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The Italian Corporate System: SOEs, Private Firms and Institutions in a Network Perspective (1952-1983)

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Abstract

How did business networks among Italian firms evolve over time? We address this question by analyzing the Italian corporate boards network in four years (1952, 1960, 1972, 1983) with network theoretical methods. We find some typical properties of these networks, such as sparsity and connectedness in the same large network component. At the same time, clustering and assortativity are relatively high and stable, while we observe, over time, an increase of the average distance coupled with a decrease of density and of the relative size of the largest component. This is an indication of a rarefaction of connections which is detected also in other national systems. In order to seek the determinants of this phenomenon, we perform a panel regression for the average nodal degree, finding that rarefaction is mostly related to a genuine time trend and only partially to cross-sectional variables. We argue that a possible explanation is a significant increase of concentration which we observe in our dataset, consistently with historical evidence. The network shows a substantial stability in some structures, such as core-periphery subdivision. Looking at the main actors we find a persistent centrality of banks and insurances, as well as of State Owned Enterprises (SOEs). These play a growing role in the community structure of the network, while communities themselves become more and more diversified by sector.

Keywords: boards networks, network theory, Italian firms.

JEL Classification: N00, L20, C49

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1 Introduction

The analysis of networks of business firms is a relatively recent and promising perspective in the study of business organization. One of the most interesting topics concerns the evolution of business networks, which factors are responsible for their characteristics at some point in time, as well as for their variations over time. In particular, this paper focuses on the connections between the boards of Italian business firms in the "long" Golden Age, using a comprehensive source with data on more than 38,000 companies in four benchmark years (1952, 1960, 1972, 1983).

We aim to extend the existing historical literature on this topic by adopting a set of methods of complex networks theory. These methods, which are mostly derived from statistical physics (Park and Newman, 2004; Squartini and Garlaschelli, 2011), allow to perform rigorously statistical inference over network properties, something which is new to the historical analysis on this subject up to date. Moreover, we are able to apply this approach also to the detection of communities, i.e. of subsets of strongly connected firms (Fortunato, 2010). By using this methodology, together with other more common analyses such as core-periphery subdivision and node centrality, we are able to revise some of the conclusions of previous works, e.g. by showing that State Owned Enterprises (SOEs) and banks maintain an important position in the system throughout the period. On the other hand, we are able to compare the Italian network with other national networks as described by the literature, showing that it is no different from the latter when looking at the most relevant network properties.

From an historical perspective, we integrate statistical network analysis with two more appreciative priors. The first one concerns the general consideration of the Golden Age as the age of Big Business, while the second one concerns the institutional environment of networks, especially the characters of a very peculiar financial system as the Italian one was. Both priors could potentially affect the structure of the network and its evolution over time. In particular, the most relevant trend we observe is a decrease of connections which is common to other national systems in the same period, although the core of the network maintains a surprising stability over the time, particularly with respect to the centrality of its main actors, banks and insurances. We circumscribe the role of cross-sectional variables, such as size or sectoral composition, then we relate the rarefaction between 1972 and 1983 to an increasing concentration of the system in terms of assets, which is an outcome of a wave of mergers due to increasing indebtedness of non financial companies with the banking system.

The rest of the paper is organized as follows. In Sec. 2 we review the main historical contributions on the topic of the Italian corporate system. In Sec. 3 we shortly describe the main source for our analysis. In Sec. 4, we recall the main results of the literature on boards networks and analyze the topological properties of the Italian system. In Sec. 5 we perform the core-periphery partition of the network. In Sec. 6 we look at the most central firms by betweenness. In Sec. 7 we perform the community decomposition of the network, and detect the statistically significant characters of each community. In Sec. 8 we test a model for node connectivity aimed at explaining the observed decrease of this quantity over time. Finally, Sec. 9 concludes. The technical apparatus of the analysis is detailed in three appendices.

2 Historical literature

In the Italian economic history the topic of the corporate system has for the most part been tackled by focusing on collusion, since a few large, monopolistic firms dominate the domestic market. In a macroeconomic perspective of backwardness and catching up, few economic historians (Zamagni, 1993; Bonelli, 1979) gave a relatively positive judgment of this configuration. According to their view, the few large, connected firms and a strong State intervention allowed to adopt the leading technologies (iron and steel, electricity, chemicals, etc.) required to catch up modern economic growth, while the financial system, regulated by the State, canalized resources to exploit these technologies. From a similar perspective, De Cecco (2001) delimited the efficiency of this collusive capitalism up to the virtuous Fifties and the early Sixties of the 20^{th} century. Afterwards negative consequences prevailed, starting in the midst of the Sixties and lasting up to the crisis of 1992, when oligopolistic collusion started to decrease slowly with liberalizations and privatizations.

On the contrary, most Italian scholars underlined that this configuration was an obstacle for economic growth. Sereni (1966) emphasized the limitation of market size, Sylos Labini (1970) the obstacle it posed to innovation. A majority of scholars emphasized the role of the specific institutional arrangement of ownership (“salotti buoni”) and of organization (business groups) entangled in a network of relationships between the banks, the State and the large private and public firms (Rossi and Toniolo, 1992; Barca, 1996; Amatori, 1995). More recently Aganin and Volpin (2005) argued that Italy is still blocked in a State and family capitalism in which a restricted élite of politically appointed bureaucrats and of wealthy families take a central position.

The empirical evidence to support the one or the other position is, for the most part, thin, although more consistent in the period after World War II. Immediately after the war, the Economic Commission of the Ministry for the Constituent Assembly made a very detailed survey of Italian joint-stock companies (Ministero per la Costituente, 1947). The results of the survey highlighted that a few large corporate groups dominated the Italian economy by controlling, directly or indirectly, three-quarters of the total equity of private firms. In the early 1960s, Benedetti and Toniolli (1963) found that electricity companies managed a dense network of connections among themselves as well as with other industrial sectors. This configuration changed drastically after the nationalization of the electrical industry (1962). Ragozzino (1969) noted that this event represented a systemic change of the industrial and financial relations centered on the big electrical firms and their close relationship with banks and insurances. The consequence was the emergence of a new order in which State firms and family groups, like Fiat and Pirelli, took the center of the system up to the age of privatizations in the Nineties.

In the Eighties, Chiesi (1982, 1985) introduced the more advanced tools of network analysis of boards to study the configuration of Italian capitalism. He identified the peculiarities of the Italian corporate network in the economic intervention of the State. Chiesi identified, in the mid Seventies, two poles represented by SOEs and private enterprises. He also identified a significant integration between the two sets, guaranteed by companies such as Sme, Bastogi, and, to a lesser extent, Snia-Viscosa. Chiesi also emphasized the key position of SOEs and the absence of the two most important private groups, Fiat and Pirelli, from the center of the network. Ferri and Trento (1997) using the same tools but a reduced sample of companies, found instead dense relations between private companies and SOEs at least until 1970. Rinaldi and Vasta (2005) explored with the same tools the structure of the Italian corporate system during the 1952-72 period using the same sample we use here. They identified dense connections among the major private firms, a significant connection with SOEs and changing leading clusters of firms. In 1952 and 1960, electrical companies showed the highest cohesion; after the nationalization, they identified a new and less cohesive network made by financial intermediaries: banks, insurances and major finance companies. In a more recent work, Rinaldi and Vasta (2012) extended their analysis to 1983, finding that the cohesion of the system had sharply declined and that SOEs were no more at its center, while a new private merchant bank, Mediobanca, emerged as key actor.

Bianco and Pagnoni (1997) analyzed the ties among board members of the Italian listed companies from 1985 to 1995. They showed that the sharing of board members was a common practice between companies in the sample. In general, these connections signaled the position of the controlling subject placed at the head of pyramidal groups. Conversely, in the presence of a legislation limiting banks participations in non financial companies (and vice versa), boards interconnections between banks and industrial companies served as substitutes of cross shareholdings. A further work by Bianco *et al.* (2009) extended the analysis from 1998 to 2008. The main results were that over the entire period a high share of the companies in the sample were connected with each other. The company network was centered around the financial and non-financial Blue Chips. The directors who ensured the bulk of connectivity by serving in a higher number of boards were mainly relevant shareholders or managers of the Blue Chips. The turnover of the main board interlockers tended to follow their turnover as shareholders in the same companies. Corrado and Zollo (2006) investigate the role of corporate governance reforms and privatization programs of the Nineties in shaping the structural characteristics of network among Italian firms, by looking at cross shareholdings. They find a significant fragmentation of the overall network, but at the same time a stability in the structure of its main component, measured by small-world coefficients, i.e. the key players in the network seem to remain relatively stable despite the major turbulence at the institutional level.

3 Dataset

The dataset of this paper is the digitalization of the serial source "Notizie statistiche sulle principali società per azioni" published between 1908 and 1926 by Credito Italiano[1] and afterwards by the Associazione fra le società

[1] In particular, in the following years: 1908, 1910, 1912, 1914, 1916, 1918, 1920, 1922, 1925.

italiane per azioni, up to 1984[2]. The source contains information regarding companies, boards of directors and balance sheets of a large sample of Italian joint-stock companies for several benchmark years. It includes all the joint-stock companies listed on the Milan stock exchange, and companies located in Italy whose equity at the closure of the last balance was higher than a given threshold, which varied from year to year. On the whole, the dataset contains data on more than 38,000 companies, almost 300,000 directors, and more than 100,000 balance sheets. Its representativeness, in terms of equity, is very high as the sample covers well over 90% of the total in all but the first two benchmark years (1911 and 1913) and the last one (1983), for which the proportion is around 85%. The digital version of the source (http://imitadb.unisi.it/) includes the data contained in the printed volumes and it is composed of three archives (Vasta, 2006):

1. a company dataset for the benchmark years (1911, 1913, 1921, 1927, 1936, 1952, 1960, 1972, 1983) covering the following items: firm name; year of foundation; head office; share capital and paid-up capital;

2. the members of board of directors and board of auditors for the same years;

3. balance sheet data covering all the years between 1960 and 1971 for the following items: share capital; reserves; physical assets; inventory; securities and investments; cash and credits; bonds; debts; sinking founds; reserves; profits (losses); total and per share dividends.

This paper uses the company data set and the list of board of directors for the years 1952, 1960, 1972, 1983. For each year the network of boards is obtained as described in Appendix A.

4 Network properties

The literature on interlocking directorates which employs network theoretical methods has detected a number of recurrent properties of boards networks[3]. These are low average distances coupled with relatively high values of the

[2]In particular in the following years: 1928, 1930, 1932, 1934, 1937, 1940, 1949, 1953, 1956, 1958, 1961, 1964, 1967, 1970, 1973, 1980, 1984.

