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Assessing the role of technological districts in regional innovation policies: a network analysis of collaborative R&D projects

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Abstract

As highlighted in systemic approaches to innovation, regions play an increasingly important role in designing and implementing place-based innovation policies. A wide debate has emerged on the limits and validity of different policy models, for example, between "platform" and "district-based" approaches or between a "corporatist" and an "evolutionary" Triple Helix. Within the EU Cohesion Policy framework, a number of technological districts (TDs) have been established since 2005 in the Italian "Convergence" regions to foster competitiveness, innovation, and research industry linkages. TDs have become critical actors in knowledge and technology transfer processes, and a significant amount of funding has been devoted to their development in the National Operational Programme for Research and Competitiveness (PON-R&C). In this work, we use methods drawn from social network analysis to locate TDs within the wider collaboration networks established through the PON-R&C programme. We highlight the specificity of TDs within the general policy and assess their ability to promote organisational and sectoral heterogeneity among project participants. We find that different network architectures coexist under the same policy umbrella and relate this variety to the ideal models identified in the literature.

Keywords Innovation networks · Technological districts · Regional development · Cohesion Policy · Policy evaluation · Social network analysis

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1 Introduction

Systemic theories of innovation have long suggested that place-based innovation policies should play a crucial role in building regional advantage (Cooke, 2007, 2012). The relevance of the regional perspective on innovation extends well beyond academic circles, as regional innovation policies have become a key component of the "smart specialisation" approach (RIS3) elected by the EU as its core strategy for the transition to a knowledge-based economy and the reduction of territorial inequalities (Barca, 2009; European Commission, 2012). Recognising that pathways to establishing or reinforcing a place-based innovation system can vary according to the local context, the RIS3 approach intends to overcome the "copying the best practices" approach that characterised earlier phases of EU regional policy. It does so by encouraging plurality within a common policy design that establishes shared procedures for the planning, implementation, monitoring and evaluation stages.[1]

Given the greater plurality that characterises the new EU regional innovation paradigm, it is relevant to ask whether the specific institutional designs adopted in each region and the actual innovation platforms that emerged from their implementation are consistent with the objectives set in the planning stage. Since one of the key aims for regional innovation policy is the transformation of the regional knowledge network, we believe that social network analysis provides a useful set of tools for assessing the coherence between the structure and composition of regional innovation networks and the policy objectives set out in the planning phase.

With this aim in mind, the study focuses on the National Operational Programme for Research and Competitiveness (hereafter PON-R&C) that financed innovation networks in the Italian Convergence regions through EU development funds. The funds were specifically targeted at the creation or further strengthening of Technological districts and Public–Private Laboratories, coalitions of heterogeneous actors (firms, universities, research centres, intermediary organisations, local governments) characterised by a permanent governance structure and formally recognised by the Italian Ministry of University and Research.

The paper seeks to assess the coherence between the strategic objectives set by the regions and how the internal and external connectivity of the subsidised innovation networks changed as the sub-programme unfolded. We also intend to investigate how Technological Districts (TDs)—the most formalised among the supported organisational models—integrate and interact with the wider innovation networks generated by the policy in these regions. We focus exclusively on assessing the effectiveness of the policy (the coherence between what has been done and what was originally planned), without attempting any consideration about its efficiency (the ratio between the resources mobilised and the obtained outcomes).

In EU evaluation parlance, our analysis can then be said to concern operational objectives rather than results and impacts. In other words, we assume that the creation of an innovation network between heterogeneous actors is in itself a desirable objective of the policy. In this respect, we adhere to the official EU evaluation framework which lists the number of enterprises cooperating with research institutions and the number of firms

[1] Member states and regions are required to produce a strategy according to the RIS3 guidelines before they can receive EU financial support through the Structural Funds (European Commission, 2012).

receiving financial support for collaborative projects among the core output indicators for Research and Innovation (R&I) policies. We nonetheless expand on this framework by considering not only the composition and internal density of the networks (the number of firms engaged in collaborative projects with research institutions), but also by tracing the changes over time of (*a*) the structural features of the networks established within each TD and (*b*) the nature and number of channels linking the internal TDs networks to the wider innovation network generated by collaborative projects taking place outside the boundaries of these formal organisations.

For the empirical analysis, we adapted to our case study the typology of Regional Innovation Systems proposed by Benneworth and Dassen (2011). Their classification of internal and external network connectivity was operationalised through measures and indicators specifically designed for the two-mode networks that represent the participation of actors in subsidised projects. The networks were built from relational data recording the joint participation of different types of actors to R&D projects financed within the sub-programme. We supplemented the relational data with individual-level data on actors and projects drawn from different sources.

The remainder of the paper is organised as follows. Section 2 introduces the theoretical background. Sections 3 and 4 describe how regional innovation strategies have been articulated in European and Italian policy, focusing on regional models and organisational forms that emerged from their implementation. Section 5 provides financial information on the PON-R&C. The sources and methods for constructing the relational dataset are detailed in Sect. 6, while results from the network analysis are in Sect. 7. The concluding section summarises the main findings alongside some indications for future research.

2 Systemic approaches to regional innovation policy

The networked nature of the innovation process provides a common ground for several influential conceptualisations of the knowledge-based economy, such as the New Production of Knowledge approach (Gibbons et al., 1994; Nowotny et al., 2001), the national (or regional) innovation systems perspectives (Cooke et al., 1997; Freeman, 1997; Lundvall, 1988) and the Triple Helix model of university-industry-government relations (Etzkowitz & Leydesdorff, 1997, 2000; Leydesdorff & Meyer, 2006). The (explicit or implicit) normative prescriptions associated with these approaches (Hessels & Lente, 2008) are being integrated into policy designs that aim at “constructing advantage” (Cooke & Leydesdorff, 2006) in Regional Innovation Systems (RIS) through increased collaboration between heterogeneous actors from the market, government and scientific realms.

Within both Economic Geography and Science and Technology Studies, there has however been an increasing recognition that the policy prescriptions associated with systemic views of innovation can be differently declined according to the local economic, institutional and socio-technical environment. Viale and dall’Orto (2002), Viale and Pozzoli (2010) identify, for example, two possible implementations of the Triple Helix, the “neo-corporatist” and the “evolutionary” model. The former is characterised by the direct intervention of national and regional governments in the design and implementation of academy-industry collaborations, generally through public planning and the provision of substantial economic support for network building. In the evolutionary implementation of the TH model (or *weak Triple Helix)*, government intervention has a more limited scope, since its main aim is to create an institutional context that favours the bottom-up emergence of hybrid innovation actors through selective incentives.

Within the field of Evolutionary Economic Geography, a parallel discussion has ensued on the relative merits of "district-based" and "platform" approaches to the construction of regional advantage (Asheim et al., 2011; Cooke, 2007, 2012). District-based approaches are criticised for being driven by a "picking-the-winner" logic. In this approach, the regionalisation of innovation policies, in fact, is equated with the promotion of specific sectors or local clusters that are identified a priori by nationallevel policymakers as promising targets of public intervention. In contrast, a platform-based approach seeks to mobilise related variety and the integration of differentiated knowledge bases, in this way mimicking (or accelerating) the processes that lead to the spontaneous evolution of regional-based growth sectors.

Apart from the variety of policy designs, the characteristics of technologies also appear to affect the effectiveness of government interventions in favour of innovation (Dolfsma & Seo, 2013). In a case study of Portugal, Salavisa et al. (2012) found that sectoral differences affect firms' networking behaviour, while Spithoven et al. (2021) found that regional context and geographical distance in Belgium impact the likelihood of firms to contract research out to universities. Furthermore, attitudes towards the "third mission" of the entrepreneurial university are not homogeneous across disciplinary divides (Philpott et al., 2011) and geographical proximity favours the transfer of knowledge and technology from universities to industries (Calcagnini et al., 2016). For recent evidence on university-industry knowledge transfer and how it takes place in Italy, see Grimaldi et al. (2021).[2]

The idea that public intervention should promote rather than flatten regional diversification has found wide currency in European policy circles (see for example Barca, 2009; European Commission, 2012). This has been in particular through the increasing centrality given to the twin although not altogether identical concepts of "Constructing Regional Advantage" and "Smart Specialisation" (Boschma, 2013). As will be clarified in Sect. 3, the shift to the place-based innovation model is also part of a more general move within the EU towards a multilevel governance system, whereby local actors are recognised as better capable of interpreting local needs and potentialities than their national-level counterparts.

The emphasis on local-level interactions as the source of competitive advantage in RIS has however been counterbalanced by an increasing recognition that spatially-bound processes necessarily interact with the global articulation of production and knowledge networks (Yeung, 2006; Yeung & Coe, 2015). The relevance of the local–global nexus to the sustained development of RIS has been most influentially expressed through the "local buzz, global pipelines" metaphor by Bathelt et al. (2004).

Drawing on these strands of literature, Benneworth and Dassen (2011) have proposed a classification of Regional Innovation Systems according to their internal and external connectivity (Fig. 1). In terms of the possible ideal configurations of their internal connections, RIS are classified as centralised, decentralised dense and decentralised sparse depending on the extent to which actors within the RIS are all connected to each other, and on whether their connections depend upon the intermediation of some focal actor(s). When looking at external connectivity, the distinction between different typologies relies instead

[2] On these aspects, see the contributions that appeared in the Special Section"University Technology Transfer, Regional Specializations, and Local Dynamics: Lessons from Italy", The Journal of Technology Transfer, Volume 46, Issue 4 (2021).

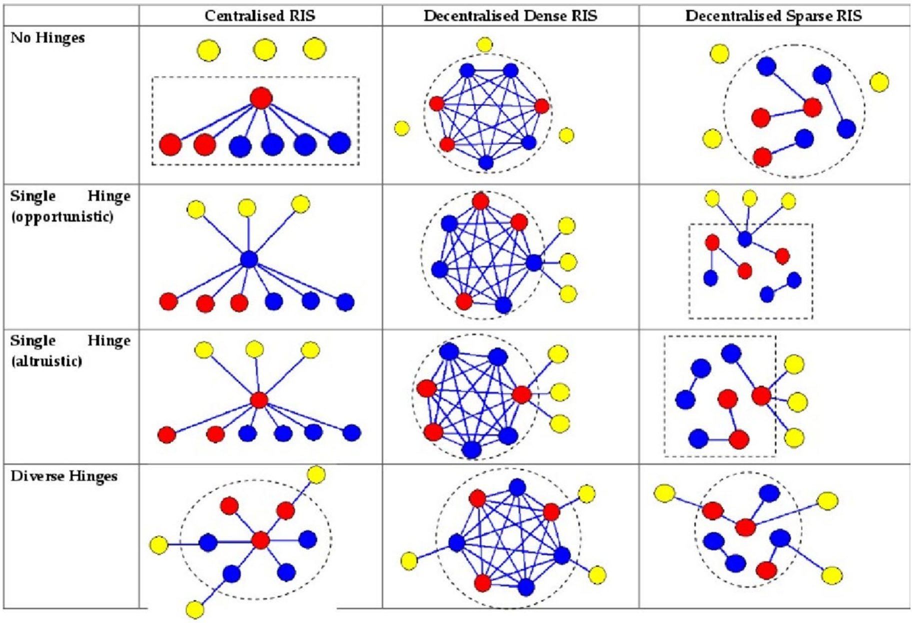

Fig. 1 Typologies of regional innovation systems. Source: (Benneworth & Dassen, 2011)

on the number and nature of "hinges", i.e. actors that connect the RIS to external innovation and/or production networks.

