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INNOVATION POLICIES IN TUSCANY: AN IMPACT EVALUATION ON SME

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“Loro scrivono e stampano, io diffondo. Loro credono che un libro valga in sé e per sé, credono nella bellezza delle idee in quanto tali.”

“Voi no?”

“Un’idea vale se viene diffusa nel posto e nel momento giusti, amico mio.”

Luther Blisset, Q

Introduction

In the last decades, evaluation has become an essential tool for policymakers. Despite possible distorsions in the interpretation of the results – due to potential conflicts of interest groups – policy evaluation is increasingly necessary in the political debate: it provides unbiased estimates of the effect(s) of a programme; it judges the development process of the policy, giving to decision makers the opportunity to comprehend how the results were produced; it points out benefits and costs of a programme, addressing future interventions. However, it is necessary to have a critical approach to any evaluation study because this topic is conditioned by subjective assumptions.

Impact evaluation has two perspectives: the first is related to accountability purposes, the second to research purposes. Policymakers are often interested in the former, but the latter is gains in importance. The aim of the second perspective is to explore the causal relationship between the implementation of a policy and its effects, i.e. the impact of a policy. It is necessary to distinguish between "*change in the results*" and "*policy impact*": the first is the contribution of an intervention added to the contribution of other factors, the second is the change that can be credibly attributed to an intervention (European Commission 2014).

Simultaneously with the increasing relevance assumed by innovation, innovation policies evaluation has assumed a relevant role too. Starting from the "*Green Paper on Innovation*" promoted in 1995 and arriving to the "*Europe2020*" programme, the European Commission has increasingly bet on innovation policy as a tool to improve Europe's economic growth, competitiveness and social cohesion. New policy instruments have been introduced, trying to reorganized the different methods of support to the innovation process. In the last years the evolutionary approach – a branch of study on innovation – have demonstrated that innovation is a nonlinear complex process within a complex system, which requires dedicated interventions. The European Commission, and the EU members, have modelled their policies in order to take into account these suggestions. One of the main results has been a renewed attention to the Regional Innovation Systems (RIS), local networks of enterprises, research organizations and public administrations active in the innovation process. RIS have a good public administration with great experience in innovation support and one or more productive industrial districts which foster cooperation among organizations. Clusters include public institutions and support services, and have in common specialization, proximity, and cooperation that lead to spillovers and synergy within a RIS.

European regional policy has set innovation promotion through the financing of RIS and local clusters in the programming periods 2000-2006 and 2007-2013. Each european country implemented different policies, mainly using financing from the European Regional Development Fund and the Cohesion Fund. Italy is an interesting case: during the programming period 2007-2013, six regions – Piedmont, Liguria, Tuscany, Umbria, Abruzzo, and Calabria – developed the *Poli di innovazione* (Innovation poles), regional innovation intermediaries that bring together a number of universities, services centres and other innovative actors which provide a range of services, including brokering and matchmaking. The novelty of this policy lies on its multiple goals, which are to foster the creation of networks between enterprises – and between enterprises and other organizations – and to stimulate enterprises' economic performance subsidizing R&D activities. Scholars have analysed cluster and RIS activities: studies on the economic impact of such structures have been widespread, but little attention has been paid to infrastructures – like the *Poli di innovazione* – which are the result of a mixed top-down/bottom up process, differently from industrial districts.

This study seeks to assess the effectiveness of the *Poli di innovazione* using Tuscany Region as case study. This region has been choosed as a case study because of its relevance in the italian context: the regional government has a great experience in the design of innovation policies, and in Tuscany are located many industrial districts. Tuscany Region created the *Poli di innovazione* in 2011, and they were active until 2014. The research question concerns the goal of those poles: have they improved networking and economic performance of their members – in particular small and medium enterprises? The aim of this research is twofold: to evaluate the impact of the R&D financing supplied by Tuscany Region, and the impact of the network structure combined with these subsidies. It is actually difficult to know if these poles have created long-term networks among firms and organizations – due to the lack of data about firms' relationships – but it is possibile to use network data between poles to assess the effect of the network structure on the firms. This data are deduced using the sharing of research centres, laboratories, incubators, employees and consultants between poles: each pole have shared these infrastructures and human resources with other poles, creating an inter-pole network that – theoretically – should have been a benefit for the firms.

According to economic literature, network analysis has hardly been used for policy evaluation purposes, but its contribution can be particularly incisive. This research is a first attempt to evaluate an innovation policy using methodological approaches typical of evaluation studies combined with Social Network Analysis (SNA). Total Factor Productivity (TFP) and Labor Productivity (LP) have been identified as measures of performance. A mixed method evaluation design has been built: it consists of difference-in-differences and matching methods, in which the counterfactual is derived from a list of active firms in Tuscany.

This study is organized as follows. The first section provides a brief overview on the evolution of innovation theory, and a specific focus on european policies – in particular the innovation policies of Germany, France, and Italy. The second section describes the main evaluation approaches present in the literature of policy evaluation, and introduce Social Network Analysis as an useful instruments for evaluation methods. The third section include the empirical model and a detailed description of the data set, with the results of the policy evaluation applied to the Tuscan case study. Conclusions and policy recommendations are given in the last section.

1. Innovation theory and innovation policies in Europe

Introduction

Innovation is one of the driver of economic growth and it is often stimulated through knowledge exchanges and other types of relationships among enterprises (Aghion and Howitt 1997, Koskinen and Vanharanta 2002, OECD 2007, Romer 1990, Solow 1956). The innovation process produces externalities which strenghten the local – and global – economy, but sometimes this spillovers do not have a positive effect. The social return from innovation can be greater than the private one, i.e. enterprises allocate less resources to R&D and the socially optimal amount is never reached. Economic literature on innovation has long been framed into two main positions on the relationship between market structure and technological performance, both derived by Schumpeter's point of views. For the early Schumpeter (1934), technological advance is a consequence of a cycle of entry by innovative enterprises, commercial application of new products or processes, and displacement of incumbents. In this case, innovation is promoted by small and medium enterprises (SME) owned by new businessmen which enter in the market bringing new products or processes. For the later Schumpeter (1942), technological progress derives from the industrial research laboratories of large enterprises that enjoyed positions of static market power. These enterprises can use their profits to finance large-scale R&D activities, that allow them to mantain positions of market dominance. It suggests that technological advance will be greater if large enterprises dominate the market, differently from the first point of view.

Modern literature has produced the recognition that "*the level of investment in research and development is likely to be too low, from a social point of view, whether market structure is nearly atomistic, a highly concentrated oligopoly, or something in between*" (Martin and Scott 2000). Market failures, limited appropriability and other factors – as discussed above – suggest that the market system is not able to achieve the socially desirable level of innovation: to ensure that enterprises will start an innovation process, or will adopt innovations acquired from other organizations, a public intervention is desirable. Public institutions can use different tools to give strength to their interventions. In Paragraph 1.1 these tools will be examinated, together with the two reference approaches: the neoclassical approach and the evolutionary approach to the public policy analysis.

In the last years the second approach has become prevalent; this situation has led to reconsider innovation as a complex process within a complex system. During the 80s and the 90s a new branch of study introduced the concepts of National System of Innovation (NSI) and Regional Innovation System (RIS). Both highlight the importance of the Systems of innovation in stimulate the conditions to innovate, even if they differ in the scale level – national and global against regional and subregional level. Basically, in a System of innovation there are interactions between public institutions, universities, schools, public and private research centres and other actors which can foster the innovation process: a NSI is more focused on the iterative process of learning that involve users, intermediaries and scientists at the national level, while a RIS is more focused on the tacit knowledge exchange and the development of innovative networks at the regional level. This concepts are examinated in Paragraph 1.2.

The importance of the Systems of innovation has been underlined by international institutions, like the European Union (EU). European institutions repeatedly state that innovation policy is the key to recovering EU competitiveness. The Lisbon strategy in 2000 set very ambitious goals, but the fragmentation of EU landscape is a barrier to reach them. There are four executive agencies which support the implementation of the centralised R&D programmes, 24 monitoring committees, 386 operational programmes under the European Regional Development Fund (ERDF) and European Social Fund (ESF) that contain an innovation component (Anvret *et al*. 2010). Regions in many European countries have legal competences and financial resources to implement regional innovation policies. This is especially true in federal or decentralized systems, where the territorial division of power allows their financial and political autonomy (Prange 2008). Usually regions fund innovation measures using European Union structural funds, which are based on the idea of supporting dynamic regional innovation systems (Landabaso *et al*. 2003). The innovation policies implemented in EU in the last decades are described in Paragraph 1.3, with a specific focus on France, UK, Germany and Italy.

1.1 Public policy analysis: neoclassical VS evolutionary approach

From a neo-classical point of view, innovation policies regard public support to scientific research; the innovation process is seen as a knowledge production function and can be decomposed into sequential – linear – steps. But the innovative activity is uncertain and related to a bounded rationality, i.e. public institutions must implement innovation policies to correct market failures, because knowledge is a non-excludable and non-rival good, and requires high investments. All these elements drive to opportunistic behaviors – "*free riding*" – and low levels of investments in R&D by enterprises. The neo-classical approach analyzed the efficiency of patents, copyrights, tax cuts, direct subsidies to private R&D, support to the public R&D and to the public demand – purchase of high-tech goods or creation of technological standards.

Patents allow the entrance of new enterprises in the local or global market. Their strenght lies in the opportunity to do radical innovations, which are characterized by high uncertainty, high costs and long-term commercialization' activities (Malerba 2000): without patents, radical innovations could not be introduced. The system of patents, however, does not guarantee an effective protection of the innovation – different countries have different legal systems – and sometimes it can give a sort of monopolistic power to the inventor. Direct subsidies were the main public instrument to support private R&D in OECD countries during the 1980s. Scholars studied if they replace private expenditures for R&D or they are additional to it: with perfect information, they are additional and contribute to increase enterprise' expenditures in R&D; if information is asimmetric, the enterprise will use public funds to finance R&D projects that would still do. Direct subsidies do not have negative effects on the technological diffusion; furthermore, they are neutral respect to the technologies (Malerba 2000) but they can replace private R&D expenditures, and create problems of moral hazard. Tax cuts are similar, in their mode of operation, to the direct subsidies, but they have been no longer used by national governments because of their limited efficacy. They have different advantages – low administrative costs, more simplicity compared to the direct subsidies, no discrimination among enterprises – but also disadvantages – a possible replacement effect of private R&D expenditures, low impact on young and small enterprises, distorsions related to fiscal operations, inadequacy for complex projects of R&D (Malerba 2000).

In contrast to the neo-classical approach, the evolutionary approach to innovation does not suggest which public policies implement or the optimal level of subsidies for the enterprises. This approach is focused on the role of the knowledge and the bounded rationality of the agents, and the learning process of the organizations involved in the innovation course. It studies interactions among different actors and linkages with technologies and institutions: the dynamic and irregular innovation process consider the possibility of a trade-off – or the failure of a trade-off – within this system, and this is what the evolutionary approach try to explain. From this point of view, the public policies for the innovation must:

- remove possibile "*lock-in*" effect to facilitate the adaptation of new technologies and avoid failures in the learning process;
- support the development and the matching of different skills;
- regulate the trade-off in the innovation process and the diffusion process (Malerba 2000).

In the first case – failures in the learning process – a set of public policies can include the support to basic research, the support to high-complexity projects, a specific orientation to the technological diffusion and the training of human capital. Moreover, these policies must avoid what is called "*lock-in effect*": if two or more technologies, or innovations, are competing for market share and one of them has an headstart, it may go on to dominate the market (Arthur 1989). This process can stop the research process and lock enterprises into an inferior design because they just want to exploit their position, i.e. they will be unable to compete against new improved technologies in the future. In the second case – different and collateral skills – the development of new technologies can involve different actors, enterprises and industrial sectors in the creation of a positive "*buzz*" of innovation and technological change. But if there is lack of informations and facilities nothing will happen. Public policies must encourage the development of networks between actors, enterprises and sectors, and operate on the potential demand of new technologies. Last but not least, the trade-off in the innovation process and the diffusion process concerns the choice among the exploration of new knowledge and the exploitation of the existing: public policies can support organizations which generate new knowledge, like universities, or support market competition to avoid the creation of dominant position, like in the computer market through the creation of Antitrust agencies. The trade-off in the innovation process and the diffusion process also concerns the balancing between protection and diffusion of the innovation: usually, this is done by the system of patents, but sometimes this system can be too constricting in the long-term (Winter 1993).

1.2 National Systems of Innovation and Regional Innovation Systems

Until the 1990s, the dominant model for innovation policies was focused on the supply of innovation inputs and support instruments to the enterprises (Tödtling and Trippl 2005). In the last two decades many European countries have adopted new strategies to stimulate the innovation process, especially at regional level. Different approaches have been attempted, and most of them have been addressed on SME and local systems of firms.

This new approaches have been implemented beacause the idea of innovation changed itself. Innovation as a linear process, defined as a sequence of temporally and conceptually distinct stages, has been challanged by theories that consider innovation as a complex process (Russo and Rossi 2009). During the 1980s, Nathan Rosenberg reviewed some classical innovation issues with a great impact on policy thinking among countries (Rosenberg 1982). He rejected the neo-classical concepts of technology and the Schumpeter's invention-innovation-diffusion schema, and influenced research programme and innovation literature for the next years. New non-linear models which emphasize the unpredictable nature of the innovation process and highlight the impact of innovation clusters were developed (Mytelka and Smith 2002). Two of the most important models use the concept of Innovation System to explain the interactions between actors that generate and use technology (Archibugi *et al*. 1998): the National System of Innovation (NSI) and the Regional Innovation System (RIS).

Freeman (1988, 1987), Lundvall (1992, 1988) and Nelson (1993) gave the first definitions of National System of Innovation to describe a network of public and private actors whose actions affect the creation and the diffusion of technologies. The main idea behind this concept is that understanding the linkages among the actors of an innovation system is the key to improve their performance. The innovative performance of a country depends on how these actors relate to each other and how they use technologies. Freeman (1987) defines the NSI as a "*network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies*". For Nelson (1993), a NSI is "*a set of institutions whose interactions determine the innovative performance...of national firms*". Lundvall (1992) affirms that the term "*National*" is not referred to the government level, and that a NSI is composed by "*the elements and relationships which interact in the production, diffusion and use of new, and economically useful, knowledge...and are either located within or rooted inside the borders of a nation state*". Archibugi (Archibugi *et al*. 1998) argues that this approach include "*systems of innovation that are sectoral in dimension and those that are at a different geographical scale*". The NSI approach highlight the importance of taking into account the whole innovation system and the growing number of institutions involved in knowledge generation. A System of innovation is composed by many actors: enterprises, organizations of the financial system, public and private research institutions, organizations of the educational system, national and local governments, and intergovernmental organization. A characteristic of the enterprises is their natural attitude to create client-supplier linkages, which can be realised at different levels – regional, national or global – and between different sectors. Local networks of enterprises are fundamental within innovation systems, because they aggregate organizations with various competences, stimulating interactions and the diffusion of suitable organizational models and technologies (Malerba 2000).

