is considered as an extension of degree centrality because it is based on the assumption that a node is more central if it has more contacts and especially if its contacts are more central, that is, if they have many central contacts. Thus, eigenvector centrality of a vertex increases when it is connected to other vertices that are themselves important. The 'important vertices' Pajek algorithm requires to fix in advance the number of important vertices to search, and we fix this numbers equal to 18. Once individuated the 18 most important vertices in the network of scholars and the 18 most important vertices in the network of affiliation (the 18 vertices that have the greatest eigenvector centrality), we compare them with the islands identified in the networks (islands of minimum size 1 and maximum size 18). In this way we will see how many of the 18 most important vertices can be considered part of a single island (e.g., research community).

2.7.1 GEV 2004-2010 of Area 13

In the 2004-2010 affinity network we get that there are 58 scholars (31 are GEV members) and 191 different affiliations that are connected through 426 number of lines. The density of network is 0,04, i.e., only the 4% of the possible lines are present. The average degree is 3,42, meaning that, on average, one scholar has 3 affiliation connections with other scholars. There are 4 isolated scholars (6,8%), i.e., four scholars do not have any affiliation in common with another scholar in the network. The highest value of connection is 25 for the set of affiliation hold by CEPR, and 16 for the set of scholars hold by Marco Pagano. In Table 2.20, are reported the 18 most important vertices in the network of scholars and in the network of affiliation, for each it is also specified in which island they belong to, and for the scholars if they are or not GEV members. In Table 2.21 are instead reported the frequency distribution of islands detected in the GEV 2004-2010 affinity network.

Table 2.20 The important vertices of the GEV 2004-2010 affinity network

Network of scholars					Network of affiliation			
Name	**Eigenvector centrality**	**Rank Eigenvector**	**Island Number**	**GEV member**	**Name**	**Eigenvector centrality**	**Rank Eigenvector**	**Island Number**
Pagano M.	0,307	1	4	No	CEPR	0,514	1	8
Ichino A.	0,286	2	4	No	NBER	0,394	2	8
Schivardi F.	0,255	3	4	Yes	Bocconi U.	0,345	3	8
Guiso L.	0,252	4	4	No	EIEF	0,289	4	8
Pistaferri L.	0,239	5	4	No	lavoce.info	0,275	5	8
Bisin A.	0,234	6	4	Yes	IGIER	0,196	6	8
Bottazzi L.	0,227	7	4	Yes	IlSole24Ore	0,176	7	8
Rustichini A.	0,224	8	4	No	LSE	0,153	8	8
Checchi D.	0,214	9	4	Yes	MIT	0,148	9	8
Peracchi F.	0,203	10	4	Yes	IZA	0,126	10	8
Ellul A.	0,189	11	4	Yes	Bank of Italy	0,114	11	8
Rossi B.	0,183	12	0	Yes	EEA	0,110	12	8
Boldrin M.	0,183	13	4	No	European UI	0,105	13	8
Terlizzese D.	0,173	14	4	Yes	Il Foglio	0,101	14	8
Weber G.	0,168	15	4	Yes	Bologna U.	0,094	15	8
Gambardella A.	0,166	16	0	Yes	Cambridge U.	0,085	16	0
Jappelli T.	0,157	17	4	Yes	CSEF	0,076	17	0
Bertocchi G.	0,154	18	3	Yes	Stanford U.	0,076	18	0

The results show that, in the network of scholars, we get 4 islands: one island that contains almost most of the 18 important scholars, i.e., 15 (the 83% of the total), and 3 other much smaller islands. Among the 18 most important scholars, 6 are not GEV members, and even the first two important scholars, Pagano M. and Ichino A, are not. In the network of affiliation, we get a similar situation: there are 8 islands, the largest of which contains 15 important affiliations (the 83% of the total). In this largest island, we get that the university with the highest eigenvector centrality is the Bocconi University, with a value of 0,35, and to this island is connected the island that contains the 15 important scholars.

Table 2.21 Frequency distribution of island values of GEV 2004-2010 affinity network

Network of scholars				**Network of affiliation**			
Island	**Scholars Number**	**Important vertices Freq**	**Important vertices Freq%**	**Island**	**Affiliations Number**	**Important vertices Freq**	**Important vertices Freq%**
0	36	2	11.1	0	153	3	16.6
1	2	0	0	1	5	0	0
2	2	0	0	2	4	0	0
3	2	1	5.5	3	6	0	0
4	16	15	83.3	4	2	0	0
				5	2	0	0
				6	2	0	0
				7	2	0	0
				8	15	15	83.3
Sum	58	18	100	**Sum**	191	18	100

In Fig. 2.12 and Fig. 2.13 there are the graph representation of the islands of the scholars and of the affiliation networks taken separately. Each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality.

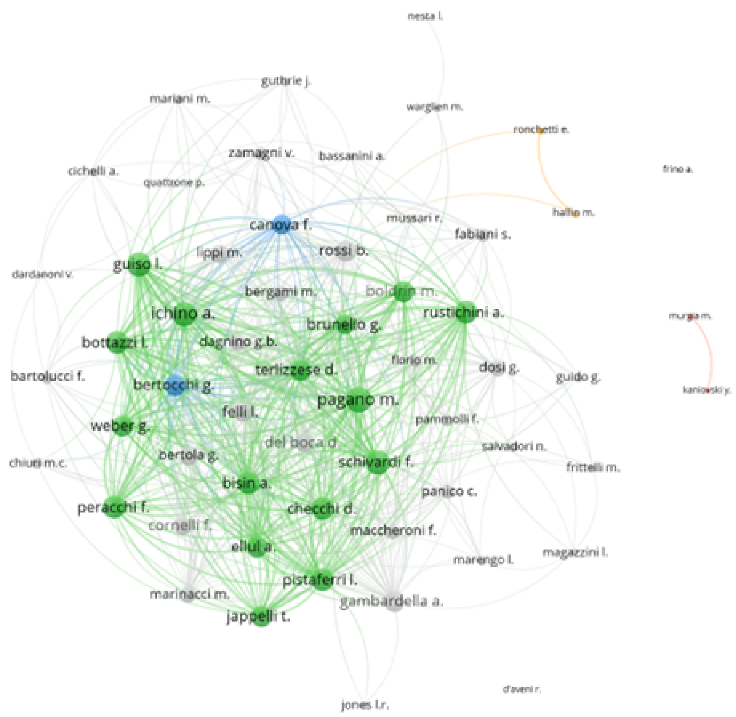


Figure 2.12 The 4 islands of the GEV 2004-2010 network of scholars (each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality)

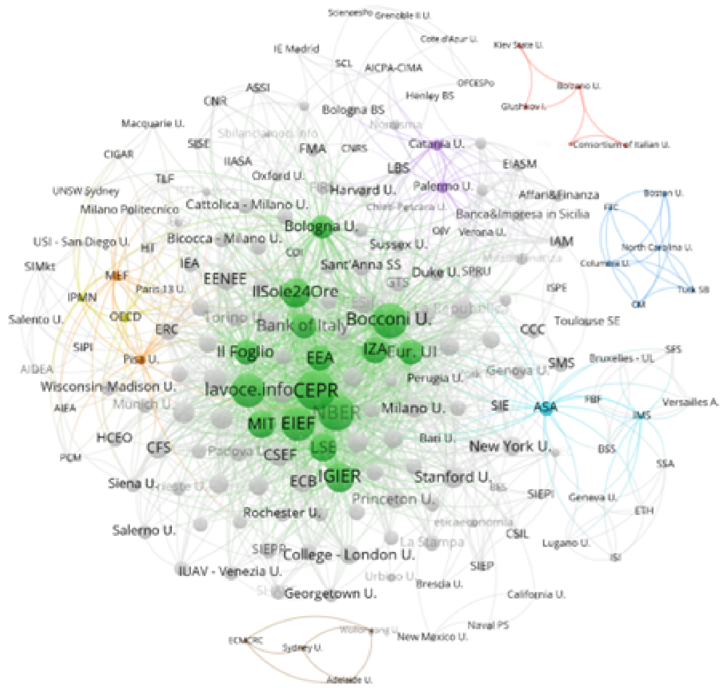


Figure 2.13 The 8 islands of the GEV 2004-2010 network of affiliations (each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality)

2.7.2 GEV 2011-2014 of Area 13

For what it concerns the 2011-2014 affinity network, we get that the network contains 40 scholars (of which 36 are GEV members) and 147 different affiliations that are connected through 306 number of lines. The density of network is 0,05, i.e., only the 5% of the possible lines are present. The average degree is 3,27, meaning that, on average, one scholar more than three affiliation connections with other scholars. There are not isolated scholars, i.e., every scholar has at least one affiliation in common with another scholar in the network. The highest value is 19 connections for the set of affiliation hold by CEPR, and 15 connections for the set of scholars hold by Marco Pagano.

In Table 2.22, are reported the names of the 18 most important vertices in the network of scholars and the 18 most important vertices in the network of affiliation, for each it is also specified in which island they belong to, and for the scholars if they are or not GEV members. In Table 2.23 are instead reported the frequency distribution of islands detected in the GEV 2004-2010 affinity network. Finally, in Fig. 2.12 and Fig. 2.13 there are the graph representation of the islands of the scholars and of the affiliation networks taken separately. Each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality.

Table 2.22 The important vertices of the GEV 2011-2014 affinity network

Network of scholars					**Network of affiliation**			
Name	**Eigenvector centrality**	**Rank Eigenvector**	**Island Number**	**GEV member**	**Name**	**Eigenvector centrality**	**Rank Eigenvector**	**Island Number**
Pagano M.	0,350	1	2	Yes	CEPR	0,519	1	2
Schivardi F.	0,294	2	2	Yes	NBER	0,383	2	2
Guiso L.	0,287	3	2	No	lavoce.info	0,348	3	2
Padula M.	0,285	4	2	No	Bocconi U.	0,341	4	2
Panunzi F.	0,282	5	2	No	EIEF	0,272	5	2
Lippi F.	0,239	6	2	Yes	Bank of Italy	0,136	6	2
Brugiavini A.	0,216	7	2	Yes	IGIER	0,119	7	2
Peracchi F.	0,215	8	2	No	LSE	0,116	8	2
Jappelli T.	0,214	9	2	No	Roma Tor Vergata U.	0,112	9	0
Bandiera O.	0,199	10	2	Yes	Napoli Federico II U.	0,110	10	0
Brusco S.	0,196	11	2	Yes	CSEF	0,108	11	0
Torrisi S.	0,196	12	2	Yes	CFS	0,108	12	0
Gambardella A.	0,195	13	2	Yes	ECGI	0,108	13	0
Sarno L.	0,193	14	2	Yes	ECB	0,100	14	0
Paiella M.	0,166	15	0	Yes	EEA	0,094	15	0
De Paola M.	0,148	16	0	Yes	IlSole24Ore	0,093	16	0
Bertocchi G.	0,144	17	0	Yes	Il Foglio	0,091	17	0
De Fraja G.	0,135	18	0	Yes	Salerno U.	0,088	18	0

Table 2.23 Frequency distribution of island values of GEV 2011-2014 affinity network

Network of scholars				Network of affiliation			
Island	**Scholars Number**	**Important vertices Freq**	**Important vertices Freq%**	**Island**	**Affiliations Number**	**Important vertices Freq**	**Important vertices Freq%**
0	23	4	22.2	0	131	10	55.5
1	2	0	0	1	8	0	0
2	15	14	77.7	2	8	8	44.4
Sum	40	18	100	**Sum**	147	18	100

The results show that, in the network of scholars, we get 2 islands, one of which contains almost most of the 18 important scholars, i.e., 14 (the 78% of the total), and the other one none. The remaining 4 important scholars are no part of any island. Among the 18 most important scholars, 5 are not GEV members. Comparing Table 2.22 with Table 2.20, we get that 7 scholars are part of the important vertices of both the 2004-2010 and the 2011-2014 affinity network (Bertocchi G., Gambardella A., Guiso L., Jappelli T., Pagano M., Peracchi F., Schivardi F.). Among these scholars, Guiso L. is the only one who is present in both but has never been a GEV member. In the network of affiliation, we get a similar situation: there are 2 islands, one of which contains almost half of the 18 important islands, i.e., 8 (the 44% of the total) an the other one none. In this largest island we get that the university with the highest eigenvector centrality is the Bocconi University, with a value of 0,34, and again to this island is connected the island that contains the 14 important scholars.

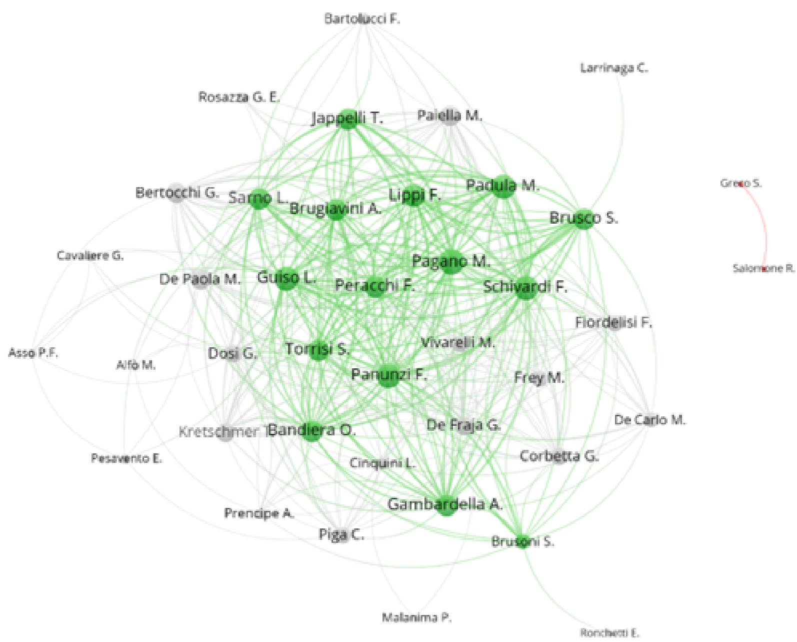


Figure 2.14 The 2 islands of the GEV 2011-2014 network of scholars (each island has a different

colour, and the dimension of vertices is proportional to eigenvector centrality)

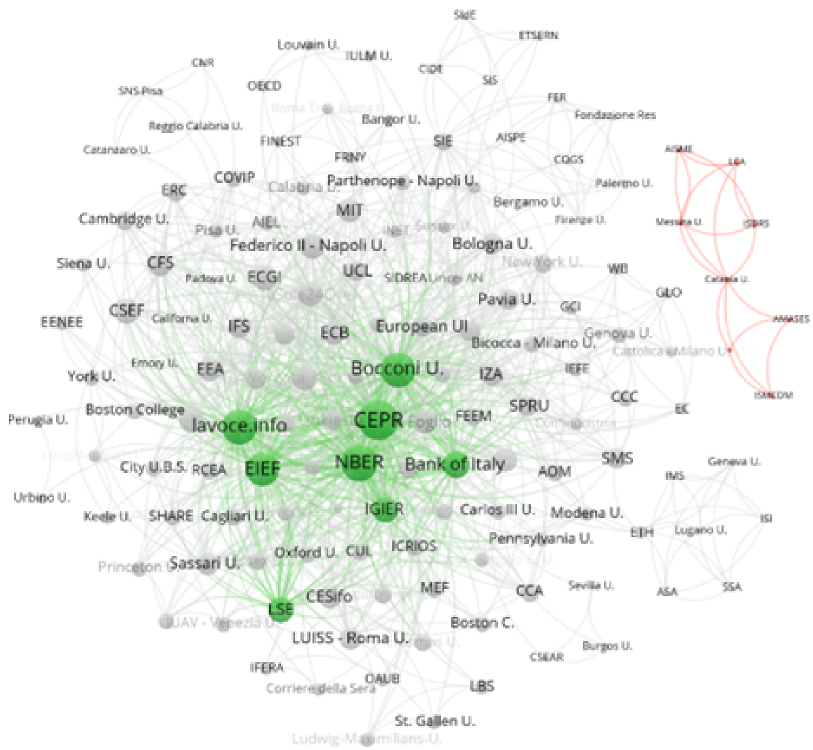


Figure 2.15 The 2 islands of the GEV 2011-2014 network of affiliations (each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality)

2.7.3 GEV 2015-2019 of Area 13

Finally, in our control group, which is the 20115-2019 affinity network we get that the network contains 48 scholars (of which 37 are GEV members) and 175 different affiliations that are connected through 302 number of lines. The density of network is 0,03, i.e., only the 3% of the possible lines are present. The average degree is 2,8, meaning that, on average, one scholar has less than 3 affiliation connections with other scholars. There is 1 isolated scholar (2%), i.e., one scholar does not have any affiliation in common with another scholar in the network. The highest value is 9 connections for the set of affiliation hold by SIS (Società Italiana di Statistica), and 15 connections for the set of scholars hold by Marco Pagano. In Table 2.24, are reported the names of the 18 most important vertices in the network of scholars and in the network of affiliation, for each it is also specified in which island they belong to, and for the scholars if they are or not GEV members. In Table 2.25 are instead reported the frequency distribution of islands detected in the GEV 2004-2010 affinity network.