Based on their characterisation of RIS, Benneworth and Dassen propose different "styles" of policy intervention to improve a region's internal density and external connectivity. They term these different policy orientations: connecting globally; cluster-building; sustaining momentum; and deepening pipelines. Furthermore, they map the typology of RIS presented in Fig. 1 to a matrix of optimal operations for building local connections (Benneworth & Dassen, 2011, p. 70). Given its capacity to link ideal local/global network configuration to desirable policy objectives, we will refer to this typology to assess whether the transformation of the funded innovation networks in Italian Convergence regions responds to the aims stated in policy documents. The operationalisation of the typology through social network analysis and its application to our case study will be discussed in Sect. 6.

3 The EU innovation policy framework

As remarked in the previous section, the systemic vision of innovation has led to a new innovative model for countries' economic development, influencing the EU innovation policy agenda and the national strategies of its member states. R&I policies are crucial to fostering the competitiveness of economic systems and reducing socioeconomic disparities among member states and localities.[3]

The innovation policy under scrutiny is based on the Smart Specialisation concept (Foray et al., 2009). It serves as a key element in developing place-based innovation policies, facilitating the transition to a knowledge-based economy, and reducing territorial inequalities (Barca, 2009; European Commission, 2012). The underlying rationale is that Smart Specialisation enables regions to enhance their competitiveness by leveraging scale and scope economies and benefiting from spillovers in knowledge production and use, which significantly drive productivity.

The economic rationale stems from the studies in the fields of "knowledge for growth", endogenous growth theories, "Innovative milieux", Evolutionary Economics, Economic Geography, Industrial districts and the "Competitive advantage of Porter". Thus, in the context of R&I interventions, there seems to be no single theory governing these mechanisms, resulting in a combined theoretical approach. As pointed out by Farole et al. (2011), indeed, there has been considerable progress in understanding the sources of uneven economic development at different scales. The traditional theories of economic growth would have been complemented by three principal advances in (a) economic geography, especially concerning spatial agglomeration and transport-trade costs, in (b) economic growth theories, with a focus on the sources of innovation and knowledge-creation in the economy, and in (c) institutionalist theories which focus on the capacities of economies to absorb knowledge and innovate. The theoretical approach encompassing all these perspectives could enhance our understanding of the driving forces and barriers for convergence among territories, thereby suggesting new foundations for economic development policy.

In European policymaking, the political responsibility for the design and implementation has been decentralised over time on different levels with a growing role for regions (European Commission, 2009). Therefore, the decentralization process assumes greater importance, given that Smart Specialisation aims to generate assets and capabilities based on the region's distinctive industry structures. According to Barca (2009), the motivations that justify a change in the mechanisms of the decisional processes are based exactly on the strength of place-based development policies in facing concretely the local needs.

The "new paradigm of regional policy" is based on a multilevel territorial strategy with the following objectives: the implementation of specific interventions depending on territorial assets and their spatial linkages; the identification and aggregation of knowledge and preferences of local actors. The new model indicates a transition from an approach based on the replication of *best-practices* with a *top-down* governance method to an approach based on local assets, experiences and the creation of independent local development models (Barca, 2009). To this aim, the Technological Districts (TDs) and Public–Private Laboratories (PPLs) have become pivotal elements in the innovation strategy, being explicitly designed for the generation, diffusion and exploitation of knowledge.

How has the Italian government adopted the communitarian directives on research and innovation? Italy employs various innovative policy instruments with distinct goals. Concerning those aimed at developing and strengthening innovative networks and public–private aggregations for technological transfer, the Italian experience is relatively recent. The promotion of local systemic aggregations to develop firms' innovation capacity and local

[3] In 2000, the "Lisbon Strategy" highlighted the importance of an economy based on knowledge and innovation, followed by the "Europe 2020 Strategy", the "Horizon 2020" and the recent "Horizon Europe" funding programme.

competitiveness dates back to 2002. However, the definition and implementation of TDs and PPLs as specific policy instruments were specified in the National Research Programme 2005–2007 for the Convergence regions.[4] To this aim, for the period 2007–2013, the central government launched the main operative instrument object of this study: the PON-R&C. Within the Convergence regions (Calabria, Campania, Puglia and Sicilia), Action Line 1 funded the constitution of high-technology districts and connected networks (Measure 1.3.1) and public–private laboratories and connected networks (Measure 1.3.2) with the specific objective of supporting structural changes and the transition to a knowledge economy.[5]

However, it is worth mentioning that funds management has been inadequate due to difficulties in complying with the EU rules. This has brought Italy to plan a procedure of reprogramming interventions and resources to avoid the risk of the automatic de-commitment of funds with the *Piano di Azione Coesione* (hereafter PAC).

4 The variety of arrangements and regional strategies

The regional innovation strategies in Southern Italy exhibit common features influenced by similar levels of socio-economic development and factor endowments. Each region has subsequently developed its strategy based on place-specific features, emphasising the weaknesses and strengths. An analysis of key regional policy documents is summarised in Table 1, highlighting their innovation strategies.

To implement the RIS3 strategy, the European Commission (2012) shared a model for the economic development potential of regions, which suggests the paths for their economic renewal based on the experience of OECD regions.[6] According to the family of strategies in the framework, we determined for each region a position depending on their implemented policies, trying to understand if and how they have moved away from the recommendations. Along the dimensions of the knowledge intensity of productive fabric, all the regions are arranged in the category "Non-S&T-driven regions" among the type "structural inertia or deindustrialising regions", with the support to socio-economic transformation as a strategic choice, and the creation of knowledge-based capabilities and the building on currents advantages as the main priority strategy.[7] Regarding internal and external connectivity of the regional innovation systems, the Southern Italy regions could be arranged among the peripheral areas lacking research strength and international connections but with solid local clusters well-networked. So, the challenge is to build a global pipeline and build up new regional hinges connected to regional firms (building critical mass), implementing policy initiatives to help actors start international cooperation and attract outside actors (Benneworth & Dassen, 2011).

[4] The strategic sectors of intervention are grouped in three macro areas: (1) Environment, energy and transports; (2) food and agriculture, health; (3) System of manufacturing, biotechnology, new materials and nanotechnology, ICT, cultural assets.

[5] Before the National Research Programme 2005–2007, public–private laboratories were conceived only as projects within the technological districts, assuming later the shape of "organisational model" for the technological transfer.

[6] See Tables 3 and 4, pp. 48–49.

[7] OECD refers to them as "regions with persistent underdevelopment traps facing a process of deindustrialisation or experiencing structural inertia. They have considerably lower GDP per capita than other groups and the highest average unemployment rate. Values on S&T-related indicators are low" (OECD 2011).

Table 1 The regional strategies

Region	Strategic sectors	Weaknesses	Established TDs	TD reference model**
Puglia	Food and Agriculture; Aerospace; Automotive; Technologies for Living; Health; Nanotechnology; Energy	Industry localized in three geographical areas; Industry dualism (few large firms and SMEs); Weak links with industry	Dare; Dhitec; Medis; Ditne; DTA*; HBIO*	Corporate research center; New entrepreneurship and attraction of investments (typical model in Italy); Technological transfer and services to SMEs
Campania	New Materials; Aerospace; Cultural Heritage; Transport and Logistics; Energy; Biotechnology; Sustainable Construction	Industry dualism (few large firms and SMEs); Traditional sectors with low technological content; Weak links with industry	Imast; Dattilo*; DAC*; Databenc*; Smart Power System*; Campania Bioscience*; STRESS*	Corporate research center
Calabria	Cultural Heritage; Logistics and Transport; Cyber Security; Agro-industrial Manufacturing	Industry dualism (few large firms and SMEs); Weak aptitude of firms in R&I activities; Weak links with industry	R&D Log; Cultura e Innovazione; Cyber Security*; AGRIFOOD-TECH*	New entrepreneurship and attraction of investments
Sicilia	Steel and Nautical Industry, Traditional Manufacturing Industry, Microelectronics, Cultural Heritage	Industry dualism (few large firms and SMEs); Traditional sectors with low technological content; High skilled human capital; Very low aptitude of firms in R&I activities; Weak links with industry	Micro e Nano Sistemi (formerly Etna Valley), AgroBioPesca, NavTec, BIO-Med*, DISAM*, ENV-ITECH*, DTBC*	Corporate research center, New entrepreneurship and attraction of investments

*New TDs established with Decree n.713/Ric. 2010

**The Reference models shown in table refer only to those TDs established before the Decree n.713/Ric. 2010

The innovation policies of the Convergence regions seem to comply with these recommendations, at least concerning the implementation of the policy instrument TD. In fact, according to the regional level of knowledge intensity, these policies are grounded on their local advantages, clearly identified in the policy documents, and are implemented with a set of parallel measures aiming at creating and developing knowledge-based capabilities. Finally, regarding the connectivity of innovation systems, the most common reference models adopted for their creation, that is, “new entrepreneurship and attraction of investments” and the “corporate research centre”, respond to the main policy options suggested in the OECD framework.

5 The PON-R&C programme: basic indicators

This section provides basic indicators about the implementation of the PONR&C programme in the convergence regions. The following summary tables describe projects funded by the policy within Action Line I. In particular, the tables specify the contribution of the PON-R&C to the strengthening and consolidating of districts and existing laboratories, both in creating new districts and public–private combinations.

The total financial resources mobilised by the policy until the end of 2014 are provided in Table 2.

Notably, PON-R&C has funded 3,589 projects with about 4.7 billion Euro. Campania is the region that initiated the highest number of projects (1,693). When we narrow our selection to projects undertaken in the specific intervention lines I.3.1 and I.3.2 (namely, “strengthening Technological Districts and related networks” and “strengthening of public–private laboratories and related networks”), and examine the number of projects and financial resources devoted to the two lines, we observe that 136 projects were started with a total funding of about 800 Mln Euro, accounting for about 14% and 17% of the total

Table 2 The PON-R&C policy in the convergence regions

Region	Number of projects	Total cost (mln Eur)	Subsidy (mln Eur)	Subsidy (as percent of cost)
Calabria	640	2.479	1.889	77
Campania	1,693	3.099	1.425	47
Puglia	635	1.246	635	54
Sicilia	621	1.413	739	52
Total	3,589	8.237	4.688	57

Table 3 The PON-R&C funding for TDs and PPLs

Region	Number of projects	Total cost (mln Eur)	Subsidy (mln Eur)	Subsidy (as percent of cost)
Calabria	17	123.5	87.6	71
Campania	54	410.0	280.7	69
Puglia	43	364.5	267.1	73
Sicilia	22	251	180.6	72
Total	136	1.149	816	71

Table 4 The PON R&C share for the intervention lines I.3.1 and I.3.2

Region	Total cost (percentage values)	Subsidy (percentage values)
Calabria	5	4
Campania	13	20
Puglia	29	42
Sicilia	18	24
Total	14	17

PON-R&C, respectively. Even within these specific lines of action, Campania scores the highest number of projects among the regions covered by the policy, as can be seen from Tables 3 and 4.