In 1992, Philip Cooke developed a different concept of System of innovation, called Regional Innovation System (RIS). The main difference compared to a NSI lies in the scale level. To give an example, a NSI differ from a RIS because it sets scientific priorities, and it funds basic research and university-level training, while a RIS influences certain allocations but without major tax-raising (Cooke 2001). The idea of a RIS is based on five axes: region (a meso-level political unit that has the power to support economic development and innovation), innovation (of products, processes and organization), network (set of reciprocal or customary trust and cooperation-based linkages among actors to pursue common interests), learning (new levels and kind of knowledge, skills and capabilities that can be embedded in the routines and conventions of firms) and interaction (formal and informal meetings or communication focused on innovation such that firm and other actors could associate to learn or pursue specific project ideas). A RIS needs specific organizational and institutional conditions to operate: regional financial competence – both public and private – and support of the regional administration in co-financing R&D projects or in providing loan guarantees; competences of the regional administration to control and influence investments in hard (transports and ICT) and soft (knowledge centres) infrastructures; cooperation and interaction between actors; trustful labor relations and worker welfare orientation at the firm level; and finally inclusivity, monitoring, consultation and networking propensities among policymakers (Cooke 2001).

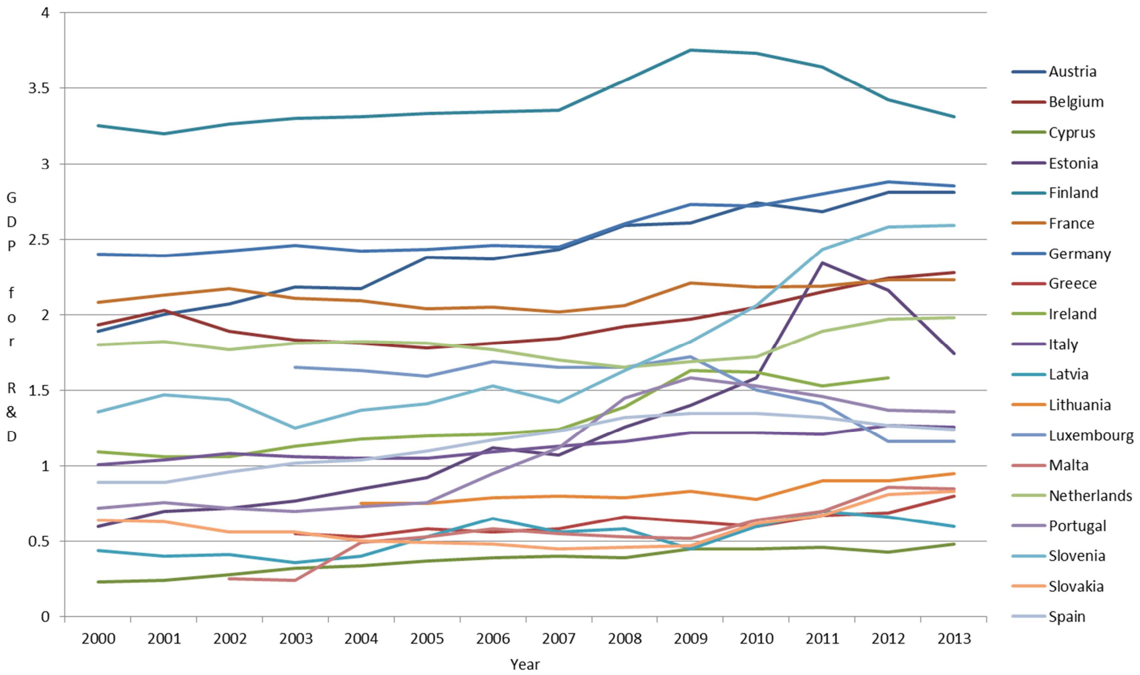
Cooke *et al*. (1997) notice that formal NSI often allocates R&D funding to large corporations, even if they are not innovative. They also noticed that sometimes innovation occurs in subnational and local clusters through the interaction of medium-sized enterprises. The concepts of RIS and cluster – and industrial district – are strictly related. A RIS has a good public administration with great experience in innovation support and one or more productive industrial districts – which foster cooperation among organizations and stimulate the (non-linear) innovation process. Clusters include public institutions and support services and have in common specialization, proximity, and cooperation that lead to spillovers and synergy within a RIS. European institutions realized that subsidize RIS and local clusters would encourage innovativeness and regional competitiveness: create proper economic and institutional conditions in a given region trigger the learning processes and allows regional firms to become more innovative, and adaptable to rapidly evolving markets. For this reason, European regional policy has set innovation promotion through the financing of RIS and clusters in the programming periods 2000-2006 and 2007-2013 (Landabaso *et al*. 2003).

European countries followed the "*Triple Helix Model*" (Etzkowitz and Leydesdorff 2000) to implement innovation policies whose aim is to finance RIS and clusters. This model take into account the pervasive development of information and communication technologies and the intensification of economic globalization. The strategic integration of research, government and industry allows to share competencies and resources, and to active knowledge flows: the local development is stimulated by the capacity – of the local sub-systems – to be synchronized and behave as a single unit, and their willingness to work together (Bertamino *et al*. 2014).

1.3 Innovation policies in Europe

Recently the EU industrial policy has become more focused on innovation cluster and this concept has been included in the 2007-2013 policy guidelines. European regions have implemented different policies which vary in type and definition. Table 1 shows the trend of the gross domestic expenditure on R&D (in percentage of the Gross Domestic Product) of the Eurozone countries, during the period 2000-2013.

Table 1 Gross domestic expenditure on R&D – % of GDP – of the Eurozone countries (2000-2013)

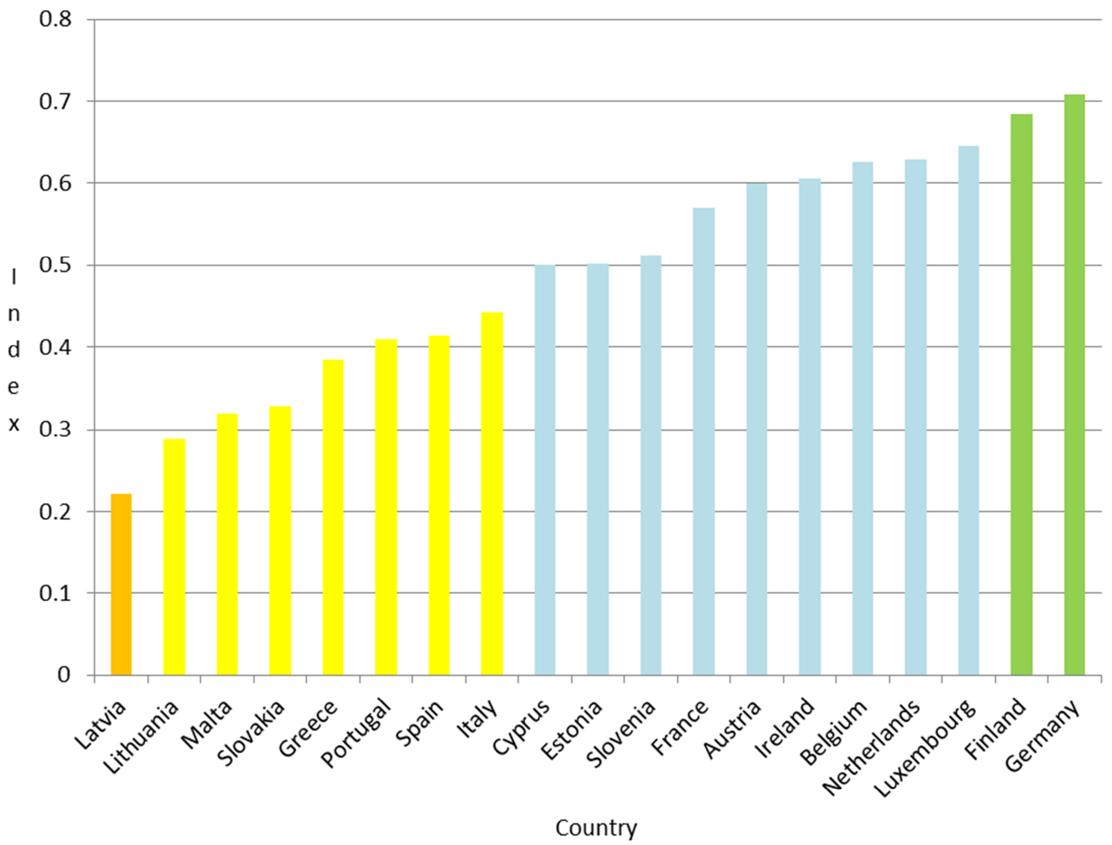


Source of Data: Eurostat

Northern european countries dedicate high levels of their gross domestic expenditures – in percentage of GDP – to R&D activities, while southern and eastern countries have low rates of investment in R&D activities. Estonia is an interesting case because it had one of the most prominent increases until 2011, but then it started to rapidly decrease.

Table 1 indicates that during 2000-2013 – a time frame which includes the programming periods 2000-2006 and 2007-2013 – there were differences among countries regarding the investments in R&D, which affect innovation and local development. Does it means that EU innovation policy in the last years has been ineffective? Actually, each country has its own features, and implements EU guidelines following an approach which can be different from others. As showed in Table 2, the innovation performance of Germany in 2013 was 0.709, while Latvia had a score equal to 0.221. It probably means that these two countries have adopted different strategies obtaining different results. The innovation performance index is obtained by an aggregation of 25 indicators used for measuring innovation performance (European Commission 2013). These indicators measure three dimensions and eight sub-dimensions: enablers (human resources; open, excellent and attractive research systems; finance and support), firms' activities (firm investments; linkages and entrepreneurship; intellectual assets) and outputs (innovators; economic effects). In Table 2, countries coloured in green are classified as "*innovation leaders*", countries coloured in blue are classified as "*innovation followers*", countries coloured in yellow are classified as "*moderate innovators*" and countries coloured in orange are classified as "*modest innovators*".

Table 2 Innovation performance index of the Eurozone countries (2013)



Source of Data: Eurostat

EU countries use european funds to finance R&D projects, but they must finance programmes which follow the main lines agreed by the European Commission. As reported above, there is a great fragmentation in EU fundings for research and innovation projects. A large part of the EU budget is managed in partnership with national and regional authorities through a system of "*shared management*". Actually, there are five main funds which operate to support economic development across all EU countries:

- European Regional Development Fund (ERDF),
- European Social Fund (ESF),
- Cohesion Fund (CF),
- European Agricultural Fund for Rural Development (EAFRD),
- European Maritime and Fisheries Fund (EMFF).

The ERDF fund is probably the most relevant for R&D activities, because one of its key priority areas is "*Innovation and research*". Their aims are: to strengthen economic and social cohesion in the EU (cooperation); to stimulate competitiveness and promote economic change through innovation (competitiveness); to support the promotion of less-developed regions (convergence). Regional innovation strategies are parts of the ERDF innovative actions, and tools to strengthen RIS in less favoured regions (Landabaso *et al*. 2003).

European regions receive financing under the ERDF actions for supporting innovation strategies. However, regions have to interact with the central government, but each government has a socio-political background which shapes its own innovation strategies and influence regional strategies. A brief comparation between Germany, France and Italy – three of the biggest economies in the Eurozone and, respectively, an innovation leader, an innovation follower and a moderate innovator – can better illustrate the differences within EU countries on this topic.

1.3.1 Germany

Germany has a multi-level governance system where responsabilities are shared between ministries and authorities on different levels of the political system. The public support for R&D activities is managed by a joint task of the federal government and the 16 Länder, and funding are divided into institutional funding and project funding. In addition to the federal ministries and the authorities of the Länder, there are also intermediaries with financing and consulting functions: the Joint Conference on Science; the German Science Council; the Office of Technology Assessment; the German Bundestag; the German Research Foundation; research organizations like the Max Planck Society, the Fraunhofer Society, the Helmholtz Association, and the Leibniz-Association.

Innovation policies in Germany are primarily developed at regional level and there are two types of programmes: federal government's programmes and Länder's programmes. The latters are not focused on specific technologies but reflect the innovative potential of each Länder (Eickelpasch 2013). On the other hand, federal programmes – cluster-based technology policies – are focused on key technologies and high value-added sectors. In the past, a weakness of the federal programmes was the complex distribution of responsibilities between political levels and different ministries. In 2005 the High-Tech-Strategy was developed to coordinate the policy instruments among the ministries involved in the definition of the innovation programmes. It has increased the focus on the commercialization of research results, it has simplified the regulation, it has supported the launch of startups, it has allowed the allocation of specific funds for small and medium enterprieses and it has implemented new line of research (Stehnken 2010).

In the 2000s the federal government funded and supported clusters that demonstrated to have competence and willingness to upgrade their structures (Dohse 2007). Due to the Germany's poor economic performance in the mid-1990s, the Federal Research Ministry pushed to a policy reorientation which had to encourage the use of lead projects as an element of technology promotion, the promotion of new technology-based firms and the support of spin-offs and SME. Region were taken into account as new reference units for technology policies (Dohse 2007). Two prototype models of cluster-based technology policies were implemented: the BioRegio contest and the InnoRegio contest. BioRegio was designed as a competition in which consortia formed from public and private sector organizations would develop a concept for biotech research and commercialization on a regional basis; an independent jury was established to select three regions that could demonstrate they had the critical mass of competence and the willingness to upgrade their biotech cluster (Dohse 2007). The three regions selected were Munich, Rhineland and the Rhine–Neckar Triangle. This was a relatively small size initiative, but had a great impact on the German biotech innovation system. InnoRegio was designed to reduce the development gap between eastern and western regions. Regional units, composed by private and public institutions, could apply to the call for tenders in order to being selected. They needed to present a strategy of network-building and intraregional cooperation to produce technical, economic and social innovations.

1.3.2 France

In France the R&D activities are mostly conducted by public research organizations and the highest contribution to R&D subsidies goes to big companies and small businesses (OECD 2014). Three separate levels of action are considered, in the french innovation system:

a) policy making,

b) implementation (funding and programming),

c) execution.

Two ministries share the responsibility for research and innovation policy in France at the policy making level: the Ministry of Higher Education and Research and the Ministry for Economy, Industry and Employment. The main actors for the implementation of innovation policies are the National Agency for Research and the OSEO innovation, but are also defined and implemented at the regional level.

There is a strong interrelationship among state, academic research, and industry. However, in the last years new forms of state intervention have emerged in this context: one of the most influential has been the creation of the *Pôle de compétitivité* (Competitiveness clusters), local systems of enterprises, research organizations and professional training centres, whose aims are to promote competitivness, strengthen high-tech activities and support growth and employment. As highlighted in the call for projects, "*a pole of competitiveness is the combination on a given geographic space of firms, training institutions and public or private research centers engaged to generate synergies in the execution of shared innovative projects. The partnerships can be organized towards a market or a scientific and technological domain*". Active partnerships were supposed to contribute to fostering synergies among organizations of the *Pôle*. An interministerial group assessed all the submitted projects basing on four themes: a) novelty of the proposal, b) internationalization, c) governance, d) economic development strategy. The 71 selected Poles (Figure 1) have been grouped in two categories: technological and industrial. This is a mixed model, in which management is entrusted to private actors in collaboration with local authorithies, and the central government address the research activities.