[3]For definitions and notation see Appendix A.

clustering coefficient, which are a signature of the so-called "small world model" (Watts and Strogatz, 1998). Regarding the former measure, typical values range, depending on network size, between 3 and 6, while the latter ranges from 0.20 for the US, Swiss networks (Davis *et al.*, 2003; Daolio *et al.*, 2011) to 0.57 for the German network (Conyon and Muldoon, 2006). A third recurrent characteristics is assortativity, according to which nodes with a similar degree value are more likely to be neighbors. This feature, which is ubiquitous in social networks, has been detected in different national (Battiston and Catanzaro, 2004) and international datasets (Heemskerk and Fennema, 2009; Burris *et al.*, 2012).

Board networks are typically very sparse, which means that only a small fraction of the potential connection are put in place. This is reflected in density values of the order of up to 5% for smaller samples (Battiston and Catanzaro, 2004) and down to 0.4% for larger samples (Conyon and Muldoon, 2006). At the same time, most nodes belong to the same, large, connected component, the so-called "giant component". This feature cannot be related to some special characteristics of board networks since their average node degree always exceeds unity, and a network formed by independent random links would display the same behavior under this condition. On the other hand, the fraction of nodes belonging to the giant component changes sensibly for different networks, e.g. it is 24% for Germany and 84% for U.S. according to Conyon and Muldoon (2006).

For a proper understanding of these stylized facts and of their variability, we should take into account the following considerations. Firstly, the samples employed in the literature are heterogeneous, both by selection criteria and by size. In particular, most samples include a few hundred of the largest national firms by market capitalization. These firms represent the most connected "core" of the larger, unobserved, national network. Then larger samples will typically include firms with lower degrees. This affects negatively connectivity measures, like average degree and especially density, as well as the size of the giant component. Secondly, these measures are far from stable over time, while samples take snapshots at different years. In particular, while the density of national networks appears to be decreasing in the last decades (Battiston and Catanzaro, 2004; Davis *et al.*, 2003; Bellenzier and Grassi, 2014; Heemskerk and Fennema, 2009), the density of international networks appears instead to be increasing (Heemskerk, 2011, 2013; Burris *et al.*, 2012).

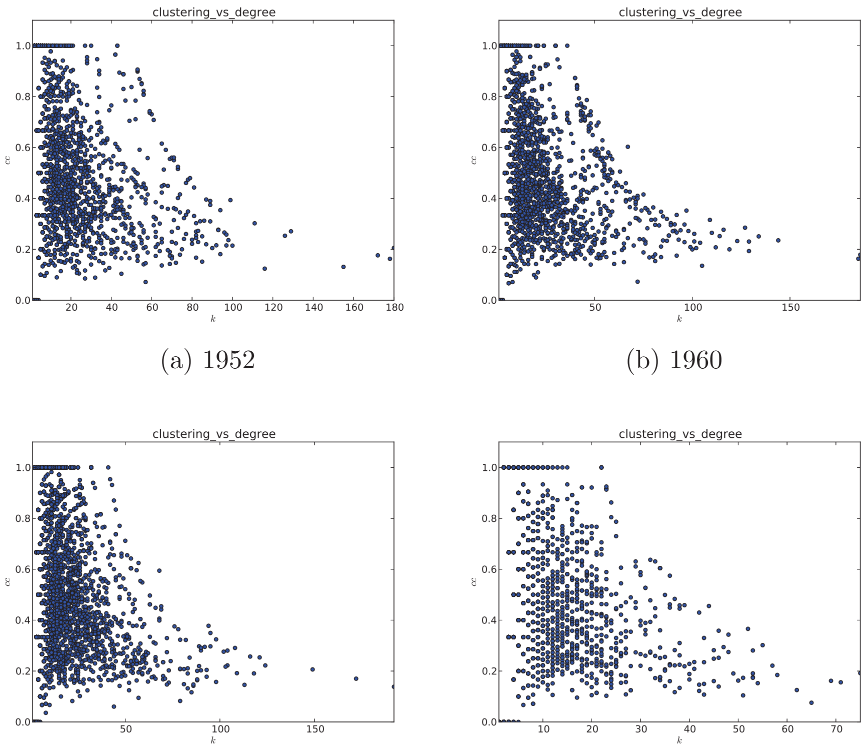
With these premises in mind, we turn to the board networks represented in our dataset. From Tab. 1 we see that the Italian boards network shares the properties mentioned above. In particular, density is relatively low, while clustering and assortativity relatively high with respect to other national networks. Regarding clustering, in contrast with poorly clustered networks (Bargigli *et al.*, 2014), we observe a large number of highly connected nodes with a large clustering coefficient, although the usual inverse relationship still holds to a large extent (Fig. 1). While assortativity and clustering are stable over time, we observe an increase of the average distance coupled with a decrease of density and of the relative size of the giant component. This is a clear indication of a rarefaction of connections which is consistent with other national boards networks, as well as with previous results obtained from the IMITA dataset (Rinaldi and Vasta, 2012) . We will develop this point further in Sec. 8.

Statistics	1952	1960	1972	1983
N	4,357	4,606	7,939	3,763
$\|C_g\|$	3,747	3,913	6,153	2,761
$\|C_g\|/N$	0.86	0.85	0.77	0.73
$\|E\|$	23,754	26,076	34,726	12,493
w	30,773	33,342	43,727	17,213
$\bar{l}$	4.51	4.49	5.09	5.00
D	0.0025	0.0025	0.0011	0.0018
ρ_k	0.3910	0.4060	0.4141	0.4023
ρ_w	0.3978	0.3887	0.3756	0.3902
$\bar{cc}$	0.5023	0.5063	0.5180	0.4835
T	296,898	332,205	368,340	74,136

N = n°of boards; $|C_g|$ = n°of boards in the giant component; $|E|$ = n°of links; w = total strength; $\bar{l}$ = average path length; D = network density; ρ_k = degree assortativity; ρ_w = strength assortativity; $\bar{cc}$ = average board clustering coefficient; T = n°of triangles.

Table 1: Network properties, full sample

In order to analyze some of the measures above, it is convenient to introduce the idea of "null network models". In practice, following a standard statistical inference approach, the significance of the observed values is evaluated against the null statistical hypothesis that nodes are randomly connected. This hypothesis is tailored to the observed network through a



(a) 1952 (b) 1960

(c) 1972 (d) 1983

Figure 1: Degree *versus* clustering coefficient.

specific set of constraints. In particular we require that both the average degree and strength of each node, in a large sample of random networks, are equal to those of the same node in the real network (for technical details see Appendix B).

While the model specification through either degrees or strengths is standard in the network literature where it is labeled as "configuration model" (Newman *et al.*, 2001; Squartini and Garlaschelli, 2011), the "generalized" specification through both constraints is rather innovative and more powerful (Garlaschelli and Loffredo, 2009; Bargigli, 2014). On the one hand, random binary models cannot evaluate weighted properties by construction, on the other hand, the models for weighted networks, which are specified only through the strength sequence, do not have a realistic topology, since they are not sparse (Bargigli, 2014). Thus any topological property of real networks becomes trivially significant against such a null model.

In order to explain why degrees and strengths are chosen as constraints, it is useful to introduce the idea of a hierarchy of network observables. First order properties of a network involve only linear combinations of the elements of the adjacency or weight matrix. These properties include the degree and strength sequences. Analogously one can define second, third, etc. order properties (generically higher order properties) as those metrics that involves sums of products of two, three, etc. elements of the adjacency or weight matrix. Since the value of higher order properties is not dictated by lower order properties, the approach is thus to specify the model through relevant low order properties and to observe whether higher order properties of the real network are reproduced by the model. For example, let us consider assortativity. After having observed a value of 0.40 in 1983, we ask: which value would we find if we allowed each board to retain the same number of neighbors it has in reality, but to randomly choose its counterparties? More generally, which interaction patterns in a real network are "unexpected" when one assumes that certain properties of nodes are preserved?

From Tab. 2 we see that all the higher order properties considered turn out to be highly significant in our networks. In other terms, our null hypothesis is always rejected, and this means that the observed values cannot be regarded as the outcome of a purely random interaction between nodes. In particular, we see that the average distance and the number of triangles are significantly high, while the size of the largest component is significantly low. These results should be read together. The high number of triangles implies that a large fraction of links runs between nodes that would belong to the same component even if these links would be absent, thus lowering the probability that a random link connects nodes in two otherwise different components. Moreover, we know that the average distance in a highly clustered network is higher than in a purely random network (Watts and Strogatz, 1998).

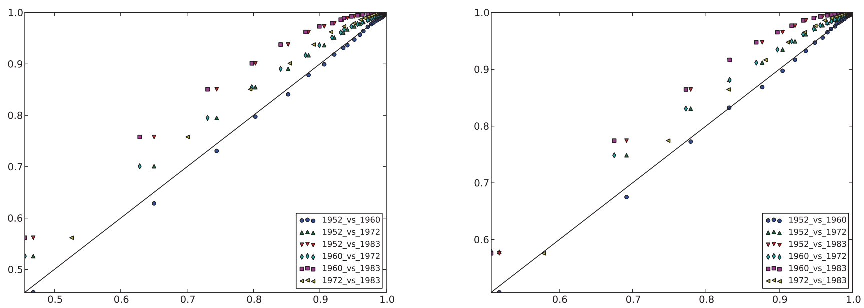
Assortativity is highly significant too, in particular we see that in a random sample of networks we would expect this quantity to be slightly negative, i.e. the networks to be disassortative. In the literature on social networks, high clustering and assortativity have a respective standard interpretation in terms of social interactions (since, as the argument goes, a friend of a friend is likely to be a friend) and homophily (Newman and Park, 2003). In the economic context, other factors may be at work. For instance, firms' size influences positively their connectivity in terms of degree or strengths. Then assortativity might reflect also the fact that larger firms form strategic alliances between themselves for a number of economically relevant reasons. We will develop this point further in Sec. 8.

	1952	1960	1972	1983
$\bar{l}$	4.515	4.489	5.092	5.000
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)
(sample average)	(2.988)	(2.986)	(3.268)	(3.301)
$\lvert C_g \rvert$	3,747	3,913	6,153	2,761
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)
(sample average)	(4,237)	(4,476)	(7,676)	(3,633)
ρ_k	0.391	0.406	0.4141	0.4023
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)
(sample average)	(-0.0301)	(-0.0289)	(-0.0165)	(-0.0136)
ρ_w	0.3978	0.3887	0.3756	0.3902
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)
(sample average)	(-0.0259)	(-0.0256)	(-0.0136)	(-0.009)
T	296,898	332,205	368,340	74,136
(p-values)	(0.000)	(0.000)	(0.000)	(0.000)
(sample average)	(129,073)	(144,817)	(74,889)	(16,570)

Table 2: Significance against the null model, full sample.