Table 2.24 The important vertices of the GEV 2015-2019 affinity network

Network of scholars					Network of affiliation			
Name	**Eigenvector centrality**	**Rank Eigenvector**	**Island Number**	**GEV member**	**Name**	**Eigenvector centrality**	**Rank Eigenvector**	**Island Number**
Mencarini L.	0,425	1	0	Yes	SIS	0,350	1	3
Pagano M.	0,414	2	5	Yes	Bocconi U.	0,336	2	4
Altomonte C.	0,349	3	5	Yes	lavoce.info	0,315	3	4
Guerriero C.	0,283	4	5	Yes	Firenze U.	0,271	4	3
Picchio M.	0,232	5	5	Yes	CEPR	0,235	5	4
Nicolis O.	0,229	6	7	No	Bologna U.	0,165	6	7
Mavilia R.	0,186	7	8	Yes	Torino U.	0,158	7	3
Fassò A.	0,181	8	7	Yes	ECB	0,155	8	4
Vasta M.	0,162	9	0	Yes	IlSole24Ore	0,155	9	4
Betti G.	0,159	10	0	No	CCA	0,144	10	4
Mosca M.	0,154	11	4	Yes	Cambridge U.	0,141	11	4
Chiodi M.	0,152	12	7	Yes	EIEF	0,141	12	4
Ghellini G.	0,151	13	0	Yes	Padova U.	0,127	13	3
Berni R.	0,145	14	0	Yes	ISPI	0,123	14	4
Adelfio G.	0,142	15	7	Yes	Napoli Federico II U.	0,121	15	2
Stingo F.	0,138	16	0	Yes	UCL - Louvain	0,118	16	4
Bajo E.	0,132	17	0	Yes	SIE	0,118	17	6
Savona M.	0,130	18	6	No	TIES	0,112	18	3

Table 2.25 Frequency distribution of island values of GEV 2015-2019 affinity network

Network of scholars				Network of affiliation			
Island	**Scholars Number**	**Important vertices Freq**	**Important vertices Freq%**	**Island**	**Affiliations Number**	**Important vertices Freq**	**Important vertices Freq%**
0	22	7	38.8	0	127	0	0
1	3	0	0	1	4	0	0
2	4	0	0	2	3	1	5.5
3	2	0	0	3	10	5	16.6
4	4	1	5.5	4	18	10	55.5
5	4	4	22.2	5	3	0	0
6	3	1	5.5	6	6	1	5.5
7	4	4	22.2	7	2	1	5.5
8	2	1	5.5	8	2	0	0
Sum	48	18	100	**Sum**	175	18	100

As we can see, we have a different situation than before. In the network of scholars, we get 8 islands, and two of them contain only 4 important scholars (the 22% of the total). 7 important scholars (39%) are no part of any island. Moreover, among the important scholars, only 3 are not GEV member, and there is only one who is also in the important vertices of the other affinity networks (incidentally in both the 2004-2010 and the 2011-2014), i.e., Pagano M. In the network of affiliation, we also find 8 islands, but the largest still contains the majority of the 18 important affiliations., i.e., 10 (the 56% of the total), of which the university with the highest eigenvector centrality is again the Bocconi University, with a value of 0,34. However, only 4 important scholars are connected to this island, and the distribution among other islands is larger.

In Fig. 2.16 and Fig. 2.17 we report are the graph representation of the islands of the scholars and of the affiliation networks taken separately. Each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality.

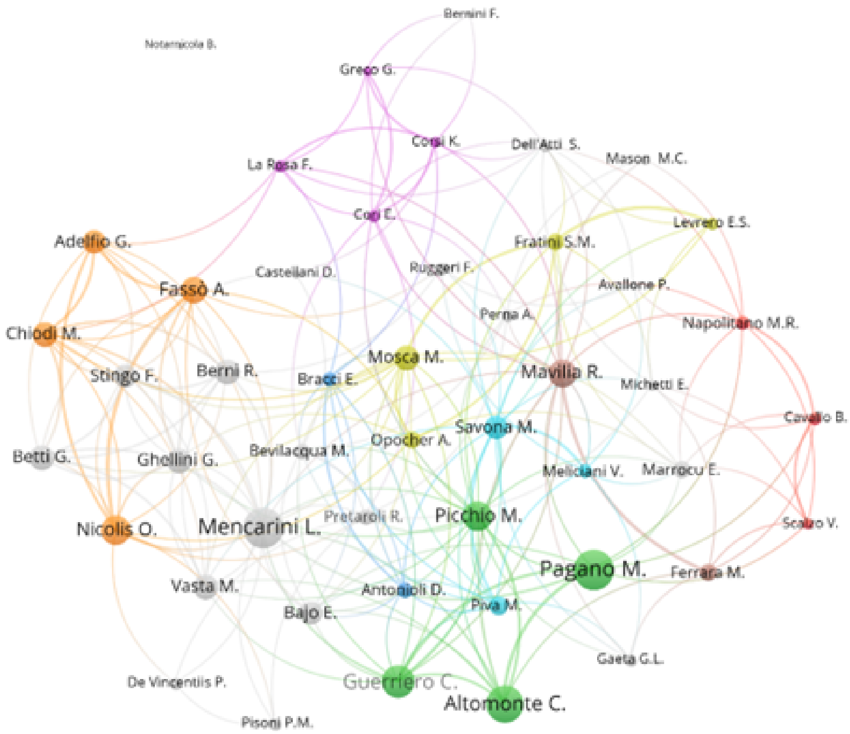


Figure 2.16 The 8 islands of the GEV 2015-2019 network of scholars (each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality)

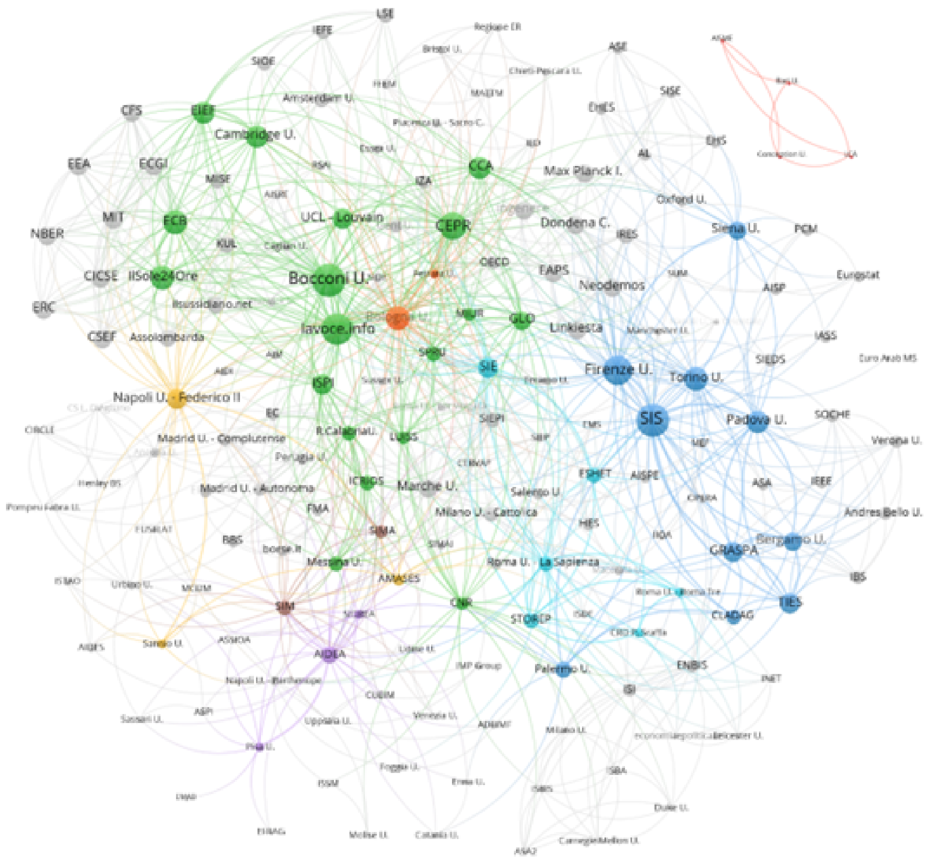


Figure 2.17 The 8 islands of the GEV 2015-2019 network of affiliations (each island has a different colour, and the dimension of vertices is proportional to eigenvector centrality)

2.7.4 Comparison of the affinity networks

We now focus on a comparison among the affinity networks, keeping in mind that the third panel is our control group. In Table 2.26 there are reported the basic statistics of the three networks, taking them as two-modes networks, and in Table 2.27 the basic statistics of the projected on-mode network of journals.

Table 2.26 Basic statistics of the affinity networks

	GEV 2004-2010	GEV 2011-2014	GEV 2015-2019
N. of affiliations	191	147	175
N. of scholars	58	40	48
Number of lines	426	306	302
Isolated scholars	4 (6.8%)	0 (0.0%)	1 (2.0%)
Density [2-Mode]	0.038	0.052	0.035
Average Degree [2-Mode]	3.421	3.272	2.708

Table 2.27 Basic statistics of the network of scholars

	GEV 2004-2010	GEV 2011-2014	GEV 2015-2019
Number of islands	4	2	8
Largest number of important vertices in the same island	15 (83.3%)	14 (77.7%)	4 (22.2%)
Number of scholars	58	40	48
Number of links between scholars	551	345	212
Lowest value of line	1	1	1
Highest value of line	7	7	5
Number of links with value =1	272	172	169
Number of links with value =2	129	95	31
Number of links with value >2	150	78	12
Density	0.327	0.431	0.184
Average Degree	19.000	17.250	8.833
All Degree Centralization	0.327	0.344	0.225
Betweenness Centralization	0.072	0.042	0.095

From Table 2.26 we can see that the three affinity networks are similar and thus comparable. The basic statistics show us very few difference in terms of cohesion: Density is quite similar among the three networks. However Average Degree of the third one is smaller, showing that there are fewer central nodes in our control group.

In Table 2.27, we notice how the third GEV has a clearly lower Density and Average Degree and therefore it is less cohesive within it. The centralization indices are instead quite similar. Our interest is again the number and dimensions of the clusters (e.g., research communities) that reveal us that even in this case the third GEV is very different from the first two. As we can see, we have in the first GEV 4 islands, the largest of which contains 15 (83%) important vertices. In the second GEV we get 2 islands, the largest of which contains 14 (77%) important vertices. In the third GEV we have instead 8 islands and only 4 important vertices are part of the same island (22% of the important vertices), while the majority of the important vertices are not part of any island (7, thus the 38.8%). In all three cases, in the biggest island the university with the highest eigenvector centrality is the Bocconi University.

We can therefore state that in the first two GEVs we have an unfair representation of the research community even with respect to affiliation. In fact, in the first one and in the second we have practically one single large cluster (e.g., research community) that contains more than half of the important vertices, while in the third GEV there are more clusters (e.g., research communities), and lesser central nodes.

2.8 Discussion and conclusions

Evaluation of research has been in the last decades a central theme on university and research policies. This attention is connected to the fact that evaluation has taken ≪the function of gatekeeping, filtering, and legitimating knowledge≫ (Lamont and Huutoniemi 2011). Considering its importance, a great focus has been given *procedural fairness*, which should be ≪concerned with procedures used to arrive at [fair] outcomes≫ (Beersma and De Breu 2003, p.220) and that includes the *fair representation* of all affected parties involved in the decision-making process. In fact, as it has been pointed out (Baccini and Ricciardi 2012), the role of panelists is very similar to that of the members of a popular jury in a trial. In order to have a fair judgment by a panel of judges, it is necessary to designate a fair jury and therefore presumably less inclined to partiality. If the composition of panels is unfair, there is the risk of a lack of diversified points of view. This may introduce biases in favour of some research programmes, methodological approaches or groups of scholars. The question of fairness is particularly delicate in discipline such as economics, characterized by the coexistence of many schools of thought with different approaches, methodologies and policy recipes. Therefore, in order to encourage the emergence of a fair judgment by the panelist, the designation of a balanced panel of evaluators, that represent the heterogeneity present in the research community, is necessary.

Formally, the recommendation for a fair representation of all affected parties involved in the decision-making process has been taken by the research evaluation assessments in UK, where the RAE is the international standard for this kind of evaluation; in the European Peer Review Guide of the European Science Foundation; and also in the Italian research evaluation assessments. However, the substantial respect of this request has been questioned in the UK case (Harley and Lee 1997; Lee 2006; Lee et al. 2013) and in the Italian one (Baccini 2011, 2013, 2014, 2016; Baccini and Ricciardi 2012; Corsi et al 2010, 2011). In particular, it has been highlighted the unrespect for fairness in the composition of the members selected for the Italian evaluation for the period 2004-2010, which homogeneity could have probably minimized the voices of dissent with respect to the evaluation methods and rules adopted, harming or gradually eliminating the so-called heterodox or non-mainstream economists, and leading to a system that is conservative and suppresses innovative research.

In fact, we cannot just focus on an apparent diversity, but we have to look more deeply in the connections among the panelists. For this reason, it is not acceptable the defence made by ANVUR when it was showed that a procedural fairness was not respected for the 2004-2010 GEV 13 panel (Baccini, 2014). The ANVUR answer was connected to two elements: the fact that, among the top 50 Italian economists in the Repec database, the co-authorship network connected to the president is similar to the one of the 2004-2010 GEV panel; and the fact that the panel ≪is a group of scholars with a high scientific profile and diversified in terms of skills and geographical origin, in full compliance with the criteria for the selection of GEVs published on the ANVUR website≫ (ANVUR 2012). The first element does not hold since there is no reason to compare the co-authorship network only with the network of the top 50 Italian economists in the Repec database. In fact, the database is not representative of the research community and is based on a concept of excellence that is biased. Firstly, because it is stated by the site itself: ≪The data presented here is experimental. It is based on a limited sample of the research output in Economics and Finance. Only material catalogued in RePEc is considered. [..] Thus, this list is by no means based on a complete sample≫ (RePEc 2017). Secondly, because in general any ranking based on bibliometrics is biased towards gender, multidisciplinary methods, and any research orientations pursued by a minority of researchers in their respective disciplines (Corsi et al., 2019). Thus, we cannot compare the composition of the panels to the top 50 Italian economists in the RePEc database or to any other ranking based on bibliometric values. The second element does not hold since it is true that formally and apparently there is a geographical difference in the affiliation of the panelists, but it does not correctly represent the hidden network. Firstly, because it was not declared the case of multiple affiliations leaving the possibility to choose the one less represented to the scholar, and secondly because there is not indicated the panelist academic career from which it would have been possible to see precedent connections.