In 2008 an evaluation of these poles was commissioned to private independent agencies. It has emerged that 39 poles have reached their goals, while 13 needed to redefine their strategies. This evaluation considered, as indicators, the adoption of cooperative dynamics, the responsabilization of the participants, the pursue of national research strategies, the use of project financing, and the integration among policies developed by the poles and national policies for R&D and innovation.

Figure 1 The 71 *Pôle de compétitivité* in France

Source of data: DGCIS/DATAR (2013)

1.3.3 Italy

The constitutional reforms made in 2001 in Italy gave to the regions the means to implement their own industrial policies. Their role in managing the support for innovation has grown in the last years, stimulated by the European Union funding policies for RIS (Coletti 2007). Regional policies are co-funded through the ERDF or through the *Fondo per lo Sviluppo e la Coesione*: they finance, respectively, the *Programmi Operativi*

Regionali – POR (Regional Operative Programmes) and the *Programmi Attuativi Regionali – PAR* (Regional Actuative Programmes). National policies are managed by different ministries – the Ministry of Education, University and Research, and the Ministry of Economic Development – and financed by national funds like the *Fondo Centrale di Garanzia*, the *Fondo Italiano di Investimento*, the *Fondo di Rotazione per l'imprenditorialità*, etc.; they are actualized by programs like the *Programma Operativo Nazionale – PON* (National Operative Program) and the *Programma Operativo Interregionale – POI* (Interregional Operative Program).

From 2000 to 2006 it was a period of policy learning for the italian regions, in which they model their interventions and policy tools. The Ministry of Education, Universities and Research (MIUR), during the National Program of Research 2002-2004, created the Technology Districts, local aggregations of high-tech activities, made up by public research centers, firms and local governments, geographically concentrated. It was a first attempt to create, through a public policy, clusters of localized advanced technology activities. Technology Districts have been legally constituted by an act of the MIUR and have been granted by public funds from European Union and from national or regional sources.

From 2007 to 2013 the italian regions reshape and improve their policies relying on the past experiences (Caloffi et al. 2013). Several good practices have arisen in this period. Region Emilia-Romagna created an High Technology Network – fourteen industrial research laboratories and eight innovation centres operating in six thematic areas – to encourage the pooling of complementary expertise. Region Piedmont, Region Trentino-Alto Adige, and Region Umbria developed the Technology Platforms: in 2001 the European Commission promote the creation of sectorial Platforms, managed by the leading firms of those sectors, which had to define a long-term Strategic Research Agenda involving all the relevant stakeholders. Technology Platforms develop research and innovation agendas and roadmaps for action at european and national level to be supported by both private and public funding. There are 36 European Technology Platforms, grouped into five sectors: Energy, ICT, Bio-based economy, Production and processes, Transport. Six regions – Piedmont, Liguria, Tuscany, Umbria, Abruzzo, and Calabria – developed the *Poli di innovazione* (Innovation poles): systems of enterprises, service centres, public and private research organizations, whose aims are to foster the creation of networks, to promote the diffusion of innovation, and sharing knowledge. These structures raised public actors – like universities, public research organiza-tions, services centres, business incubators – to a prominent position. In that sense, they are no longer only gate-keeper of knowledge (Kauffeld-Monz and Fritsch 2013) or innovation intermediary (Howells 2006) but also managers of specific structures created for the promotion and the diffusion of knowledge and innovation, as occurs in natural networks (Caloffi and Mariani 2011).

Innovation poles are considered as an important lever for econonomic and productive systems: italian regions implemented this policy considering the recommendations of the European Commission. The financial support of the Innovation poles is regulated by the Community framework for State Aid for Research and Development and Innovation (2006/C 323/01), and it regards:

- infrastructures for education and research,
- laboratories with open access,
- broadband infrastructures.

The assistance is temporary and financing are continuously decreasing. Organizations which manage the Innovation poles use these funds to pay employees' wages and administrative activities (marketing, management, organization of seminars, networking).

2. Evaluation methods

Introduction

Evaluation studies must achieve a practical result: the measurement of the impact of a policy reform on a set of outcomes variables. To measure this impact, it is fundamental to know the difference between the participants' outcome with and without the treatment. Unfortunately, it is not possibile to observe both outcomes for the same participants, and using the mean effect on the not treated as comparison value is uncorrect, because the two groups differ even in the absence of treatment. This problem is known as "*selection bias*" (Caliendo and Kopeinig 2005), and it arises when non-experimental data are using. Non-experimental data are the most common type of data in social sciences, but they are more difficult to deal with, respect to experimental data.

This bias can be reduced constructing a counterfactual group, in which the characteristics of the members are similar to the characteristics of the – hypotetical – group of treated participants which have not received the treatment. Evaluation methods in empirical economics are grouped into five categories: pure randomised social experiment, natural experiment, matching method, selection model, and structural simulation model (Blundell and Costa Dias 2000). The first method take into account the presence of a comparison group which is a randomised subset of the eligible population. This method can not be easily implemented, because it requires an ex ante definition of the comparison group, and that this group will be completely unaffected by the policy. The second method tries to find a naturally occurring comparison group that can mimic the properties of the control group. It allows to measure the average effect of the treatment on the treated removing individual effects and macro effects, but it requires common time effects across groups and no composition change within each group. The matching method try to find common values of observable factors among individuals – or organizations: each of them which has been affected by the policy is matched with an individual – or an organizations – that have the same values of observable factors. The main problem lies in the selection of the factors which address the matching. The fourth method relies on the definition of a variable that determines the participation but not the outcome of the programme itself. It diverges from the matching because it accounts for selection on the unobservables factors. The final method is closely related to the selection model: it separates preferences from constraints, but requires a believable behavioural model for individuals.

Methodology for non-experimental data depends on three factors: the type of available informations, the underlying model and the parameter of interest (Blundell and Costa Dias 2000). Based on these factors, the choice of the estimator of the impact of the treatment is between the Instrumental Variables (IV) estimator, the Heckman selection estimator, the difference-in-differences estimator, and the matching estimator. The IV estimator is discussed in Paragraph 2.2.1, the Heckman selection estimator is discussed in Paragraph 2.2.2, the difference-in-differences estimator is discussed in Paragraph 2.2.3, and the matching estimator is discussed in Paragraph 2.2.4. Paragraph 2.2.5 illustrates a combined estimator of matching and difference-in-differences.

Despite their applications, evaluation methods do not take into account a relevant issue: the presence of spillovers. Not treated actors could be not interested in participate to a policy, because they can obtain in any case some indirect benefits from a connection with another actor. Relationships among actors are often not considered in evaluation desing. Social Network Analysis can map these relationships, and provide new insights on the evaluation of the policy impact. This method will be described in Paragraph 2.3.

2.1 To evaluate the effect of a policy

It is not possible to observe the outcomes of a policy on an individual – or an organization – in both treatment and non treatment condition at the same time. A credible estimate of a counterfactual group is needed, in order to calculate the impact of the policy as the difference in mean outcomes between the treated and the counterfactual group. This approach is only valid under a precise condition: the counterfactual group must be statistically equivalent to the treated group, the only difference must lie in the fact that actors in the first group do not receive the treatment, while actors in the second group receive the treatment (Heinrich *et al*. 2010).

Suppose that there is a policy for which it is necessary to measure the impact on some outcome variable Y. The difference between the potential outcome in case of treatment and the potential outcome in its absence is defined as the impact of a treatment for an individual i:

$$\alpha_i = Y_{id_1} - Y_{id_0} \tag{1}$$

where d_1 indicates the presence of a treatment and d_0 the absence of a treatment. Two problems arise: in non-experimental data the assignment process is most probably not random, and only one of the potential outcomes is observed for each actor. This lack of data makes it difficult to estimate α_i, so it is necessary to concentrate on average treatment effect on the entire population.

Generally, an evaluation seeks to estimate the mean impact of the programme, obtained by averaging the impact across all the actors in the population: this parameter is called Average Treatment Effect (ATE):

$$ATE = E(Y_{d_1} - Y_{d_0}) \tag{2}$$

which can be rewritten as:

$$ATE = E(Y_{d_1} \mid d_1) - E(Y_{d_0} \mid d_0) \tag{3}$$

But some actors are affected by a policy treatment, while others are not. The Average Treatment effect on the Treated (ATT) is more explicative of the ATE, because it considers only the actors which have been affected by the policy:

$$ATT = E(Y_{d_1} - Y_{d_0} \mid d_1) \tag{4}$$

and equation (4) can be reformulate considering the fact that the average of a difference is the difference of the averages:

$$ATT = E(Y_{d_1} \mid d_1) - E(Y_{d_0} \mid d_1) \tag{5}$$

One parameter is not observable – the expected value $E(Y_{d_0} \mid d_1)$, the average outcome that the treated actors would have obtained in absence of treatment – but to assess the impact of the treatment it is necessary to find a proxy in order to estimate ATT. As pointed out before, using the mean outcome of the non treated actors is not useful, because of the characteristics which can determine both the participation to the policy and the outcome of interest. A solution is offered comparing equations (3) and (5). It can be noted that:

$$E(Y_{d_1} \mid d_1) - E(Y_{d_0} \mid d_0) = ATT + E(Y_{d_0} \mid d_1) - E(Y_{d_0} \mid d_0) \tag{6}$$

where the term $E(Y_{d_1} \mid d_1) - E(Y_{d_0} \mid d_0)$ in the right sight of equation (6) is the so-called "*selection bias*": the difference between the counterfactual for treated actors and the observed outcome for the untreated actors. If it is equal to zero, the ATT can be estimated as the difference between the mean observed outcomes for treated and not treated. However, it is very rare to achieve this result, but the main goal of an evaluation is to estimate it.

2.2 Methods for non-experimental data

As reported in the Introduction, the correct methodology to estimate the effect of a policy depends on the type of available informations, the underlying model and the parameter of interest (Blundell and Costa Dias 2000). Longitudinal or repeated cross-sectional datasets support less restrictive estimators due to the richness of information. Two estimators are considered when using cross-sectional data: the Instrumental Variables (IV) estimator, and the Heckman selection estimator. If the dataset is longitudinal or a repeated cross-section, difference-in-differences or matching methods are more robust to estimate the impact of the treatment.

2.2.1. Instrumental Variables (IV)

The method of Instrumental Variables (IV) deals directly with selection on the unobservables. An IV, called *Z*, has the property that changes in *Z* are associated with changes in *X* – an exogenous variable – but do not led to change in the outcome *Y*. The IV must follows three conditions:

- it determines the programme participation,
- it exists a transformation *g* such that *g(Z)* is uncorrelated with the error term,
- it is not completely – or almost – determined by *X*.

This variable provides an exogenous variation used to approximate randomised trials, that is correlated with the participation decision but does not affect the outcomes which derive from the treatment (Blundell and Costa Dias 2000). For regression with scalar regressor *X* and scalar instrument *Z*, the IV estimator is defined as:

$$E\widehat{\beta_{IV}} = (Z'X)^{-1}Z'Y \tag{7}$$

where in the scalar regressor case *Z*, *X* and *Y* are *Nx1* vectors. This estimator provides a consistent estimator for the coefficient β in the linear model

$$Y = \beta X + \epsilon \tag{8}$$

if Z is correlated with X and uncorrelated with the error term ϵ.

This estimator suffers from two main drawbacks (Blundell and Costa Dias 2000). Firstly, it is very difficult to find an observable variable that satisfies the above conditions. Furthermore, in the case of heterogeneous effects with selection on expected gains, IV will not identify the ATT because actors will make a more informed participation decision, and the resulting selection process breaks the independence between β and Z.

2.2.2. Heckman selection estimator

Heckman (1976, 1979) has proposed a practical solution to solve the problem of sample selection that lead to biased estimations with OLS in econometrics. This method is well-known as the two-steps – or the limited information maximum likelihood – method, and it became very popular in evaluation studies.

To estimate the treatment effect of a policy, at least one variable with non-zero coefficient – independent of the error term – is required in the decision rule equation. Moreover, the ability to estimate consistently the joint density of the distribution of the errors is required. This estimator control directly for the part of the error term in the outcome equation that is correlated with the participation dummy variable. The procedure of estimation is divided into two steps: in the first, the part of the error term which is correlated with the participation dummy variable is estimated; then, it is included in the outcome equation and the effect of the policy is estimated.

Given the following model:

$$Y_{1i}^{*} = X_{1i}'\beta_1 + \epsilon_{1i} \tag{9}$$

$$Y_{2i}^{*} = X_{2i}'\beta_2 + \epsilon_{2i} \tag{10}$$

where $Y_{1i} = Y_{1i}^{*}$ if $Y_{2i}^{*} > 0$ and $Y_{1i} = 0$ if $Y_{2i}^{*} \leq 0$. The outcome variables $Y*_{1i}$ and $Y*_{2i}$ are unobserved, whereas Y_{1i} is observed. The error terms ϵ_{1i} and ϵ_{2i} are are expected to be positively correlated, both with a bivariate normal distribution. For the subsample with a positive $Y*_1$ the conditional expectation of $Y*_1$ is given by:

$$E(Y_{1i}^*|X_{1i},\ Y_{2i}^* > 0) = X_{1i}'\beta_1 + E(\epsilon_{1i}|\epsilon_{2i} > -X_{2i}'\beta_2) \tag{11}$$

Assuming a bivariate normal distribution of the error terms ϵ_{1i} and ϵ_{2i}, the conditional expectation of the error term ϵ_{1i} is:

$$E(\epsilon_{1i}|\epsilon_{2i} > -X_{2i}'\beta_2) = \frac{\sigma_{12}}{\sigma_2}\frac{\phi\,(-(\frac{X_{2i}'\beta_2}{\sigma_2}))}{1-\Phi(-(\frac{X_{2i}'\beta_2}{\sigma_2}))} \tag{12}$$

where $\phi(.)$ is the density function of the standard normal distribution and $\Phi(.)$ is the cumulative density function of the standard normal distribution. Equation (11) can be rewrite as:

$$E(Y_{1i}^*|X_{1i},\ Y_{2i}^* > 0) = X_{1i}'\beta_1 + \frac{\sigma_{12}}{\sigma_2}\frac{\phi\,(-(\frac{X_{2i}'\beta_2}{\sigma_2}))}{1-\Phi(-(\frac{X_{2i}'\beta_2}{\sigma_2}))} \tag{13}$$

Heckman's proposal is to estimate the ratio at the right side of equation (13) with a probit model, obtaining λ, and then estimate:

$$E(Y_{1i}) = X_{1i}'\beta_1 + \frac{\sigma_{12}}{\sigma_2}\lambda(\frac{\widehat{X_{2\iota}'\beta_2}}{\sigma_2})\ e_{1i} \tag{14}$$

in the second step. Heckman (1979) characterises the sample selection problem as a special case of the omitted variable problem, with λ being the omitted variable if OLS is used on the subsample for which $Y_1^* > 0$.

2.2.3. Difference-in-differences

An exogenous intervention may create a sort of natural randomization across actors. It happens when a natural disaster occurs, creating a separation between damaged and not damaged zones, or a policy change makes a certain group eligible to some treatment but keeps a similar group ineligible. If longitudinal or repeated cross-section informations are available, it is possibile to estimate the treatment effect without imposing the restrictive conditions exposed for IV and Heckman selection estimator.