According to network theory, the degree / strength distributions are very important to explain some network properties like resilience to the removal of nodes. This issue is not tackled systematically in the literature on board networks. Notable exceptions are Grassi (2010), who rejects the hypothesis that the right tail of degrees is power-law distributed, Piccardi *et al.* (2010) and Heemskerk (2013), who claim that it is exponentially distributed. Caldarelli and Catanzaro (2004) compare instead degrees with strengths, observing that, while the behavior of the former looks exponential, the latter seem to follow a power-law distribution. In order to assess comprehensively this issue, we follow the approach suggested by Clauset *et al.* (2009), namely we compute the log-likelihood ratios of a set of alternative distributions (power-law, power-law with exponential cutoff, exponential, lognormal) which are consistently estimated from the data through maximum likelihood methods[4]. Regarding degrees, we observe a weak evidence in favor of a power-law with cutoff. In fact, the log-likelihood ratios are generally in favor of this hypothesis, but significant only in 1983 against the lognormal and simple power-law, while the exponential distribution can never be rejected. Regarding strengths, the power-law with cutoff is significantly preferred to a simple power-law in all years but one (1972), while the lognormal and exponential alternatives cannot be rejected.

These results are rather inconclusive, suggesting that the "true" data-generating probability distribution for degrees, if any, could be almost impossible to detect. This difficulty is not surprising once we take into account the finite size effects which make the rightmost part of the distributions unobservable. Furthermore, we should take into account the fact that the empirical distributions are changing with time (Fig. 2). Thus the hypothetical "true" distribution is not even stable over time. This "lack of universality" in distributions appears to be typical of economic networks (Bargigli *et al.*, 2014).



(a) degree (b) weight

Figure 2: PP-plots

5 Core-Periphery

The core-periphery subdivision is a widely investigated feature of networks. In the baseline model, the core is a subset of nodes which are maximally

[4]The results of this procedure are detailed in Tab. D.1 below.

connected with other core members, while the periphery is the complementary subset of nodes with no reciprocal connections (Borgatti and Everett, 2000). Following Lip (2011) it is possible to show analytically that the core-periphery subdivision in a symmetric network depends only on the degree distribution of the network. In fact, once the nodes are sorted in decreasing order of degree, the necessary and sufficient condition for the i^{th} node to be included in the core is that its degree k_i satisfies the inequality $i - 1 < k_i$. From this condition we see that the core is empty only if the network is trivially void of links.

The relationship between core-periphery structure and disassortativeness may be explained through the following informal argument. Suppose that core members have a degree equal to n on average, while the core size is k with $n \gg k$. Then the average core member must have at least $n - k$ links with peripheral nodes, i.e. with lower degree nodes since by construction the latter are included in the periphery. Thus we have a large part of links (eventually a majority) originating from core nodes which contribute negatively to degree-degree correlation. Moreover, since links between peripheral nodes (which would increase the degree-degree correlation) are rare, most peripheral nodes will link with core nodes, adding a further negative contribution to degree-degree correlation, in this case originating from peripheral nodes.

Following this argument we may distinguish between *strong* and *weak* cores. The former are associated with disassortativeness, which implies that core members have many connections with peripheral nodes, i.e. their average degree is largely in excess of core size. This feature is typical of highly concentrated economic networks such as the interbank credit market, whose core nodes are connected to virtually any other node in the network (Bargigli *et al.*, 2014). Nodes belonging to *weak* cores have instead an average degree which is not too distant from the size of the core itself. In our case we see from Tab. 3 that, for instance, there are 69 boards in the core in 1952. These boards have on average a degree equal to 89[5]. Thus they simply cannot be connected to a large part of peripheral nodes, which count in the thousands in our networks. This conclusion is consistent with the overall assortative behavior of the networks highlighted in the previous section. Thus we may conclude that, loosely speaking, the cores of our networks are weak in all years.

We characterize cores in terms of a set of node properties or characters,

[5]We observe a similar behavior also in the other years.

following the approach of Tumminello *et al.* (2011). In this case we make the null hypothesis that the frequency of each (discrete) character (e.g. belonging to a given sector or being a SOE) in the core is expected not to be different from the frequency of the same character in the overall sample. In other terms, according to the null hypothesis, the frequency of node characters in the core follows an hyper-geometric distribution. Thus we evaluate the p-value of observed community frequencies according to this distribution, while taking care of multiple hypothesis testing by means of the FDR (False Discovery Rate) procedure at confidence level $\alpha = 1\%$.

The results are summarized in Tab. 3. For each year, we report the size of the core in term of nodes, its share of total assets, which sectors and State-owned business groups are significant characters in the sense specified above, and eventually other significant characters[6]. For each significant character, in brackets we report the percentage frequency in the overall sample and in the core. With the obvious exception of 1952, we also consider as a significant character that of being part of the core in the previous benchmark year. In this way we can test the temporal continuity of cores, which turns out to be high, since core membership in each year is always significantly related to core membership in the previous year. Cores are mostly composed of large listed companies, with a significant participation of SOEs of the IRI group. The sectoral characterization confirms the marginalization of electrical firms after nationalization in 1962, which were already highlighted in previous works (Bargigli and Vasta, 2006). On the other hand, banks turn out to have a role in the core even before the nationalization of electrical companies.

6 Betweenness

The centrality of a node can be captured by the fact that this node acts as an intermediary in the network. The betweenness of a node is equal to the number of shortest paths between all couples of nodes that pass through that node. A node with high betweenness centrality has a large influence on the transfer of items through the network, under the assumption that items follow the shortest paths.

Tables 4-7 below show the twenty most central companies according to betweenness firms in the benchmark years. Only three firms are present in

[6] The characters taken into consideration are being a large firm (i.e. belonging to upper ten percentiles of the distribution of total assets in the year) and being a quoted company.

year	Nodes	TA(%)	Sector (%)*	SOE (%)*	Other (%)*
1952	69	26	40(3;36), 66(2;9)	IRI(3;26)	QF(3;46), LF(8;75)
1960	71	20	40(3;49), 65(8;28)	IRI(3;17)	QF(3;49), LF(8;70), 52.core(3;66)
1972	66	17	64(0;3), 65(7;33), 66(1;15)	IRI(2;23)	QF(1;41), LF(8;68), 60.core(2;46)
1983	40	6	65(23;55), 66(2;15)	IRI(6;20)	QF(3;55), LF(10;65), 72.core(4;47)

Legend: 40 = Electricity, 64 = Telecoms, 65 = Banks, 66 = Insurance, LF = Large firm, QF = Quoted firm. * The first percentage in brackets refers to the frequency among all nodes, the second percentage to the frequency in the core.

Table 3: Core characterization

all of them, one insurance company (RAS Riunione Adriatica di Sicurtà), and two banks (Istituto centrale di Banche e Banchieri; Banca d'America e d'Italia). More in general banks and insurance firms are central in all the years considered. Banks prevail in all years with around 50% on average of the 20 most central firms. Insurances come always as the second sector. As to industrial sectors, electricity and gas companies appear before the nationalization of electricity (1962), while the chemical sector occurs in 1983. Regarding ownership, most of central firms are listed, private companies. Among banks, both State and private financial holdings have an important role. On the private side, for example, Strade Ferrate Meridionali in 1952, as the most important private financial company which later changed its name in Bastogi (that we find in 1971), and La Centrale in 1983, were often main players in several Italian financial affairs. Bastogi, for example, was the first "salotto buono" of Italian capitalism and managed the funds resulting from the nationalization of electrical industry. It was also the first company to be defended by Mediobanca, in name of the stability of the system, against an IPO launched in 1971 by Michele Sindona. La Centrale was involved both in Sindona and Roberto Calvi affairs. SO financial holdings are also present with STET (Telecommunications) in 1960 and 1971 and Finsider (Steel) in 1960.

The continuity in the sectoral composition of central firms along the entire period has its roots in the systemic view of the Italian economy established in 1933 and lasting without significant changes up to the end of the Seventies.

The Italian economy in the postwar period was managed under the State control of financial flows, including the funding of State owned and private industrial firms. In this context Bank of Italy played a crucial role inspired to a "sui generis monetarism". According to this view, the balance of payments depended both on the relationship between money demand and supply, and on domestic and external prices. This mechanism regulated also financial flows to companies that had at the center the banking system which was, since 1933, predominantly State owned. Commercial banks supplied short-term funds and could not have a stake in industrial companies. Private and SO financial companies instead provided medium and long term funds to industrial firms, collecting resources within forms and limits set by the Central Bank. In legal terms, the system was formed mainly by public bodies, which were supervised by the Bank of Italy to avoid bankruptcy through careful administrative inspections. Credit was supplied, in short, as a public good by which the authorities were able to guide the strategies of enterprises, mainly according to national industrial strategies.

This framework was strengthened by the role of SOEs which shared the same goals and mentality. The planned nature of business financing was further strengthened in 1967 when a branch of government, the CIPE (Interministerial Committee for Economic Planning) received the task of issuing directives and to approve corporate plans, and in 1977 when the inter-ministerial Committee for industrial Policy (CIPI) was established. This institutional framework started to crush down at the end of Seventies, but lasted up to the outbreak of the 1992 crisis and the following wave of liberalization and privatizations.

7 Communities

In this section we perform the community decomposition of the Italian boards network. The general intuition behind the notion of community is that nodes may eventually form subsets which are more densely interconnected among themselves than with the rest of the network. In terms of matrix representation, community decomposition is equivalent to finding a permutation matrix (i.e. a reordering of nodes) according to which the original adjacency

Company	Characters
RAS RIUNIONE ADRIATICA DI SICURTÀ	66, QF
TORINO ESPOSIZIONI	74
E.F.I. ENTE FINANZIAMENTI INDUSTRIALI	65
ISTITUTO CENTRALE DI BANCHE E BANCHIERI	65
SOCIETÀ ITALIANA PER LE STRADE FERRATE MERIDIONALI	65, QF, IRI
BANCA PROVINCIALE DI DEPOSITI E SCONTI	65
CONIEL COMPAGNIA NAZIONALE IMPRESE ELETTRICHE	40, IRI
ITALGAS SOCIET ITALIANA PER IL GAS	40, QF
BANCA COMMERCIALE ITALIANA	65, IRI
CARTIERE BURGO	21, QF
VIZZOLA	40, QF, IRI
CHATILLON	24, QF
BANCA MILANESE DI CREDITO	65
COMPAGNIA DI ROMA RIASSICURAZIONI	66
DOMUS AMBROSIANA	70
BANCA POPOLARE DI NOVARA	65
BANCA D'AMERICA E D'ITALIA	65
BANCA PROVINCIALE LOMBARDA	65
L'ASSICURATRICE ITALIANA	66, QF
SOCIETÀ SVILUPPO AGRICOLO MEZZOGIORNO SVAM	73