Thus, in order to detect hidden connections, in our study we have deeply investigated the fairness of the composition of the panels appointed to evaluate research in economics and statistics during the Italian research assessment exercises. The panels of three evaluation exercises are considered for the years 2004-2010, 2011-2014, 2015-2019. The first two panels were appointed directly by the member of the governmental agency for the evaluation of university and research (ANVUR); the third was instead selected randomly by a lot from among those who had applied to be panelists. This permits to consider the third panel as a control group. For investigating the fairness of the panels, a network analysis approach is adopted by comparing the co-authorship networks, the networks of journals in which panelists have published and the network of universities, research centres and newspapers that connect them.

The results show that the members of the first two panels had connections in terms of co-authorship, affiliation and cultural approaches much higher than the members of the control group. In particular, for the authorship networks, we get that in the first panel we have practically one single large cluster (e.g. research community) that contains more than half of the network (65%) and panelists (66%), the second one is similar to the first one (43% of the network and 41% of panelists), while in the third GEV there are more clusters (e.g. research communities), and these groups are much smaller (the biggest contains only the 25% of the network and the 13% of panelists). For the networks of journals, we have that the number of clusters (e.g., research communities) are quite similar among the three panels, but in the first one and in the second one the dimension of the biggest cluster contains more than half of panelists (58.3% in the first one and 54.8% in the second one), while in the third one only the 16%. For the affinity networks, in the first one and in the second we have practically one single large cluster that contains more than half of the central nodes (83% in the first panel and 77% in the second one) while in the third panel there are more clusters (e.g., research communities), and these groups contains maximum the 22% of the important vertices. In all three cases, in the biggest island the university with the highest eigenvector centrality is the Bocconi University.

We can conclude saying that the fairness of composition of panels was not guaranteed for the first two Economics panels in the Italian research assessment exercises, that a particular group connected to the Bocconi University was over-represented and hence that the results of the Italian research assessments in Economics from 2004 to 2014 should be considered as possibly unfair.

Further research will lead us to search for social proximity among GEV members using network fusion techniques (Baccini F. et al. 2022), which is going to be useful also to understand which of the three-layer networks gives the major contribution to the structure of the fused network.

CHAPTER 3

Who Makes Economics Knowledge? The Gender Composition, Geographic Diversity, and Social Networking of Editorial Boards of Economics

Abstract

Members of editorial boards play the role of gatekeepers of science, because through their selection of manuscripts to be published in journals, they can determine both the development of research in a given discipline, by choosing which research to support and which to exclude, and the career of the scholars who turn to them for the publication of their works. In this paper we analyse the national distribution of editorial boards members of economics journal, their affiliation, and their gender. We will also study the network generated by the presence of the same person on the editorial board of more than one journal (interlocking editorship). The analysis is based on a unique database comprising all the 1.517 journals indexed in the database EconLit as of 2019. For each journal, we manually collected the names of the board members along with their affiliation, obtaining a database containing more than 44.000 members from more than 6000 institutions and 141 countries. These unique data allow to investigate the phenomenon of gatekeeping in contemporary economics on an unprecedented large scale. The obtained results highlight some common issues concerning the editorial gatekeeping, leading to the conclusion that in Economics the academic publishing environment is governed by an elite group composed mainly of men affiliated with US elite universities. This level of homophily in terms of geographic, institutional and gender distribution is higher in the most prestigious journal and among Editors-in-Chief. The network analysis is also used to individuate the most influential gatekeepers, from the level of the individual scholar and of journals, and to check for cohesive groups. Finally, it is uncovered the fact that all those who are part of the editorial board generate the same connections among journals indistinctly from the role, but with different intensity. In the determination of the network, those who are No Editors-in-Chief have more influence than Editors-in-Chief.

3.1 Introduction

Quantitative approaches have recently gained increasing attention from economists, as they allow to reconstruct features of the recent history of economic thought or of the professional role of economist that may remain invisible to standard qualitative methods (Duarte and Giraud 2016; Marcuzzo and Zacchia 2016). In this paper, we use quantitative tools to investigate the role of the gatekeepers of economics. Specifically, we focus on the members of Editorial boards and on the Editors-in-Chief of economics journals, as these figures play a key role in shaping both the direction of the economic sciences and the career of economists (De Grazia 1963; Crane 1967). In fact, members of editorial boards play the role of gatekeepers of science, because through their selection of manuscripts to be published in journals, they can determine both the development of research in a given discipline, by choosing which research to support and which to exclude, and the career of the scholars who turn to them for the publication of their works. Considering the crucial role that editors are playing, many studies have focused on the composition of editorial boards, its correlation with publication outcome and its evolution during time.

In this paper the main objective is to update and enrich the knowledge of the composition of editorial boards of Economics in order to understand what the characteristic of the gatekeepers of economics are. The analysis is based on a unique database comprising all the 1.517 journals indexed in the database EconLit as of 2019. For each journal, we manually collected the names of the board members along with their affiliation, obtaining a database containing more than 44.000 members from more than 6000 institutions and 141 countries. This unique dataset allows to investigate the phenomenon of gatekeeping in contemporary economics on an unprecedented large scale. Until now, in fact, the editorial boards of economics have been studied or in limited dataset or with specific approaches.

The first analysis in this sense was done by Hodgson and Rothman (1999) and was based on the institutional backgrounds of editors and authors of the top 30 economics journals of 1995. They revealed that 70,8% of the journal editors were located in the United States, and that twelve universities accounted for the location of more than 38,9% of editors. Their main concern with such a high concentration of institutional power is the threat it poses to “the potential for innovation and change” (p.166). This result is consistent with the study of Gibbons and Fish (1991) on the 25 top journals of economics from 1970 to 1979. They also discovered that, among the 575 editors, Harvard had the most members (36, or 9,1 percent of all members), Stanford was second (29 members, or 7,3 percent), followed by MIT (25), Chicago (24), and Pennsylvania

(22). More recently, Wu et al. (2020), using a sample for the year 2019 that comprised 6916 editors who were affiliated with 246 economics journals, showed that academic journals in the field of economics are still heavily dominated by US institutions (48,55% of editors are from the US). Addis and Villa (2003), instead, focused the analysis on gender distribution and examined the presence of men and women economists on the editorial boards of thirty-six Italian economics journals published from 1970 to 1996, showing that women are scarcely present and work mostly in the lower positions. Then, Baccini and Barabesi (2010) firstly proposed and analysed the editorial board network that is generated by the presence of the same person on the editorial board of more than one journal.

In this study, we will search for all this information on an unprecedented large scale. The organization of the article is as follows: in Section 2, it is reported a literature review of the study on the editorial boards in different fields; in Section 3, it is presented the dataset and the methodology; in Section 4, it is reported the geographic distribution and the institutional distribution of the editorial seats of economics outlining the differences among gender and among All Editorial roles and Editors-in-Chief, and with a specific focus on the Top Five Journals; in Section 5, it is studied the interlocking editorship (IE) network that is generated by those scholars who hold more than one seat, that at least one is Editor-in-Chief; in Section 6, it is reported the comparison among three different network to understand if the Editors-in-Chief have ore not a particular power in the construction of the IE network.

3.2 Literature review

Since the beginning of the analysis of the gatekeeping phenomenon in sociology of science, a central focus has been given to the role of the editors of journals, defined as 'the' gatekeepers of science (De Grazia 1963; Crane 1967). This attention is connected to the role of editors in shaping the direction of scientific knowledge, through the selection of works worthy of publication, and indirectly of the scientific career of the scholars, that in the last 20-30 years has increasingly depended on quantitative bibliometric indicators. For the crucial role that editors are playing, it is expected that their selection processes follow the normative ideal of 'universalism' (Merton 1942), whereby scientific contributions are judged solely on its intellectual merit. However, confidence in the extent to which editors promote the best scientific production has been eroded by questions about whether social biases, correlated with the demographic or institutional characteristics of the scholar, could also play a role. Firstly, Crane (1967) has found empirical evidence that an author's academic affiliation, doctoral origin, and professional age happened to be rather similar to the distribution of those characteristics among journal editors, and these highly affect editorial decisions in the selection of journal articles. This situation has as a consequence that the narrow composition of the editorial board, based on similar education, research background, and academic experience, can lead to a limitation on thematic and methodology that are published in a journal (Teixeira and Oliveira 2018). For these reasons, since then, many studies focused on the composition of editorial boards, its correlation with publication outcome and its evolution during time. Moreover, studies of the composition of editorial boards have been applied for the evaluation of journal internationalization or gender balance, as well as an indicator of research power of geographic areas, institution, gender, or groups of scholars.

In particular, Zsindely et al. (1982), studying the *geographic distribution* of the editorial boards of 252 scientific journals, showed a strong correlation between the number of editorial board members from a given country and the number of journals and authors associated with that country. Specifically, Israel, Western Europe, the United States, and Canada were better represented on editorial boards than it could be expected based on the number of academic publications and scholarly journals, while the number of editorial-board members from Japan, India, and the Soviet Union were lower than expected. The authors of larger scale studies made similar conclusions, pointing out that, manuscripts submitted by authors from countries different than those of the editorial board members are more likely to be rejected and that, for the majority of international journals, editorial board members are primarily represented by citizens of the United States (US) (see Mazov and Gureev 2016 for a review). Braun and Dióspatonyi (2005a, b) interpreted this fact as an indicator that shows that the US has been, since 1982, the leading scientific power and it does not show any decline in this respect until then. This conclusion is driven even considering the fact that other countries are rising the numbers of published papers and citations (Leydesdorff and Wagner 2009 showed that Chin has recently become the second largest nation in both behind the US), because this power is still not reflected in the editorial boards member and, as Braun and Dióspatonyi (2005a: p.1548) said, ≪journal papers and citations are just a corollary≫ and ≪the control and screening activity of journal editorial boards [..] is of paramount importance≫. The dominance of US scientists as editorial board members and as Editors-in-Chief, they believe, ≪represents one of the explanations, and probably one of the most important one, which interprets the world dominant position of the US in science publication in most of science fields≫ (Braun and Dióspatonyi 2005b: p.319).

Another stream of connected studies has been the analysis of the *gender com-*

position of editorial boards. In a similar manner to the analysis of the geographic distribution, the objective of such studies is to see what the gender composition of an editorial board is, and if there are differences among the share of men and women in the scientific field that is covered by a journal. As in the case of editorial boards that are dominated by representatives of the same country, the prevalence of the editorial board members of one sex can lead to biased selection of papers, not only for gender but also for specific topics, approaches, or theories (Stegmaier et al. 2011; Metz et al. 2016). It is also believed that a higher involvement of women in editorial boards can positively affect the attraction of female researchers to respective scientific disciplines, because women in gatekeeper positions can be perceived as role models for graduate students and junior researchers (Mauleón et al. 2013). The first analysis on the topic of female presence in the editorial positions was that of Hatfield et al. (1995) who, starting from the observation of a low female presence in the research sector, raised the question of whether this was also true at the editorial level. To analyse this aspect, 100 of the most influential clinical medicine were taken and the gender of the Editor-in-Chief was recorded. The most important editorial positions were occupied by men in 92 out of 96 magazines, while only 4 by women. In one case, the position occupied by a woman was shared with three other men. The following studies conducted so far on the same topic in different fields showed the same characteristic: a male domination in editorial boards connected to a significant gap between the number of female researchers and their representation on editorial boards; a rise of the number of women in editorial boards but at a lower speed of the presence of women in scientific fields; a smaller number of women in editorial boards of the most prestigious journals and in the role of Editor-in-Chief (see Mazov and Gureev 2016 for a review).

Relatively recently, a framework that has been proposed to examine the structural properties of editorial board networks is that of *interlocking editorship* (IE). An IE network has been firstly defined by Baccini (2009) as the network generated by the presence of the same person on the editorial board of more than one journal. The underlying idea is that the number of editorial board members that two journals share can be viewed as an indicator of journal similarity, i.e., the IE approach measures journal proximity based on common editorial board membership. From another perspective, the IE network can be also used to try to identify scholarly communities, also called 'invisible colleges', and 'academic elite' (editors who occupy a large number of board seats, or are more central in the network have more power in shaping the editorial decisions). Moreover, Baccini et al. (2020) showed that the social structure of the IE network is similar to the one of co-citation networks among journals and the one of interlocking authorship (the networks of journals generated by authors writing in more than one journal). This means that studying communities in the IE network gives similar result as studying communities in the other two. This framework has been used to explore with Social Network Analysis (SNA) the IE network of statistics, of economics and of information science and library science. In statistics, the IE network is compact, and this is viewed as the result of a common perspective about the appropriate methods in the field (Baccini et al. 2009). In economics, the authors found a compact network of the editors (90% of the journals are directly or indirectly connected) containing different components, and this has been interpreted as the result of a plurality of perspectives concerning the best research practices and economic theories (Baccini and Barabesi 2010). In information science and library science, instead, the editorial board members form two loosely connected sub-fields, and this has been considered connected to the fact that this field is relatively young, so it has not reached a general consensus through scholars on research aims, methods and instruments (Baccini and Barabesi 2011). Since then, the IE network analysis has been used in various field, among which library and information science (Liwei and Chunlin 2015; Ni and Ding 2010), finance (Andrikopoulos and Economou 2015), knowledge management and intellectual capital fields (Teixeira and Oliveira 2018), communication sciences (Goyanes and de-Marcos 2020), tourism (Lockstone-Binney et al. 2021), revealing insights in journal clusters within a given field or research area and in the structure of editorial gatekeeping. Lately, IE network has also been applied to investigate the geographies of the co-editor network in oncology, showing a core–periphery geographical structure (Csomós and Lengyel 2022).

3.3 Data and methodology

The main objective of this study is to update and enrich our knowledge of the composition of editorial boards of economics by studying it on a unique database comprising all the 1.516 journals indexed in the database EconLit with an active editorial board in 2019. EconLit is a database published by the American Economic Association that provides bibliographic coverage of the major scientific economics-related literature and is the main source of references in the field of economic literature worldwide. The data on the members of the editorial boards was directly obtained from the websites of the journals. For each member, the following data were manually entered: name and surname, role, journal name, affiliation if declared. Then, all the information was manually standardized. We obtained a database with 60.638 seats connected to 477 distinct roles occupied by 44.460 scholars, which means that the average number of seats per journal turned out to be 39,9 and the average number of seats occupied by each scholar (i.e., the mean rate of participation) was 1,36. For 6.680 scholars, which represent the 15% of the total, no affiliation was declared. The remaining 37.764 have declared 55.471 affiliations, for 5.953 distinct affiliations, which means an average number of affiliations per scholars of 1,46.

We used the Google Maps Text Search API to attribute a country to each distinct affiliation in the dataset, manually cleaning wrong attributions. In this way, we have been able to connect 53.700 affiliations to 142 different countries, that is the 96,8% of total affiliations. The gender was attributed to scholars using an algorithm that considered both the first name and the country of the member's affiliation, in order to take into account geographical variability in the association between names and gender (e.g., the name 'Andrea' is mainly attributed to men in Italy but to women in English-speaking countries).We coded gender on a binary scale (male – female) not having the possibility to obtain self-reported gender data. We apologize to all those who are represented in the sample and who do not self-identify along the heteronormative binary and hope that future studies might have more resources to contact people individually to report on self-identified data. We have been able to attribute gender to 39.761 scholars, i.e., the 89,4%.

From this dataset we have isolated the publication's editorial leaders. We have adopted two different procedures for identifying the editorial leader of a journal. The first one simply consisted in considering as editorial leaders the scholars classified by journals as Co-Editor-in-Chief, Deputy Editor-in-Chief, Editor-in-Chief, Joint Editor-in-Chief, which represents 981 people for 687 journals, i.e., the 45,28%. For the rest of journals, we adopted the second more complex procedure, by manually searching the publication's editorial leaders who were classified with a different name (for example, Editor, Co-Editor, Director, Chair, ecc) and that are listed as first or last in the description of the editorial board. This second procedure permitted to identify 1.906 people for 761 of journals. In sum, we obtained 2.893 distinct editorial leaders, that now on we are going to call Editor-in-Chief for simplicity, for a total of 1.448 journals, which represents the 95,45% of the journals, and an average number of Editors-in-Chief per journal of 2.