The difference-in-differences (DID) approach uses a before-after comparison across groups to estimate the treatment effect. In the case of a policy reform, DID explores a change in the policy occurring at some time period k, which introduces the possibility of receiving treatment for some actors. Each actor is observed at time $t_0<k$ and $t_1>k$, respectively the pre-treatment period and the post-treatment period. The DID estimator measures the excess outcome growth for the treated actors compared with the not treated actors. Formally:

$$\alpha = (\overline{Y_{t_1}^T} - \overline{Y_{t_0}^T}) - (\overline{Y_{t_1}^C} - \overline{Y_{t_0}^C}) \tag{15}$$

where $\overline{Y^T}$ and $\overline{Y^C}$ are the mean outcomes for the treatment (T) and the comparison (C) group; the estimator α identifying the ATT.

The DID estimator uses a common trend assumption and assumes no selection on the transitory shock, so the randomization hypothesis ruling out selection on not treated outcomes. Some restrictions are imposed on the error composition of the outcome equation for each actor. Considering the following decomposition of the unobservables:

$$\epsilon_{it} = \eta_i + \theta_t + \mu_{it} \tag{16}$$

where η_i is an individual-specific effect, θ_t is a common macroeconomic effect, and μ_{it} is a temporary individual-specific effect: if the expectation of ϵ_{it} conditional on the treatment status depends on μ_{it} , DID is inconsistent. Therefore, this approach has two main weakness (Blundell and Costa Dias 2009):

- it does not control for unobserved temporary individual-specific shocks that influence the participation decision,
- treated and controls must experience common trends – the same macroeconomic shocks.

If the actors of the two groups have different trends, DID do not consistently estimate the ATT. Considering the registred outcomes for both groups – treated and controls – during a defined time window, the common trends assumption holds when the observed values for treated and controls are parallel.

The possibility of differential trends motivates the use of the "*differential trend adjusted DID*" estimator. If the treatment selection is independent of the temporary individual-specific under differential trends but the common trends assumption does not hold, it is possibile to compare the behaviors of treated and controls before the introduction of the policy. It is necessary to find a time period (t*, t**) in which similar macro trends have occurred, and comparing the DID estimate of the treatment impact – with the bias –from differential trend with the estimate of the differential trend over (t*, t**). This estimator has been proposed by by Bell, Blundell, and Van Reenen (1999), and consistently estimate ATT; equation (15) can be reformulated as:

$$\alpha = (\overline{Y^T_{t_1}} - \overline{Y^T_{t_0}}) - (\overline{Y^C_{t_1}} - \overline{Y^C_{t_0}}) - (\overline{Y^T_{t_{**}}} - \overline{Y^T_{t_*}}) - (\overline{Y^C_{t_{**}}} - \overline{Y^C_{t_*}}) \tag{17}$$

2.2.4. Matching

Matching is a non parametric approach to reproduce the treatment group among not treated actors. The strenght of this method is the chance to re-establish the condition of an experiment: it constructs a sample counterpart for the missing information on the treated outcomes had they not been treated by matching each treated actor with not treated actors. The matching assumptions ensure that the remaining difference between the two groups is due to the programme participation (Blundell and Costa Dias 2009).

Matching can be used with longitudinal or cross-sectional data, and can be combined with other methods to obtain more accurate estimates of the treatment effect. A general starting point considers the outcome equations of treated and not treated:

$$Y^T = g^T(X) + \epsilon^T \tag{18}$$

$$Y^C = g^C(X) + \epsilon^C \tag{19}$$

where Y^T is the outcomes of the treated, Y^C is the outcomes of the not treated (control group), X is a set of observable variables and ϵ^T and ϵ^C are the error terms for treated and controls. To identify the ATT, matching assumes the conditional independence between not treated outcomes and programme participation:

$$Y^C \perp d_1 \mid X \tag{20}$$

This assumption is called Conditional Independence Assumption (CIA), and it means that the outcome of the not treated actors is independent of the participation d_1, once one control for the observable set of variables X. This is the so-called counterfactual: given X, Y^C is what the treated outcome would have been they not been treated. For each treated actor, one can look for a not treated actor – or a set of not treated actors. Matching is explicitly a process of rebuilding an experimental data set (Blundell and Costa Dias 2009): a correct data collection is needed, in order to avoid the presence of observations which could invalidate the matching process.

Moreover, matching assumes that the probability of being treated is between zero and one, in order to guarantee that everyone can receive the treatment and each treated actor will be matched with a counterpart:

$$0 < P(d_1 \mid X) < 1 \tag{21}$$

In equation (21) d_1 indicates the reception of the treatment, and X is a set of explanatory variable(s). The matching estimator is calculated as it follows. Let S represents the subspace of the distribution of X that is both represented among the treated and the controls: this subspace is the "*common support*" of X, and is the whole domain of X represented among the treated. The ATT over S is:

$$\alpha = \frac{\int_{X \in S} E(Y^T - Y^C \mid X,\ d_1)\, dF(X \mid d_1)}{\int_{X \in S} dF(X \mid d_1)} \tag{22}$$

The numerator of equation (22) is the expected gain from the programme among the treated actors for whom has been found a comparable group of not treated actors. This gain is integrated over the distribution of observables among treated and re-scaled by the measure of the common support. It can be interpreted as the mean difference in outcomes over the common support, weighted by the distribution of participants.

Matching does not requires particular restrictions on the outcome equation or the unobservable term, but the assurance that comparisons are statistically similar to what the treated observations would be had they not participated to the programme. Another limitation is related to the range of variables which compone *X*: if the number of variables is too high, there can be "*curse of dimensionality*", a problem that arises when analyzing and organizing data in high-dimensional spaces. To deal with this problem, Rosenbaum and Rubin (1983) suggest to use a balancing score. If the potential outcomes are independent of treatment conditional on variables *X*, they are also independent of treatment conditional on a balancing score *g(X)*. Usually, this is carried out on the propensity to participate; given the matching assumptions of equation (20) and equation (21), the conditional independence assumption is still valid controlling for *P(X)* instead of *X*:

$$(Y^T, Y^C \perp d_1 \mid P(X) \tag{23}$$

where Y^T and Y^C are the outcomes for treated and controls, and *P(X)* is the "*propensity score*", the probability for an actor to be treated given *X*. The ATT can be estimated as:

$$\alpha = E_{P(X) \mid d_1} \{E(Y^T \mid d_1, P(X)) - E(Y^C \mid d_0, P(X))\} \tag{24}$$

which is the mean difference in outcomes weighted by the propensity score distribution of participants. To implement the propensity score matching, some rules have to be followed. To estimate the probability of participation, logit and probit models must be used for the binary treatment case; in the case of multiple treatment, it is possible to use both multinomial logit and multinomial probit models, even if the latter is preferable because it has less stronger assumptions than multinomial logit (Caliendo and Kopeinig 2005). Another importan issue is the choice of the variables to insert in the propensity score model: omitting important variables can increase bias in the estimates, but variables need to influence simultaneously the participation decision and the outcomes variable, and must be unaffected by the participation. Moreover, Heckman, LaLonde and Smith (1999) point out that data for treated and not treated actors should come from the same source. Propensity score offers the chance to assign different weights to the neighbours in the process of matching. There are different matching algorithms which can be implemented, as illustrated in Table 3.

Table 3 Characteristics of the algorithms of matching

Algorithm of matching	Characteristics
Nearest Neighbor	– with replacement the quality of matching increase, while bias decrease – with oversampling variance decrease, while bias increase
Caliper	– high quality of the matches – risk of increasing variance – need to choose an appropriate tolerance level
Radius	– same characteristics of the Caliper matching, but it avoids the risk of bad matches – trade-off between the dimension of the neighbourhood and the quality of the matches
Stratification	– problem: it discards observations in blocks where either treated or controls are absent – need to choose an appropriate number of strata
Kernel	– lower variance (more information used) – problem: use of observations that lead to bad matches
Local Linear	– similar to the Kernel, but includes a linear term in the weighting function
Weighting	– the propensity score need to be known

Source of Data: Author's elaboration

Caliendo and Kopeinig (2005) highlight the peculiarity of each algorithm in terms of bias and efficiency. The Nearest Neighbor (NN) takes each treated actor and searches for the control actor with the closest propensity score. Variants of NN are represented by matching with replacement – using the not treated actors more than once as a match – and without replacement – using the not treated actors just as one match. It is also possibile to use more than one nearest neighbor ("*oversampling*"): it reduces variance because more informations are available to construct the counterfactual for each actor, but usually increase the bias because of the average poorer matches.

In addition to the NN, Caliper matching imposes a maximum level to the propensity score distance (caliper) among actors. The quality of the match increases, but if fewer matches are available the variance of the estimates increases too. Dehejia and Wahba (2002) suggest a variant of this algorithm called Radius matching: the novelty lies in the use of all the comparison actors within the caliper as counterfactual, and not only the nearest neighbor within each caliper.

Stratification matching divides the range of variation of the propensity score into intervals, and calculates the impact within each interval by taking the mean difference in outcomes between treated and controls.

With Kernel matching all the treated actors are matched with a weighted average of all controls, and the weights are inversely proportional to the distance between the propensity scores of treated and controls. Using so many controls increase the number of informations, decreasing variance. Local Linear (LL) matching is another non-parametric estimator that uses weighted averages of all the controls to construct the counterfactual, but it differs from Kernel matching because it includes a linear term in the weighting function, which helps to avoid bias.

Finally, Weighting assumes that propensity scores can be used as weights to obtain a balanced sample of treated and controls. If the propensity scores are known, the estimator can be calculated as the difference between the weighted average of the outcomes for treated and not treated actors (Caliendo and Kopeinig 2005).

2.2.5. Difference-in-differences and matching

Difference-in-differences (DID) allows to compare actors which received a treatment and actors which do not received a treatment, taking into account the restriction on common trends. This comparison, however, is still affected by the problem of non-random sample selection: matching methods can help in addressing endogeneity and provide more accurate estimates. Matching controls for the selection bias restricting the DID estimates to a sub-sample of actors based on a set of observable characteristics. As method of matching to employ, propensity score matching is very attractive because the set of observable characteristics can be very high ("*curse of dimensionality*"), and using propensity score gives the opportunity to obtain unbiased estimates.

The implementation of these technique follows three steps. In the first step, a logit/probit model – or a multinomial logit/probit model, it depends by the considered treatment – is launched, in order to discover which actor's characteristics drive the process of involvement in the treatment. The second step consists in matching treated actors with controls according to their propensity scores. In the last step, DID is applied to analyse the gap in the outcomes of interest between the two groups before and after the treatment period.

The combination of difference-in-differences and matching is the optimal way to control for divergences in performances between treated and controls. It decreases the selection bias and addresses the endogeneity problem, providing more accurate estimates. Blundell and Costa Dias (2000) emphasize the benefits of this combination to control for observable and unobservable but constant differences between treated and controls: matching accounts for differences in observable characteristics, DID accounts for the unobserved determinant of participation to the treatment represented by individual/time-specific components of the error term. Combining equation (16) with equation (18) and equation (19), it is possible to assume the following model:

$$Y_{it}^{T} = g_t^{T}(X) + \eta_i + \theta_t^{T} + \mu_{it}^{T} \tag{25}$$

$$Y_{it}^{C} = g_t^{C}(X) + \eta_i + \theta_t^{C} + \mu_{it}^{C} \tag{26}$$

where the error term is decomposed into an individual-specific effect η_i , a common macroeconomic effect θ_t, and a temporary individual-specific effect μ_{it}, and where the function *g(X)* change over time. The conditional independence assumption expressed in equation (20)

$$Y_{t_1}^{C} - Y_{t_0}^{C} \perp d_1 \mid X \tag{27}$$

where t_1 and t_0 stand for the period of post-treatment and the period of pre-treatment. This is equivalent to:

$$(g_{t_1}^C(X) + \theta_{t_1}^C) - (g_{t_0}^C(X) + \theta_{t_0}^C) \perp d_1 \mid X \tag{28}$$

which can be rewritten as:

$$(g_{t_1}^C(X) - g_{t_0}^C(X)) + (\theta_{t_1}^C - \theta_{t_0}^C) \perp d_1 \mid X \tag{29}$$

where the matching now is expressed in terms of before-after evolutions instead of levels. Equation (29) means that controls have evolved in the same way the treated would have done had they not been treated (Blundell and Costa Dias 2000). The effect of the treatment on the treated can be estimated as:

$$\alpha = \sum_{i \in T} [(Y_{it_1} - Y_{it_0}) - \sum_{j \in C} W_{ij} (Y_{jt_1} - Y_{jt_0})] w_i \tag{30}$$

where *T* is the group of the treated, *C* is the group of the controls, *Wij* is the weight placed on comparison actor *j* for actor *i*, and w_i accounts for the reweighting that reconstructs the outcome distribution for the treated sample.

2.3 The Social Network Analysis (SNA)

A policy can affect hundreds – or thousands – of actors for various purposes: to increase individual earnings, to support the integration of disadvantaged people, to finance R&D, etc. Sometimes these actors are involved in a relationships network, which can affect the policy programme and which depends on the individual characteristics of the actors themselves. The evaluation methods described in the previous paragraphs account for individual-specific characteristics, but not for network characteristics. These characteristics could interfere with actors' behavior. The presence of positive spillovers affects the participation to a policy: some actors can decide to ignore a policy programme because they have connections to actors which are involved anyway. Social Network Analysis (SNA) allows to consider this factor: it maps the relationships among a group of actors and analyse the characteristics of the network. The attributes of the actors can be interpreted as a function of their location in the network: network position becomes a key variable, since it could be considered an intangible strategic resource (Wasserman and Faust 1994).

Sometimes the policy itself considers, as related purpose, the support in the creation – or the improvement – of a network. Organizations which are embedded in systems of social relations enjoy a privileged position relative to isolated ones, and this is why policymakers are interested in the development and the strenghtening of local networks. For Granovetter (1985) transaction costs can be kept to a minimum if firms are embedded in networks of social relations that monitor and sanction opportunistic behaviors. Powell (1990) investigates the relationship between governance structure and state policies, and discovers that networks are significant in a domain between the flexibility of the market and the rigidity of organizational authority. For Burt (2000), networks provide order to disconnected parts of organizations and markets.

Being involved within a network fosters the creation of advantages. The establishment of a web of collaborations allows to reduce socioeconomic risks, to obtain informations which are usually not available, to establish new standards of communications which can increase social benefits, etc. There is a wide variability in the presence of linkages across actors, and a wide variability of benefits deriving from the membership. In a network of firms, the main advantages are related to:

- the exchange of knowledge and capabilities from partner firms (Mowery *et al*. 1996), which is justified by the consideration that firms are characterized by heterogeneous knowledge,
- the rapidity through which the network puts organizations in contact, even when they are not formally connected to each other (Giuliani and Pietrobelli 2011),
- the ability to maintain stable and high-quality relationships over time, fostering trust and reciprocity (Giuliani and Pietrobelli 2011).