Although TDs and PPLs constitute the main focus of the policy, not all the projects financed under the analysed intervention lines (I.3.1 and I.3.2) took place within or otherwise involved TDs. Therefore, we narrowed our scope to just four TDs considered in our analysis (Dare, Dhitec, Imast, AgroBio). However, in the following analysis, we include data for all the TDs in the four analysed regions as a term of reference. These data will be referred to as "None", to indicate that these projects and actors are not part of our analysed districts.

6 Methodology and data

The conceptual and normative emphasis on networked innovation systems within systemic approaches to innovation has opened a novel space for the use of methodological tools drawn from social network analysis (SNA) in regional economics and innovation studies. The potential contribution of SNA has been the focus of theoretical debates and comprehensive review articles in leading journals in the field (Cantner et al., 2010; Glückler, 2007; Ter Wal & Boschma, 2009). The literature on the evaluation of innovation policies has similarly recognised the usefulness of a network perspective. Alongside input and output additionality indicators traditionally associated with the linear model of innovation, evaluation models now often include *network additionality* indicators in order to account for policy-induced changes in the relational behaviour of actors involved in the innovation process.

In this case, social network analysis will be used to calculate structural and topological indicators that will help us classify the analysed Technological Districts according to the typology proposed by Benneworth and Dassen (2011). We will trace the evolution of these indicators over time in order to understand whether the networks constructed through the financial support of the policy have moved according to the policy recommendations advanced by Benneworth and Dassen, and whether these changes are compatible with the objectives stated in each region's strategic planning documents. In a similar vein, Biggiero and Angelini (2015) employed a topological approach focusing on the hierarchical structure of EU-subsidized research joint ventures networks in the aerospace sector, providing new evidence on the organizational structures within R&D projects and discussing the policy implications.

The relational data used for the study are based on affiliation matrices recording the joint participation of actors in collaborative R&D projects funded by the PON-R&C measures

1.3.1 and 1.3.2 described in Sect. 5. Our initial source for constructing the network was the open-access PON-R&C database, which lists all the beneficiaries (fund recipients) for each project.[8] Since the database is driven by a transparency logic in the use of public funds that only partially responds to the needs of a network analysis, the construction of the nodeset (the list of projects and the list of actors) required some manipulation of the raw data. The main choices and operations we performed on the data were the following.

In the PON-R&C database projects can be univocally identified at two nested hierarchical levels according to their Local Project Number (*Codice Locale Progetto*, hereafter CLP) or to their Unique Project Code (*Codice Unico Progetto*, hereafter CUP). The CLP corresponds to an overall project (e.g., the application of a new technology in a specific field or the development of a new material), while the CUP identifies individual lines of funding for distinct activities within the general project framework such as training, basic research activities, development and testing, technology transfer and so on. As we were interested in all types of connections established between project participants regardless of the kind of activities they were involved in, we decided to aggregate our data at the CLP level.

The beneficiaries listed in the PON-R&C database as participants in a project are instead identified as the legal recipients of funding within a specific CUP financing line. This creates several problems when attempting to construct an innovation network, as the legal accountability logic driving the dataset identifies highly aggregate entities that have little relation to the actual units participating in a project. For example, in the case of a university department, the beneficiary listed in the database is the central administration of the university. This means that there is no way to distinguish between individual departments of the same university; they would be conflated in a single node and would all appear to be participating in the same projects. The same happens in the case of the National Research Council (*Centro Nazionale delle Ricerche*, hereafter CNR), the largest public research institution in Italy articulated in laboratories and local centres which is instead represented as one single legal entity in the database. The identification of actors is further complicated because Technological Districts, Public–Private Laboratories and temporary consortia appear as the final recipients of funds in the PON-R&C database, while in reality they redistribute the funding among the subset of their members that actually take part in a specific project.

For this reason, we had to rely on different sources to disaggregate the nodeset into useful units of analysis: university departments, CNR laboratories, and individual member firms that participated in a specific project. Our supplementary sources were: the official websites of individual TDs, PPLs, projects and consortia; official project documents such as yearly balance sheets, contracts signed with firms and research institutions, calls for tenders and researchers; CNR, corporate and university websites. These sources were triangulated and, in the case of private firms, checked against company databases (*Aida*-Bureau van Dijk) to produce a list of harmonised actors' names disaggregated at the department/laboratory/firm level. After the two nodesets (actors and projects) were constructed, we could build the disaggregated affiliation matrices recording the participation of actors to projects.

The relational data we collected were therefore originally a two-mode network; for some of the analyses performed in this study, the data were projected onto a one-mode

[8] http://www.ponrec.it/

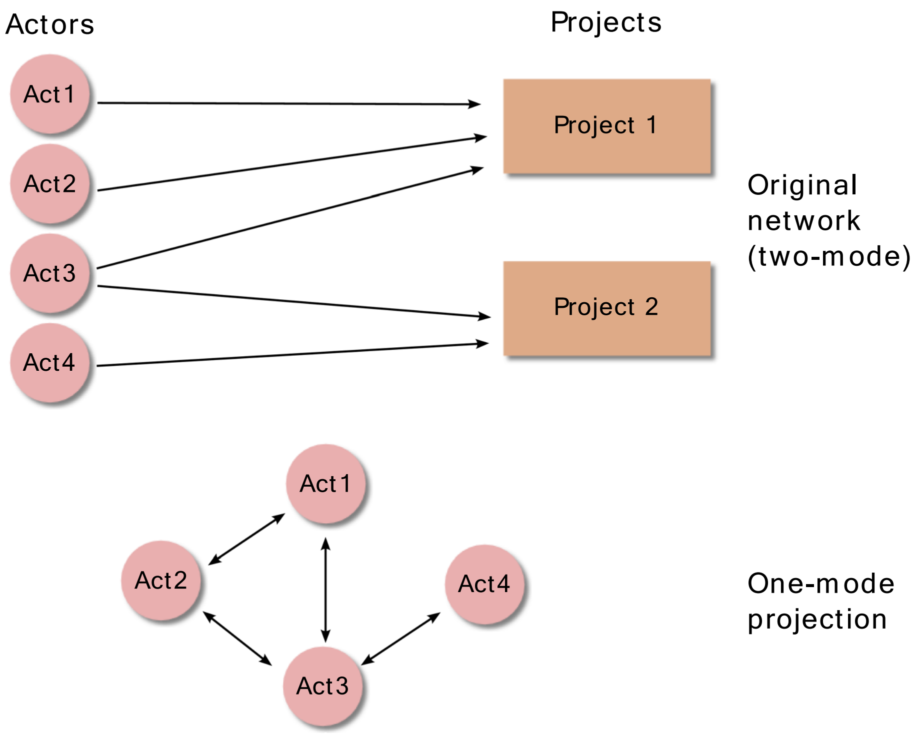

Fig. 2 Projection from two-mode to one-mode network data

Table 5 The affiliation networks

	All	Dare	Imast	Dhitech	Agrobio	None
Institutions	15	1	1	2	1	10
Firms	258	62	17	9	22	160
Universities	155	25	24	8	33	84
Total	428	88	42	19	56	254
Projects	133	5	14	10	6	98
Total	561	93	56	29	62	352

(actor-by-actor) matrix, in which actors *i* and *j* are linked by an edge if they took part in the same project (see Fig. 2). The edge can be binary (absent/present) or can be given a weight proportional to some selected feature of the two-mode network.

6.1 Data description

Table 5 presents the data used to create the affiliation networks at each time for each technological districts considered: Dare, Agrobio, Imast, Dhitech. The first four rows provide information about the number of actors in each TD by type of organization. The last two rows, instead, report the number of projects funded in each district over the whole period

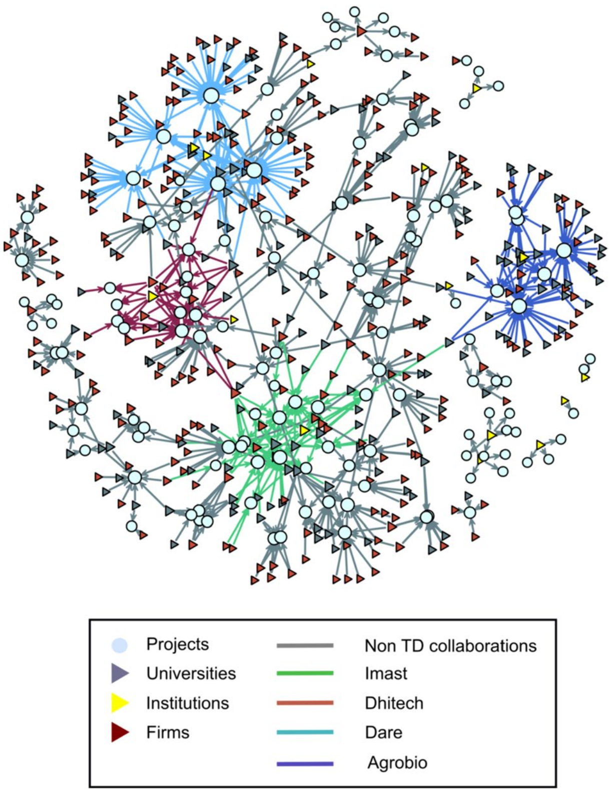

Fig. 3 The whole affiliation network

considered. As explained in Sect. 5, the data used for the study records collaboration beyond the four specific technological districts, including all R&D projects funded by the PON-R&C measures 1.3.1 and 1.3.2 in the targeted regions. We reported in the column labelled "None" the number of actors (254) and projects (98) that were funded by the program outside the four TDs considered. This represents the network of spontaneous collaborations occurring among firms, institutions and research centres without the direct involvement of the TD management, and they will be used to assess TDs network additionality.

The analysis of two-mode data is one of the least developed areas of social network analysis since most network indicators have been originally developed for one-mode data, and they result distorted when directly applied to two-mode matrices. While the projection of the two-mode network to its one-mode representation overcomes this limitation, the projection itself is not devoid of problems since the projection is at best a partial and inevitably a biased representation of the two-mode relational structure.[9] For these reasons we adopted, whenever it proved possible, SNA methods specifically designed for two-mode data or adjusted projection methods. Figure 3 shows the whole affiliation network. In this visualization, the four TDs are highlighted by link colour. Light-blue circles represent projects, while actors are triangles: red triangles denote firms, blue triangles represent research

[9] On these points see for example the contributions in the Special Issue on Advances in Two-Mode Social Networks, Social Networks, Volume 35, Issue 2 (2013).

centres and universities, and yellow triangles represent institutions. It is possible to see that the four districts are embedded in a wider network of non-TD members represented by grey ties. All the analyses presented in the following section were performed using the *sna* and *tnet* packages under the statistical software R.