Table 3.1 reports the main quantitative features of the final dataset.

Table 3.1 Data description

Elements	**N**
Distinct seats	60 638
Distinct scholars	44 460
Distinct journals	1 516
Distinct affiliations	5 953
Distinct countries	142
Distinct roles	477
Seats without affiliation	6 674
Seats without country	8 416
Seats without gender	5 603
Distinct Editors-in-Chief	2 893
Distinct Editors-in-Chief seats	3 010

This rich dataset has been used to study the geographic distribution and institutional distribution of editorial boards of economics, also underlying its gender distribution and the differences among all editorial roles and Editors-in-Chief. Our aim is to see how heterogenous or homogeneous the editorial boards in economics, and if it there are differences among the characteristics of the members of the boards and of the Editor-in-Chief. Moreover, we are interested in understanding if the composition of editorial boards is more ore less homogeneous if we focus on the most prestigious journals of economics. Thus, we isolate the editorial boards of the journals that have been named 'The Top Five Journals', i.e., those 5 journals that have a particular power in shaping the direction of scientific knowledge in economics and influence tenure decisions and career advancement (Heckman and Moktan 2020). These journals are *The American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*.

Finally, we focused on the analysis of IE before in statistical terms and then in network terms. A particular focus is given to the IE network constructed by those scholars that holds more seats of which at least one is Editor-in-Chief, analysing it as a two-mode network and then as the two different projected one-mode networks, and looking for the more central journals and scholars. Then, in order to understand if the role of Editors-in-Chief is or not relevant in the entire IE network, we compare three IE networks: the entire network; the network created by those who are Editors-in-Chief at least once; the network created by those who are never Editors-in-Chief. The comparison among these three networks it has also been used to see if there are differences among the structural properties of the network of Editors-in-Chief and of the other board members. The network methods and mapping were made with Pajek (version number 5.14) and Gephi (version number 0.9.5).

3.4 Statistical description

We start our study focusing on a data analysis. We report below before the geographic distribution and then the institutional distribution of the editorial seats of economics outlining the differences among gender and among All Editorial roles and Editors-in-Chief. Namely, a member may be counted more than one if she or he has more than one affiliation and/or if they work in more than one journal. Results for the Top 5 journals in economics, i.e. *The American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*, are reported also separately.

3.4.1 Geographic roles distribution

We start the analysis of the geographic roles distribution of the editorial seats with a map visualization (Figure 3.1). We then focus on the 10 countries that have more editorial seats, reporting their distribution in Table 3.2. The percentage of each country has been calculated over the total seats, i.e., 60.638, of which we have 8.422 seats (13%) that have not an attributed country. The percentage of gender has been instead computed on the total number of seats for each country, that it was possible to assign a gender (seats without gender are therefore excluded, which in total are 5.603, the 9,2%).

As we can see in Figure 3.1 and Table 3.1, the most represented country is by far United States with almost the 30% of all seats and of Editor-in-Chief seats that are connected to an affiliation in US, followed by United Kingdom (UK) with 8% and 7,64%. In the top 10 countries there are no non-Western countries. This confirm that the US is the leading scientific power in economics, followed by UK and other Western countries. Moreover, the 5 most represented countries hold the 42% of all editorial seats and the 49% of Editors-in-Chief seats, but in all Editorial roles there are 151 countries declared, while in Editors-in-Chief only 84. This shows us that the geographic concentration is similar among the editorial board roles, but in Editors-in-Chief there is less heterogeneity in terms of countries with the exclusion of non-Western countries in the highest and most important roles of the board.

As for the gender composition, men occupy more than 75,8% seats, if we consider the entire dataset and a similar 74,6% if we just focus on the Editors-in-Chief. Among the top 10 countries, if we consider all Editorial roles, the one that has more women in percentage is Turkey (26,4%) and the one that has less is Netherlands (15%); if we focus only on Editors-in-Chief, the one that has more women in percentage is France (32%) and the one that has less is Switzerland (14,5%).

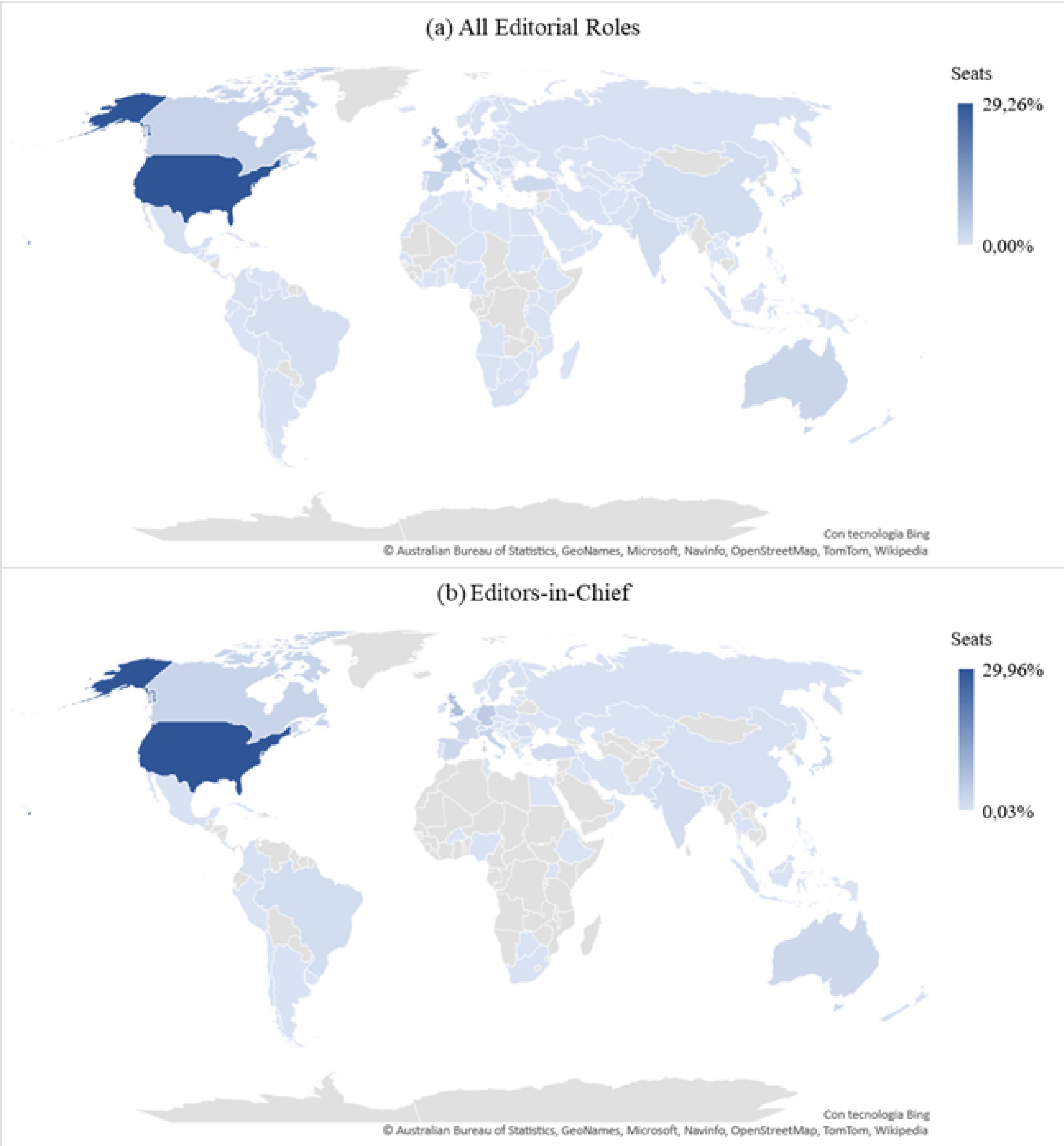


Figure 3.1 Geographical roles distribution

Table 3.2 Seats at the editorial tables: the 10 most represented countries

All Editorial Roles				Editors-in-Chief			
Country	**Female**	**Male**	**Total**	**Country**	**Female**	**Male**	**Total**
United States	3483 (21,94%)	12392 (78,06%)	17748 (29,26%)	United States	161 (19,85%)	650 (80,15%)	902 (29,96%)
United Kingdom	993 (22,41%)	3439 (77,59%)	4906 (8,09%)	United Kingdom	56 (25,81%)	161 (74,19%)	230 (7,64%)
Italy	515 (24,24%)	1610 (75,76%)	2257 (3,72%)	Germany	25 (17,99%)	114 (82,01%)	144 (4,78%)
France	444 (22,27%)	1550 (77,73%)	2190 (3,61%)	Canada	16 (17,20%)	77 (82,80%)	98 (3,25%)
Canada	423 (22,75%)	1436 (77,25%)	2074 (3,42%)	Italy	14 (15,05%)	79 (84,95%)	97 (3,22%)
Germany	295 (16,32%)	1513 (83,68%)	1945 (3,20%)	Spain	21 (30,43%)	48 (69,57%)	72 (2,39%)
Spain	439 (25,61%)	1275 (74,39%)	1777 (2,93%)	Australia	15 (22,73%)	51 (77,27%)	70 (2,32%)
Australia	346 (22,91%)	1164 (77,09%)	1693 (2,79%)	France	21 (32,31%)	44 (67,69%)	68 (2,25%)
Turkey	324 (26,45%)	901 (73,55%)	1257 (2,07%)	Netherlands	10 (17,54%)	47 (82,46%)	63 (2,09%)
Netherlands	137 (15,48%)	748 (84,52%)	982 (1,61%)	Switzerland	7 (14,58%)	41 (85,42%)	50 (1,66%)
Total seats	13282 (24,13%)	41753 (75,87%)	60638 (100%)	**Total seats**	706 (25,38%)	2076 (74,62%)	3010 (100%)

3.4.2 Institutional roles distribution

Once analyzed the country distribution, we further focus the analysis at the institutional level to detect if there are universities or research centers that have more power than others in editorial terms. In Table 3.3, it is reported the 10 institutions that are more represented in the editorial boards of economics journal. Also in this case, the percentage of each institution has been calculated over the total seats, while the percentage of gender has been computed on the total number of seats that it was possible to assign a gender.

Table 3.3 shows that the most represented institution is University of California both in all Editorial roles and in Editors-in-Chief. However, this result is amplified because, in the standardization of affiliations, it was impossible to uniformly understand to which campus of the University of California scholars belong to. Appendix 3.A reported the declared affiliations as written in websites of the journals, by showing that a generic 'University of California' would have been ranked at a second position in all editorial roles with 507 seats, and at a first position in Editors-in-Chief with 35 seats. In any case, the most represented institutions are American universities: in all editorial roles there are two exception that are the London School of Economics and the

University of Oxford; among Editors-in-Chief only the London School of Economics is represented outside US. Even in this case, affiliation diversity is greater for all editorial roles, which count 5.953 different institutions, than for Editors-in-Chief which count only 1.031 institutions. However, we register less concentration in terms of institution, because all the top 10 institutions taken together represents only the 8% of total seats for all editorial roles, and the 9,75% of Editors-in-Chief.

The gender distribution is coherent with previous results. The institution with more women in percentage is the University of Oxford (28,4%) in all Editorial roles, and the MIT (33%) in Editors-in-Chief. The institution with less women in percentage is the New York University both in all Editorial roles (11,5%), and in Editors-in-Chief (4,7%).

Table 3.3 Seats at the editorial tables: the 10 most represented institutions (*See Appendix 3.A for the University of California campus)

All Editorial Roles				**Editors-in-Chief**			
Institution	**Female**	**Male**	**Total**	**Institution**	**Female**	**Male**	**Total**
University of California*	191 (19,96%)	766 (80,04%)	1103 (1,81%)	University of California*	12 (18,75%)	52 (81,25%)	71 (2,35%)
London School of Economics	118 (21,77%)	424 (78,23%)	587 (0,96%)	University of Pennsylvania	6 (25,00%)	18 (75,00%)	31 (1,02%)
University of Pennsylvania	93 (17,21%)	350 (82,79%)	505 (0,83%)	MIT	9 (33,33%)	18 (66,67%)	29 (0,96%)
Harvard University	79 (20,99%)	380 (79,01%)	494 (0,81%)	University of Chicago	1 (3,85%)	25 (96,15%)	27 (0,89%)
Columbia University	44 (11,80%)	329 (88,20%)	423 (0,69%)	London School of Economics	4 (16,67%)	20 (83,33%)	25 (0,83%)
New York University	42 (11,51%)	323 (88,49%)	403 (0,66%)	Harvard University	4 (18,18%)	18 (81,82%)	24 (0,79%)
Michigan State University	87 (25,97%)	248 (74,03%)	384 (0,63%)	University of Washington	4 (18,18%)	18 (81,82%)	23 (0,76%)
University of Oxford	93 (28,44%)	234 (71,56%)	349 (0,57%)	New York University	1 (4,76%)	20 (95,24%)	22 (0,73%)
Stanford University	48 (15,69%)	258 (84,31%)	345 (0,56%)	Northwestern University	6 (30,00%)	14 (70,00%)	22 (0,73%)
University of Washington	84 (27,81%)	218 (72,19%)	336 (0,55%)	Stanford University	3 (15,79%)	16 (84,21%)	21 (0,69%)
Total seats	13282 (24,13%)	41753 (75,87%)	60638 (100%)	**Total seats**	706 (25,38%)	2076 (74,62%)	3010 (100%)

3.4.3 The Top Five Journals case

A particular focus is given to those that have been called 'The Top Five Journals', i.e., those 5 journals that have a particular power in shaping the direction of scientific knowledge in economics and influence tenure decisions and career advancement

(Heckman and Moktan 2020). These journals are *The American Economic Review*, *Econometrica*, the *Journal of Political Economy*, the *Quarterly Journal of Economics*, and the *Review of Economic Studies*. The choice of this focus is connected to the fact that Heckman and Moktan (2020) showed that the reliance on the Top Five Journals «centralizes power to shape the profession into the hands of a select group of editors [..], incentivizes professional incest and creates incentives for clientele effects» (p.462). It is still open the question of what the characteristics of this 'academic elite' are.