Networks are particularly relevant for the diffusion of innovation, which is stimulated by the interaction and the cooperation of different actors (Powell *et al*. 1996). In a situation of market failure, firms may find inter-organizational networks as safety nets against unfavorable business climate; networks reduce information asymmetries and strengthen the lobby power of the firms, and enable an upgrade of their capabilities.

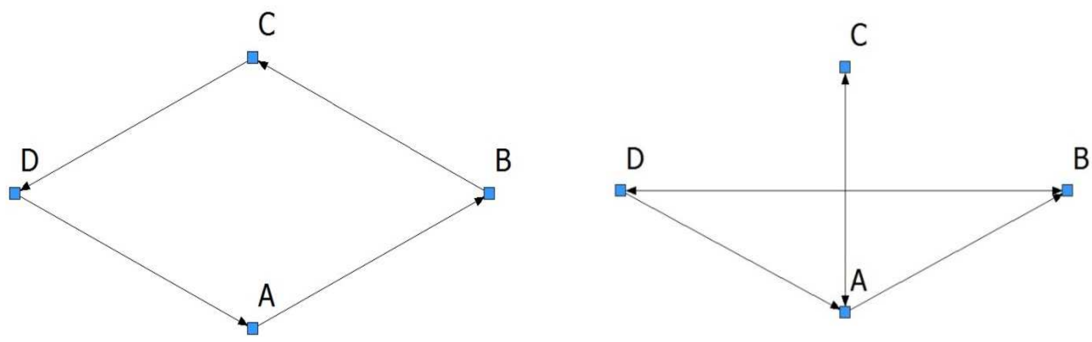
SNA is a social sciences branch that is based on the assumption that relationships among actors are important to explain their nature, behavior, and outputs. A "*social network*" can be defined as a set of relationships that apply to a set of actors, as well as any other additional informations on these actors (Prell 2012). SNA uses graph theory – a branch of mathematics that focuses on the quantification of networks – to describe and visualize social networks: a graph is a visual representation of a network, were actors are represented as nodes or vertices and ties are represented as lines. Studying networks has multiple advantages. The first advantage is the clearness in explaining the structure of relationships between actors. SNA provides a method to investigate this structure, to represent it graphically, and building on that to achieve new developments. Another advantage is its applicability to various fields of research. SNA is widely recognized as a multidisciplinary pursuit, even if its historical development has followed a nonlinear path. Scholars tend to agree that this discipline started with psychiatrist Jacob Moreno, that – in collaboration with Helen Hall Jennings – developed in 1934 a technique called "*sociometry*", a quantitative method for studying the structure of groups and the position of individuals within groups (Moreno and Jennings 1934). During the same period, a british social anthropologist called Alfred Radcliffe-Brown started to explore new ways for studying structural issues. He made a number of generalizations about the nature of social relations, and argued that society developed certain structures naturally in efforts to fulfil certain functions (Radcliffe-Brown 1952). Radcliffe-Brown was the supervisor of W. Lloyd Warner, who worked in the Anthropology Department and the Business School at Harvard and was the first to to use the social networks approach to empirically analyse the interpersonal relationships among a group of workers of the Western Electric company in Illinois – with the psychologist Elton Mayo. Ideas related to social networks were presented also in the studies of sociologists Simmel, Durkheim and Weber, but only in the 1950s – with the theoretical work of Homans on social relations (Homans 1950) – and in the 1970s – thanks to the dedication of the Harvard Sociology Department's leader Harrison White – sociology's contribution to social network analysis became evident. Modern developments of SNA have been involved statistics, computer science and economics: in 1980s and 1990s the development of statistical models for the analisys of social networks data has increased, in particular for Exponential Random Graph Models (ERGM), which treat the social network as the dependent variable and whose aim is to explain it. SNA is in continue development: computer simulations of networks evolution often make a set of simplifying assumptions regarding network dynamics, but the availability of big data is changing it, and in the future the real challenge will be the collection of those data.

2.3.1. SNA and evaluation methods

SNA has hardly been used for policy evaluation purposes, but its contribution can be particularly incisive. Most of the available evaluation attempts are based on a very poor understanding of what networks are, and key concepts like "*networking*" and "*connections*"are often measured through rough indicators (Giuliani and Pietrobelli 2011).

Its strenght lies in the identification of the relationship types existing between different actors. Figure 2 shows two different network structures of the same set of actors. In the first case (a) each actor is connected with just another actor; in case (b) every actor is connected with actor A, and the edges between actor A and actor C – and actor B and actor D – are bi-directional. These differences are very important, as they have implications on the way assets (advices, goods, resources, etc.) circulate; actors' position changes and the way to measure it assumes a relevant role.

Figure 2 Example of network structures



(a) (b)

Source of Data: Author's elaboration

SNA allows to use a reliable network measurement. Depending on the nature and characteristics of the linkages, the position of an actor may reflect its power, its prestige, or its access to – or control of – resources (Giuliani and Pietrobelli 2011). Generally, if an actor has a central position it is favored compared to the others, but SNA can shows that it is not always true. Measures of centrality – referred to single actors – are the first attempt to start the analysis of the prominent actors within a network. The most widely used measures of centrality for complete networks are:

- Degree centrality,
- Eigenvector centrality,
- Betweenness centrality,
- Closeness centrality,
- Bonacich power centrality (beta-centrality).

To calculate these measures – and to visualize networks – a proper systematization of data is necessary. For this reason, network data are organized as network matrices. Matrices produce algebraic representations of network relations and facilitate quantitative analyses. A network matrix is different from the classical case-by-variable matrix: data are organized as case-by-case matrices ("*adjacency matrices*") or case-by-events matrices ("*incidence* *matrices*"), where the cells represent the presence or the absence of a tie among actors (Prell 2012). If in an adjacency matrix the values are 1's and 0's it is called "*binary adjacency matrix*", and it only conveys the presence or the absence of a relation; but the intensity of the ties can be expressed through values, and in this case the matrix is called "*valued adjacency matrix*". Matrices can be symmetric or asymmetric, it depends on the direction of the ties: a symmetric matrix contains data for an undirected network, an asymmetric matrix records the direction of ties.

Degree centrality is the most simple form of centrality measure: it is the number of contacts of an actor in a network. To obtain it, it is necessary to count the number of alters adjacent to the actor:

$$C_i = \sum_{j=1}^{n} x_{ij} = \sum_{i=1}^{n} x_{ji} \qquad (31)$$

where C_i stands for "*degree centrality of actor i*", x_{ij} is the value of the tie from actor i to actor j, x_{ji} is the value of the tie from actor j to actor i, and n is the number of nodes (actors) in the network. If directional data are available, indegree centrality and outdegree centrality can be calculated. Indegree centrality is the number of ties received by an actor, outdegree centrality is the number of ties given by that actor. The former is a measure of "*popularity*", the latter is a measure of "*expansiveness*".

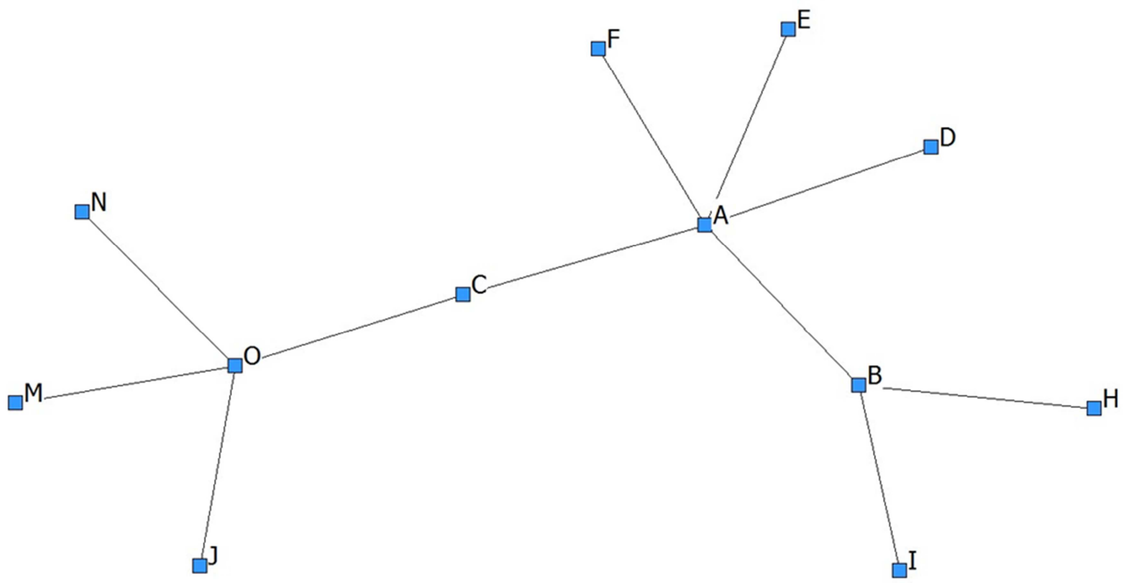
Eigenvector centrality expands the notion of degree centrality. It is the sum of an actor's connections to other actors, weighted by their degree centrality. To compute this type of centrality, the network must have undirected data, i.e. a symmetric matrix. The eigenvector centrality for node i is calculated solving the equation:

$$Ax = \lambda x \qquad (32)$$

where A is the adjacency matrix of the graph G with eigenvalue λ, and x is the largest eigenvalue of the adjacency matrix.

Degree centrality is very intuitive, but it is not considered the most powerful measure of centrality, because it looks at the immediate ties of each actor (Prell 2012). Eigenvector centrality takes into account the rest of the network, but it is still concentrated on the number of actors reached by every single actor. Betweenness centrality captures another dimension: it considers where actors are placed within the network. If an actor is placed among two disconnected actors it means that it has an high value of centrality, because it acts as a bridge between two parts of the network that – in its absence – would never been in contact (Figure 3).

Figure 3 Betweenness graph



Source of Data: Author's elaboration

Figure 3 perfectly illustrates this situation, in which actor C connects actor O – and the actors which are connected with it – and actor A – and the group of actors which gravitate around it. It is clear that the importance of C is higher than what it emerges only considering its degree centrality. Betweenness centrality is calculated as:

$$C_i = \sum \frac{g_{ikj}}{g_{ij}} \qquad with\ i \neq j \neq k \tag{33}$$

where g_{ikj} is the number of geodesics linking actor *i* and *j* that pass through *k*, and g_{ij} is the number of geodesics linking actor *i* and *j*.

Closeness centrality is another measure of centrality which consider the network as a whole, differently from degree centrality. Its peculiarity lies in the fact that it emphasizes actors' independence. If an actor is very close to many other actors, it can quickly reach anyone without having to pass through intermediaries: in this sense, an actor with an high closeness centrality is someone who could easily mobilize a network (Prell 2012). Closeness centrality is determined by the shortest path lenghts linking actors together: actors which have the shortest distance to other actors have the most closeness centrality. Closeness centrality is calculated as:

$$C_i = \sum_{j=1}^{n} d_{ij} \tag{34}$$

where d_{ij} is the distance connecting actor *i* to actor *j*. To calculate this measure it is necessary to remove all the isolate actors of the network, as closeness centrality can be calculated only on fully connected networks. Moreover, using a directed network is completely different from using an undirected network: in the first case actor *i* can reach actor *j* only if there is a tie from *i* to *j*, while in the second case the existence of a connection allow both *i* and *j* to reach each other.

Finally, Bonacich power centrality – also called beta-centrality – is a slightly different measure of centrality. The above measures are referred to single actors, and their importance in the network depends on their own connections and positions. Philip Bonacich (Bonacich 1987) pointed out that the classical measures – degree, eigenvector, betweenness, closeness – to calculate actors' centrality only considering their immediate contacts and not the wider network structure; this limitation is due to the nature of the relational context, and bring to different results. Beta-centrality is calculated as:

$$C_i = \alpha(I - \beta A)^{-1} A1 \tag{35}$$

where α is a scaling vector, which is set to normalize the score, β reflects the extent to which the centrality of actors related to actor *i* is weighted, *A* is the adjacency matrix, *I* is the identity matrix, and *1* is a matrix of all ones. The magnitude of β reflects the radius of power: small values weight local structure, larger values weight global structure. If $\beta > 0$, actor *i* has higher centrality when tied to actors which are central; if $\beta < 0$, actor *i* has higher centrality when tied to actors which are not central; if $\beta = 0$, beta-centrality is equal to degree centrality.

There are many qualitative and quantitative approaches to assess the effect(s) of a policy. Qualitative methods can provide a rich description of a policy process, but they generally fail to assess its impact. Impact evaluation seeks the causal link between the policy and the impact, and it can be found through quantitative approaches. SNA allows to integrate qualitative and quantitative methods. With SNA it is possibile to visualize changes in the network before and after the introduction of a policy, and assessing whether the policy-targeted network has achieved the expected results. Scholars have applied SNA to policy evaluation: Maffioli (2005) analysed the impact of networking policies on firm-level performance, using centrality measures within econometric models; Ubfal and Maffioli (2010) evaluated the impact of funding on research collaboration, applying centrality measures in a difference-in-differences model. SNA offers valuable network indicators – both at actor and network level – which can be used in econometric estimates of a policy impact. Including actor-level centrality indicators in econometric estimates can test whether a policy has made an impact on actors' relationships, which are in turn held responsible for the effectiveness of the programme (Giuliani and Pietrobelli 2011); including network-level centrality indicators can test if the structure of a network affects actors' performance, and how much it is affected. SNA can be very helpful in an evaluation process, as it detects the presence of relationships between a group of actors, i.e. to control for possible spillovers from treated to not treated actors and find a proper counterfactual.

Looking at the actor-level perspective, indicators of position can be included as independent variables in an impact assessment. Using this approach, evaluators may test whether an improvement in the performance of an actor is due to its connections, and if its position, combined with certain characteristics of the actor, is most likely to generate an improvement in the performance:

$$Y_i = k + \alpha C_i + \beta X_i + \epsilon \tag{36}$$

In equation (36), the performance Y_i of actor i is affected by its centrality in the network (C_i) and set of covariates X_i which describe some characteristics of i. As centrality measure, one can use degree centrality, eigenvector centrality, betweenness centrality, closeness centrality, and beta-centrality. This is just a little contribution of SNA to evaluation methods, because its potential is certainly more expansive.

3. Case study: the Tuscan *Poli di innovazione*

Introduction

This Chapter illustrates the results of an analysis on the innovation policies promoted by Tuscany Region. This Region is particularly indicated as a case study because it has great experience in the design of innovation policies, and because it is one of the most industrialized Italin regions. Difference-in-differences and matching evaluation, in combination with Social Network Analysis, are used to test the impact of these policies.

Tuscan policies are characterized by the recourse to R&D subsidies and the promotion of local networks. The empirical evidence about the efficacy of R&D subsidies has been widely discussed, but the results are mixed. Analyzing the Small Business Innovation Research programme in the United States, Wallsten (2000) finds that public grants displace firm expenditures dollar for dollar. Lach (2002) shows that subsidies have been effective for small firms in Israel, while they had a negative effect on large firms. Gonzalez *et al*. (2005) in analysing Spanish data find that only a small subset of firms would not have undertaken R&D activity in the absence of the subsidy, while there is no evidence of crowding out among the innovation active firms. Gorg and Strobl (2007), using an Irish sample of firms, conclude that public subsidies replace private R&D expenditure when the award is substantial. Sissoko (2013) analyses Eureka, an European program which subsidizes the formation of joint venture for R&D activities, and discovers that less productive firms gain more from R&D subsidies.