Table 4: Top 20 firms by betweenness, 1952

Company	Characters
RAS RIUNIONE ADRIATICA DI SICURTÀ	66, QF
ISTITUTO CENTRALE DI BANCHE E BANCHIERI	65
ITALGAS SOCIETÀ ITALIANA PER IL GAS	40, QF
SOCIETÀ ITALIANA PER LE STRADE FERRATE MERIDIONALI	65, QF
TORINO ESPOSIZIONI	74
BANCA PROVINCIALE LOMBARDA	65
CREDITO COMMERCIALE	65
L'ASSICURATRICE ITALIANA	66, QF
CREDITO LOMBARDO	66
BANCA UNIONE	65
LINIFICIO E CANAPIFICIO NAZIONALE	17, QF
CARBOLIO FORNITURE INDUSTRIALI DI OLII E COMBUSTIBILI	23
CARTIERE BURGO	21, QF
ELETTRICA BRESCIANA	40, QF
STET SOCIETÀ FINANZIARIA TELEFONICA	65, QF, IRI
CHATILLON	24, QF
ISTITUTO COMMERCIALE LANIERO ITALIANO	65
FINSIDER SOCIETÀ FINANZIARIA SIDERURGICA	65, QF, IRI
BANCA D'AMERICA E D'ITALIA	65
STEI SOCIETÀ TERMOELETTRICA ITALIANA	40, ENI

Table 5: Top 20 firms by betweenness, 1960

Company	Characters
RAS RIUNIONE ADRIATICA DI SICURTÀ	66, QF
ISTITUTO CENTRALE DI BANCHE E BANCHIERI	65
BASTOGI FINANZIARIA	65, QF
L'ASSICURATRICE ITALIANA	66, QF
STET SOCIETÀ FINANZIARIA TELEFONICA	QF, IRI
UNIONE ITALIANA DI RIASSICURAZIONE	66
S.I.A.T. SOCIETÀ ITALIANA ASSICURAZIONI TRASPORTI	66
EFIBANCA ENTE FINANZIARIO INTERBANCARIO	65
BANCA D'AMERICA E D'ITALIA	65
BANCA CATTOLICA DEL VENETO	65
ITALGAS SOCIETÀ ITALIANA PER IL GAS	QF, ENI
ISTUD ISTITUTO STUDI DIREZIONALI	73
TRAFORI DELLO SPLUGA E DELLO STELVIO	45
CREDITO VARESINO	65
MAGAZZINI STANDA	52
COTONIFICIO OLCESE VENEZIANO	17
SNIA VISCOSA	24
ING. C. OLIVETTI & C.	30, QF
CREDITO COMMERCIALE	65
BANCA PROVINCIALE LOMBARDA	65

Table 6: Top 20 firms by betweenness, 1972

Company	Characters
ISTITUTO CENTRALE DI BANCHE E BANCHIERI	65, IRI
BANCA D'AMERICA E D'ITALIA	65
SNIA BPD	24, QF
RAS RIUNIONE ADRIATICA DI SICURTÀ	66, QF
I.M.I. ISTITUTO MOBILIARE ITALIANO ROMA	65
I.M. INTERMETRO	45, EFIM, IRI
MIRA LANZA	24, QF
LA CENTRALE FINANZIARIA GENERALE	65, QF
SOCIETÀ ITALIANA ASSICURAZIONE CREDITI SIAC	66, IRI
UNIONE ITALIANA DI RIASSICURAZIONE	66, IRI
ING. C. OLIVETTI & C.	30, QF
MONTEDISON	24, QF
CONSORTIUM	65
LA RINASCENTE	52, QF
COMPAGNIA FINANZIARIA LIGURE PIEMONTESE COFILP	65
COMPAGNIE INDUSTRIALI RIUNITE CIR	65, QF
FINANZIARIA REGIONALE PIEMONTESE	65
CIGAHOTELS COMPAGNIA ITALIANA GRANDI ALBERGHI	65, QF
BANCA CATTOLICA DEL VENETO	65, QF
PIRELLI	65, QF

Table 7: Top 20 firms by betweenness, 1983

matrix is as similar as possible to a block diagonal matrix[7]. This general intuition has found numerous applications in a wide range of fields, by means of various specifications and tools [8].

We adapt the original idea of defining communities with respect to a statistical null hypothesis, proposed by Newman (2006), to the statistical inference framework outlined in Sec. 4. The null hypothesis is given by the "generalized" specification mentioned above (see also Appendix B). In this random network model, connections depend only on degrees and strengths. We define a community as a subset of nodes whose reciprocal connections are significantly in excess of what we could expect to observe in a large sample of these random networks. In particular, we employ z-scores in order to test not only intramodular connections but also intermodular connections (see appendix C). In the first case, if the null hypothesis is rejected we obtain a statistical validation of the community partition. In the second case, under the same condition, we obtain a set of statistically significant links between different communities.

Similarly to hierarchical data clustering, community detection requires that we choose a "preferred" level of description, which equates to determining the number of communities we would like to obtain. We follow a bottom-up approach, according to which we determine the number of communities and the decomposition at the same time. For all details see Appendix C.

In order to avoid the potential biases stemming from the very different sample size in different years, we use restricted samples by selecting, for each year, the largest $3,763$ companies by total assets, corresponding to the size of the smallest sample (see Tab. 1). The algorithm is applied on the largest component of each of these sub-networks, since the decomposition in case of different components is trivial (in fact each component is a distinct community).

Our algorithm turns out to be very effective: all communities are significant in terms of z-scores ($z \geqslant 1.96$), and a number of significant connections between communities emerge (Fig. C.2). In Fig. 3 we depict only the latter. Their decline over time reflects the "rarefaction" of links already observed for other national systems (see Sec. 4). Moreover, we see that the number of communities is steadily decreasing, from 30 in 1952 to 18 in 1983. At the

[7]For more details see appendix C, where we also explain the difference between community and core-periphery partitions.

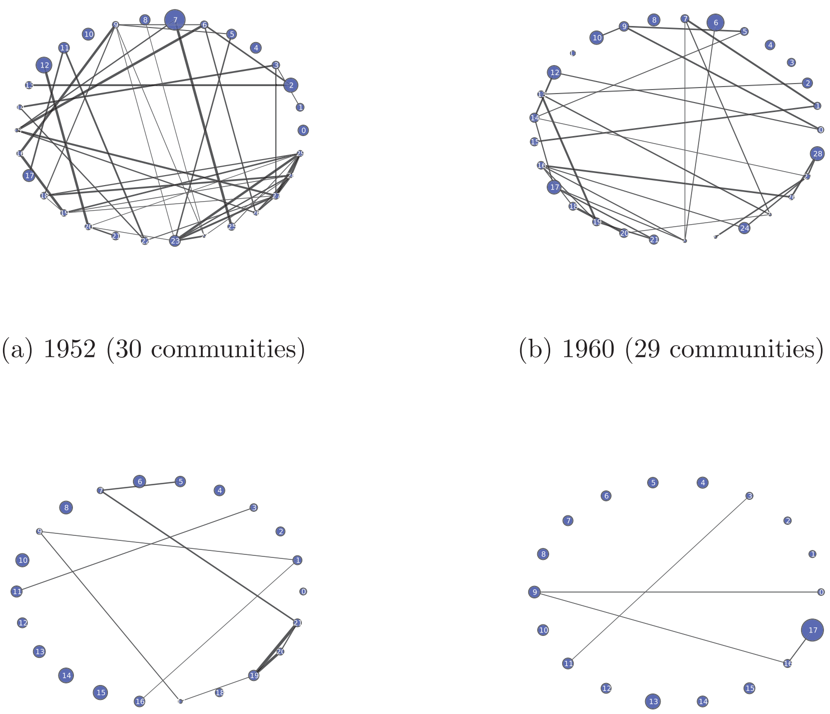
[8]For a general introduction to this field see Fortunato (2010).

same time, the relative weight of the largest community in terms of nodes is relatively stable around 10% in the first three benchmark years, but doubles to 22% in 1983. The impression we get at first glance from Fig. 3 is that of a system undergoing a transformation, whereby a network formed by a larger number of smaller and variously connected communities is replaced by a network whose nodes entertain fewer, but more focused, relationships.

We characterize each community in terms of a set of node properties, following the methodology described in sec. 5. The results of this analysis are summarized in Tabs. 8-11. For each community, we report the size in term of nodes, the share of total assets, which sectors and State-owned business groups are significant characters of the community in the sense specified above, and eventually other significant characters[9]. For each significant character, we report in brackets the percentage frequency in the overall sample and in the given community. With the obvious exception of 1952, we also consider as a significant character that of being part of a given community in the previous benchmark year. In this way we can test the temporal continuity of communities, which turns out to be pretty low: only a small number of communities is significantly related to some community in the previous network observation. This result contrast with the relative stability of core composition shown above. We also observe that in each year the core is significantly related to, although not perfectly overlapping with, one or more communities.

The fraction of nodes belonging to non characterized communities (last line of each table) decreases from 34% in 1952 to 23% in 1960, then increases to 33% in 1972 and finally falls to zero in 1983. This result supports the idea that relationships have become more focused, with sectoral variables seemingly playing a major role. An interesting result regards the relative frequency of diversified and not diversified communities, i.e. whether a community is characterized or not by a single sector or few strongly related sectors. The typical Big business organizational form of the Fifties and Sixties was specialized, while the conglomerate form, which is typically diversified, diffused in the Seventies. In our case the timing of the diffusion of big business in the Golden Age seems to correspond to the standard view: in 1952 diversification is low (10% of communities), increases a bit to 24% of total

[9] The characters taken into consideration are being a large firm (i.e. belonging to upper ten percentiles of the distribution of total assets in the year), being a quoted company and being in the core of the network in the same year.



(a) 1952 (30 communities)

(b) 1960 (29 communities)

(c) 1972 (22 communities)

(d) 1983 (18 communities)

Figure 3: Communities and their significant relationships. Circles are proportional the size of communities. Edge thickness is proportional to z-scores.

communities in 1960, but decreases in 1972 when diversified communities cover 9% of the total. This may be related to the industrial policy of the time pursuing economies of scale according to the paradigm of Big Business. The 1983 benchmark shows instead a typical diversified feature (55% of communities are diversified).

Historical evidence helps to explain these figures. The decline of profits which characterized the Seventies and the need to reduce their debt burden pushed firms to concentrate, regardless of industrial motivations. In 1975, for example, the governor of Banca d'Italia Guido Carli proposed without success to convert corporate debt obligations with the banking sector into shares and in 1977 a law proposed by the finance minister Pandolfi reduced the taxation of mergers, divisions, transfer of assets and exchange of shares between companies. As we show below, there is a significant increase of concentration in our sample, which is consistent with this historical argument.

An original feature of the Italian system is the growing presence of SOEs. The share of communities characterized by the presence of SOEs increases from 13% in 1952 to double in 1960 (26%) and 1972 (23%) up to 44% in 1983. In this year the IRI financial holding belongs the large community 17, which is connected, through community 10, to two communities (0 and 9) in which we observe a very high frequency of IRI firms. Thus, SOEs retain their central position up to the end of the period under consideration.