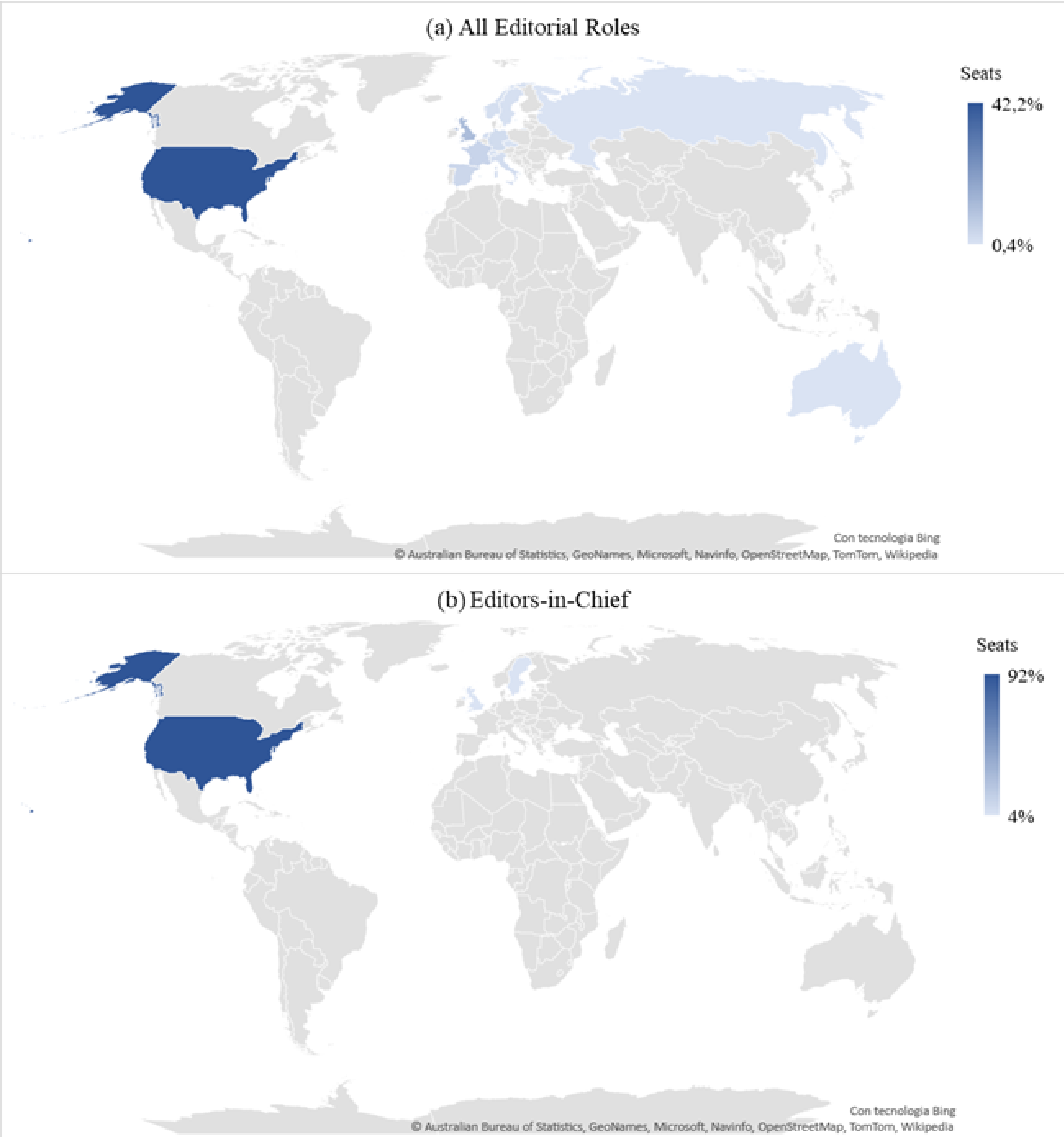


Figure 3.2 Geographical roles distribution in the Top Five Journals of Economics

Even in this case, we report before the geographic distribution and then the institutional distribution of the editorial seats outlining the differences among gender and among All Editorial roles and Editors-in-Chief. In Figure 3.2, it is reported the map visualization of the geographic roles distribution of the editorial seats of the Top Five Journals. Table 3.4 reports data about the 10 most represented countries in the Top Five Journals.

Table 3.4 Seats at the editorial tables: the 10 most represented countries in Top Five Journals

All Editorial Roles				**Editors-in-Chief**			
Country	**Female**	**Male**	**Total**	**Country**	**Female**	**Male**	**Total**
United States	21 (21,65%)	76 (78,35%)	98 (42,24%)	United States	3 (13,04%)	20 (86,96%)	23 (92,00%)
United Kingdom	7 (25,93%)	20 (74,07%)	27 (11,63%)	United Kingdom	0 (0,00%)	1 (100%)	1 (4,00%)
France	1 (9,09%)	10 (90,91%)	11 (4,74%)	Sweden	1 (100%)	0 (0,00%)	1 (4,00%)
Spain	3 (33,33%)	6 (66,67%)	9 (3,87%)				
Germany	1 (16,67%)	5 (83,33%)	6 (2,58%)				
Italy	0 (0,00%)	5 (100%)	5 (2,15%)				
Netherlands	0 (0,00%)	4 (100%)	4 (1,72%)				
Norway	1 (25,00%)	3 (75,00%)	4 (1,72%)				
Switzerland	0 (0,00%)	3 (100%)	3 (1,29%)				
Sweden	1 (33,33%)	2 (66,67%)	3 (1,29%)				
Total seats	50 (21,65%)	181 (78,35%)	232 (100%)	**Total seats**	4 (16,00%)	21 (84,00%)	25 (100%)

As we can see, the editorial boards of the Top Five Journals present less heterogeneity respect to all journals both in terms of countries and of gender. United States is predominant with 42% of all Editorial roles and 92% of Editors-in-Chief. It is again followed by United Kingdom with 11,6% and 4%. Moreover, we have an enormous concentration in term of countries. In fact, in all Editorial roles there are 14 countries declared, while in Editors-in-Chief only 3. The 5 most represented countries hold the 65% of all editorial seats.

As for the gender composition, men are more than 78%, if we consider all Editorial Roles, and the 84% if we just focus on the Editors-in-Chief. When all editorial roles are considered, among the most represented countries, the ones that has more women in percentage are Spain and Sweden (33%) and there are three countries that have zero women. The only Editor-in-Chief position occupied by a woman is shared with six other men.

The decrease in diversity is detected also for the affiliation distribution. In fact, for the Top Five Journals, the editorial boards member come from only 63 different institutions and, if we focus on Editors-in-Chief, from only 13 institutions (only the 0,21% of the total distinct affiliations). Table 3.5 reports the 10 most represented institutions in the editorial boards of the Top-Five. As we can see, the most represented institutions in the boards of the Top Five Journals are similar to those seen before for the whole set of economics journals (Table 3.3), but the concentration is higher. Thus, in this case few American institutions covered almost all available seats. In particular, Editors-in-Chief of the Top Five Journals are concentrated in very few powerful institutions: University of Chicago, Harvard University and Stanford University concentrate the 52% of the available Editor-in-Chief seats.

Table 3.5 Seats at the editorial tables: the 10 most represented institutions in Top Five Journals

All Editorial Roles				**Editors-in-Chief**			
Institution	**Female**	**Male**	**Total**	**Institution**	**Female**	**Male**	**Total**
London School of Economics	4 (25,00%)	12 (75,00%)	16 (6,89%)	University of Chicago	0 (0,00%)	6 (100%)	6 (24,00%)
University of California*	0 (0,00%)	12 (100%)	12 (5,17%)	Harvard University	1 (25,00%)	3 (75,00%)	4 (16,00%)
Harvard University	4 (36,36%)	7 (63,64%)	11 (4,74%)	Stanford University	0 (0,00%)	3 (100%)	3 (12,00%)
Stanford University	3 (30,00%)	7 (70,00%)	10 (4,31%)	MIT	1 (50,00%)	1 (50,00%)	2 (8,00%)
University of Chicago	1 (11,11%)	8 (88,89%)	9 (3,87%)	Yale University	1 (50,00%)	1 (50,00%)	2 (8,00%)
University College London	3 (33,33%)	6 (66,67%)	9 (3,87%)	Northwestern University	0 (0,00%)	1 (100%)	1 (4,00%)
Yale University	6 (66,67%)	3 (33,33%)	9 (3,87%)	University of California Los Angeles (UCLA)	0 (0,00%)	1 (100%)	1 (4,00%)
University of Pennsylvania	0 (0,00%)	7 (100%)	7 (3,01%)	New York University	0 (0,00%)	1 (100%)	1 (4,00%)
Princeton University	0 (0,00%)	5 (100%)	6 (2,58%)	University of Edinburgh	0 (0,00%)	1 (100%)	1 (4,00%)
MIT	1 (20,00%)	4 (80,00%)	5 (2,15%)	Stockholm University	1 (100%)	0 (0%)	1 (4,00%)
Sciences Po	1 (20,00%)	4 (80,00%)	5 (2,15%)	Boston University	0 (0,00%)	1 (100%)	1 (4,00%)
				University of Pennsylvania	0 (0,00%)	1 (100%)	1 (4,00%)
				Princeton University	0 (0,00%)	1 (100%)	1 (4,00%)
Total seats	50 (21,65%)	181 (78,35%)	232 (100%)	**Total seats**	4 (16,00%)	21 (84,00%)	25 (100%)

3.5 The interlocking editorship network of Editors-in-Chief

Heretofore, we have analysed the editorial board seats as taken separately. However, we have to consider that a single scholar can hold more seats at the same time. This is due to the fact that being part of an editorial boards is something that gives prestigious to a journal, thus, in order to increase the reputation of the journals and to attract the best papers, are nominated as editors scholars that are 'famous' or 'influential' (Baccini and Barabesi 2009). This phenomenon, seen from another point of view, is also connected to the fact that editors of journals with strong reputations enjoy an enormous amount of power in their hands (Faria 2005), so scholars tend to accept more roles in different editorial boards. Thus, the presence of the same person on the editorial board of more than one journal can be analysed to study the 'academic power' or 'academic prestigious' of a scholar and of a journal. In order to do so, it has been very useful the SNA that, through different tools (community detection, centrality measures, etc), it has been used to study the characteristic of the IE network, i.e., the network generated by the presence of the same person on the editorial board of more than one journal.

In our case, we get that the 21,5% of scholars hold more than one seat in All editorial roles with a maximum of 24 seats hold by a single person. In the Editor-in-Chief case, instead, only the 3,8% of scholars hold more than one seat with a maximum of 4 seats hold by the same person. Moreover, women tend to hold less seats at the same time in the case of All editorial roles, in fact, only 17,5% hold more than one seat with a maximum of 13 seats hold by a single person. The distribution is quite similar among gender in the case of Editor-in-Chief with a similar 3,3% of women scholars that hold more than one seat with a maximum of 3 seats hold by the same person. The seats distribution is reported in Figure 3.3.

Thus, we get that there are 'important' economists that sit in many boards of editors, but very few scholars that act as Editor-in-Chief in more than one journal. This may suggest that Editors-in-Chief have a high workload and hence it is difficult for a scholar having more one of this seats. At the opposite, the role of member of editorial board may appear as honorary for high renowned scholars. For testing this hypothesis, Table 3.6 reports the top multiple editors, i.e., the 10 scholars who occupy the highest number of seats in the editorial boards of economics journals. Data are separated for all editorial role seats and for Editor-in-Chief seats. For Editors-in-Chief, scholars are reported only if they hold more than 2 seats.

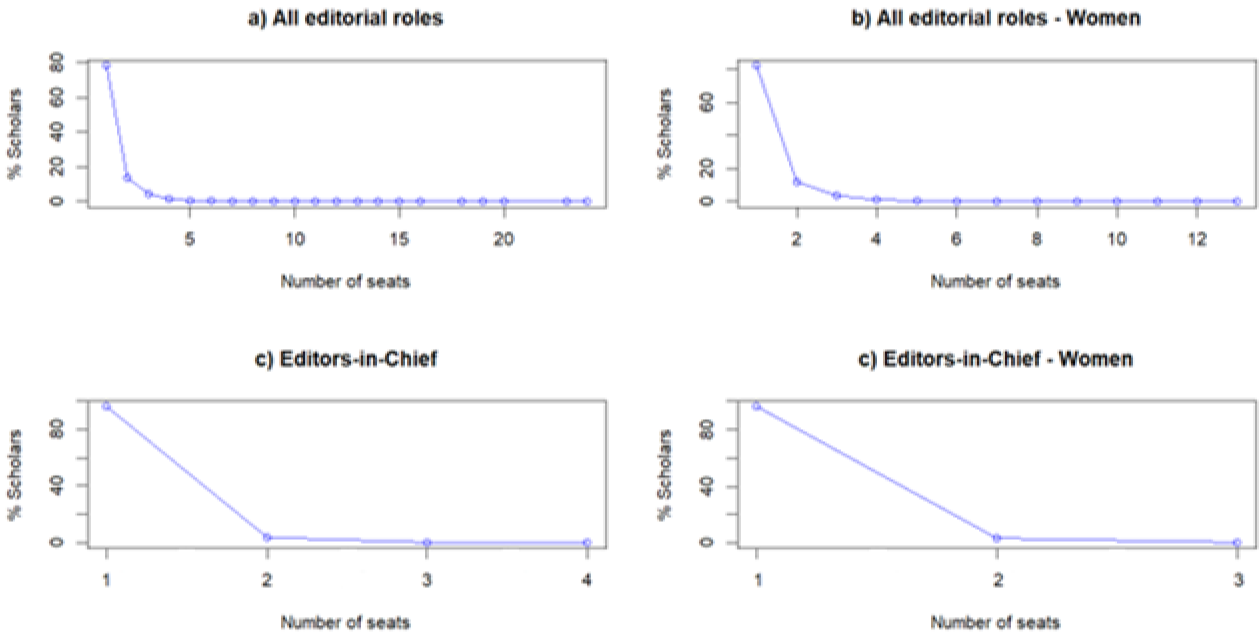


Figure 3.3 Editorial board seats distribution

Table 3.6 The 10 most represented scholars

All Editorial Roles		Editors-in-Chief	
Name and Surname	**N° of seats**	**Name and Surname**	**N° of seats**
Amartya K. Sen *(Harvard University)*	24	Robert C. Merton *(MIT)*	4
Barry Eichengreen *(University of California Berkeley)*	23	Atila Abdulkadiroglu *(Duke University)*	4
Mohammad Kabir Hassan *(University of New Orleans)*	20	Raj Aggarwal (*University of Akron*)	3
Andrés Rodríguez Pose *(London School of Economics)*	19	Mohammad Kabir Hassan (*University of New Orleans*)	3
Douglas J. Cumming *(Florida Atlantic University)*	18	Mercedes Jalbert *(The Institute for Business and Finance Research)*	3
Wing-Keung Wong *(Hong Kong Baptist University)*	16		
Peter Nijkamp *(Vrije University)*	16		
Iftekhar Hasan *(Fordham University)*	15		
Geoffrey M. Hodgson *(University of Hertfordshire)*	15		
Giovanni Dosi *(Scuola Superiore S. Anna, Pisa)*	14		
Total seats	60638	**Total seats**	3010

As we can see, it looks that being selected as an editorial board member can also be connected to give prestigious to a journal, and not just to give an effective power to the scholar in the editorial board. For example, this seems the case if we consider that the scholar that hold more seats is the Nobel price Amartya Sen. To check this hypothesis, we report in Table 3.7 the 10 scholars that hold more seats of which at least one is Editor-in-Chief. Comparing Table 3.6 with Table 3.7, we can see that some scholars (namely Amartya Sen, Barry Eichengreen, Peter Nijkamp, Geoffrey M. Hodgson) are not anymore in the top 10 scholars that holds most seats, while we found some other scholars (namely Dani Rodrik, Brian M. Lucey, Bruno S. Frey, James J. Heckman) that enter in the Top 10. This can give an idea of the difference among power and prestige. Since we are interested in focusing on those scholars who exercise an actual editorial power, we are going to construct the IE network taking into account only those scholars who act at least once as Editors-in-Chief.

Table 3.7 The 10 scholars that holds most seats, of which at least one is Editor-in-Chief

Name and Surname	**N° of seats**	**Name and Surname**	**N° of seats**
Mohammad Kabir Hassan *(University of New Orleans)*	20	Giovanni Dosi *(Scuola Superiore S. Anna, Pisa)*	14
Andrés Rodríguez Pose *(London School of Economics)*	19	Dani Rodrik (*Harvard University)*	14
Douglas J. Cumming *(Florida Atlantic University)*	18	Brian M. Lucey *(University of Dublin Trinity College)*	14
Wing-Keung Wong *(Hong Kong Baptist University)*	16	Bruno S. Frey *University of Zurich; University Basel)*	13
Iftekhar Hasan *(Fordham University)*	15	James J. Heckman *(University of Chicago)*	13
Total seats 60638			

In Figure 3.4 is drawn, by using the Force Atlas 2 algorithm on Gephi 0.9.5 (Bastian et al. 2009), the two-mode network of the IE where in blue are scholars who act at least once as Editor-in-Chief, and in red economics journals. It is composed by a giant central component in which there is the majority of economics journals and Editors-in-Chief. Around this giant component there is a belt of smaller groups of journals and Editors-in-Chief. In particular, the network can be divided in 372 weak components; the giant component contains 1103 journals and 2361 editors for a total of 3464 nodes, which is the 78,56% of total network. In total, outside the big component, there are 413 journals (the 27%) and 532 Editors-in-Chief (18,4%). These are clustered in 371 different weak components, of which 40 different components contain only 1 node, i.e., there are 40 isolated journals. This number is smaller compared to the 68 journals for which we could not find an Editor-in-Chief, meaning that the editorial board members of 28 of these journals have as a member of the board someone who is Editor-in-Chief in another journal. Then, we get that 219 different components contain 2 nodes, 59 different components contain 3 nodes. The distribution of the rest of the network among weak components is reported in Table 3.8.