In the last years, because of the number of interventions and the amount of public resources involved, the number of studies which examine the effect of italian innovation policies has increased. Merito *et al*. (2008) evaluate the efficacy of the subsidies awarded in 2000 by the Special Fund for Applied Research of the Ministry of University and Research, introduced with the aim of supporting the research component of industrial R&D; they find that four years after the award of the subsidy, the policy had had little effect on number of employees, sales, productivity, labor costs and patent applications. Fantino and Cannone (2011) examine the efficacy of two European regional programs aiming at supporting innovative activity of small and medium firms in Piedmont and find limited effectiveness. Bronzini and Iachini (2011) when considering another regional program in Emilia Romagna find a positive effect only for small firms. de Blasio *et al*.

(2011) study an an italian programme of subsidies for the applied development of innovations, and they discover that it was not effective in stimulating innovative investment.

The promotion of local networks if often related to R&D subsidies. Being involved in a network offer incentives and opportunities which can upgrade their effect, and sometimes they are conditioned by the involvement within the network. In 2008, Tuscany Region decided to active a call for tender for small and medium enterprises called *Bando per l'acquisizione di servizi qualificati*[1] to finance the purchase of qualified services. In 2011, this call for tender has been related to the creation of the *Poli di innovazione*: twelve local network founded to support the diffusion of knwoledge and innovation among Tuscan enterprises. The firms which joined these networks could receive a benefit in the call for tender. The purpose of this research is twofold:

- to assess the impact of the subsidies on the Total Factor Productivity (TFP) and the Labor Productivity (LP) of the firms;
- to assess the presence of a relationship between the above performance and the network created by the *Poli di innovazione*.

The measurement of the performance of a firm lead to a non-negligible problem. The impact of a policy is commonly evaluated by comparing the performance of a firm the period before and after the treatment, or the performance of the treated and the non-treated firms. Unfortunately, the impact of a policy can only be known in comparison with would have happened to the firm had it not treated by the policy, i.e. the application of a proper evaluation method is required. In Paragraph 3.1 it is proposed a description of the Tuscan framework for innovation policies. Paragraph 3.2 illustrates the creation process of the dataset used for the evaluation, while in Paragraph 3.3 the empirical strategy and the results of the analysis are exhibited.

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[1] This call for tender has been funded by the POR CREO 13.b (*Programma Operativo Regionale – Obiettivo Competitività Regionale e Occupazione*, Regional Operative Programme – Object Regional Competitivity and Occupation); its extended name is "*Bando per la presentazione delle domande di contributo Aiuti alle Pmi per l'acquisizione di servizi qualificati*".

3.1 Innovation policies in Tuscany Region: a brief overview

The Tuscan production system is marked by the significative presence of small and medium enterprises. Within this system, tacit knowledge assumes a relevant added value, even if Tuscany is also a repository of a wealth of codified knowledge spread by universities and scientific centres. Tuscany Region is particularly focused in supporting the processes of technology transfer and innovation within productive systems, aimed at improving the competitiveness of enterprises (Bellandi *et al*. 2014).

The first regional innovation policies have been developed in the late 1990s. The European Union sponsored the diffusion of Regional Innovation Strategies, in the form of RITTS (Regional Innovation and Technology Transfer Strategies), RTP (Regional Technology Plans), and other activities. The Region built three ad hoc public structures which had the aims to facilitate technological transfer and create linkages between universities and firms.

During the programming period 2000-2006 the Region changed its strategy and strated to support specific projects of technological transfer. The main problem observed in this strategy was an increase of the flows of resources destined to similar projects. Another problem was the intensification of subjects in the research support system.

Due to these problems, in the programming period 2007-2013 the Region approved four (plus one) strategies for the reorganization of the regional system of innovation:

- in 2008 it created a catalogue of advanced and qualified services (*Catalogo dei servizi avanzati e qualificati per le PMI toscane dell'industria, artigianato e servizi alla produzione*), in which SME could find a list of the qualified services offered by Tuscan research organizations and services centres. Tuscany Region created a permanent call for tender in which every three months the firms could apply to obtain a loan dedicated to the purchase of services for an innovative project: the so-called *Bando per l’acquisizione di servizi qualificati*.
- In 2009 it created a business incubators network called *Tecnorete – Rete regionale del sistema di incubazione di impresa*, which include all the regional subjects involved in the technological transfer.

- In 2011 it approved the Strategic Documents of the fourteen *Centri di competenza*, infrastructures dedicated to the technological transfer, the diffusione of innovation, the support of business start-up, and the supply of advanced and qualified services;
- In 2011 it approved the creation of the twelve *Poli di innovazione* (Innovation poles), local networks of firms, universities, public and private research centres, services centres, training centers, incubators, and laboratories. The identification of such local networks has been the result of a mix top-down/bottom-up approach, in which the membership has been setted without restrictions.

These strategies have been linked together because the *Centri di competenza*, whose assignment is to supply advanced and qualified services, belong to the *Tecnorete*, i.e. they are allowed to establish a pole with other public research organizations, business incubators or other subjects involved in the technological transfer.

In addition to the above strategies, another policy is going to be implemented – in the next years – by the Tuscany Region: the constitution of the *Distretti Tecnologici* (Technological Districts). The Technological Districts are structures for industrial research, and their aim is to plan integrated activities of R&D among firms and research organizations. They have been developed consistent with the National Research Plan 2010-2012, who defined these structures as local aggregations of research organizations, small and big firms, and local institutions created for the reinforcement of the productive areas through research on key technologies. Moreover, that Plan provided specific funds for them. The original idea of the Region was to transform the *Poli di innovazione* into the technical secretariat of the *Distretti Tecnologici*, but this reorganization is developing in this years and the new assett is actually unknown.

3.1.1. Features of the *Poli di innovazione*

The *Poli di innovazione* are particularly relevant in this context because they are an element of novelty compared to the classical italian industrial district. Tuscany Region, in order to promote innovation and technology transfer according to the communication n° 323/2006 of the European Union Commission, constituted twelve poles since July of 2011.

These poles are structures of synergistic coordination among different actors of the innovation process and their creation has been inspired by the European Union regulation on state aid for research, development and innovation. A mixed top-down/bottom-up approach has been followed in the guidelines, because Tuscany Region forced their creation but gave to the local actors the opportunity to develop an autonomous strategy. The twelve poles are:

- *Polo Optoscana – Optoelettronica e Spazio* (optoelectronics);
- *Innopaper* (paper business sector);
- *Otir 2020* (fashion);
- *Polo di innovazione Scienze della Vita* (life sciences);
- *Polo Pietre Toscane* (stone sector);
- *Polo per l'eccellenza nautica toscana – PENTA* (nautical sector);
- *Polis* (technologies for sustainable cities);
- *Nanoxm* (nanotechnology);
- *CENTO – Polo di competenza per il sistema interni* (furniture);
- *PIERRE – Polo Innovazione Energie Rinnovabili e Risparmio Energetico* (renewable energies);
- *Polo12* (mechanics);
- *Politer* (ICT and robotics).

Each pole has its own characteristics – in terms of internal organization, management, strategic plan – but they also have common features imposed by the Region. They can have one or more managers – public or public-private organizations which belong to the *Tecnorete* – and one of them must be the "*leader*": a supervisor that control business activities – networking, technological and knowledge diffusion – and communicates with the Region. The partnership among two or more managers need to be legally institutionalize using the legal form of an ATS (*Associazione Temporanea di Impresa*, an enterprises temporary association).

There are three categories of poles according to the starting number of member firms and other financial parameters, and managers have the pledge to increase the number of the member firms (Table 4). Another target is to increase the supply of qualified services and to develop new systems of knowledge transfer. The ATS can be organized in scientific committees and strategic committees, which can be arranged according to the decisions of the managers.

Table 4 Categories of the *Poli di innovazione*: classification parameters, targets and maximum subsidy

	Initial members	Target1: scouting of new firms	Target2: increase of new firms (%)	Target3: Contractualized services	Target4: Supplied services	Target5: turnover	Max subsidy
Category 1	>160	160	50	80	40	500,000 €	800,000 €
Category 2	>80	80	50	40	20	300,000 €	600,000 €
Category 3	>40	40	50	20	10	150,000 €	400,000 €

Source of Data: Tuscany Region

Managers and member firms can belong to more than one pole, but member firms can participate in a maximum of three poles.

Each pole adopted its own three-year activities program of knowledge and technological transfer (2011-2014), with a specific business plan for the achievement of the following operational objectives:

- to stimulate and to accept demand of innovation from the enterprises of the pole, and in general, from external enterprises which belong to the reference technology sector;
- to accompany enterprises in the process of acquiring qualified services with high added value and to support the diffusion of innovation between enterprises inside and outside the pole;

- to facilitate to enterprises the access to scientific and technological knowledge, to facilitate the access to national and international networks, and to facilitate the access to funding sources;
- to ensure the sharing of equipments and laboratories (Bellandi *et al*. 2014).

3.2 Data

The dataset is the merger of the *Bando per l'acquisizione di servizi qualificati* dataset, the list of the member firms of the *Poli di innovazione*, and the AIDA dataset.

The first one includes all the informations about the participants to the call for tender, which has been structured as an open call with 16 windows for the presentation of the financing requests (Table 5).

Table 5 Deadlines of the *Bando per l'acquisizione di servizi qualificati*

Deadlines					
2008	2009	2010	2011	2012	2013
December31	March31 June30 September30 December31	April30 August31 December31	April30 August31 December31	April30 August31 December31	April30 August31

Source of Data: Tuscany Region

Qualified services are defined as "*support services for the innovation, finalised to the improvement of the management, the production line, the organizational system or the marketing system of an enterprise*" by the Tuscany Region. The Region has listed different types of services to whom an enterprise can require a subsidy, grouped into three main categories (Appendix A):

- first level qualified services,
- specialized qualified services,
- internazionalization services.

The informations contained in the dataset are referred to the enterprises which applied from 2008 to 2013. An enterprise could apply more than once – for different projects – with a maximum of two qualified services per project. On the whole, 2.638 enterprises received a subsidy for 3.597 services, with an admitted total investment of around 128 millions of euro – and a total expenditure of around 71 millions of euro. Observations in the dataset are coded by project, with informations concerning the name of the enterprise that applied to the call for tender, the name of the project, the day of the presentation, the type(s) of service(s) required, the amount of subsidy required, the result of the evaluation, the amount of the dispensed subsidy.

The second dataset include the list of the members of the *Poli di innovazione*. The poles were launched in 2011, and the number of member firms was 1,685; in 2014, at the end of the policy period, the number of members was 3,912, an increase of 132% (Table 6).

Table 6 Member firms of the twelve poles in 2011 and in 2014

Pole	Members (July 2011)	Members (July 2014)	% increase (2011-2014)
Optoscana	67	92	37.31
Innopaper	89	139	56.18
Otir2020	223	501	124.66
Scienze della Vita	41	158	285.37
Pietre Toscane	52	122	134.62
Penta	225	352	56.44
Polis	228	643	182.02
Nanoxm	70	128	82.86
Cento	177	322	81.92
Pierre	120	368	206.67
Polo12	198	390	96.97
Politer	195	697	257.44
Total	1,685	3,912	132.17

Source of Data: Tuscany Region

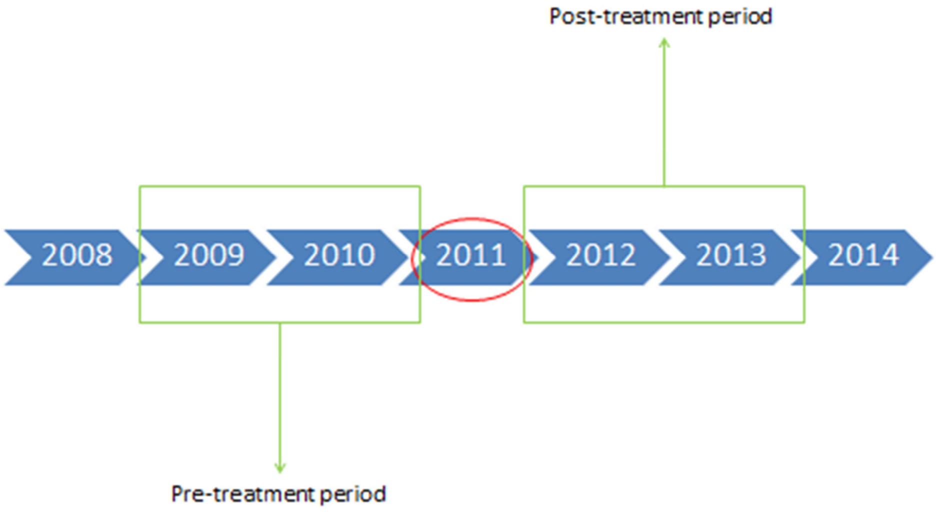
The poles has been connected to the *Bando per l'acquisizione di servizi qualificati* by the Tuscany Region. To increase the memberships of the poles, a benefit for the members has been provided in the call for tender, changing the regulation in 2011.

The third dataset include the list of the Tuscan enterprises extracted from AIDA, a commercial archive mantained by the Bureau Van Dijk. AIDA contains financial accouting data and other informations – business register code, geographic location, economic activity, etc. – on a large number of enterprises. This dataset is particularly helpful because it supplies micro-data for modelling dynamic economic behavior, especially at regional level. Data collection regards – for each firm – the business register code, the geographic location, the economic activity, the year of birth, the value added, the number of employees, the labor costs, the amount of debts, the revenues, and the capital. Data are from 2009 to 2013 (unbalanced panel), and variables have been deflated.

The construction of the final dataset has followed various steps. The aim of this research is to investigate the effect of the integrated system of Tuscan innovation policies (innovation poles plus the subsidies for the purchase of qualified services) on the firms' performance. From the first dataset, it has been extracted a list of the firms subsidized in 2011: in this year the *Poli di innovazione* were launched, i.e. it is possibile to observe enteprises which received a "*double*" treatment – members of a pole and subsidized from the *Bando per l'acquisizione di servizi qualificati*. Moreover, choosing 2011 as reporting year allows to use firms' financial accouting data for 2009-2010 (pre-treatment period) and 2012-2013 (post-treatment period). Then, the firms which were also members of the poles hase been identified with a dummy variable. Finally, the informations extracted from the *Bando per l'acquisizione di servizi qualificati* and the list of the members of the poles have been attached to the dataset extracted from AIDA[2].

[2] A clarification about the AIDA dataset is necessary. To avoid problems related to the evaluation process, the firms extracted from AIDA belong to the same industries of the firms funded in 2011 through the *Bando per l'acquisizione di servizi qualificati*. Obviously, the funded firms are a sub-group of the list extracted from AIDA, even if 91 firms on 573 have not been found in AIDA. AIDA is one of the largest dataset with accounting data of italian enterprises, but it does not include all the existing italian enterprises.