ID	Size	% Assets	Sector (%)[*]	SOE (%) [*]	Other (%)[*]
0	134	0.9	15(7;15)	-	-
1	75	3.7	45(3;16)	-	-
2	248	2.8	17(10;23)	-	-
3	70	1.6	-	IRI(3;16)	-
4	145	4.7	11(1;5),23(2;6)	-	LF(11;22)
5[**]	120	2.8	20(1;5),51(8;17)	IRI(3;15)	-
8[**]	130	1.5	21(2;9),22(2;7),23(2;8)	-	-
10	175	2.6	17(10;30)	-	-
12[**]	307	7.3	61(2;7),92(1;5)	-	-
17	176	2.4	40(4;14)	-	-
18	55	6.0	40(4;18)	IRI(4;18)	LF(11;27)
19	51	0.9	17(10;29)	-	-
20	50	4.8	26(4;16)	-	LF(11;32)
21	73	1.5	26(4;25)	-	-
23	147	7.7	64(0;3)	-	LF(11;21)
25	67	1.6	60(3;13)	-	52.CORE(2;13)
27	59	4.0	-	IRI(3;15)	52.CORE(2;10)
Others	1,090	42.9	-	-	-

Legend: 11 = Oil & Gas extr., 15 = Food & Bev., 17 = Textile, 20 = Wood, 21 = Paper, 22 = Publishing, 23 = Oil refin., 26 = Minerals, 34 = Cars, 40 = Electricity, 45 = Construction, 51 = Wholesales, 60 = Ground Transport, 61 = Water Transport, 64 = Telecoms, 92 = Movies & Broadcast, LF = Large firm, QF = Quoted firm. [*] The first percentage in brackets refers to the frequency among all nodes, the second percentage to the frequency in the community. [**] We define these communities as diversified on the basis of their characterizing sectors.

Table 8: Community characterization, 1952

ID	Size	% Assets	Sector (%)*	SOE (%)*	Comm.52 (%)*	Other (%)*
0	48	1.0	40(4;15)	-	-	-
1	62	1.7	61(3;30)	-	-	-
2	126	1.2	15(8;19)	-	-	-
3	82	0.7	17(9;22),19(1;6)	-	-	-
4**	114	0.6	15(8;17),93(0;5)	-	-	-
5**	76	3.2	01(2;9),40(4;14)	Iri(4;21)	-	-
6**	358	4.1	17(9;13),65(10;15)	-	-	-
7**	79	1.8	35(1;9),61(3;18)	-	-	-
9**	112	14.4	23(2;10),64(0;4)	Eni(1;6) Iri(4;17)	-	-
10**	222	2.7	13(0;3),20(1;5)	-	-	-
11	31	1.2	23(2;19)	-	-	-
12	228	2.3	17(9;14)	-	5(2;9)	-
14	103	1.1	60(2;9),61(3;10)	-	-	-
17	237	8.8	26(4;11)	-	-	-
20	93	6.3	40(4;19)	-	-	LF(12;29), 52.core(3;18), 60.core(2;10)
22	13	0.4	30(0;15)	-	-	-
24**	157	4.8	11(0;4),26(4;11)	Eni(1;15)	-	-
26	35	1.6	62(0;6)	Iri(4;20)	-	-
28	241	18.7	40(4;8)	Iri(4;12)	-	QF(4;9),LF(12;24), 52.core(3;10), 60.core(2;8)
Others	705	22.8	-	-	-	-

Legend: 01 = Farming, 11 = Oil & Gas extr., 13 = Metals mining, 15 = Food & Bev., 17 = Textile, 19 = Leather, 20 = Wood, 23 = Oil refin., 26 = Minerals, 30 = Electr. machines, 35 = Other vehicles, 40 = Electricity, 45 = Construction, 60 = Ground trans., 61 = Water trans., 62 = Air trans., 64 = Telecoms, 65 = Banks, 85 = Health, 93 = Personal services, LF = Large firm, QF = Quoted firm. * The first percentage in brackets refers to the frequency among all nodes, the second percentage to the frequency in the community. ** We define these communities as diversified on the basis of their characterizing sectors.

Table 9: Community characterization, 1960

ID	Size	% Assets	Sector (%)*	SOE (%)*	Comm.60 (%)*	Other (%)*
2	100	1.6	15(7;18)	-	-	-
3	70	0.8	24(10;24)	-	-	-
5**	154	1.5	26(6;13), 61(3;19)	-	-	-
6	188	8.1	23(2;15), 24(10;18),25(2;7)	Eni(2;19)	-	-
8	202	10.9	23(2;15)	-	-	-
11	152	6.5	24(10;28)	Iri(6;29)	-	LF(22;33)
13	177	1.6	17(7;15)	-	-	-
12**	121	12.1	16(0;3), 32(1;8),64(0;3)	Iri(6;16)	-	-
14	271	9.7	21(3;6)	Iri(6;12)	-	1960.core(3;8) 1972.core(2;7)
15	251	18.3	-	Iri(6;13) Efim(1;15)	-	-
16	139	1.7	29(7;15)	-	-	-
20	59	5.6	65(10;25)	-	-	-
Others	915	21.0	-	-	-	-

11 = Oil & Gas extr., 15 = Food & Bev., 17 = Textile, 16 = Tobacco, 18 = Clothes, 21 = Paper, 23 = Oil refin., 24 = Chemicals, 25 = Plastics, 26 = Minerals, 29 = Mechanical equip., 32 = TV & radio, 34 = Cars, 61 = Water trans., 62 = Air trans., 64 = Telecoms, 65 = Banks, 73 = R&S, LF = Large firm, QF = Quoted firm. * The first percentage in brackets refers to the frequency among all nodes, the second percentage to the frequency in the community. ** We define these communities as diversified on the basis of their characterizing sectors.

Table 10: Community characterization, 1972

ID	Size	% Assets	Sector (%)*	SOE (%)*	Comm.72 (%)*	Other (%)*
0**	54	0.9	25(2;9),31(2;17),32(1;15)	IRI(8;20)	-	-
1**	61	0.4	13(0;3),18(1;8),26(4;15)	ENI(3;11)	-	-
2	67	0.6	-	-	-	-
3	62	2.9	23(1;14)	-	-	-
4	151	1.3	36(1;4)	-	8(4;13)	-
5	136	15.9	66(3;9)	-	-	-
6**	121	2.0	17(5;14),24(5;23),70(4;10)	ENI(3;18)	-	-
7	124	3.3	27(4;10)	-	6(2;10), 11(2;9)	1972.CORE(4;16)
8**	154	4.2	35(2;6),40(1;7),63(2;11)	EFIM(2;27) ENI(3;10)	-	-
9**	179	9.2	35(2;9),73(0;2),64(0;2)	IRI(8;45)	-	LF(13;21)
10	143	1.5	26(4;11),27(4;10)	-	-	-
11**	144	3.1	61(1;7),24(5;12)	-	-	-
12	123	5.0	-	ENI(3;19)	-	LF(13;24)
13**	278	19.2	26(4;8),55(1;4),65(24;32)	IRI(8;13)	-	-
14	144	0.8	02(0;3)	EFIM(2;7)	-	-
15**	147	3.2	17(5;12),36(0;3)	-	-	-
16**	79	1.0	17(5;13),45(4;16)	-	-	-
17**	600	25.3	30(0;1),65(24;32),66(3;6)	-	-	QF(4;7) 1983.CORE(1;3)

Legend: 02 = Forests, 13 = Metals mining, 17 = Textile, 18 = Clothes, 23 = Oil refin., 24 = Chemicals, 25 = Plastics, 26 = Minerals, 27 = Metallurgy, 30 = Electr. machines, 31 = Other machines, 32 = TV & radio, 35 = Other vehicles, 36 = Other manufacturing, 40 = Electricity, 45 = Construction, 55 = Hotels 61 = Water trans., 63 = Other trans., 64 = Telecoms, 65 = Banks, 66 = Insurance, 70 = R. Estate, 73 = R&S, LF = Large firm, QF = Quoted firm. * The first percentage in brackets refers to the frequency among all nodes, the second percentage to the frequency in the community. ** We define these communities as diversified on the basis of their characterizing sectors.

Table 11: Community characterization, 1983

8 Panel analysis

In the previous sections we observed for the Italian board network a tendency towards a "rarefaction" of connections which is shared by other national systems. Now we try to investigate the factors behind this tendency. In order to do so, we fit our dataset to the following fixed-effect panel model

$$k_{it} = \alpha_i + \beta x_t + \gamma y_{it} + \eta A_{it} + \mu b_{it} + \theta z_{it} + \epsilon \tag{1}$$

where k_{it} is the log-degree of node i at t, x_t and y_{it} are vectors of time and sectoral dummies, A_{it} and b_{it} are respectively the logarithm of total assets and of board size, z_{it} is a vector of dummies codifying respectively if the i^{th} unit belongs to one of the three State-owned business groups (Iri, Eni, Efim) and if it is quoted on the Italian stock exchange.

Our dataset consists of an unbalanced panel with $t = 1, 2, 3, 4$ and $10,307$ cross-sectional units[10]. The choice of a RE model is rejected by the Hausman test. We resort to the unrestricted fixed-effect generalized least square estimator (unrestricted FGLS) since in a first, restricted, estimation we observed a significant serial correlation of residuals. In the final estimation we find that individual and sectoral effects are significant, and reject the hypothesis of cross-section correlation of residuals with Pesaran's CD test[11]. Multicollinearity between regressors is also excluded.

From Tab. 12 we see that our model explains 90% of the observed variance. This result supports the idea that the degree of board networks is determined largely by economic variables. In particular, we see that both firm and board size have a significant positive effect on k, while State-ownership has either a non significant effect (Iri, Eni) or a significant positive effect (Efim) with respect to private firms. Regarding time effects, we obtain a strong confirmation of the "rarefaction" dynamics between 1972 (used as reference) and 1983, as well as between 1952 and subsequent years.

In Tab. 13 we decompose the average log-difference of k into the contributions of the regressors. We see that the decrease between 1960 and 1972 can be attributed to firm-specific effects, a decline in the average board size, and a relatively small year effect. The decline between 1983 and 1972, instead, is entirely determined by the latter, while all other regressors, and especially firm and board size, together with firm-specific effects, contribute against it.