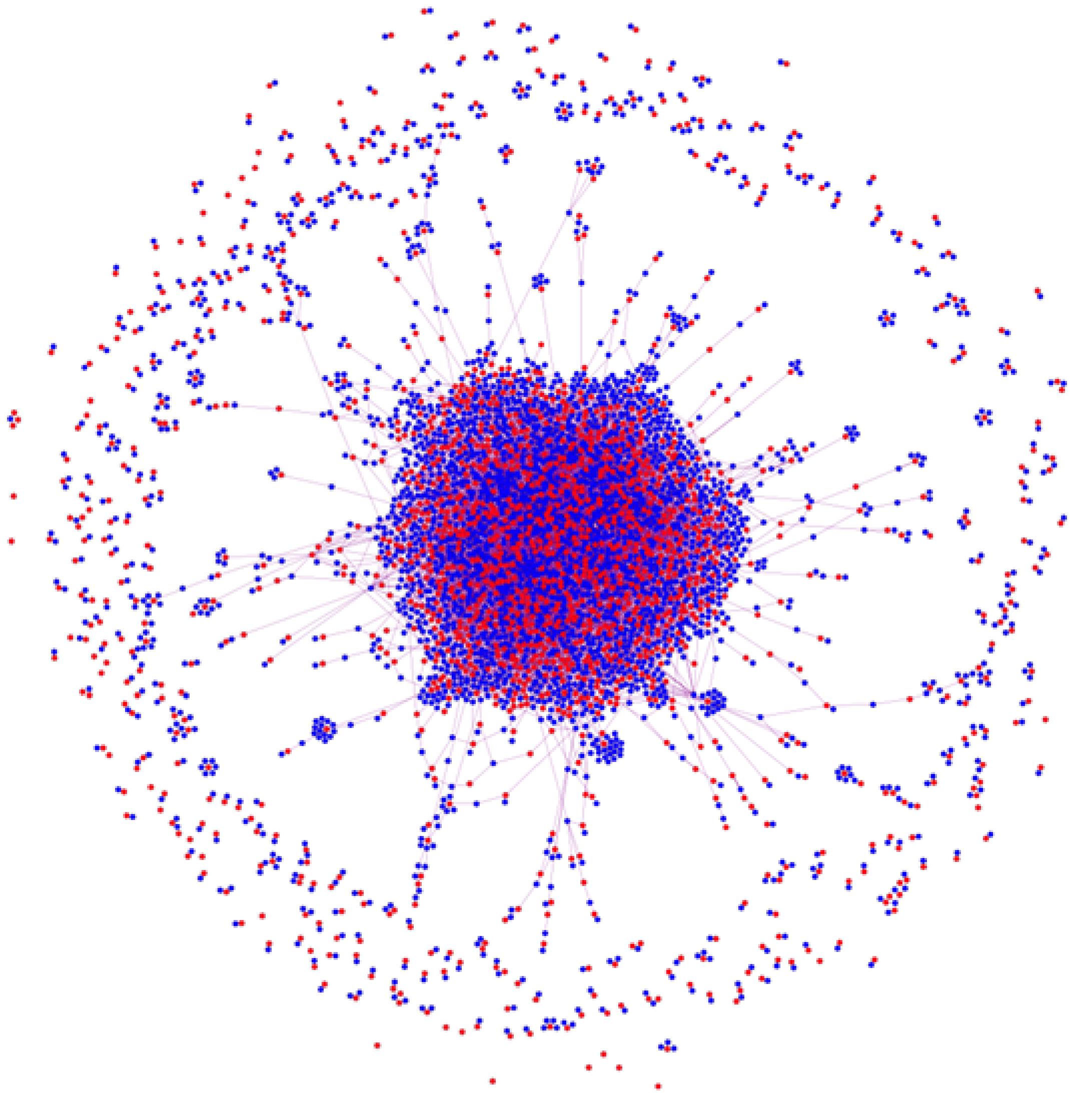


Figure 3.4 The two-mode interlocking editorship network (in red the journals and in blue scholars who act at least once as Editors-in-Chief)

Thus, the IE interlocking editorship network is compact and presents a typical core-periphery structure. In the giant component we get the most powerful editors and journal (there are also included the Top Five journals). Outside the biggest component instead we have regional journals (like for example *Iberian Journal of the History of Economic Though, Iranian Journal of Trade Studies*), interdisciplinary journals (like *Journal of Behavioral Public Administration* or *World Competition Law and Economics Review*), non-English language journals (i.e. *Rivista Economica del Mezzogiorno, Revue d'Histoire de la Pensée Économique/Journal of the History of Economic Thought*), journals edited by institutions (*FDIC Quarterly, World Trade Review*).

Table 3.8 Distribution of the two-mode interlocking editorship among weak components

Frequency	**% Frequency**	**N° of different clusters**	**Frequency**	**% Frequency**	**N° of different clusters**
3464	78,56%	1	7	0,15%	5
13	0,29%	1	6	0,13%	5
12	0,27%	1	5	0,11%	14
11	0,24%	1	4	0,09%	23
10	0,22%	1	3	0,06%	59
9	0,20%	1	2	0,04%	219
8	0,18%	1	1	0,02%	40

For individuating more precisely the most important journals and editors of the network it is possible to use the the 'important vertices' Pajek algorithm, which is based on an eigenvector centrality approach, a two-mode variant of Kleinberg's hubs and authorities (Batagelj, 2015). This algorithm requires to fix in advance the number of important vertices. In Figure 3.5 it is represented the distribution of the eigenvector values. Table 3.9 reports the 20 journals and the 20 scholars who act at least once as Editors-in-Chief that have the greatest eigenvector centrality. We then isolate the network created by these important vertices and we report the result in Figure 3.6.

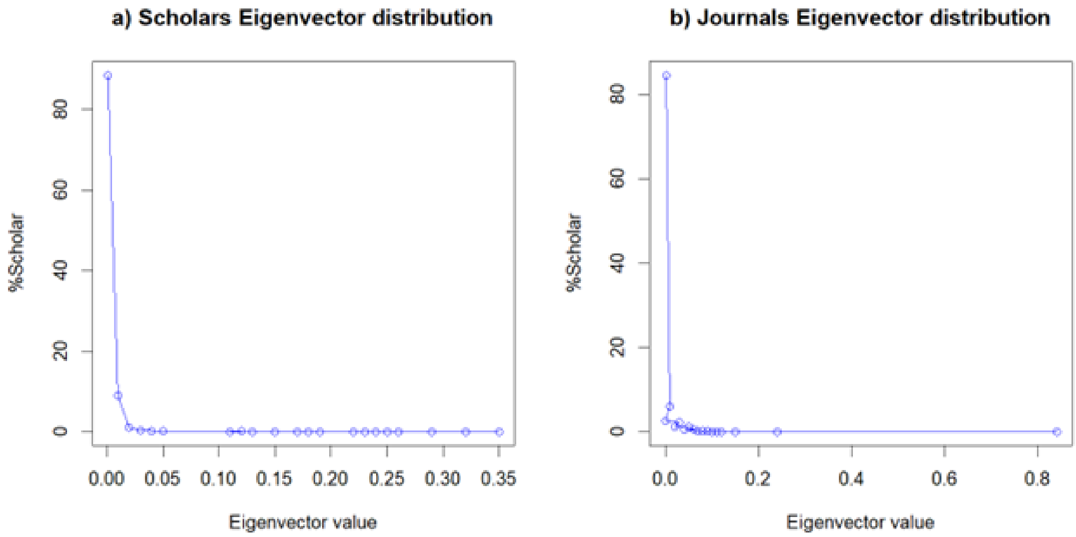


Figure 3.5 Eigenvector value distribution in the IE network of Editors-in-Chief

Considering Figure 3.5 and Table 3.9 it is evident that there are few journals and scholars with a slightly higher eigenvector centrality and the rest that have zero or close to zero values. In particular, for the network of scholars, 2561 nodes (88,5%) have an almost zero eigenvector centrality, and only 20 scholars (0,69%) have a value higher than 0,05 with the maximum value that is 0,35. For the network of journals, instead, 40 nodes (2,6%) have zero eigenvector centrality, 1280 (84,43%) have an almost zero value, only 22 (1,45%) have a value higher than 0,05 with the maximum value of 0,24 except one journal that have an incredibly high value, 0,84. Moreover, by comparing Table 3.9 and Table 3.7, it appears that only three scholars are in both rankings (Douglas J. Cumming, Wing-Keung Wong and Brian M. Lucey), while the others central scholars where not detected previously. We also get that the more central journals are mainly on finance, business and econometrics. There are also regional journals, like *Brazilian Journal of Business Economics* and *Ekonomska Istraživanja.* None of the Top Five Journals are included. These results look like an anomaly, probably driven by an unusual journal with a very high eigenvector centrality, i.e., the *Journal of Risk and Financial Management.* Thus, to get a deeper insight of the network, we explore separately the projection of the two-mode network, i.e., the network of journals and the network of Editors-in-Chief.

Table 3.9 The 20 most important vertices of the two-mode interlocking editorship network

The 20 most important Editors-in-Chief		**The 20 most important Journals**	
Name	**Eigenvector centrality**	**Name**	**Eigenvector centrality**
Wing-Keung Wong	0,35	Journal of Risk and Financial Management	0,84
Donald Lien	0,32	Annals of Financial Economics	0,24
Chia-Lin Chang	0,29	Journal of Mathematical Finance	0,15
Giuseppe Cavaliere	0,29	Theoretical Economics Letters	0,12
Thanasis Stengos	0,26	Journal of Risk and Control	0,11
James R. Barth	0,25	Journal of Reviews on Global Economics	0,10
Xuezhong (Tony) He	0,24	Economics: The Open-Access, E-Journal	0,09
Michael McAleer	0,23	Emerging Markets Finance and Trade	0,09
C. Michael Hall	0,22	Brazilian Journal of Business Economics	0,08
Tatsuyoshi Okimoto	0,22	Economies	0,08
Douglas J. Cumming	0,19	Journal of Time Series Analysis	0,08
Brian M. Lucey	0,18	Economics, Management, and Financial Markets	0,07
Richard J. Cebula	0,17	Review of Financial Economics	0,07
Dilip B. Madan	0,15	International Journal of Applied Economics	0,06
Esfandiar Maasoumi	0,13	Journal of Research in Economics	0,06
Pierre Perron	0,12	Journal of Economic Asymmetries	0,06
Massimo G. Colombo	0,12	International Review of Accounting, Banking and Finance	0,06
Donald S. Siegel	0,12	Ekonomska Istrazivanja	0,06
Stan Uryasev	0,11	Journal of Econometrics	0,06
Abe De Jong	0,11	Journal of Regional Analysis and Policy	0,06

Figure 3.6 The 40 important vertices of the two-mode interlocking editorship network (in red the journals and in blue the Editors-in-Chief, dimension of nodes is proportional to eigenvector centrality degree)

3.5.1 The network of journals

The network of journals is composed by 1516 nodes, which are distributed among 372 weak components, the biggest of which contains 1103 nodes that is the 72,75% of the network. The number of lines linking the journals is 7.183, and the density of network (i.e., the ratio of the actual number of lines to the maximum possible number of lines in the network) is 0,006. This means that only 0,6% of the possible lines are present. Table 3.10 reports the degree distribution of the journals, where a degree is the number of scholars that a journal editorial board shares with the other journals.

Table 3.10 Degree frequency distribution of the economics journals

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
0	314	20,71	22	19	1,25	44	1	0,07
1	155	10,22	23	18	1,19	45	2	0,13
2	141	9,30	24	6	0,40	46	1	0,07
3	75	4,95	25	13	0,86	47	2	0,13
4	82	5,41	26	12	0,79	48	4	0,26
5	58	3,83	27	13	0,86	49	1	0,07
6	53	3,50	28	9	0,59	50	2	0,13
7	44	2,90	29	7	0,46	51	3	0,20
8	43	2,84	30	10	0,66	54	2	0,13
9	39	2,57	31	5	0,33	55	1	0,07
10	33	2,18	32	3	0,20	58	1	0,07
11	28	1,85	33	7	0,46	60	1	0,07
12	27	1,78	34	9	0,59	65	3	0,20
13	41	2,70	35	6	0,40	70	1	0,07
14	21	1,39	36	6	0,40	72	1	0,07
15	30	1,98	37	7	0,46	75	1	0,07
16	23	1,52	38	7	0,46	77	1	0,07
17	14	0,92	39	2	0,13	82	1	0,07
18	23	1,52	40	4	0,26	84	1	0,07
19	27	1,78	41	4	0,26	108	1	0,07
20	16	1,06	42	2	0,13	197	1	0,07
21	22	1,45	43	6	0,40			

The average degree is 9,47, meaning that, on average, one journal shares 9 editors with other journals. The isolated journals that have no common editors, i.e., journals with zero degree, are 314 (20%). Then 155 journals (10%) have only one editor in common with other journals. This confirm that it is common to have as members of the editorial boards scholars that are at least once Editor-in-chief. Moreover, we can also see that there are two journals that are composed of an anomalous number of members of editorial board. These are: the *Journal of Risk and Financial Management* with 197 scholars that at least once are Editors-in-Chief (the journal itself has only one Editor-in-Chief), and the *Economics: The Open-Access, Open-Assessment E-Journal* that have connection with 108 scholars that at least once are Editors-in-Chief (also this journal has only one Editor-in-Chief). This can be seen as strategic decision to get more prestigious in the first case, and to promote open access science in the second one.

In order to understand which are the journals that have a central position in the network, three centrality measures can be used: degree, betweenness centrality and closeness centrality. If we rank the journals on the basis of this centrality measures, we get three different rankings. In Table 3.11, we report those journals that are under the top 25 positions for all three measures, in order to weight these differences.

Table 3.11 Centrality rankings of the most central economic journals

Journal name	Betweenness	Rank Betweenness	Closeness	Rank Closeness	Degree	Rank Degree
Economics: The Open-Access E-Journal	0,054	1	0,295	1	108	2
Journal of Risk and Financial Management	0,053	2	0,284	2	197	1
Panoeconomicus	0,034	3	0,276	3	82	4
Industrial and Corporate Change	0,020	4	0,267	4	84	3
Eurasian Business Review	0,011	11	0,266	5	72	7
Emerging Markets Finance and Trade	0,014	7	0,262	8	65	9
Economic Theory	0,018	5	0,258	12	60	12
Macroeconomic Dynamics	0,010	15	0,262	7	70	8
Journal of Economic Studies	0,013	9	0,264	6	54	15
Econ Journal Watch	0,008	24	0,252	22	58	13

If we compare these results with the previous one obtained in the two-mode important vertices network (Table 3.9), we get that only three journals were part of that network, *Economics: The Open-Access E-Journal*, *Journal of Risk and Financial Management* and *Emerging Markets Finance and Trade*, while the others were not. Moreover, again, none of the Top Five Journals are part of this ranking. This anomaly can be explained by the previous seen 'strategic choice' that some journals are taking and that affect these centrality measures. To have another comparison, in Table 3.12, we report the correlation among the four centrality rankings.

Table 3.12 Correlation among the centrality rankings of the network of journals

	All degree rank	Betweenness rank	Closeness rank	Eigenvector rank
All degree rank	1	0,798	0,922	0,905
Betweenness rank		1	0,769	0,714
Closeness rank			1	0,954
Eigenvector rank				1

As we can see, the rankings are highly correlated one to another (all values are higher than 0,71), with the maximum correlation among Closeness rank and Eigenvector rank (0,95), while the minimum correlation is among Betweenness rank and Eigenvector rank (0,71). This fact can be interpreted as, being a journal that is well-connected to other well-connected journals (high eigenvector), means that the journal has a lot of connections (high degree), is close to all the other journals in the network (high closeness), and it is needed as a link within the network (high betweenness).