Figure 4 Periods of treatment, pre-treatment, and post-treatment



Source of Data: Author's elaboration

The enterprises included in the dataset belong to the following industries: mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities; construction; wholesale and retail trade, repair of motor vehicles and motorcycles; transportation and storage; accomodation and food service activities; information and communication; real estate activities; professional, scientific and technical activities; administrative and support service activities; education; other service activities (Table 7).

Table 7 Number of firms grouped by economic activities (initial dataset)

Category	Frequency	Percentage	Cumulative
Mining and quarrying	258	0.38	0.38
Manufacturing	14,840	21.85	22.16
Electricity, gas, and steam	549	0.81	22.97
Water supply	376	0.55	23.52
Construction	11,849	17.44	40.91
Wholesale and retail trade	8,530	12.56	53.43
Transportation and storage	2,439	3.59	57.01
Accomodation and food service	3,775	5.56	62.56
Information and communication	2,532	3.73	66.27
Real estate activities	13,808	20.33	86.54
Professional activities	5,063	7.45	93.97
Administrative activities	2,715	4.00	97.96
Education	532	0.78	98.74
Other service activities	660	0.97	100.00
Observations	67,926	100.00	

Source of Data: Author’s elaboration

This dataset has been modified to remove observations which were irrelevant for the analysis – and which could have negatively affected the evaluation process. In the first step observations without informations have been deleted, i.e. firms with the business register code, the geographic location, or the economic activity as unique information. This operation has deleted 1,256 firms. In the second step observations active from 2011 onwards have been deleted, because of the lack of information on the years before the subsidization and the creation of the poles. This operation has deleted 9,178 firms. The last step has concerned the cancellation of observations with negative values for value added, raw materials, and capital. This operation has deleted 24,310 firms. The final dataset is an unbalanced panel of 33,182 firms, with 24,349 observations participating continuously from 2009 to 2013. Patterns of observations are showed in Table 8.

Table 8 Patterns of observations (final dataset)

Pattern	Frequency	Percentage	Cumulative	Type of pattern
Pattern1	24,349	73.38	73.38	11111
Pattern2	1,793	5.40	78.78	. 1111
Pattern3	1,578	4.76	83.54	11 . . .
Pattern4	1,470	4.43	87.97	1111 .
Pattern5	1,398	4.21	92.18	111 . .
Pattern6	524	1.58	93.76	. . 111
Pattern7	253	0.76	94.52	. . . 11
Pattern8	246	0.74	95.27	. 1 . . .
Pattern9	231	0.70	95.96	1 . . . .
Pattern10	1,340	4.04	100	(others)
Total	33,182	100.00		

Source of Data: Author's elaboration

Table 9 illustrates the number of firms – grouped by economic activities – in the final dataset, with an additional classification by subsidization and involvement into the poles.

Table 9 Population, subsidized firms, and members of the poles

	Population			*Subsidized firms (Bando Servizi)*		
	N° obs.	Percentage	Cumulative	N° obs.	Mean	Cumulative
Mining and quarrying	143	0.43	0.43	4	0.99	0.99
Manufacturing	8,784	26.47	26.90	243	60.00	60.99
Electricity, gas, and steam	86	0.26	27.16	1	0.25	61.23
Water supply	223	0.67	27.83	7	1.73	62.96
Construction	5,184	15.62	43.46	53	13.09	76.05
Wholesale and retail trade	4,416	13.31	56.77	5	1.23	77.28
Transportation and storage	1,341	4.04	60.81	6	1.48	78.77
Accomodation and food service	1,671	5.04	65.84	1	0.25	79.01
Information and communication	1,510	4.55	70.39	40	9.88	88.89
Real estate activities	5,899	17.78	88.17	1	0.25	89.14
Professional activities	2,094	6.31	94.48	30	7.41	96.54
Administrative activities	1,275	3.84	98.32	12	2.96	99.51
Education	258	0.78	99.10	-	-	-
Other service activities	298	0.90	100.00	2	0.49	100.00
Total	33,182	100.00		405	100.00	

	Members of the poles			*Subsidized & Members*		
	N° obs.	Percentage	Cumulative	N° obs.	Mean	Cumulative
Mining and quarrying	11	1.51	1.51	-	-	-
Manufacturing	420	57.61	59.12	52	59.77	59.77
Electricity, gas, and steam	3	0.41	59.53	-	-	-
Water supply	3	0.41	59.95	-	-	-
Construction	58	7.96	67.90	6	6.90	66.67
Wholesale and retail trade	34	4.66	72.57	1	1.15	67.82
Transportation and storage	12	1.65	74.21	-	-	-
Accomodation and food service	1	0.14	74.35	-	-	-
Information and communication	64	8.78	83.13	16	18.39	86.21
Real estate activities	2	0.27	83.40	-	-	-
Professional activities	103	14.13	97.53	12	13.79	100.00
Administrative activities	10	1.37	98.90	-	-	-
Education	8	1.10	100.00	-	-	-
Other service activities	-	-		-	-	-
Total	729	100.00		87	100.00	

Source of Data: Author’s elaboration

3.3 Empirical strategy and results

3.3.1. Evaluation of R&D subsidies on performance

As discussed in the Introduction, many studies have explored the effects of R&D subsidies on economic performance at firm level, reaching different results. This topic has been widely explored and it has been demonstrated that factors such as firm heterogeneity, simultaneity of input and output decisions, measurement errors and business cycle may introduce bias into the empirical results (Brasini and Freo 2011). Many characteristics can affect firm performance, and for this reason the effect of a treatment – in this case, the financing obtained through the *Bando per l'acquisizione di servizi qualificati* and being a member of a pole – should be disentangled by firm heterogeneity. Knowing what would happened to the treated firms if they had not been treated allows to properly estimate this effect, but in the social sciences it is impossibile to observe both outcomes for the same firm at the same time.

To solve this problem, propensity score matching and difference-in-differences evaluation are used to investigate the relationship between innovation policies and productivity. The basic idea behind this method is to create a counterfactual unobservable comparison group, matching treated firms with not treated firms, and to compare the outcomes of the two groups controlling for systematic difference by applying difference-in-differences. Matching and difference-in-differences provide accurate estimates, because this approach aims at addressing endogeneity. Matching provides a key missing control group that gives information on the behavoir of treated firms if they had not been treated, and that decreases the endogeneity bias linked to the self-selection of the firms which participated to the Tuscan innovation policies. Difference-in-differences takes into account for time trends, and reduces the endogeneity related to the natural propensity of firms to grow (Arnold and Javorcik 2009, Sissoko 2013).

Three different models have been built to assess the effect of the innovation policies implemented by the Tuscany Region:

- a combined propensity score matching/difference-in-differences model to evaluate the economic impact of the subsidies distributed through the *Bando per l'acquisizione di servizi qualificati*[3];

- a combined propensity score matching/difference-in-differences model to evaluate the economic impact of the *Poli di innovazione*;

- a combined propensity score matching/difference-in-differences model to evaluate the economic impact of the above subsidies on the members of the *Poli di innovazione*;

- a regression model to evaluate the network's effect on the economic performance of the firms.

In each model, the pre-treatment period is the two-year period 2009-2010, while the post-treatment period is the two-year period 2012-2013. Variables are computed as means of the two-year pre and post period.

3.3.2. Estimation of firm productivity

The Total Factor Productivity (TFP) is widely recognized as a performance benchmark to measure the rate of performance of firms over time. Robert Solow (1957) demonstrated that the output growth of a firm can be decomposed into the contribution of input growth and a residual productivity term. TFP growth is usually measured by the Solow residual: let g^Y denote the growth rate of aggregate output, g^K the growth rate of aggregate capital, g^L the growth rate of aggregate labor and α the capital share, the Solow residual (*Sr*) is then defined as:

$$S_r = g^Y - g^K - (1 - \alpha)g^L \quad (37)$$

[3] I do not use the, as control group, the firms which applied to the call for tender but did not receive the subsidy: in 2011 the number of subsidized firms – compared to the total number of requests – was around 90%.

The Solow residual accurately measures TFP growth if the production function is neoclassical, there is perfect competition in factor markets, and the growth rates of the inputs are measured accurately.

During the 1980s, the National Bureau of Economic Research was the first to start a systematic survey of the sectorial TFP in the United States (Gullickson and Harper 1987). In the 1990s, the number of the studies on the TFP increases quickly, although there are still some criticism to the use of this indicator. Hulten (2001) points out three general criticisms:

- the assumption of constant returns to scale is needed to estimate the return to capital as a residual, but if another measure is used in constructing the share weights, the residual can be derived without the assumption of constant returns;
- the assumption of marginal cost pricing is too restrictive: when imperfect competition leads to a price greater than marginal cost the residual yields a biased estimate of the Hicksian shift parameter of the production function;
- the assumption that innovation improves the marginal productivity of all inputs equally is too strong.

In this research, it is used the method developed by Levinsohn and Petrin (2003) to estimate the productivity function. Classical OLS estimates of production functions – and productivity – are biased when productive shocks lead firms to decrease or increase their input usage. To solve this problem, Olley and Pakes (1996) develop an estimator that use investments as a proxy for these unobservables shocks. Levinsohn and Petrin (2003) extend this idea, using intermediate inputs – electricity or raw materials – instead of investments. There are three main benefits of using this approach. The first is strictly data driven: investment proxy is only valid for plants with nonzero investment, while intermediate inputs are almost always reported by active firms. The second benefit is that for a firm it is less costly to adjust the intermediate inputs – instead of investments – to respond to a productivity shock. The last benefit is that intermediate inputs are not typically state variables.

For the productivity estimation, the production technology is assumed to be Cobb-Douglas:

$$Y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + \omega_t + \eta_t \tag{38}$$

where Y_t is the logarithm of the firm's output, measured as value added (also gross revenue is allowed as firm's output), l_t and m_t are the logarithm of the freely variable inputs labor and the intermediate input, and k_t is the logarithm of the capital. The error has two components: ω_t, the transmitted productivity component, and η_t, an error term that is uncorrelated with input choices.

The demand for the intermediate input m_t is assumed to depend on the firm's state variables k_t and ω_t:

$$m_t = m_t(k_t, \omega_t) \tag{39}$$

Levinsohn and Petrin show that the demand function is monotonically increasing in ω_t, and this allows inversion of the intermediate demand function, in order to identify unobservable productivity term as a function of two observed inputs:

$$\omega_t = \omega_t(k_t, m_t) \tag{40}$$

Finally, they assume that productivity is governed by a first-order Markov process:

$$\omega_t = E[\omega_t|\omega_{t-1}] + \xi_t \tag{41}$$

where ξ_t is an innovation to productivity that is uncorrelated with k_t, but not necessarily with l_t (Levinsohn and Petrin 2003).

The estimation is structured in three steps. In this case, value added has been chosen as firm's output. In the first step, given the production function:

$$Y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + \omega_t + \eta_t = \beta_l l_t + \varphi_t(k_t, m_t) + \eta_t \tag{42}$$

where

$$\varphi_t(k_t, m_t) = \beta_0 + \beta_k k_t + \omega_t(k_t, m_t) \tag{43}$$

substituting a third-order polynomial approximation in k_t and m_t in place of $\phi t(k_t, m_t)$ makes it possible to consistently estimate parameters of the value added equation using OLS:

$$Y_t = \delta_0 + \beta_l l_t + \sum_{i=0}^{3} \sum_{j=0}^{3-i} \delta_{ij} k_t^i m_t^j + \eta_t \tag{44}$$

To estimate β_k it is necessary to compute the estimated value for ϕ_t using

$$\widehat{\varphi_t} = \widehat{Y_t} - \widehat{\beta_l} l_t \tag{45}$$

For any candidate value β_k it is possible to compute (up to a scalar constant) a prediction for ω_t for all periods t using

$$\widehat{\omega_t} = \widehat{\varphi_t} - \beta_k k_t \tag{46}$$

Using these values, a consistent – nonparametric – approximation to $E[\omega t|\omega t-1]$ is given by the predicted values from the regression

$$\widehat{\omega_t} = \gamma_0 + \gamma_1 \omega_{t-1} + \gamma_2 \omega^2{}_{t-1} + \gamma_3 \omega^3{}_{t-1} + \epsilon_t \tag{47}$$

Given the estimated values of β_l, β_k, and $E[\omega t|\omega t - 1]$, the estimate of β_k is defined as the solution to

$$min_{\beta_k} \sum (Y_t - \widehat{\beta_l} l_t - \beta_k k_t - E[\widehat{\omega_t | \omega_{t-1}}])^2 \tag{48}$$

Another productivity measure used in this research is the Labor Productivity (LP), defined as the ratio among value added and the number of employees per year. Many studies highlight the existence of a positive correlation between innovation and LP (Apergis *et al*. 2008, Hall 2011), and this relationship assume great relevance in this study because Tuscan innovation policies indirectly – and sometimes directly – operate on human capital.

3.3.3. Innovation policies effect on productivity

The apparent differences among the groups of firms included within the dataset – those subsidized through the call for tender *Bando per l'acquisizione di servizi qualificati* in 2011, the members of the poles, the group of firms resulting from the combination of these two policies, and the not treated firms – say little about the direction of causality (Table 10). The application of the methodology proposed in Paragraph 3.3.1 will provide more insight for the causality attribution to the specific policies.

Table 10 Summary statistics

	Subsidized pre-treatment			*Subsidized post-treatment*		
Variables	N° obs.	Mean	Std. Dev.	N° obs.	Mean	Std. Dev.
Age	405	16.86	13.08	405	19.86	13.08
Revenues (thousands €)	398	5,970	8,739	390	6,739	11,500
Employees	363	23.41	40.15	386	30.29	55.53
Intermediate inputs (thousands €)	398	2,619	5,173	390	3,170	7,993
Wages (thousands €)	398	1,011	1,304	390	1,129	1,511
Capital (thousands €)	398	1,782	4,042	390	1,773	3,769
Value added (thousands €)	398	1,496	1,894	390	1,648	2,270
Debts (thousands €)	398	3,933	6,414	390	4,154	6,473
	Members pre-treatment			*Members post-treatment*		
Variables	N° obs.	Mean	Std. Dev.	N° obs.	Mean	Std. Dev.
Age	729	18.08	14.13	729	21.08	14.13
Revenues (thousands €)	716	15,700	143,000	695	16,100	144,000
Employees	654	47.65	248.28	690	44.33	166.69
Intermediate inputs (thousands €)	716	7,283	63,100	695	10,400	116,000
Wages (thousands €)	716	2,476	18,100	695	2,185	14,300
Capital (thousands €)	716	4,922	46,100	695	2,982	12,800
Value added (thousands €)	716	3,898	36,400	695	2,983	19,700
Debts (thousands €)	716	12,800	130,000	695	17,800	300,000
	Subsidized & members pre-treatment			*Subsidized & members post-treatment*		
Variables	N° obs.	Mean	Std. Dev.	N° obs.	Mean	Std. Dev.
Age	87	17.58	14.23	87	20.58	14.23
Revenues (thousands €)	87	5,790	8,752	85	7,868	17,100
Employees	81	26.79	35.69	84	29.26	34.04
Intermediate inputs (thousands €)	87	2,514	5,182	85	4,130	13,300
Wages (thousands €)	87	1,044	1,339	85	1,169	1,502
Capital (thousands €)	87	1,313	2,579	85	1,315	2,496
Value added (thousands €)	87	1,518	2,003	85	1,876	2,780
Debts (thousands €)	87	3,305	4,489	85	3,802	5,545
	Not treated pre-treatment			*Not treated post-treatment*		
Variables	N° obs.	Mean	Std. Dev.	N° obs.	Mean	Std. Dev.
Age	32,135	13.60	12.38	32,135	16.60	12.38
Revenues (thousands €)	30,807	2,540	24,900	28,409	2,753	27,200
Employees	28,966	6.89	63.89	27,913	9.97	62.29
Intermediate inputs (thousands €)	30,809	1,301	18,800	28,409	1,477	21,700
Wages (thousands €)	30,809	330	2,621	28,409	349	2,478
Capital (thousands €)	30,954	1,267	20,400	28,409	1,251	19,600
Value added (thousands €)	30,953	560	5,482	28,409	586	5,633
Debts (thousands €)	30,956	2,164	27,000	28,409	2,212	29,100

Source of Data: Author's elaboration

In order to implement propensity score matching, the probability of being treated needs to be modeled empirically. Three different models have been created, one for each group of firms exposed to the different innovation policies implemented by the Tuscany Region.