7 Structure and trajectory of the networks

Figure 4 shows the changes in the two-mode network between 2005 and 2015. Since the cooperation formalised in project co-participation can be thought to extend in time before the actual start of the subsidised project (in the planning and funding application phase) and after the formal end of the project (in the exploitation phase), we trace the trajectory of

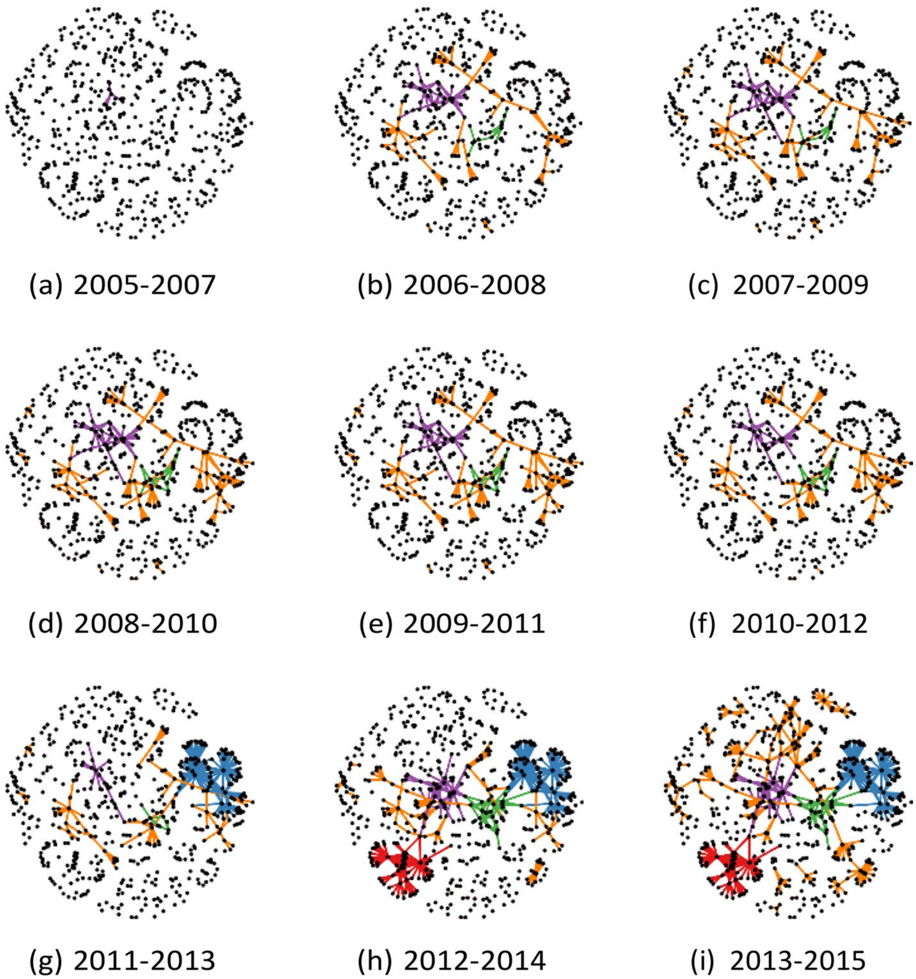

Fig. 4 The network at different times

the network using 3-years overlapping time slices (full-page figures are in the "Appendix"). As suggested by Batagelj et al. (2014), the use of overlapping time slices is appropriate in the case of large temporal networks as this technique smooths out the transitions between different time periods and permits to identify the underlying temporal patterns by reducing the noise due to momentary fluctuations. The length of the time windows (3 years) was chosen based on the average project duration. For each time window, links are considered present for all projects which were running in any year included in the corresponding time interval.[10]

In Fig. 4, blue squares represent projects and red circles represent actors; projects are aggregated at the CLP level. Nodes are positioned using the Fruchterman-Reingold algorithm on the full network for 2005–2015. Links are colour-coded to identify projects belonging to different TDs. Blue is used for the Dare district; green for Dhitech; purple for Imast; and red for AgroBio. Links painted orange correspond to projects that did not involve any of the analysed TDs.[11]

From Fig. 4 it is possible to observe that, after an initial period of growth, the network remains quite stable in the years 2008–2012, and its density only increases again after the adoption of the PAC stimulus for Structural Funds spending. This evidence highlights the critical importance of enhancing administrative capacity at the local level for an effective management of development funds and the achievement of policy objectives. It is also apparent that the positions of the analysed TDs in the overall network are quite different. While Imast and Dhitech occupy a central place in the network, Dare and AgroBio remain peripheral and only weakly connected to the rest of the graph. Furthermore, Dare seems to be primarily connected to its regional counterpart Dhitech.

Returning now to the Benneworth-Dassen typology, we have sought to operationalise the two axes used for the classification (internal connectivity and external connectivity) regarding the connections existing within and between each TD and the external collaboration network established in the Convergence regions with policy support (measures 1.3.1 and 1.3.2).

With regard to the first dimension (internal connections), we rely on two global network indicators: degree centralization and the global clustering coefficient. The former indicates whether the network is characterised by the presence of particularly prominent nodes (hubs with a significantly higher number of links than the network average) or conversely by a more egalitarian degree distribution.[12] The latter can be used to assess the degree to which nodes in a network tend to cluster together into tightly-knit groups.

When taken together, the two indicators can help discern different RIS types. A centralised RIS would have a high degree of centralization score since it would be close

[10] For example, the time window 2006–2008 includes all projects that were started before 2008 and whose end date was not earlier than 2006.

[11] This amounts to adopting a relational definition of the boundaries of TDs, rather than a membership-based definition. District members are identified according to their participation in projects involving the TD, whether or not they are formally listed in the roster of district members. More formally, we can say that a TD, as defined here, is an edge-induced subgraph of the entire network. This choice is consistent with the fact that districts have a dual membership structure composed of members (internal members) and partners (external members) and that, for most districts, the membership structure is not fixed in time.

[12] The degree centralization of a network is measured on a range between zero and one; it is zero when the degree distribution is entirely egalitarian, and one for star-shaped networks in which one node has degree $n-1$ and the remaining $n-1$ nodes have degree equal to one.

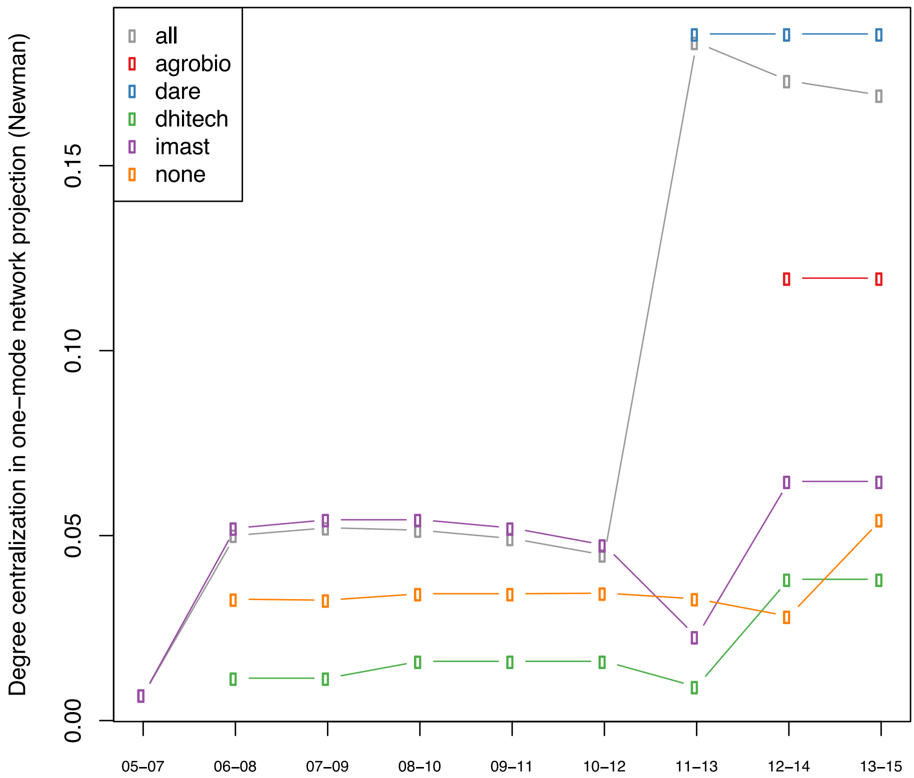

Fig. 5 Degree centralization

to a star-shaped graph, while a decentralised dense or decentralised sparse RIS would exhibit lower values on this indicator. A decentralised sparse and a decentralised dense RIS can further be distinguished based on the global clustering indicator, which would be higher for decentralised networks characterised by separate groups of tightly-knit nodes.[13]

Figure 5 shows how the degree centralization index has changed for the TDs as well as for the external network in the analysed timeframe. Following Opsahl et al. (2010), degree centralization measures have been adjusted for the two-mode network using the Newman weighted projection (Newman, 2001). The degree centralization coefficient clearly separates the TDs into two groups. The more decentralised group includes Imast and Dhitech, for both of which the indicators remain at a low level although with some increase after the PAC adoption. Similarly, decentralised is the nature of the network outside TDs, which also scores consistently below 0.05 on this indicator. Conversely, the AgroBio and even more the Dare districts show a markedly more centralised structure with the presence of

[13] The clustering coefficient ranges between zero and one; it is zero when there is no clustering and one for maximal clustering which happens when the network consists of disjoint cliques.