Finally, a graphic representation of the network is provided in the following Figure 3.7, obtained by using the Fruchterman Reingold algorithm on Gephi 0.9.5 (Bastian et al. 2009).

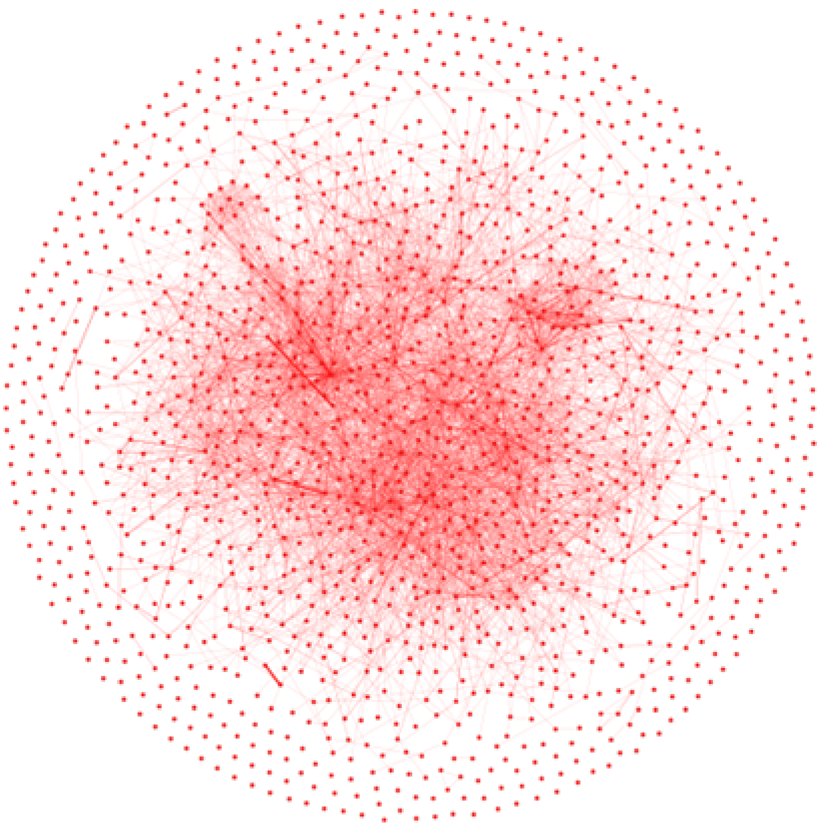


Figure 3.7 The network of journals of the Editors-in-Chief IE network

3.5.2 The network of Editors-in-Chief

The network of Editors-in-Chief is composed by 2893 nodes, which are distributed among 332 weak components, the biggest of which contains 2361 nodes that is the 81,6% of the network. The number of lines linking the journals is 16.732, and the density of network (i.e., the ratio of the actual number of lines to the maximum possible number of lines in the network) is 0,004. This means that only 0,4% of the possible lines are present. In Table 3.13 we report the degree distribution of the Editors-in-Chief, that in this case is the number of editorial boards that a scholar shares with the other scholars.

Table 3.13 Degree frequency distribution of Editors-in-Chief

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
0	197	6,81	30	13	0,45	60	2	0,07
1	311	10,75	31	17	0,59	62	3	0,10
2	222	7,67	32	16	0,55	63	3	0,10
3	240	8,30	33	14	0,48	64	1	0,03
4	201	6,95	34	10	0,35	65	2	0,07
5	143	4,94	35	17	0,59	66	1	0,03
6	157	5,43	36	11	0,38	67	1	0,03
7	94	3,25	37	5	0,17	68	2	0,07
8	144	4,98	38	7	0,24	69	2	0,07
9	92	3,18	39	9	0,31	70	1	0,03
10	75	2,59	40	7	0,24	71	2	0,07
11	45	1,56	41	16	0,55	72	2	0,07
12	72	2,49	42	6	0,21	73	3	0,10
13	50	1,73	43	10	0,35	74	2	0,07
14	57	1,97	44	10	0,35	75	1	0,03
15	53	1,83	45	7	0,24	76	1	0,03
16	66	2,28	46	10	0,35	79	2	0,07
17	31	1,07	47	5	0,17	80	1	0,03
18	29	1,00	48	5	0,17	84	1	0,03
19	44	1,52	49	2	0,07	85	2	0,07
20	37	1,28	50	2	0,07	86	1	0,03
21	44	1,52	51	4	0,14	90	1	0,03
22	45	1,56	52	2	0,07	100	2	0,07
23	22	0,76	53	2	0,07	102	1	0,03
24	27	0,93	54	1	0,03	105	1	0,03
25	55	1,90	55	5	0,17	106	1	0,03
26	19	0,66	56	2	0,07	108	1	0,03
27	19	0,66	57	2	0,07	112	1	0,03
28	25	0,86	58	2	0,07	113	2	0,07
29	9	0,31	59	2	0,07	116	1	0,03

The average degree is 11,56, and this means that scholars that are at least once Editors-in-Chief are connected on average by 11 journals. The isolated Editors-in-Chief, i.e., with zero degree, are 197 (6,8%), which is much lower than the 20% of the journals. There are also 10 scholars that are connected to more than 100 other Editors-in-Chief, with the maximum of 116 that are connected to Giuseppe Cavaliere (in himself he is present in only 8 boards). This result confirms a very close network of scholar.

Having a lot of connections does not automatically mean that a person is the most central or 'more important', and in order to understand who are those Editors-in-Chief that have a central position in the network, we used three centrality measures: degree, betweenness centrality and closeness centrality. If we rank the editors on the basis of this centrality measures, we get three different rankings, thus also in this case we reported in Table 3.14 those Editors-in-Chief that are at least at the top 25 positions for all three measures.

Table 3.14 Centrality rankings of the most central Editors-in-Chief

Editors-in-Chief name	**Betweenness**	**Rank Betweenness**	**Closeness**	**Rank Closeness**	**Degree**	**Rank Degree**
James J. Heckman	0,034	1	0,290	1	112	4
Brian M. Lucey	0,029	3	0,288	2	105	7
Douglas J. Cumming	0,034	2	0,282	7	106	6
Thanasis Stengos	0,018	11	0,286	3	113	2
Vernon L. Smith	0,020	6	0,274	13	90	11
Stephen J. Turnovsky	0,017	14	0,275	12	102	8
Keun Lee	0,014	18	0,275	11	100	10
Richard J. Cebula	0,019	7	0,272	17	79	17
Iftekhar Hasan	0,018	9	0,273	15	74	21
Oliver E. Williamson	0,023	4	0,269	25	76	19

We get that among the Editors-in-Chief the most central is James J. Heckman, who is Editors-in-Chief of one of the Top Five Journals, the *Journal of Political Economy*. As we can see, if we compare these results with the previous one obtained in the two-mode important vertices network (Table 3.9), we get that only four Editors-in-Chief were part of that network, Brian M. Lucey, Douglas J. Cumming, Richard J. Cebula and Thanasis Stengos, while the others are not present anymore. Moreover, if we compare Table 3.14 with Table 3.7, where it was reported the name of the Editors-in-Chief who hold more seats, we get that 5 scholars are in both tables but in total different rankings demonstrating how the network analysis can show hidden hierarchies.

None of this ranking for itself is sufficient to understand the position of single scholar or journal in the analysed network, but the comparison is useful to detect similarities and differences among different centrality measures. Thus, we report in Table 3.15 the correlation among the four centrality rankings.

Table 3.15 Correlation among the centrality rankings of the network of Editors-in-Chief

	All degree rank	Betweenness rank	Closeness rank	Eigenvector rank
All degree rank	1	0,897	0,807	0,773
Betweenness rank		1	0,772	0,732
Closeness rank			1	0,948
Eigenvector rank				1

As we can see, even in this case, the rankings are highly correlated one to another (all values are higher than 0,73), with again the maximum correlation among Closeness rank and Eigenvector rank, while the minimum correlation is among Betweenness rank and Eigenvector rank. Thus, being an Editor-in-Chief that is well-connected to other well-connected Editor-in-Chief (high eigenvector), means that the scholar has a lot of Editor-in-Chief (high degree), is close to all the other Editor-in-Chief in the network (high closeness), and it is needed as a link within the network (high betweenness).

3.6 Networks comparison

To understand the role of those scholars that hold more seats of which at least one is Editor-in-Chief in the structure characteristic of the network, it is useful to compare this network with other two networks: the entire network and the network created by those who are never Editors-in-Chief.

3.6.1 The entire interlocking editorship network

The entire IE network can be seen as composed almost by only one giant central component in which there are almost all economics journals and editorial members. Around this giant component there are smaller groups of journals and editorial board members. In particular, the network can be divided in 50 weak components; the giant component contains 1467 journals and 43739 board members for a total of 45206 nodes, which is the 98.32% of total network. Outside the big component, there are only 49 journals (the 3,23%) and 721 board members (1,6%). These are clustered in 49 different weak components, of which 4 different components contain only 2 node, 1 component contain 3 nodes, 4 different components contain 4 nodes, the distribution of the rest of the network among weak components is reported in Table 3.16.

Table 3.16 Distribution of the two-mode entire IE network among weak components

Frequency	% Frequency	N° of different clusters	Frequency	% Frequency	N° of different clusters
45206	98,32%	1	16	0,03%	1
112	0,24%	1	15	0,03%	1
87	0,19%	1	13	0,03%	3
35	0,08%	1	12	0,03%	3
32	0,07%	1	11	0,02%	2
28	0,06%	1	9	0,02%	4
27	0,06%	1	8	0,02%	3
25	0,05%	2	7	0,02%	3
24	0,05%	1	6	0,01%	1
21	0,05%	1	5	0,01%	4
19	0,04%	1	4	0,01%	4
18	0,04%	1	3	0,01%	1
17	0,04%	1	2	0,00%	4

Comparing Table 3.8 with Table 3.16, it is possible to see that the entire IE network has less components than the Editors-in-Chief network. This can be interpreted as the fact that the entire editorial word is less fragmented than the one of the Editors-in-Chief, and also that are not necessarily the Editors-in-Chief those who structure the entire network. For confirming this hypothesis, it is needed to study the degree distribution of the projection of the two-mode network, i.e., the network of journals. In Table 3.17, the degree distribution of this network is reported, and in Figure 3.8 the network is graphically represented by Fruchterman Reingold algorithm on Gephi 0.9.5 (Bastian et al. 2009).

Comparing Table 3.10 with Table 3.17, it is confirmed that the entire network is much more connected than the network of Editors-in-Chief. In fact, in the first case, the journals that are disconnected without any common board members with other journals, i.e., journals with zero degree, are only 46 (3,03%), that is way lower than the 314 (20%) of the Editors-in-Chief network. This is also visible by comparing Figure 3.7 and Figure 3.8.

Another interesting thing is that even in this case we have two journals with an anomalous number of connections: *Economics: The Open-Access, Open-Assessment E-Journal* with an editorial board that is connected to 257 other journals (the journal itself has a board of 189 members), and the *Journal of Risk and Financial Management* connected to 194 other journals (the journal itself has a board of 249 members). As seen before, the 'strategic choice' can be due to different reasons.

Table 3.17 Degree frequency distribution of the economics journals of the entire IE network

Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)	Degree	Frequency	Frequency (%)
0	46	3,03	27	23	1,52	54	9	0,59	85	2	0,13
1	27	1,78	28	32	2,11	55	8	0,53	86	1	0,07
2	30	1,98	29	23	1,52	56	13	0,86	87	1	0,07
3	49	3,23	30	24	1,58	57	8	0,53	88	2	0,13
4	51	3,36	31	17	1,12	58	2	0,13	89	3	0,20
5	33	2,18	32	20	1,32	59	7	0,46	90	1	0,07
6	47	3,10	33	26	1,72	63	7	0,46	92	1	0,07
7	46	3,03	34	17	1,12	64	5	0,33	93	1	0,07
8	30	1,98	35	15	0,99	65	9	0,59	94	3	0,20
9	35	2,31	36	19	1,25	66	6	0,40	96	2	0,13
10	40	2,64	37	20	1,32	67	4	0,26	97	3	0,20
11	32	2,11	38	14	0,92	68	2	0,13	98	1	0,07
12	25	1,65	39	23	1,52	69	1	0,07	100	1	0,07
13	33	2,18	40	16	1,06	70	2	0,13	101	4	0,26
14	35	2,31	41	18	1,19	71	3	0,20	102	2	0,13
15	34	2,24	42	13	0,86	72	2	0,13	103	1	0,07
16	19	1,25	43	14	0,92	73	5	0,33	104	2	0,13
17	37	2,44	44	19	1,25	74	4	0,26	107	1	0,07
18	35	2,31	45	10	0,66	75	3	0,20	108	1	0,07
19	30	1,98	46	13	0,86	76	1	0,07	109	2	0,13
20	28	1,85	47	13	0,86	77	4	0,26	113	1	0,07
21	33	2,18	48	11	0,73	78	1	0,07	128	1	0,07
22	31	2,04	49	11	0,73	79	3	0,20	133	2	0,13
23	17	1,12	50	13	0,86	80	2	0,13	163	1	0,07
24	22	1,45	51	9	0,59	81	2	0,13	176	1	0,07
25	22	1,45	52	7	0,46	82	2	0,13	194	1	0,07
26	25	1,65	53	5	0,33	83	3	0,20	257	1	0,07

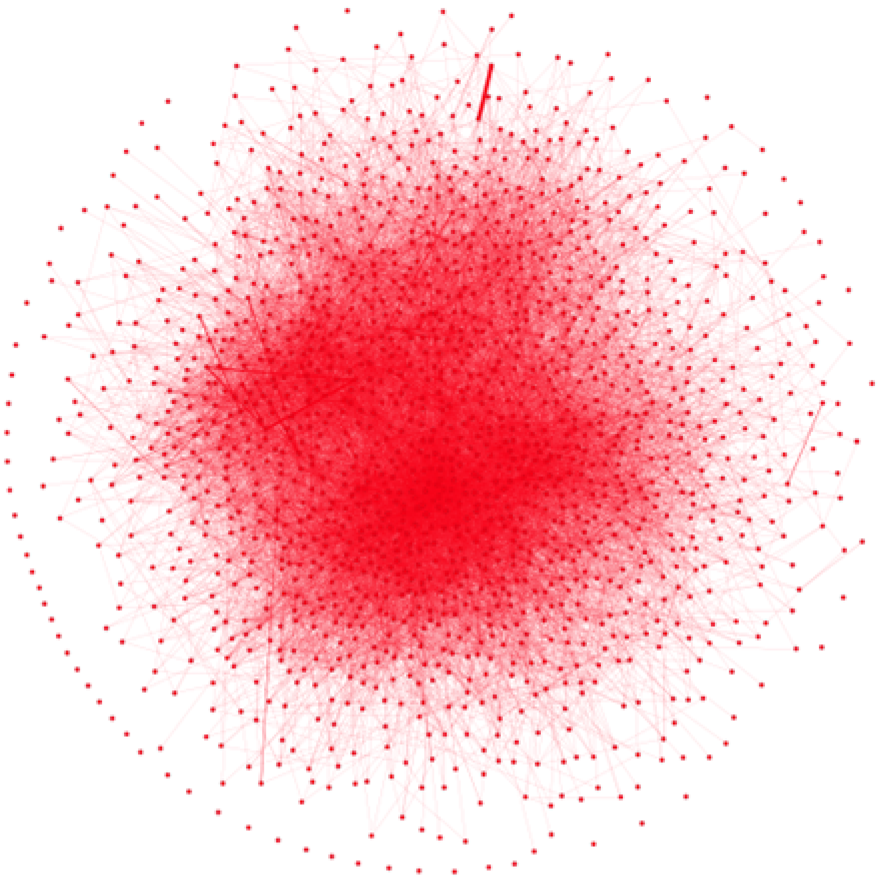


Figure 3.8 The network of journal of the entire IE network

3.6.2 The interlocking editorship network of No Editors-in-Chief

Finally, the network created by those who are never Editors-in-Chief is more similar to the characteristic of the entire network than of the characteristic of the Editors-in-Chief network. In fact, also in this case we have that almost all economics journals and editorial members are part of only one giant component, and smaller groups of journals and scholars. In particular, the network can be divided in 74 weak components; the giant component contains 1442 journals and 40757 No Editors-in-Chief board member for a total of 42199 nodes, which is the 97,95% of total network. Outside the big component, there are only 74 journals (the 4,88%) and 810 No Editors-in-Chief board member (1,95%). These are clustered in 73 different weak components, of which 12 different components contain only 1 node, 4 different components contain 2 nodes, 6 different components contain 3 nodes, the distribution of the rest of the network among weak components is reported in Table 3.18.