[10] We perform the analysis in `R` (2008) with the `plm` package (Croissant and Millo, 2008)

[11] For details and references see Croissant and Millo (2008).

```
         Estimate Std. Error  z-value  Pr(>|z|)
1952    0.1264619  0.0214194   5.9041 3.546e-09 ***
1960    0.0279453  0.0159786   1.7489 0.0803053 .
1983   -0.8001490  0.0243981 -32.7956 < 2.2e-16 ***
A       0.0805971  0.0080310  10.0357 < 2.2e-16 ***
b       0.7637770  0.0175933  43.4131 < 2.2e-16 ***
ENI     0.0035179  0.0787608   0.0447 0.9643738
EFI     0.7161572  0.0805559   8.8902 < 2.2e-16 ***
IRI     0.0645928  0.0474235   1.3620 0.1731851
LS      0.1147904  0.0445735   2.5753 0.0100151 *
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1
Total Sum of Squares: 24103
Residual Sum of Squares: 2320.3
Multiple R-squared: 0.90374
```

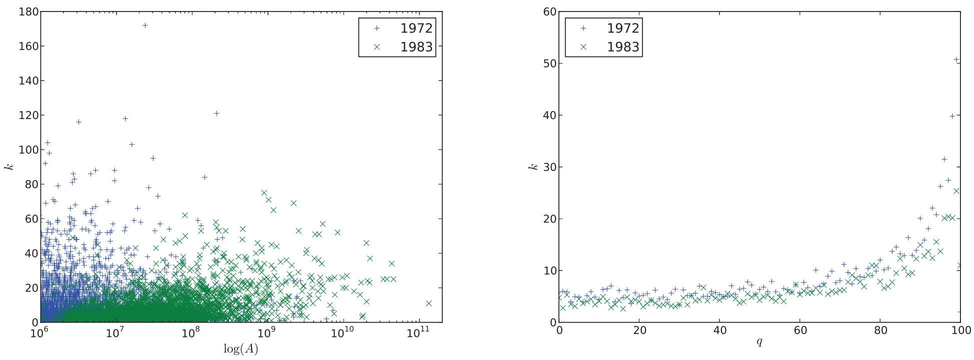
Table 12: Unrestricted FGLS, dependent variable: log - degree (k). Sectoral effects not displayed.

We also observe that State-ownership is never contributing significantly to degree variations. In this sense, we find no evidence of a "marginalization" of SOE as suggested by Rinaldi and Vasta (2012).

t	1960	1972	1983
$t-1$	1952	1960	1972
Firm eff.	0.005	-0.136	0.227
Year eff.	-0.099	-0.028	-0.800
Sector eff.	0.017	0.008	0.044
A	0.097	0.035	0.235
b	0.001	-0.092	0.109
SOE	0.000	0.006	0.007
List	-0.000	-0.002	0.002
$\bar{k}_t - \bar{k}_{t-1}$	0.022	-0.208	-0.176

Table 13: Decomposition of the average log-difference of k.

The interpretation of time effects is not easy. One possible explanation is provided by non linear effects associated with firms' size. If we compare for instance the last two years, we see that a non linear relationship between k and A is in place (Fig. 4, panel a). In fact, k is decreasing in the rightmost part of the size distribution. In order to take this effect into account, we have extended the model with a quadratic term in A. The resulting coefficient is non significant, while the magnitude and significance of the others remain stable (Tab. D.2). We have also estimated the model on a subsample, from which we have excluded, for each year, firms belonging to the largest 20 percentiles of the size distribution. We see that, although the coefficient of the time effect for 1983 is larger, it still remains significant and negative (Tab. D.3). These results are consistent with Fig. 4, panel (b), which shows that the rarefaction occurs for all percentiles of the size distribution, although it is stronger at the top.



(a) A *versus* k

(b) Average degree by percentile of size

Figure 4: Non linear relationship between size and degree: 1972 *versus* 1983.

Thus, although large firms have a greater role in the transformation of the Italian boards network in the Seventies, we should seek for a factor affecting firms of all sizes in order to explain rarefaction. In particular, we can envisage the following mechanism connecting decreasing degree with increasing concentration. A merger of two firms i and j, if their neighborhood is overlapping, originates a new firm with combined size $A' \geqslant A_i + A_j$ and a combined degree $k' < k_i + k_j$. As a consequence, the merger lowers the degree of neighbors which, thanks to assortativity, are mostly of the same size. Thus we can make the hypothesis that an intense merger activity, especially between large firms, may have contributed to the "rarefaction" of the overall network, while being consistent with the nonlinear relationship between k and A that we found. We have already mentioned in Sec. 6 the historical evidence in favor of such a wave of mergers, especially in the late Seventies. From Tab. 14 we see that our data provide robust evidence of an increasing concentration of the corporate system. We leave for future research the task of a rigorous statistical test of this hypothesis.

	1952	1960	1972	1983
Herfindahl	0.011 ± 0.000	0.010 ± 0.000	0.017 ± 0.000	0.025 ± 0.000
Entropy	-5.738 ± 0.002	-5.883 ± 0.003	-5.722 ± 0.004	-5.219 ± 0.006
C4	0.112 ± 0.000	0.110 ± 0.000	0.162 ± 0.001	0.203 ± 0.001

Table 14: Concentration measures: average and 95% confidence intervals (bootstrap estimation).

9 Conclusions

We describe how business networks among Italian firms evolve over the Long Golden Age (1952-1983). We find some typical properties of these networks, such as sparsity and connectedness in the same, large, giant component. Density is relatively low, while clustering and assortativity are relatively high and stable over time. We compare the Italian network with other national networks as they emerge from the literature, showing that it is not different from the latter when looking at the most relevant network properties. Since the core of the network maintains a surprising stability over the time, particularly with respect to the centrality of its main actors, most notably banks and insurances, we are able to revise some of the conclusions of previous works, e.g. by showing that SOEs and banks maintain an important position in the system throughout the period. SOEs in particular play a growing role in the community structure of the network, while communities themselves become more and more diversified by sector according to the conglomerate model of the Seventies.

From an historical perspective, we integrate statistical network analysis with two appreciative priors. The first one concerns the general consideration of the Golden Age as the age of Big Business, while the second one concerns the institutional environment of networks, especially the characters of a very peculiar financial system such as the Italian one. Both could potentially affect the structure of the network and its evolution over time. In particular, the most relevant trend we observe is a decrease of connections which is common to other national systems in the same period. We circumscribe the role of cross-sectional variables, such as size or sectoral composition, and relate this trend to an increasing concentration of the system in terms of assets. The latter is an outcome of a wave of mergers, due to increasing indebtedness of non financial companies with the banking system, which occurred in the late Seventies. A rigorous statistical test of this hypothesis is left for future research.

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A Appendix: definitions

A graph or network G is given by the couple (V, E), where V is the vertex or node set, typically assumed to be mapped onto a subset of $\mathbb{N}$, while E is the edge or link set, with $E \subset \mathbb{N} \times \mathbb{N}$, and $(i, j) = e_{ij} \in E$ can eventually map onto a subset D of $\mathbb{R}$ or $\mathbb{N}$. In this case $w(e_{ij}) = w_{ij} \in D$ is said to be the strength of the link (i, j) and G is said to be *weighted*. In our case, as explained below, the integer weights are given by the number of shared directors between a couple of firms. If (i, j) maps onto $0, 1$ we say that the network is *binary* or *unweighted*. Further we set $N = |V|$ and $L = |E|$.

We say that G is undirected or that it is a graph if we suppose $e_{ij} \equiv e_{ji}$ for each $i, j \in V$. Otherwise we say that G is directed or that it is a digraph. In general, G may be represented by the adjacency matrix A with elements $a_{ij} = 1$ if $e_{ij} \in E$ and $a_{ij} = 0$ otherwise. If G is undirected, A is symmetric. The strength between nodes may be represented by the matrix W with elements w_{ij}. From our definitions we see that a weighted network can be always transformed onto a a binary network by setting $a_{ij} = 1$ if $w_{ij} > 0$.

In order to obtain the boards network, we build in each year the matrix representation of individual board membership. This is a $N \times M$ binary matrix A, where N is the number of firms and M the number of individuals in the dataset. Its entries a_{ij} are equal to one if the individual j is member of the board of firm i. The matrix representation of the boards network is obtained by self-multiplication $W = AA^T$ and we say that the boards network is *projected* from the original bipartite network A. Each cell value w_{ij} with $i \neq j$ is equal to the number of shared directors between firms i and j. Diagonal cells w_{ii}, which would take the board size of firm i as value after multiplication, are set to zero in the undirected and weighted graph G which is the subject of our analysis. The following definitions are tailored to this case of interest.

The *neighborhood* of a node i is defined as the set $\psi(i)$ of nodes such that $e_{ij} \in E$ for all $j \in \psi(i)$. Then the *degree* k_i is the cardinality of $\psi(i)$. By extension, the *strength* of a node may be defined as follows:

$$w_i = \sum_{j \in \psi(i)} w_{ij} \tag{2}$$

The strength of a symmetric network is defined as $w = \frac{1}{2} \sum_i w_i$. The degree (strength) *assortativity coefficient* ρ_k (ρ_w) is defined as the Pearson correlation coefficient of degrees (strengths) between pairs of linked nodes. Then a network is said to be assortative if the degree (strength) of a node is positively correlated with the degree (strength) of its neighbors. Otherwise, it may be disassortative or uncorrelated.

An important set of network measures is related to connectivity. The simplest example is given by *density* which for undirected graphs reads

$$D = \frac{2L}{n(n-1)} \tag{3}$$

Most social networks are found to display low density, i.e. to be sparse. A network is said to be *sparse* when $L \ll N^2$. Otherwise the network is said to be *dense*. A *path* in a graph is a sequence of vertices such that from each of its vertices there is an edge to the next vertex in the sequence. Two vertices i and j are said to be connected if G contains a path from i to j. A *connected component* is a maximal connected subgraph of G. If most nodes are connected by a path, we also say that G has a giant component C_g, meaning that most of the nodes lie on this single component. This property is generally detected in social networks along with sparsity.

The *distance* or *path length* l_{ij} between two nodes i and j is defined as length of the shortest (geodesic) path between i and j for $i \neq j$. If i and j are not connected, we set $l_{ij} = +\infty$. Then the average distance $\bar{l}$ must be computed separately for each of the connected components of G. In the text we refer to the average distance in the largest component C_g.