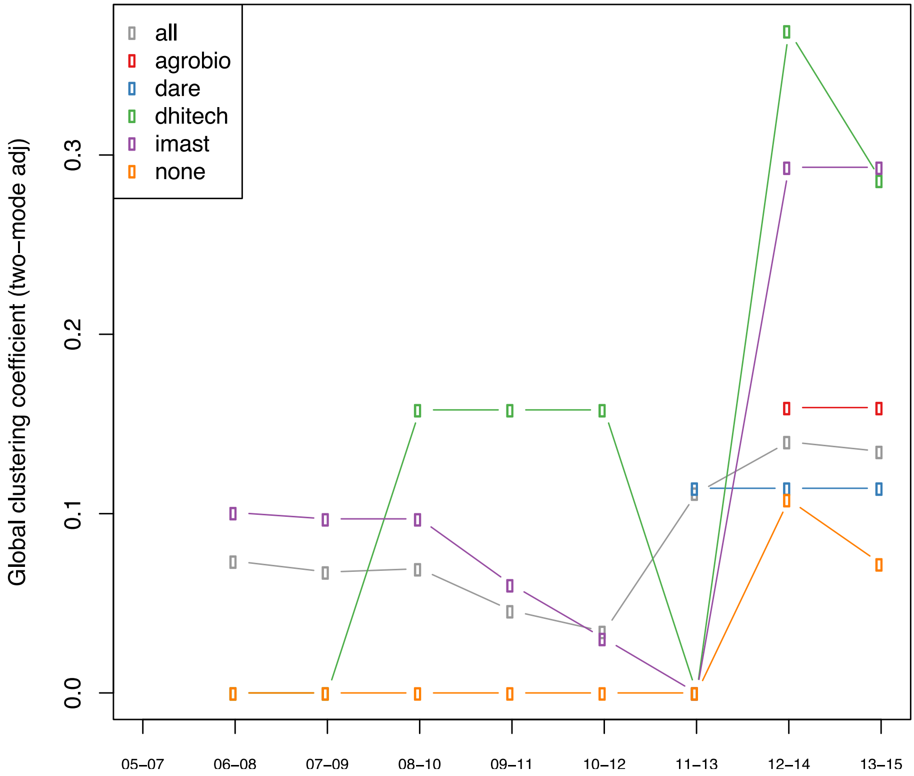

Fig. 6 Global clustering coefficient

prominent nodes and as such are closer to the Centralised RIS model in the Benneworth-Dassen's typology.

Figure 6 shows the changes in time of the global clustering coefficient for the four TDs and the external network. To account for the two-mode nature of the data, the adjusted global clustering coefficient has been calculated using the methodology proposed by Opsahl (2013). The same two groups identified above are also apparent in this case. Imast and Dhitech show, in fact, a similar pattern in the temporal trajectory of their clustering coefficient, starting both from a relatively lower value and shifting to a highly clustered structure after the implementation of the PAC. On the other hand, Dare and AgroBio's clustering coefficient remains relatively low throughout the period of their operation.

When taken together, the two indicators would signal a shift from Decentralised Dense RIS to Decentralised Sparse RIS for Imast and Dhitech, while AgroBio and Dare would seem to be closer to the Centralised RIS model. Although the latter two districts have been active project members for a much shorter time, they seem to be on a rather different path for the time being.[14]

[14] It is worth noticing that, although their active participation in projects has been shorter, both Dare and AgroBio were formally established at around the same time as Imast and Dhitech.

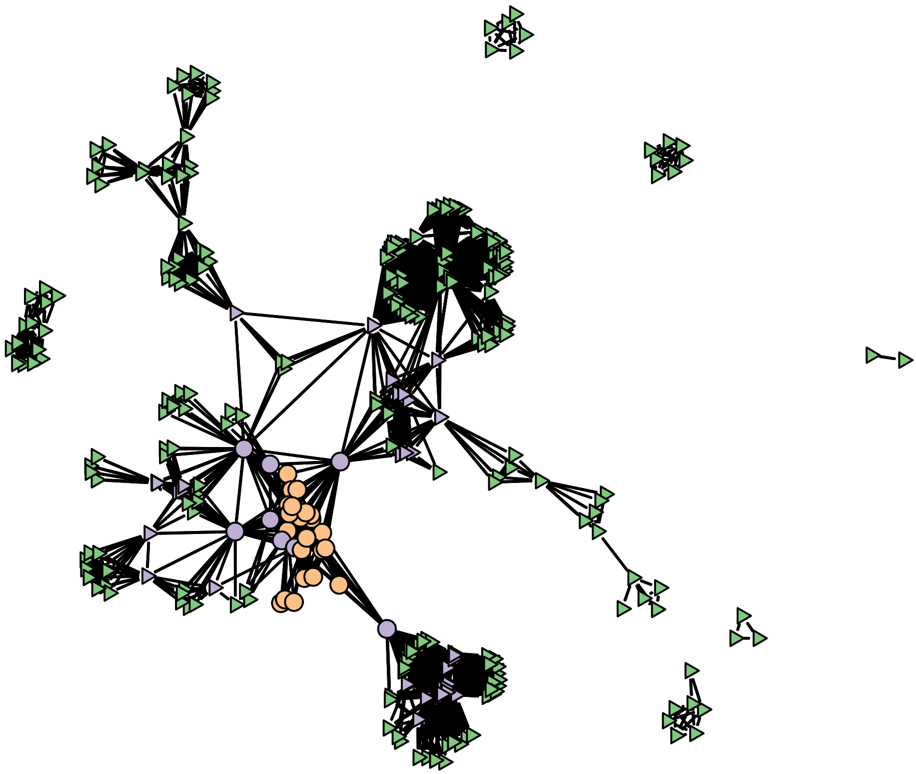

Fig. 7 Example of gatekeepers (IMAST in 2013–2015)

To assess the different modes of external connectivity referred to in the Benneworth-Dassen typology (no hinges, single hinge and diverse hinges), we performed a brokerage analysis to identify the actors (gatekeepers) that were spanning the boundaries of the internal and external network for each TD. Gatekeepers were identified in the one-mode network projection (actor by actor) using the Gould Fernandez brokerage analysis (Gould & Fernandez, 1989). As an example, Fig. 7 shows the gatekeepers that connect Imast district members to the external cooperation network subsidised by the policy. Circles represent district members, while triangles represent external partners. Internal and external gatekeepers can be identified by their violet colour; light orange is used for non-gatekeeping members and green for non-gatekeeping external partners.

The next three figures show the changes in the number of gatekeepers with reference respectively to: the number of internal nodes that have connections with nodes outside the TD (Fig. 8); the number of external nodes connected to the internal gatekeepers (Fig. 9); and the ratio between internal and external gatekeepers (Fig. 10).

Even in this case, the two groups of districts identified before seem to be following different patterns. In the case of Imast and Dhitech, the number of gatekeepers ("hinges") rises after the PAC and ends up being higher than in the remaining districts. This is particularly true with regard to the number of external connections that these gatekeepers are

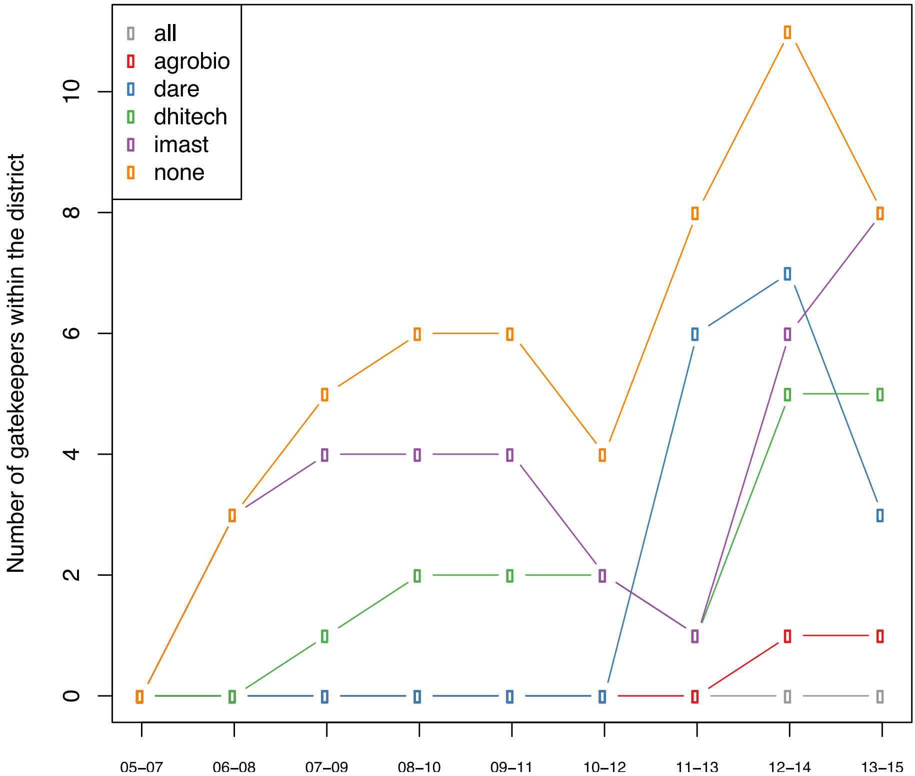

Fig. 8 Number of gatekeepers within the districts

able to activate. For all the districts, however, there is a tendency for internal gatekeepers to increase the number of their external connections, as shown by the declining ratio depicted in Fig. 10. When assessed in terms of their external connectivity, Imast and Dhitech would appear to have shifted from a single-hinge model to a diverse-hinges model, while this transition is much less evident for Dare and AgroBio.

Based on these analyses, we can then define two different trajectories for the two groups of districts. Imast and Dhitech have moved from a decentralised dense RIS with a single hinge model to a decentralised sparse RIS with diverse hinges. Agrobio and Dare have instead remained closer to the centralised RIS model, although they show signs of a transition from a single-hinge to a diverse-hinges model.

The evidence presented so far results from a straightforward approach we employed to analyze the policy. We used two network measures of centralization and clustering to operationalise the framework proposed by Benneworth and Dassen. This choice was made

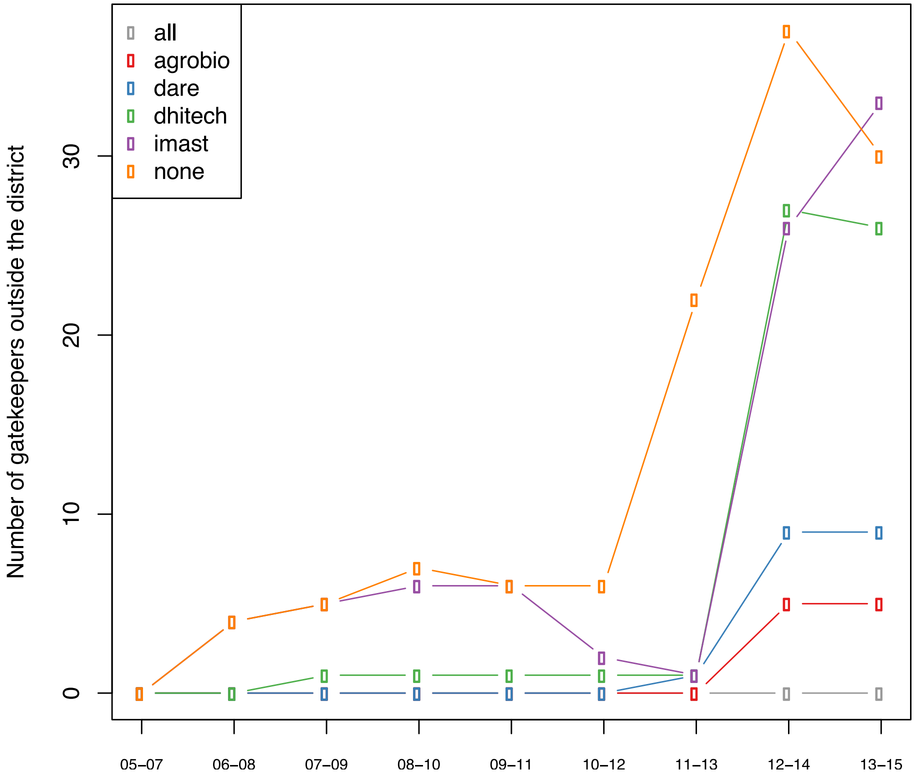

Fig. 9 Number of gatekeepers outside the district

to capture not only the connectivity within each TD (clustering) but also to assess the centralized versus sparse nature of the ties (centralization). Additionally, we used gatekeeper analysis to explore the connectivity of TDs through global pipelines.[15]

[15] We also explored other network statistics, including density. The results confirm the findings of the previous analyses: Imast and Dhitech exhibited relatively high density throughout the entire period, with a peak in 2011–13. On the other hand, Agrobio and Dare joined the network in 2012, maintaining a consistently low density of less than 0.3%.