Table 3.18 Distribution of the two-mode No Editors-in-Chief IE network among weak components

Frequency	% Frequency	N° of different clusters	Frequency	% Frequency	N° of different clusters
42199	97,95%	1	14	0,03%	2
111	0,26%	1	13	0,03%	1
86	0,20%	1	12	0,03%	5
39	0,09%	1	10	0,02%	5
35	0,08%	1	9	0,02%	2
30	0,07%	1	8	0,02%	6
26	0,06%	1	7	0,02%	3
24	0,05%	4	6	0,01%	2
22	0,05%	1	5	0,01%	3
20	0,05%	2	4	0,01%	4
18	0,04%	1	3	0,01%	6
17	0,04%	1	2	0,00%	4
16	0,04%	1	1	0,00%	12
15	0,03%	1			

Comparing Table 3.17 with Table 3.18, it looks confirmed that the network created by those who are never Editors-in-Chief is very similar to the entire IE network. Also in this case, studying the degree distribution of the projection of the two-mode network, i.e., the network of journals, is useful to detect this similarity. In Table 3.19, the degree distribution of this network is reported, and in Figure 3.9 the network is graphically represented using the Fruchterman Reingold algorithm on Gephi 0.9.5 (Bastian et al. 2009).

We have a similar situation than before: the No Editors-in-Chief IE network is much more connected than the network of Editors-in-Chief and has similar connection of the entire network. Also in this case, in fact, the journals that are disconnected without any common No Editors-in-Chief board members with other journals, i.e., journals with zero degree, are only 69 (4,55%). The different structure is also visible by comparing Figure 3.7 and Figure 3.9.

Moreover, the same two journals detected before have an anomalous number of connections even here: *Economics: The Open-Access, Open-Assessment E-Journal* with an editorial board of No Editors-in-Chief that is connected to 203 other journals (the journal itself has a board of 189 members), and the *Journal of Risk and Financial Management* connected to 132 other journals (the journal itself has a board of 249 members).

Table 3.19 Degree frequency distribution of the economics journals of the No Editors-in-Chief IE network

Degree	**Frequency**	**Frequency (%)**	**Degree**	**Frequency**	**Frequency (%)**	**Degree**	**Frequency**	**Frequency (%)**	**Degree**	**Frequency**	**Frequency (%)**
0	69	4,55	23	30	1,98	46	6	0,40	69	4	0,26
1	42	2,77	24	21	1,39	47	9	0,59	70	2	0,13
2	42	2,77	25	31	2,04	48	6	0,40	71	1	0,07
3	60	3,96	26	25	1,65	49	7	0,46	72	2	0,13
4	49	3,23	27	21	1,39	50	5	0,33	74	2	0,13
5	38	2,51	28	36	2,37	51	10	0,66	76	1	0,07
6	41	2,70	29	23	1,52	52	4	0,26	79	3	0,20
7	45	2,97	30	22	1,45	53	3	0,20	81	4	0,26
8	38	2,51	31	13	0,86	54	7	0,46	83	2	0,13
9	42	2,77	32	13	0,86	55	3	0,20	84	5	0,33
10	46	3,03	33	14	0,92	56	7	0,46	87	2	0,13
11	29	1,91	34	19	1,25	57	2	0,13	90	1	0,07
12	48	3,17	35	22	1,45	58	2	0,13	95	2	0,13
13	46	3,03	36	13	0,86	59	4	0,26	106	1	0,07
14	38	2,51	37	17	1,12	60	3	0,20	114	1	0,07
15	41	2,70	38	13	0,86	61	7	0,46	121	1	0,07
16	35	2,31	39	13	0,86	62	2	0,13	122	1	0,07
17	29	1,91	40	13	0,86	63	5	0,33	125	1	0,07
18	39	2,57	41	7	0,46	64	4	0,26	132	1	0,07
19	41	2,70	42	16	1,06	65	1	0,07	203	1	0,07
20	34	2,24	43	12	0,79	66	2	0,13			
21	32	2,11	44	11	0,73	67	1	0,07			
22	36	2,37	45	9	0,59	68	4	0,26			

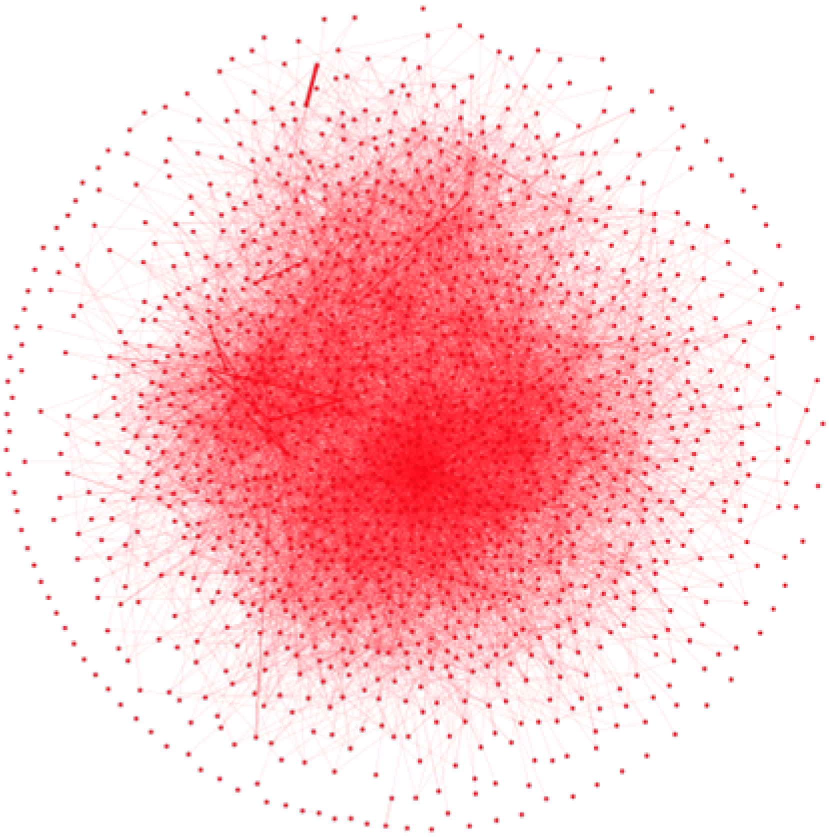


Figure 3.9 The network of journal of the No Editors-in-Chief IE network

3.6.3 Additional remarks

The insofar analysis make it thinks that the entire IE network and the No Editors-in-Chief IE network are less fragmented than the Editors-in-Chief IE network. This would suggest that the Editors-in-Chief are not those editorial board members who are fundamental to structure the IE network. Thus, also if the Editors-in-Chief have an unquestionable greater editorial power, probably they have a high workload and hence it is difficult for a single scholar to have many board seats, if he/she is already holding an Editor-in-Chief seat. However, the Editors-in-Chief can exercise indirectly the connection among editorial boards by selecting those scholars who have more disponible time, and maybe have similar characteristics. To understand if the characteristics among the Editors-in-Chief and the rest of the editorial board member are similar or not, we compare the three networks by searching for communities and by computing the distance correlation for economic journals.

We start by searching for the communities through the Louvain Method in the two-mode networks and in the one-mode network of journals. The results are reported separately in Table 3.20, with the number of clusters detected and the connected modularity.

Table 3.20 Modularity of two-mode networks and one-mode networks of journals

	Two-mode networks		One-mode networks of journals	
Network	**Number of Clusters**	**Modularity**	**Number of Clusters**	**Modularity**
Entire network	136	0,866	63	0,508
Editors-in-Chief network	408	0,826	387	0,611
No Editors-in-Chief network	164	0,879	89	0,528

As expected, we get that the number of Louvain communities is much higher for the Editors-in-Chief network than for the other two networks, both in the case of the two-mode network than of the one-mode network. Moreover, the modularity values are similar among the networks, and are higher for the two-mode networks. Modularity measures how well a selected partition divides a network into communities (De Nooy et al. 2018). It is a scale value between -1 (there are no edges connecting nodes within the community) and 1 (all the edges in a community are connecting nodes within the community) that measures the relative density of edges inside communities with respect to edges outside communities. Thus, in our case, the connections between nodes in the communities are dense, while between nodes of different communities are sparse, independently of the considered network. This means that the role played by the scholars in the editorial boards does not have a different weight in the definition of communities.

To see if this consideration is consistent, we compare the partitions that result from different methods for searching communities through statistical indices of association. The starting point is the Cramer's V statistic, that is an index that range from 0 to 1. As a rule of thumb, we may say that values between 0 and 0,05 mean that there is no association, values between 0,05 and 0,25 indicate a weak association, values from 0,25 to 0,60 indicate a moderate association, and values higher than 0,60 indicate a strong association (De Nooy et al. 2018). The results are reported in Table 3.21, and as we can see the value is very high, showing that there is a strong association among the community partitions of the three compared networks.

Table 3.21 Cramer's V statistics of network of journals

	Entire network	**Editors-in-Chief network**	**No Editors-in-Chief network**
Entire network	1	0,950	0,943
Editors-in-Chief network		1	0,801
No Editors-in-Chief network			1

Finally, the last analysis to understand if in the construction of the network communities it is important being in a role or another is the generalized and partial distance correlation of economic journals. In Table 3.22 it is reported the generalized distance correlation.

Table 3.22 Generalized distance correlation of network of journals

	Entire network	**Editors-in-Chief network**	**No Editors-in-Chief network**
Entire network	1	0,936	0,999
Editors-in-Chief network		1	0,926
No Editors-in-Chief network			1

We obtained as a result the fact that the structure of the entire network is correlated with the structure of Editors-in-Chief network of 0,936 and with the structure of No Editors-in-Chief network of 0,999. Thus, we can read it as the fact that we get the same result and information if we take one or another network. The same can be seen if we take the correlation among Editors-in-Chief network with No Editors-in-Chief network, that is 0,926.

Moreover, if we consider the partial distance correlation, we get that the No Editors-in-Chief are more important in the construction of the IE network. In fact, the partial distance correlation of Editors-in-Chief on the entire network given the influence of No Editors-in-Chief is 0,776, while the partial distance correlation of No Editors-in-Chief on the entire network given the influence of Editors-in-Chief is 0,987. Meaning that in the determination of the entire network those who are No Editors-in-Chief have more influence than Editors-in-Chief.

We can conclude saying that the comparison of networks shows that the Editors-in-Chief IE network is more fragmented that the entire IE network and the No Editors-in-Chief IE network. However, there is no structural difference among the communities inside this networks that are highly correlated one to another. Thus, all those who are part of the editorial board generate the same connections among journals indistinctly from the role, but with different intensity. This result can be seen as a confirmation of a high degree of homophily among all journal editorial boards, because is not possible to detect dissimilarities among them. Moreover, probably, the Editors-in-Chief play an indirect role by selecting as editorial boards those that are ‘similar’ to them but have more time to be part of more boards, in order to multiplicate their editorial connections.

3.7 Conclusions

Editorial board members have been defined as the gatekeepers of scientific knowledge since they decide what research gets published and since their decisions shape individual careers. As a result, editorial positions come with considerable power over the discipline, especially in the Editor-in-Chief position and in the most influent journals. In order to update and enrich our knowledge of the composition of editorial boards of economics, we have investigated the individual characteristic of editorial members and their IE networks on a dataset of 1.516 economics journals indexed in the database EconLit with an active editorial board in 2019.

We found that the editorial boards of economics are characterised by high degrees of homophily. This manifests itself in various ways. Firstly, because the boards member come in majority from an US institution (almost the 30% of all seats and of Editor-in-Chief seats are connected to an affiliation in US) with a uniform distribution among different elite universities. The geographic concentration is higher in Editors-in-Chief seats, whose scholars come from 84 countries, compared to 151 countries declared in all Editorial roles. Moreover, the 5 most represented countries hold the 42% of all editorial seats and the 49% of Editors-in-Chief seats. The second cause of homophily is connected to the fact that the editor members are mainly men: they occupy more than 75,8% seats, if we consider the entire dataset and a similar 74,6% if we just focus on the Editors-in-Chief. This homophily is even more evident if we restrict the analysis on the most prestigious journals of economics, i.e., the Top Five Journals. The members of their boards in fact come from United States for the 42% of all Editorial roles and the 92% of Editors-in-Chief. In all Editorial roles there are 14 countries declared, while in Editors-in-Chief only 3. The 5 most represented countries hold the 65% of all editorial seats and few American institutions covered almost all available seats. In particular, Editors-in-Chief of the Top Five Journals are concentrated in very few powerful institutions: University of Chicago, Harvard University and Stanford University concentrate the 52% of the available Editor-in-Chief seats. As for the gender composition, men are more than 78%, if we consider all Editorial Roles, and the 84% if we just focus on the Editors-in-Chief. The only Editor-in-Chief position occupied by a woman in a Top Five Journal is shared with six other men.

Through the SNA analysis we have been able to isolate the most central journals and scholars, detecting also 'strategic decisions' in the selection of the editorial board members to get more prestigious to the journal, or to promote open access science. We have also seen that there are few Editors-in-Chief that hold more than one seat, compared to other board members that hold more often multiple seats. The comparison among the network of the entire IE network, the IE network created by those who are never Editors-in-Chief and the IE network of those who are least once Editor-in-Chief showed that the Editors-in-Chief IE network is more fragmented that the entire IE network and the No Editors-in-Chief IE network, but also that there is no structural difference among the communities inside the networks. This result can be interpreted as indicating that Editors in-Chief played a role in selecting as editorial board members scholars that are 'similar' to them but have more time to be part of more boards in order to multiplicate their editorial connections.

The obtained results suggest that the discipline of economics is still characterized by editorial boards that are dominated by representatives of US, the prevalence of men, and a high concentration of editorial power in few scholars and institutions. Thus, as already warned by Hodgson and Rothman in 1999, there is a serious risk for innovative research in economics.

The next steps of the research will go towards the comparison of these results relating to 2019 with those relating to the years 1996, 2006, 2012 with the aim of searching for intertemporal similarities and differences.

APPENDIX 3.A

For the affiliations we have focused our attention on what it was declared on the websites of the journals. For the University of California, it was not always declared the campus, so it was not possible to uniformly understand to which campus the scholars belong to, since the majority have declared a generic 'University of California'. We are thus going to indicate here the distribution of affiliations as declared. We will count each member more than one because we will count them as distinct if they have declared more than one affiliation and if they work in more than one journal.

Table A.1 University of California seats distribution

	All Editorial Roles	Editors-in-Chief	Top Five All Editorial Roles	Top Five Editors-in-Chief
University of California	507	35	6	0
University of California Berkeley	207	11	3	0
University of California Los Angeles (UCLA)	133	8	3	1
University of California Irvine	65	5	0	0
University of California Davis	71	6	0	0
University of California Riverside	47	4	0	0
University of California Santa Barbara	36	1	0	0
University of California Santa Cruz	27	1	0	0
Rady School of Management at the University of California	6	0	0	0
University of California San Francisco	3	0	0	0
University of California at Merced	1	0	0	0
Total	1103	71	12	1

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