In a binary undirected network the *clustering coefficient* cc_i of a node i is defined as follows

$$cc_i = \frac{\sum_{h \neq j} a_{ij} a_{jh} a_{hi}}{k_i(k_i - 1)} \tag{4}$$

Instead the number of triangles T is defined as follows:

$$T = \frac{1}{3} \sum_i \sum_{j \neq h} a_{ij} a_{jh} a_{hi} \tag{5}$$

B Appendix: Null Network Models

In this appendix we summarize briefly the methodology of Park and Newman (2004). As stated in the main text (sec. 4), since network observables depend on network realizations, their average are computed with respect to the probability $P(G)$ of observing a given realization G in an ensemble of graphs $\mathcal{G}$:

$$\langle x_i \rangle = \sum_{G \in \mathcal{G}} P(G) x_i(G) = \bar{x}_i \tag{6}$$

Since the $x_i(G)$ are a given, we need to specify a parameter dependent functional shape of $P(G)$ in order to solve the system (6). By adopting the basic concepts of equilibrium statistical mechanics we obtain a solution for this task by maximizing the following Lagrangean:

$$\mathcal{L} = S + \lambda \left(1 - \sum_G P(G) \right) + \sum_i \theta_i \left(\bar{x}_i - \sum_G P(G) x_i(G) \right) \tag{7}$$

where $S = -\sum_G P(G) \ln P(G)$ is Gibbs entropy. By taking the f.o.c. we obtain

$$\ln P(G) + 1 + \lambda + \sum_i \theta_i x_i(G) = 0 \tag{8}$$

Rearranging and taking antilogs:

$$P(G) = \frac{e^{-H(G)}}{Z} \tag{9}$$

where $H(G) \equiv \sum_i \theta_i x_i(G)$ is the graph Hamiltonian which, thanks to matrix representation of G, can be rewritten in terms of the matrix W or A, and $Z \equiv e^{(\lambda+1)}$ is the partition function. From the normalization constraint we easily obtain that $Z = \sum_G e^{-H(G)}$. The model is solved when the values of the parameters $\{\theta_i\}$, which fully determine P, are obtained from the system (6). It is possible to show that, if we adopt the Boltzmann-Gibbs distribution (9), then the system (6) provides the maximum likelihood estimates for the parameters $\{\theta_i\}$ (Garlaschelli and Loffredo, 2008).

B.1 Binary Configuration Model (Fermi networks)

When the constrained observables are the degree values $\{k_1, \ldots, k_n\}$ of a binary symmetric network, the main quantities of the model read:

$$
\begin{aligned}
H(G) &= \sum_i \sum_{j>i} [(\theta_i + \theta_j)a_{ij}] = \sum_i \sum_{j>i} \Theta_{ij} a_{ij} \\
Z &= \prod_i \prod_{j>i} \left(1 + e^{-\Theta_{ij}}\right) \\
F &= -\ln Z = -\sum_i \sum_{j>i} \ln\left(1 + e^{-\Theta_{ij}}\right)
\end{aligned}
$$

where $\Theta_{ij} = \theta_i + \theta_j$. The probability $P(G)$ takes the form of the product of $\frac{n\,(n-1)}{2}$ independent Bernoulli variables with parameters

$$
p_{ij} = \langle a_{ij} \rangle = \frac{\partial F}{\partial \Theta_{ij}} = \frac{1}{e^{\Theta_{ij}} + 1} \qquad \begin{array}{l} i = 1, \ldots, n-1 \\ j = i+1, \ldots, n \end{array} \tag{10}
$$

Substituting the last equation into the constraints we obtain the following specialization of system (6):

$$
\sum_{j \neq i} \frac{1}{e^{\Theta_{ij}} + 1} = \bar{k}_i \qquad i = 1, \ldots n \tag{11}
$$

The system can be solved numerically in order to obtain the values θ_i which satisfy the constraints.

B.2 Weighted Configuration Model

The Park & Newman maximum entropy model for weighted networks with given average strength distribution leads to the following system:

$$
\sum_{j \neq i} \frac{1}{e^{\Theta_{ij}} - 1} = \bar{w}_i \qquad i = 1, \ldots n \tag{12}
$$

where $\bar{\mathbf{w}} = \{\bar{w}_1, \ldots, \bar{w}_n\}$ is the strength sequence we want our ensemble to have in average. Unfortunately this ensemble, in which the w_{ij} are geometrically distributed, has one serious drawback. In fact, networks in this ensemble are not bound to follow any topological property, such as the degree distribution or even connectivity. Regarding the latter, recent papers

(Mastromatteo *et al.*, 2012; Musmeci *et al.*, 2013) have highlighted that networks in this ensemble are, with high probability, dense while real networks are mostly sparse (see appendix A). This property holds in particular for the Italian board network we are analyzing (see sec. 4). In other words, the topology of the weighted model is unrealistic by construction in most cases, and in particular for networks in our dataset.

Bargigli (2014) develops an alternative weighted ensemble by introducing the statistical weight $W(G)$ of a network configuration and redefining the Gibbs entropy as follows:

$$S = -\sum_G W(G)\, P(G) \ln \left[W(G)\, P(G)\right] \tag{13}$$

The statistical weight counts the number of ways a given configuration can be realized. The model of eq. (12) is derived for $W(G) = 1$, in analogy with Bosonic systems of statistical physics. If we choose instead the Boltzmann weights $W(G) = \Pi_i \Pi_{j<i} w_{ij}!$, we conclude that the w_{ij} follow a Poisson probability distribution and the system (6) becomes

$$\sum_{j \neq i} \lambda_{ij} = \bar{w}_i \qquad i = 1, \ldots n \tag{14}$$

where $\lambda_{ij} = e^{\Theta_{ij}}$ is the parameter of the Poisson distribution. Even if the Poisson distribution just specified is much easier to estimate than the system (12), it still leads to a unrealistic dense topology. In order to solve rigorously this problem we would need to specify the network model with a joint constraint on degrees and strengths (Bargigli, 2014).Unfortunately, these models are in general rather difficult to solve numerically. For this reason in our analysis we opt for a less rigorous approach, namely we suppose that the weighted links of artificial networks in the ensemble are the product of two independent variables:

$$w_{ij} \equiv a_{ij} b_{ij} \sim \text{Bernoulli}(p_{ij}) \; [\text{Poisson}(\lambda_{ij}) + 1] \tag{15}$$

with $p_{ij} = \dfrac{1}{e^{\Theta_{ij}} + 1}$ obtained from (11). In order to obtain the parameters $\lambda_{ij} = x_i x_j$ we proceed to solve numerically the following specialization of system (6):

$$
\begin{aligned}
\sum_{j\neq i}\langle w_{ij}\rangle = \sum_{j\neq i}\langle a_{ij}b_{ij}\rangle = \sum_{j\neq i}\langle a_{ij}\rangle\langle b_{ij}\rangle = \\
= \sum_{j\neq i} p_{ij}(\lambda_{ij}+1) = \\
= \sum_{j\neq i} p_{ij}(x_i x_j + 1) = \bar{w}_i \qquad i = 1,\dots n \qquad (16)
\end{aligned}
$$

It's easy to see that the ensemble defined in this way satisfies also the constraints (11). In fact the topology is given by $H(w_{ij}) = a_{ij}$. This is the specification employed in sec. 4.

Finally, it is useful to compare our approach to the one proposed by Conyon and Muldoon (2006). They compare real observations with an average computed for the configuration model of the original bipartite network of boards and directors represented by the matrix A introduced in appendix A. There are two fundamental departures from our approach. The first one is that we simulate samples of random networks in order to derive the complete probability distribution of the different observables, whose knowledge is necessary for statistical inference. By doing so, we need to rely on numerical methods, since an analytical derivation of these probability distribution is still lacking in the literature. The second one is that we specify our model directly with respect to the projected network of boards (see appendix A). We choose to proceed in this way because we want our model to follow the original degree / strength distributions of the boards networks. Following the approach of Newman *et al.* (2001), instead, Conyon and Muldoon (2006) obtain boards networks with a degree distribution which is quite different from the observed one.

C Appendix: community detection

The community detection algorithm we employ in sec. 7 is a variant within the well known set of spectral community detection methods, which rely on the fact that eigenvectors represent the optimal solution for bisection problems if the latter are "relaxed" to the real field (Newman, 2006; Fortunato, 2010). While Donetti and Muñoz (2005) have already employed clustering algorithms to partition eigenvectors, their approach to community detection relies on modularity optimization, which is affected by well known biases (Fortunato, 2010). We leverage instead on the mutual orthogonality of eigenvectors in order to iteratively bisect nodes until a partition is finally obtained. In practice, our algorithm works as follows:

1. perform the eigendecomposition of the matrix $K = D^{-\frac{1}{2}}\, W\, D^{-\frac{1}{2}}$, where D is a diagonal matrix having on the main diagonal the strength sequence $\mathbf{w} = (w_1, w_2, \ldots, w_n)$.
2. sort eigenvectors in decreasing order according to the magnitude of the corresponding eigenvalue
3. set $i = 2$
4. bisect the i^{th} eigenvector with a clustering algorithm[12]
5. if nodes in the smaller community are at least $k = 5$, assign them to the i^{th} community
6. delete the corresponding rows of the eigenvectors
7. if some nodes are not assigned to some community, set $i = i + 1$ and to go to 4); else, end the procedure.

Once the partition is obtained, we perform a statistical validation of the results using as statistical null hypothesis the "generalized" model detailed by eqs. (15) and (16). The statistics we put to test are intramodular and intermodular connections. The former are defined as $w_{HH} = \sum_{i \in H} \sum_{\substack{j \in H \\ j \geqslant i}} w_{ij}$, where H stands for the set of nodes included in the h^{th} community, while the latter are $w_{HQ} = \sum_{i \in H} \sum_{\substack{j \in Q \\ j \geqslant i}} w_{ij}$ for two distinct communities H and Q. This approach is consistent with the multiscale view of communities, according to which there are multiple optimal decompositions at different detail levels [13].

[12] In particular we employ the hierarchical clustering algorithm with cosine metric and complete linkage.

[13] Lambiotte *et al.* (2008) obtain these optimal decompositions by tuning a parameter-dependent community detection algorithm. These decompositions may be related to the time evolution of a diffusion or synchronization process taking place over the same network. Loosely speaking, a finer decomposition corresponds to the early stages of these processes, while a coarser one to later stages, at which the system is close to statistical equilibrium.

Thus two distinct communities which are significantly connected would be considered as a single community at a coarser level of description.

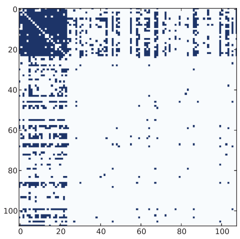
The inference is performed with respect to z-scores. In order to compute the latter we need to know the variance of w_{HH}, w_{HQ}. Since these are sum of independent variables, their variance is the sum of the variance of the summands which is obtained as follows:

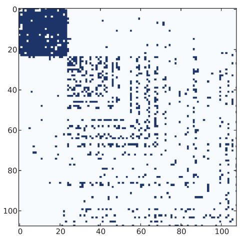
$$\begin{aligned}\sigma^2(w_{ij}) =& E(a_{ij}^2)\, E(b_{ij}^2) - E(a_{ij})^2\, E(b_{ij})^2 = \\ =& p_{ij}\,(1 + 3\lambda_{ij} + \lambda_{ij}^2) - p_{ij}^2\,(1 + \lambda_{ij})^2 = \\ =& p_{ij}\, \left[\lambda_{ij} + (1 - p_{ij}^2)(1 + \lambda_{ij})^2\right]\end{aligned}$$

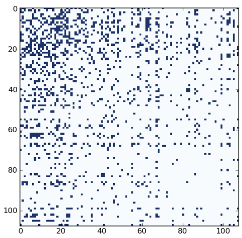
In order to highlight the relationship between core-periphery partitions, community partitions and statistical validation, we depict the matrix representation of three different binary networks with the same number of nodes and links. The first network (panel a) is strongly disassortative ($\rho_k = -0.39$) and displays a strong core in the sense of Sec. 5. It is evident that there is no way to obtain a block diagonal arrangement of this matrix, i.e. a community decomposition of the network. The second network (panel b) is obtained from the first by randomly reassigning links between core and periphery to the periphery alone. It is strongly assortative ($\rho_k = 0.39$), with two communities.