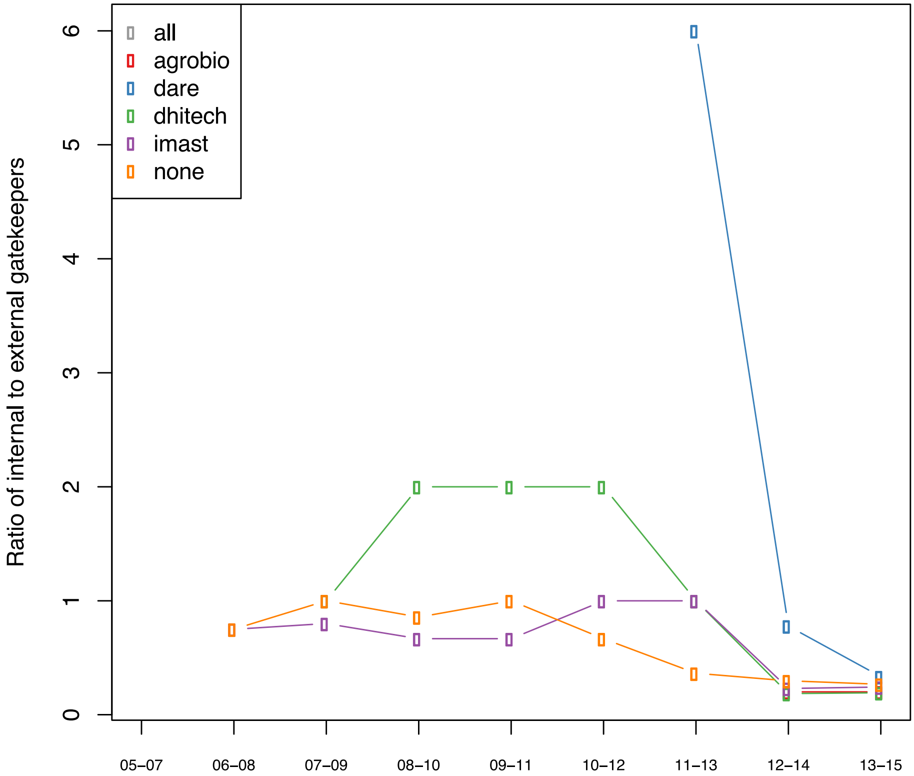

Fig. 10 Ratio of internal to external gatekeepers

8 Conclusions

This study presents a new approach for evaluating innovation policies based on a combination of social network analysis indicators. We analysed the PON-R&C programme implemented by the Italian government between 2005 and 2015 to foster scientific research, industrial competitiveness, and innovation in underdeveloped regions. Specifically, our focus was on two measures designed to increase R&D collaborations among heterogeneous actors (firms, universities, research centres) and strengthen technological districts as accelerators of innovations.

The proposed methodology aims to provide a tool for assessing the coherence between the strategic objectives set by the policy and the changes in internal and external connectivity of the innovation networks as the sub-programme unfolds. We also intend to investigate how Technological Districts (TDs)—the most formalized among the supported organizational models—integrate and interact with the wider innovation networks generated by the policy in the regions examined. First, we model R&D collaborations as networks that evolve over time. Subsequently, we follow the classification of network topologies proposed by Benneworth and Dassen (2011) to compare our observed collaboration networks with each other and over time.

Building on this classification, innovation networks can be categorised according to two main parameters: "local buzz" representing the connectivity between actors within the TD, and the "global pipelines", representing the capacity of the TD to connect to wider national and global R&D networks (Bathelt et al., 2004). In our analysis, we employed two network measures to capture the "local buzz": degree centralization and the global clustering coefficient. The former allowed us to determine whether the network is characterised by particularly prominent nodes, that is hubs with a significantly higher number of links than the network average (measuring therefore how hierarchical was the structure of local interactions). Conversely, to capture more egalitarian structures we used the global clustering coefficient, which provided a measure of the extent to which each node is embedded into nested cliques (density measure). Finally, to analyse the types of connections linking the TD to external partners, we conducted a gatekeeper analysis.

We found that the four Technological Districts (TDs) we analysed can be separated into two groups. The first group, which includes the Imast and the Dhitech districts, shifted from a decentralised dense RIS model with a single hinge to a decentralised sparse RIS model with diverse hinges. This result implies that these TDs emerged from a dense cluster of pre-existing collaborations dominated by lead firms. This is, for example, the case of Imast where a pool of large national companies such as Alenia, STMicroelectronics, ENEA, and CIRA were already established in the region. Over time, new hubs emerged and were able to establish direct connections with other national and international industries through specialized pipelines, such as FCA (Fiat Chrysler Automobiles). These results are in line with previous studies conducted on the case of Imast in the same period (Prota et al., 2013, 2017).

Our results also highlighted a second group of TDs (Agrobio and Dare) which appeared to be still close to a centralised RIS model. According to Benneworth and Dassen's framework, these configurations imply the TDs are still dominated by lead firms/institutions (high centralization coefficient) that selectively involve local actors within projects relying mostly on their external contacts. For instance, Dare district was led by public institutions and research centres such as CNR, and the University of Bari and Foggia. Similarly, for Agrobio the leading institution was the CNR and the University of Palermo. According to our framework of reference, this configuration of centralised RIS can be considered a first step to creating local clustering, but it can also give rise to opportunistic behaviours by the lead firm/institution.

The ultimate reason for tracing the topological evolution of the innovation networks funded by the PON-R&C was to assess the coherence between the objectives of the regional innovation policies and the actual nature of the networks elicited by their implementation. We also intended to investigate how Technological Districts (TDs)—the most formalised among the supported organizational models—integrate and interact with the wider innovation networks generated by the policy in the regions under analysis.

In such a situation, according to the RIS3 strategy, the main policy prescription would be to strengthen local networking in preparation for establishing global linkages. These objectives seem to have been achieved differently in the two groups of districts. In the case of Imast and Dhitech, the most established TDs, which have been running projects since 2005, there are signs that the networks subsidised by the policy have evolved in a direction that is consistent with these overall objectives. The dependence on a single (or a few) hinges has been limited, which according to Benneworth and Dassen also potentially reduces the chances for opportunistic behaviour on the side of the few externally connected actors. Different is the case of Dare and AgroBio, which have only started running projects in the aftermath of the PAC initiative. In this case, the networks remain highly centralised, dependent on a few focal actors for their internal connections, and have only marginally increased the number of external hinges. It would appear that in this case, the chances for opportunistic behaviour remain high since a few actors hold together the network and mediate the relations between the TDs and the external environment. Further insights on the properties and implications of networks can be found in Biggiero and Angelini (2015). They underline the relevance of scale-free topological properties of the networks for the resilience and sustainability of socio-economic systems, while also discussing the implications of these properties in relation to the effectiveness of research policies.

Finally, it is worth remarking on how the weak spending capacity of local governments during the policy period directly influenced structural changes and the transition to a knowledge-based economy in these regions, as demonstrated by the evolution of networks. This confirms the critical importance of enhancing administrative capacity at the local level for an effective management of development funds, a point recently emphasised by Peiró-Palomino and Perugini (2022) in relation to local innovation activities in Italy.

It needs to be kept in mind that this study provides a partial view of the operational objectives attained by the PON-R&C policy. Future extensions of the analysis could also look at the attributes of the actors and projects constituting the network, employing an Exponential Random Graph Model approach as in Spithoven et al. (2021). In this respect, grounding also on recent evidence on the development of the entrepreneurial ecosystems in Italy (Perugini, 2023), a closer look at the local spatial dynamics and the individual characteristics of the actors would help to understand and enhance the relevance of TDs and PPLs for knowledge transfer and knowledge spill-over. This notwithstanding, we showed that social network analysis can be usefully integrated into theory-driven analyses of Regional Innovation Systems since it provides the methodological tools for tracing and comparing the changes occurring in innovation networks undergoing place-based policy interventions.

Appendix

The evolution of the two-mode network presented in Sect. 7 is reported below with full-page figures for each time slice between 2005 and 2015. Blue squares represent projects and red circles represent actors. Links are colour-coded to identify projects belonging to different TDs. Blue identifies the Dare district, green is the Dhitech, purple is the Imast and red is the AgroBio. Links painted orange correspond to projects that did not involve any of the analysed TDs.

See Figs. 11, 12, 13, 14, 15, 16, 17, 18, 19.

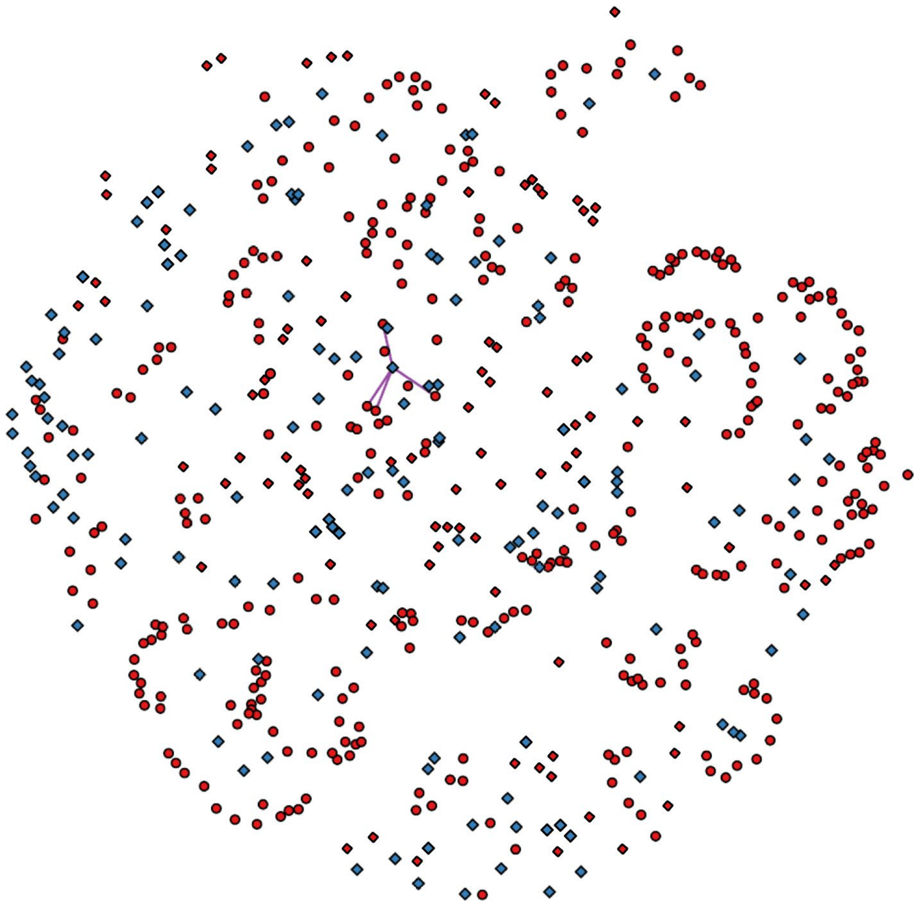

Fig. 11 2005–2007

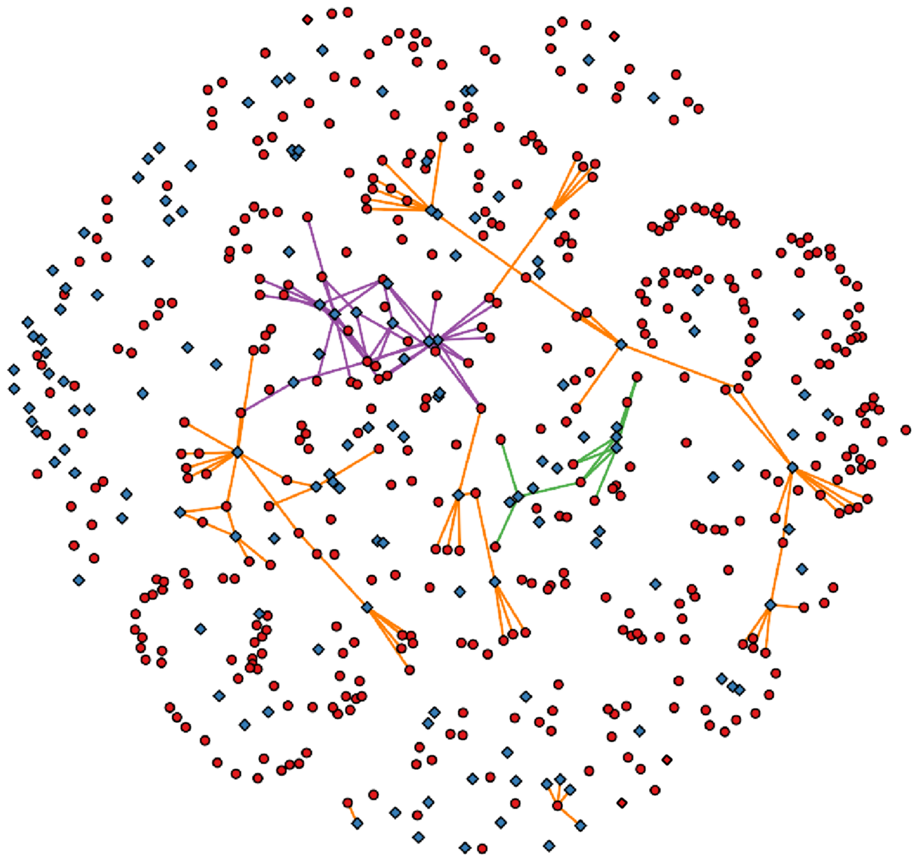

Fig. 12 2006–2008

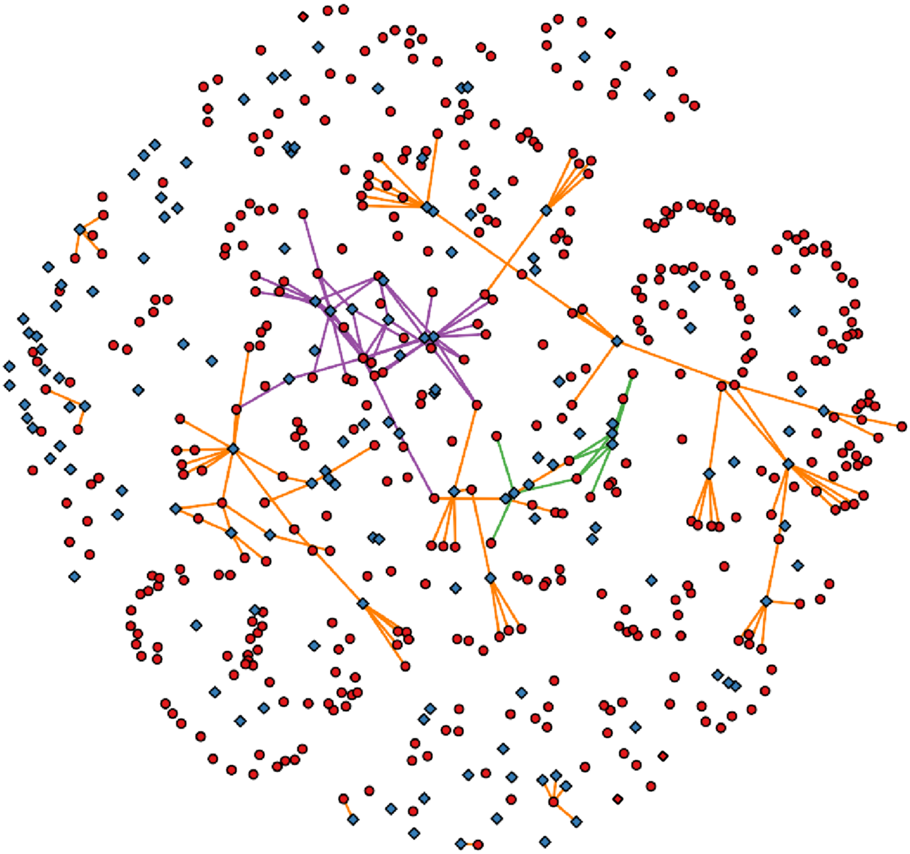

Fig. 13 2007–2009

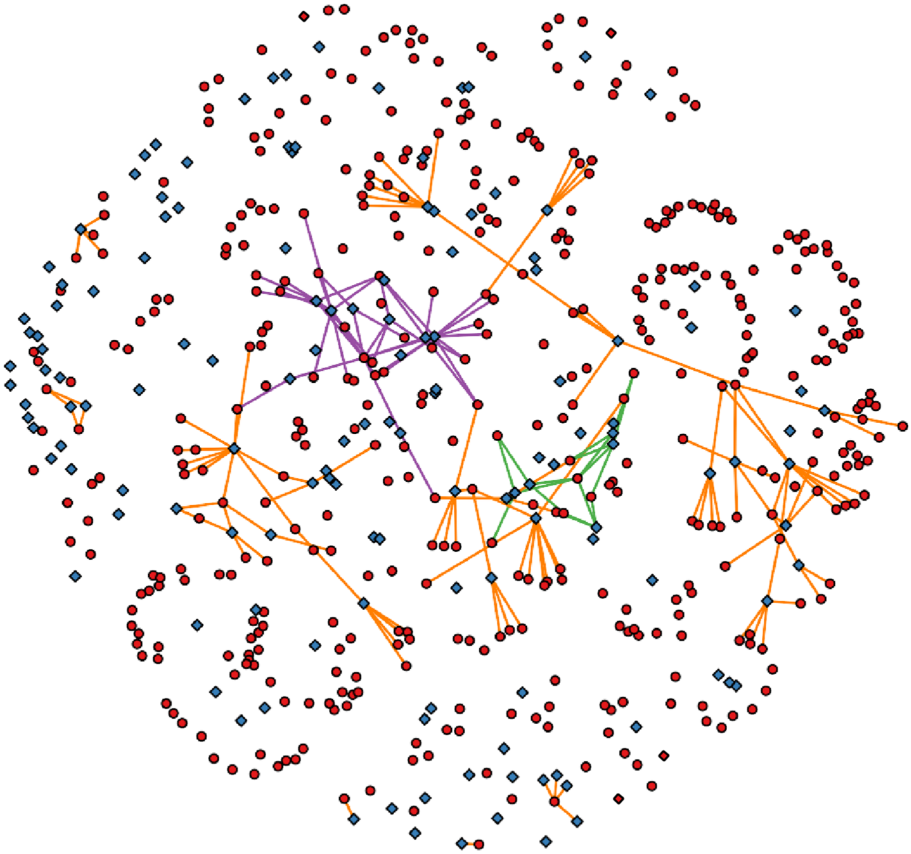

Fig. 14 2008–2010

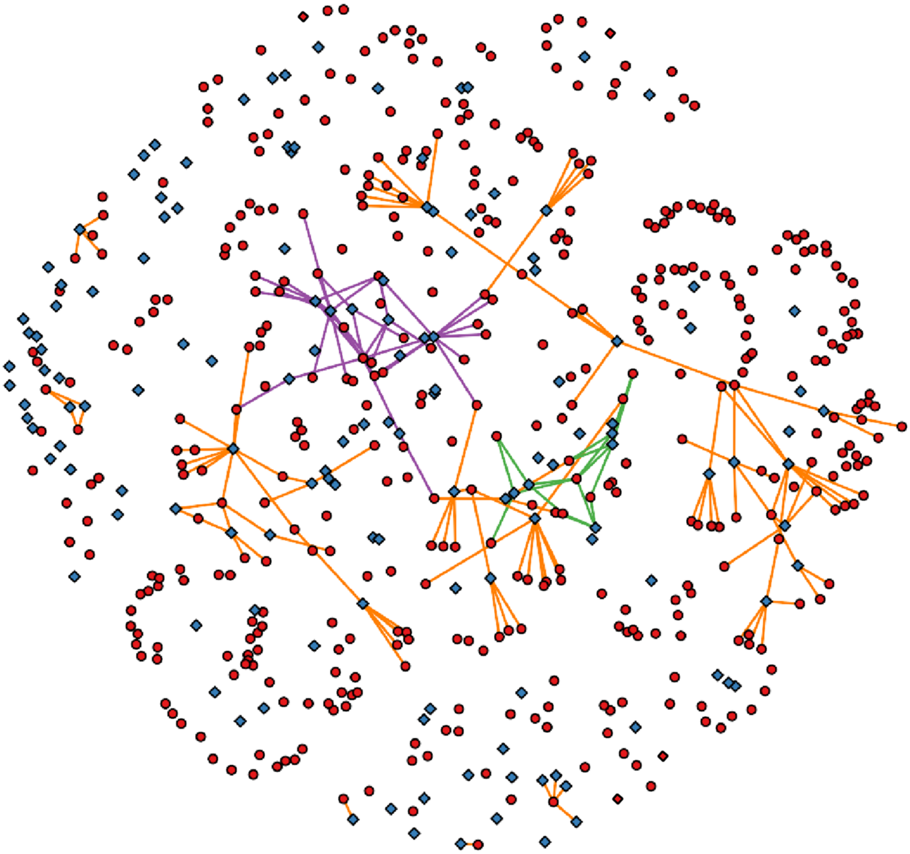

Fig. 15 2009–2011