While, as it appears, a strong core cannot coexist with a community structure, this is not necessarily the case for a weak core. Indeed, the network (b) has a weak core which, beyond sharing 18 members out of 21 with the core of network (a), almost entirely overlaps with one of its communities. Finally, in panel (c) we represent a realization of a Fermi network obtained using the degree distribution of network (b). This network is weakly unassortative ($\rho_k = -0.05$), with no clear community structure as we expected. Indeed the value of intramodular connections observed in the first community of network (b) ($w_{11} = 532$) is 1.78 times larger than the maximum corresponding value observed in a sample of $100,000$ Fermi networks derived from the same degree distribution. Thus we can conclude that the community decomposition of network (b) is validated against the null model.

The results of z-score computations for our dataset are depicted in Fig. C.2. Our algorithm turns out to be very effective: all communities are significant in terms of z-scores ($z \geqslant 1.96$), and a number of significant interconnections emerge among communities.

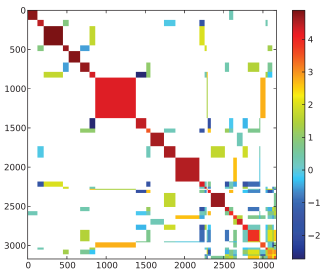




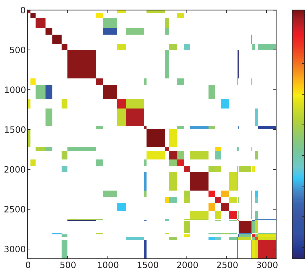


(a) Strong core network (b) Two communities network (c) Fermi network

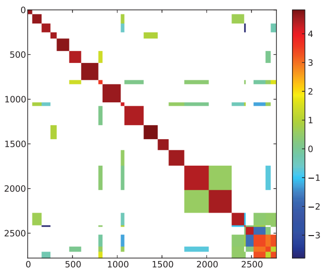
Figure C.1: Cores, communities and statistical validation



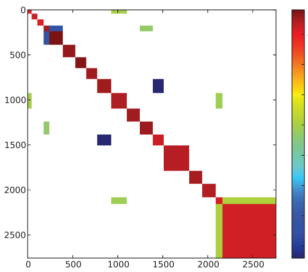
(a) 1952



(b) 1960



(c) 1972



(d) 1983

Figure C.2: Community detection results. The squares on the main diagonal are proportional to the node size of communities. Colors correspond to z-scores.

D Supplementary Information

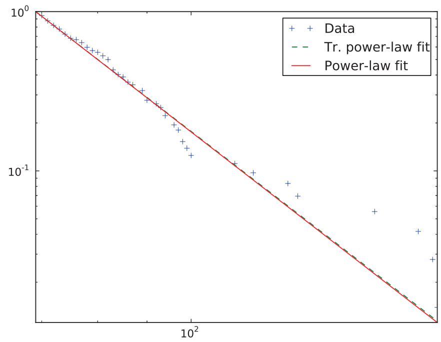
LLR	1952	1960	1972	1983
trunc. powerlaw vs powerlaw	0.0053	0.1161	0.0114	6.8915
(p-value)	0.9183	0.6299	0.8802	0.0002
trunc. powerlaw vs lognormal	0.0143	0.0218	-3.5936	0.9196
(p-value)	0.8739	0.4123	0.0258	0.0088
trunc. powerlaw vs exponential	1.7598	0.2333	0.6896	1.8434
(p-value)	0.2574	0.6792	0.3513	0.2600
trunc. powerlaw vs stretched exp.	51.937	30.822	22.885	120.14
(p-value)	0.0000	0.0000	0.0000	0.0000

(a) Degree

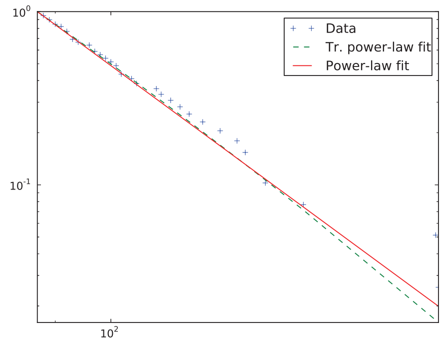
LLR	1952	1960	1972	1983
trunc. powerlaw vs powerlaw	10.941	6.0232	0.0544	14.726
(p-value)	0.0000	0.0005	0.7414	0.0000
trunc. powerlaw vs lognormal	0.9027	0.7012	0.0160	0.9926
(p-value)	0.1173	0.0460	0.5676	0.1074
trunc. powerlaw vs exponential	1.0405	0.5624	2.0122	1.0392
(p-value)	0.5095	0.5727	0.3080	0.5111
trunc. powerlaw vs stretched exp.	83.018	81.049	60.732	132.35
(p-value)	0.0000	0.0000	0.0000	0.0000

(b) Strength

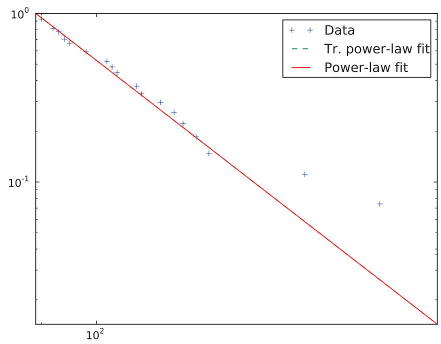
Table D.1: Log-likelihood ratios of alternative degree / strength distributions



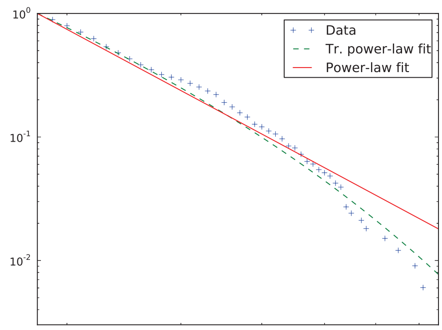
(a) 1952



(b) 1960

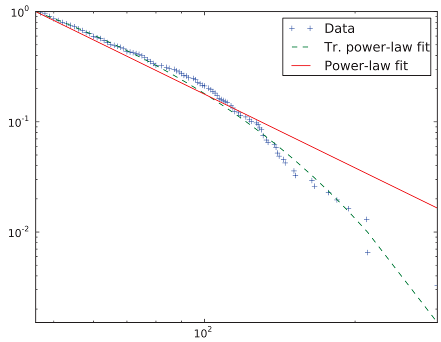


(c) 1972

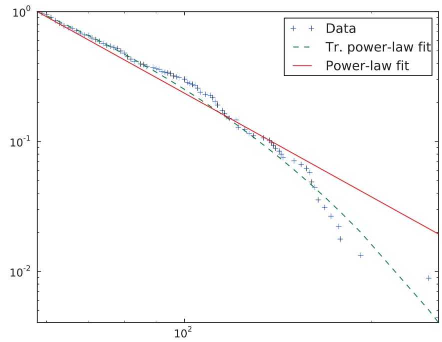


(d) 1983

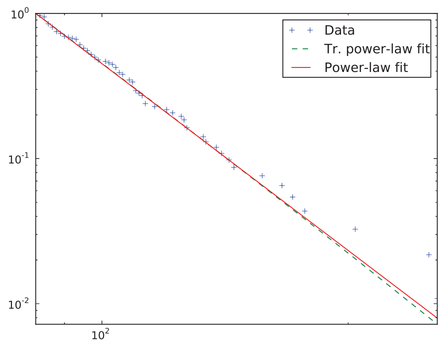
Figure D.1: Degree distributions and fit



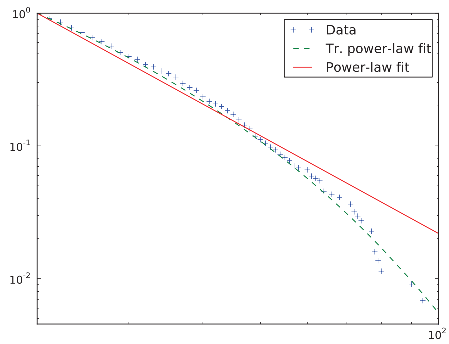
(a) 1952



(b) 1960



(c) 1972



(d) 1983

Figure D.2: Strength distributions and fit.

```
Coefficients
              Estimate  Std. Error  z-value  Pr(>|z|)
Y.f1952      0.12728935  0.02150346   5.9195 3.230e-09 ***
Y.f1960      0.02785868  0.01597402   1.7440 0.0811593 .
Y.f1983     -0.79656967  0.02549124 -31.2488 < 2.2e-16 ***
A            0.09347088  0.02953806   3.1644 0.0015539 **
A^2         -0.00041912  0.00092088  -0.4551 0.6490134
b            0.76346588  0.01759842  43.3826 < 2.2e-16 ***
EN           0.00645830  0.07900343   0.0817 0.9348478
EF           0.71708083  0.08054388   8.9030 < 2.2e-16 ***
IR           0.06538786  0.04744116   1.3783 0.1681126
L            0.11651034  0.04471587   2.6056 0.0091721 **
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
Total Sum of Squares: 24103
Residual Sum of Squares: 2320.1
Multiple R-squared: 0.90374
```

Table D.2: Unrestricted FGLS with a quadratic term in A (see Sec. 8), dependent variable: log - degree (k). Sectoral effects not displayed.

```
Coefficients
          Estimate  Std.Error  z-value  Pr(>|z|)
1952      0.251953   0.018193  13.8486 < 2.2e-16 ***
1960      0.129061   0.013794   9.3566 < 2.2e-16 ***
1983     -0.585260   0.028399 -20.6089 < 2.2e-16 ***
A         0.113993   0.008647  13.1829 < 2.2e-16 ***
b         0.498213   0.013330  37.3748 < 2.2e-16 ***
ENI      -0.157236   0.172823  -0.9098 0.3629226
EFIM      0.834766   0.106331   7.8506 4.139e-15 ***
IRI       0.169895   0.062409   2.7223 0.0064832 **
LS        0.160822   0.077232   2.0823 0.0373118 *
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
Total Sum of Squares: 9795.8
Residual Sum of Squares: 1118.2
Multiple R-squared: 0.88585
```

Table D.3: Unrestricted FGLS for a subsample of smaller firms (see Sec. 8), dependent variable: log - degree (k). Sectoral effects not displayed.