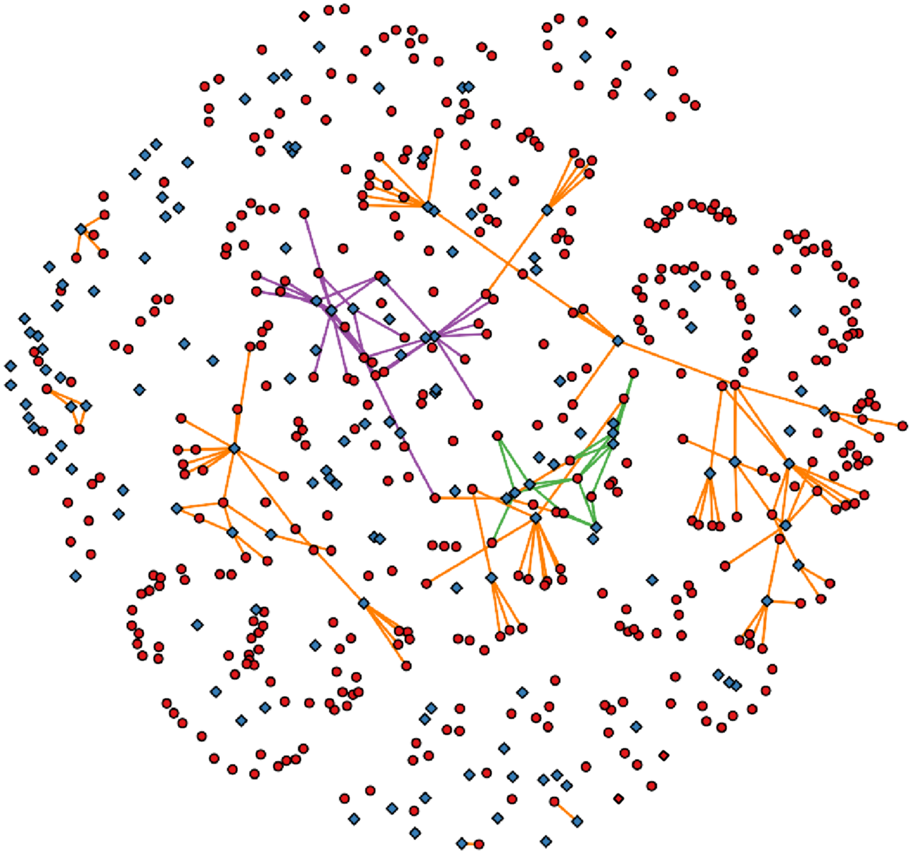

Fig. 16 2010–2012

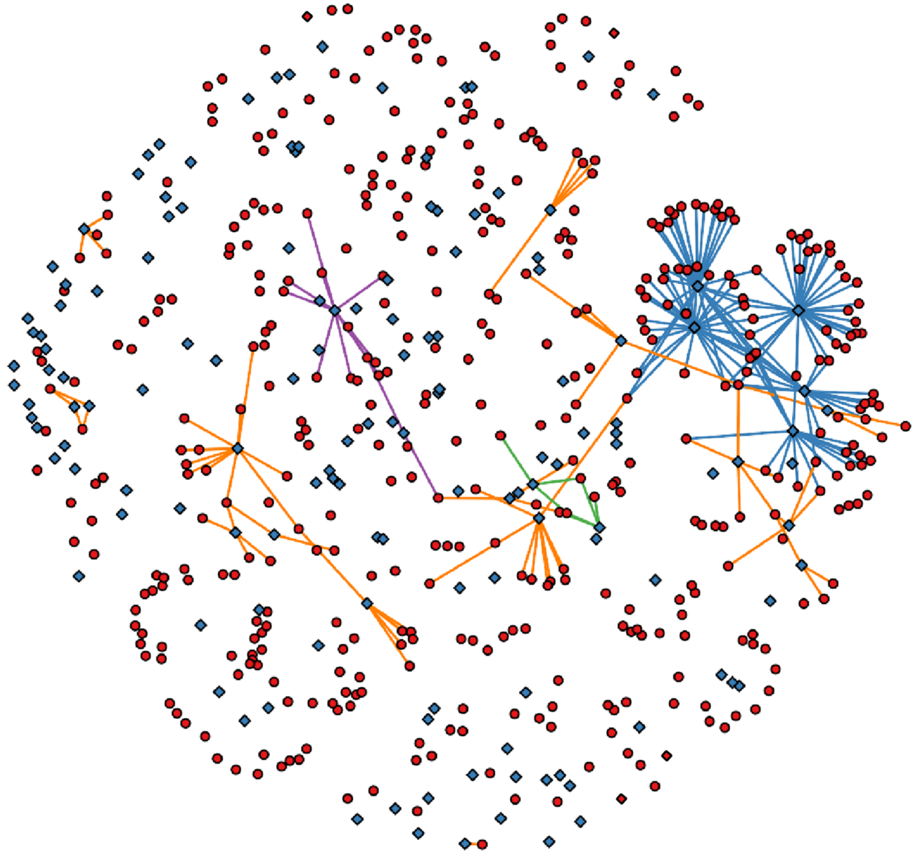

Fig. 17 2011–2013

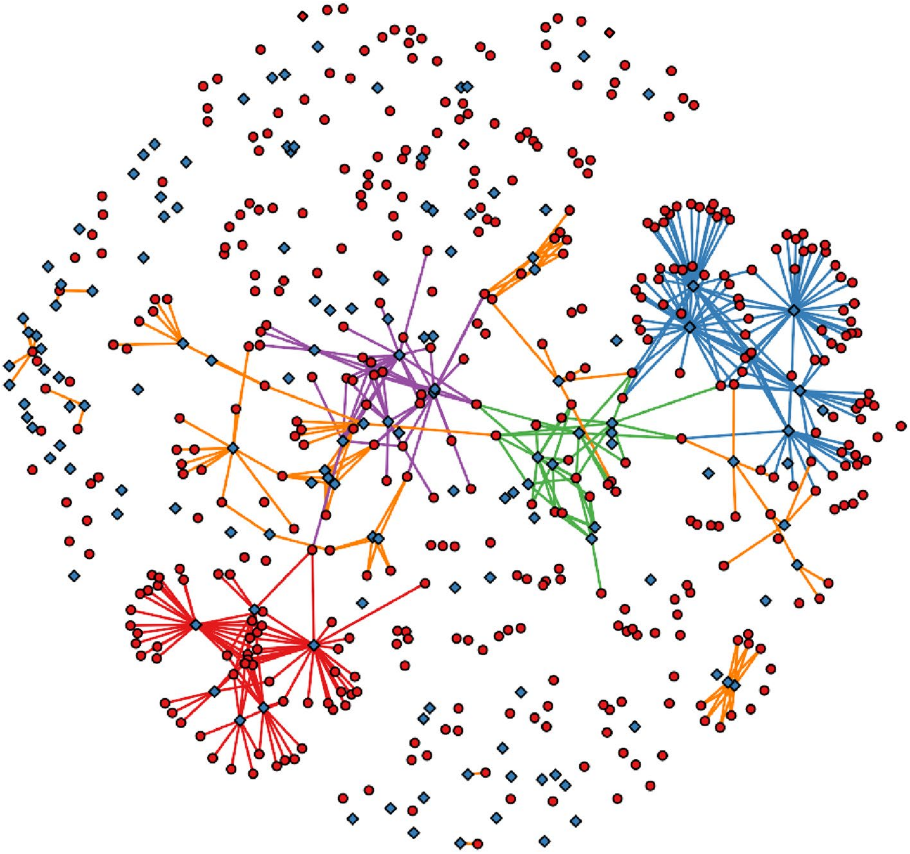

Fig. 18 2012–2014

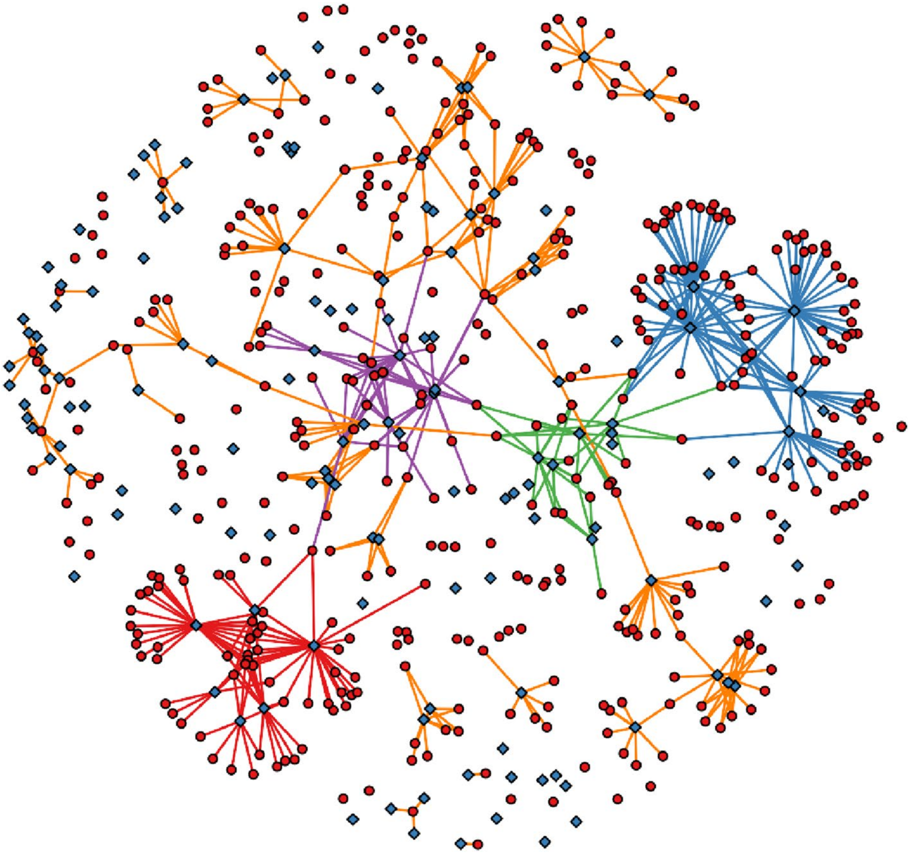

Fig. 19 2013–2015

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