In the first case – firms subsidized through the *Bando per l'acquisizione di servizi qualificati* – a probit model is estimated in order to assess the probability to receive a R&D subsidy, with observable firms characteristics in the pre-treatment period as explanatory variables. The underlying assumption for the validity of the procedure is that, conditional on the observable characteristics that are relevant for the subsidiation – excluding the quality of the project – potential outcomes for the treated and the not treated are independent to the treatment[4].

Table 11 Probit results, predicting the probability to be subsidized through the *Bando per l'acquisizione di servizi qualificati* (first model)

Variables	Mechanical firm	Manufacturing firm	Services firm
Age_{pre}	0.0150	-0.00113	0.00562
	(0.0173)	(0.00753)	(0.00938)
Age_{pre}^{2}	-0.000217	1.98e-05	-0.000175
	(0.000331)	(0.000121)	(0.000193)
$Revenues_{pre}$	-2.15e-08	-4.55e-09	8.13e-11
	(2.26e-08)	(5.73e-09)	(7.47e-09)
$Intermediate\ inputs_{pre}$	2.46e-08	8.83e-10	-2.65e-08
	(2.86e-08)	(8.41e-09)	(1.71e-08)
$Debts_{pre}$	1.17e-09	8.34e-10	-5.45e-09
	(1.47e-08)	(2.59e-09)	(7.62e-09)
LP_{pre}	-1.129***	-0.859***	-0.993***
	(0.319)	(0.195)	(0.150)
TFP_{pre}	1.387***	1.298***	1.301***
	(0.358)	(0.210)	(0.175)
Intercept	-4.222***	-6.012***	-4.973***
	(1.570)	(0.825)	(0.637)
Observations	1,215	4,111	9,488

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source of Data: Author's elaboration

[4] The choice of covariates is influenced by the empirical literature on R&D subsidy policies (Girma *et al.* 2007, Bronzini and Iachini 2011, Sissoko 2013).

Data presented in Table 11 suggest the presence of differences between treated and not treated, for mechanical, manufacturing and services firms. Variables are referred to the pre-treatment period. Younger mechanical and services firms – identified by the variable "Age_{pre}^{2}" – are more likely to be not subsidized, even if the difference is almost zero; it means that old and structured firms are considered more reliable than firms with less experience. Small firms, in terms of "$Revenues_{pre}$", are more likely to be subsidized if they are mechanical and manufacturing. Productive firms, in terms of TFP in the pre-treatment period, are also more likely to be subsidized, differently from organizations which had an high LP in the pre-treatment period.

The predicted probability of being subsidized, or propensity score, resulting from the model in Table 11, forms the basis of the matching procedure. To assess how well the propensity score matching performs, it has been calculated the difference between the treated and the controls in terms of each of the above variables and it has been run a simple t-tests on the differences. This is a necessary condition for the balancing hypothesis (Dehejia and Wahba 2002). No statistically significant differences have been found between the treated and control group in terms of all the above variables.

After testing the balancing hypothesis, to estimate the Average Treatment effect on the Treated (ATT) in terms of Total Factor Productivity and Labor Productivity it has been used the Radius Matching (RM), using two different radius (0.0005 and 0.0002). It has been computed both restricting the analysis over the common support and not. As a robustness check, in order to control for industry-specific effects, the ATT is computed for three different types of firms: mechanical firms, manufacturing firms, and services firms. The ATT is estimated using the next equations:

$$ATT_{TFPfin} = \sum_{i \epsilon T} [(Y_{it_1} - Y_{it_0}) - \sum_{i \epsilon C} W_{ij} (Y_{jt_1} - Y_{jt_0})] \, w_i \tag{49}$$

$$ATT_{LPfin} = \sum_{i \epsilon T} [(Y_{it_1} - Y_{it_0}) - \sum_{i \epsilon C} W_{ij} (Y_{jt_1} - Y_{jt_0})] \, w_i \tag{50}$$

where T stands for Treated group, C for non treated (Comparison) group, Y_{it_1} and Y_{it_0} are the outcomes of (treated) firm i after – and before – the programme time period, Y_{jt_1} and Y_{jt_0} are the outcomes of (non treated) firm j after – and before – the programme time period, *Wij* is the weight placed on comparison observation *j* for firm *i*, w_i account for the reweighting that reconstructs the outcome distribution for the treated sample.

Table 12 Estimation results of the first model (treatment: subsidized firms), with different Radius Matching (0.0005 and 0.0002 as radius), grouped by economic activities

	RADIUS 0.0005				RADIUS 0.0002			
	CS		NCS		CS		NCS	
	LP	TFP	LP	TFP	LP	TFP	LP	TFP
Mechanical firms	*0.129*	*0.110*	*0.128*	*0.107*	*0.117*	*0.092*	*0.122*	*0.096*
	(0.056)	*(0.052)*	*(0.056)*	*(0.052)*	*(0.066)*	*(0.061)*	*(0.066)*	*(0.061)*
Treated	36	36	36	36	31	31	31	31
Control group	346	346	361	361	155	155	161	161
T-test	2.308	2.093	2.303	2.057	1.783	1.517	1.859	1.583
Manufacturing firms	*0.080*	*0.070*	*0.079*	*0.069*	*0.093*	*0.083*	*0.091*	*0.081*
	(0.040)	*(0.038)*	*(0.040)*	*(0.038)*	*(0.041)*	*(0.039)*	*(0.041)*	*(0.039)*
Treated	125	125	125	125	125	125	125	125
Control group	2,423	2,423	2,445	2,445	1,363	1,363	1,371	1,371
T-test	1.993	1.821	1.983	1.807	2.272	2.122	2.209	2.064
Services firms	*0.076*	*0.075*	*0.072*	*0.071*	*0.076*	*0.074*	*0.072*	*0.069*
	(0.051)	*(0.044)*	*(0.051)*	*(0.044)*	*(0.052)*	*(0.045)*	*(0.052)*	*(0.045)*
Treated	99	99	99	99	99	99	99	99
Control group	6,918	6,918	7,017	7,017	4,628	4,628	4,675	4,675
T-test	1.477	1.699	1.407	1.613	1.471	1.656	1.381	1.551

Legend:

NN = Nearest Neighbor

RM = Radius Matching

CS = Common Support

NCS = No Common Support

Standard errors in brackets

Source of Data: Author's elaboration

Using different radius produces different results – even if the gap is not particularly elevated. Both mechanical, manufacturing and services firms have positive increases of TFP and LP when the ATT is calculated both over the common support and not.

Mechanical firms show the best results in terms of TFP and LP increases, while services firms show positive but not statistically significant results. Estimates for manufacturing firms, in terms of statistically significance, have a better result when the radius is fixed to 0.0002. While analyzing these results, a caveat is necessary. The group of services firms include industries with different specializations, and different business-cycle trends: e.g., the textile sector is one of the most relevan in Tuscany but in the last year it suffered a long crisis, while other sectors – like the renewable energy sector – grown considerably, and this situation could affect the ATT estimates.

In the second case – members of the *Poli di innovazione* as treated – it has been calculated a probit model of the binary outcome "*poles membership*" (Table 13).

Table 13 Probit results, predicting the probability to be a member of the *Poli di innovazione* (second model)

Variables	Mechanical firm	Manufacturing firm	Services firm
Age_{pre}	0.00628	0.00299	0.0137**
	(0.0110)	(0.00676)	(0.00577)
Age_{pre}^{2}	3.52e-05	-1.84e-05	-0.000149
	(0.000188)	(0.000110)	(9.58e-05)
$Revenues_{pre}$	-3.84e-09	-1.21e-09	-2.66e-09
	(7.63e-09)	(2.76e-09)	(2.39e-09)
Intermediate $inputs_{pre}$	-2.16e-09	1.86e-09	-5.46e-10
	(6.76e-09)	(3.15e-09)	(2.12e-09)
$Debts_{pre}$	5.48e-09	1.56e-09	2.26e-09
	(7.14e-09)	(1.63e-09)	(1.44e-09)
LP_{pre}	-1.084***	-0.764***	-0.496***
	(0.218)	(0.163)	(0.107)
TFP_{pre}	1.552***	1.039***	0.703***
	(0.236)	(0.170)	(0.120)
Intercept	-5.951***	-4.275***	-4.067***
	(1.110)	(0.672)	(0.453)
Observations	1,215	4,111	9,488

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source of Data: Author's elaboration

Old firms – variable "*Age_{pre}*" – seem to be more likely to become members of the poles, as well as small firms – in terms of "*$Revenues_{pre}$*". Like in the previous case, firms with low levels of LP and high levels of TFP have an highest probability of being treated.

To test for the balancing hypothesis, it has been computed the difference between the treated and the controls in terms of the above variables and it has been run a simple t-tests on the differences. No statistically significant differences have been found between the treated and the control groups.

The ATT can be estimated using the next equations:

$$ATT_{TFPpole} = \sum_{i \epsilon T} [(Y_{it_1} - Y_{it_0}) - \sum_{i \epsilon C} W_{ij} (Y_{jt_1} - Y_{jt_0})] w_i \quad (51)$$

$$ATT_{LPpole} = \sum_{i \epsilon T} [(Y_{it_1} - Y_{it_0}) - \sum_{i \epsilon C} W_{ij} (Y_{jt_1} - Y_{jt_0})] w_i \quad (52)$$

where T stands for Treated group, C for non treated (Comparison) group, Y_{it_1} and Y_{it_0} are the outcomes of (treated) firm *i* after – and before – the programme time period, Y_{jt_1} and Y_{jt_0} are the outcomes of (non treated) firm *j* after – and before – the programme time period, *Wij* is the weight placed on comparison observation *j* for firm *i*, w_i account for the reweighting that reconstructs the outcome distribution for the treated sample.

Table 14 Estimation results of the second model (treatment: members of the poles), with different Radius Matching (0.0005 and 0.0002 as radius), grouped by economic activities

	RADIUS 0.0005				RADIUS 0.0002			
	CS		NCS		CS		NCS	
	LP	TFP	LP	TFP	LP	TFP	LP	TFP
Mechanical firms	*0.061*	*0.050*	*0.061*	*0.050*	*0.068*	*0.061*	*0.068*	*0.061*
	(0.056)	*(0.051)*	*(0.056)*	*(0.050)*	*(0.074)*	*(0.066)*	*(0.074)*	*(0.066)*
Treated	72	72	72	72	59	59	59	59
Control group	307	307	309	309	139	139	139	139
T-test	1.088	0.990	1.089	0.983	0.928	0.923	0.928	0.923
Manufacturing firms	*-0.006*	*-0.009*	*-0.001*	*-0.003*	*-0.002*	*-0.004*	*-0.002*	*-0.004*
	(0.039)	*(0.037)*	*(0.039)*	*(0.037)*	*(0.041)*	*(0.039)*	*(0.041)*	*(0.039)*
Treated	178	178	179	179	169	169	169	169
Control group	2,886	2,886	2,887	2,887	1,765	1,765	1,765	1,765
T-test	-0.161	-0.233	-0.026	-0.080	-0.059	-0.115	-0.059	-0.115
Services firms	*0.091*	*0.092*	*0.091*	*0.092*	*0.093*	*0.094*	*0.093*	*0.093*
	(0.039)	*(0.034)*	*(0.039)*	*(0.034)*	*(0.039)*	*(0.035)*	*(0.039)*	*(0.035)*
Treated	185	185	185	185	183	183	183	183
Control group	7,519	7,519	7,554	7,554	6,640	6,640	6,657	6,657
T-test	2.357	2.686	2.348	2.674	2.375	2.692	2.367	2.682

Legend:

NN = Nearest Neighbor

RM = Radius Matching

CS = Common Support

NCS = No Common Support

Standard errors in brackets

Source of Data: Author’s elaboration

Excluding mechanical firms, in which the gap between the models with different radius is around 10% percentage points, using different radius leads to similar results. The ATT in terms of TFP and LP is lower compared to the previous case: furthermore, for manufacturing firms it is negative. Results are not statistically significant, except for the increase of TFP and LP of services firms. It probably means that the *Poli di innovazione* are stimulating environments for high-qualified organizations – services firms – which are very receptive to share knowledge and informations, but their effect on traditional – manufacturing – productions is limited.

In the third case – members of the poles which have been subsidized – the probit model accounts for the probability of receive a R&D subsidy for the members of the *Poli di innovazione*. In this case, a membership should have facilitate the path of the firms in the call for tender, generating a double benefit:

- to the firms, which receive the subsidy and improve their performance,
- to the pole, which increases the number of members thanks to the advertising effect of the success in the call for tender.

Table 15 Probit results, predicting the probability of being subsidized for the members of the *Poli di innovazione* (third model)

Variables	Mechanical firm	Manufacturing firm	Services firm
Age_{pre}	0.0280	0.00326	-0.00323
	(0.0291)	(0.0127)	(0.0158)
Age_{pre}^{2}	-0.000318	2.86e-06	-4.91e-05
	(0.000533)	(0.000191)	(0.000330)
$Revenues_{pre}$	3.50e-09	-8.37e-09	4.69e-09
	(2.42e-08)	(1.75e-08)	(1.35e-08)
Intermediate $inputs_{pre}$	-5.36e-08	7.05e-09	-2.51e-08
	(6.67e-08)	(1.86e-08)	(3.04e-08)
$Debts_{pre}$	1.13e-08	-2.89e-09	-1.15e-08
	(2.33e-08)	(1.16e-08)	(1.95e-08)
LP_{pre}	-1.413***	-0.846**	-0.750***
	(0.423)	(0.366)	(0.252)
TFP_{pre}	1.465***	1.299***	1.014***
	(0.457)	(0.411)	(0.292)
Intercept	-2.747	-6.858***	-5.044***
	(2.422)	(1.555)	(1.080)
Observations	1,215	4,111	9,488

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source of Data: Author’s elaboration

The results of the third probit model are different from the first and the second model, but also in this case firms with low levels of LP and high levels of TFP are more sensitive to receive a subsidy if they are members of a pole. To control for the balancing hypothesis of the propensity score, it has been calculated the difference between treated and controls in terms of each of the variables in Table 15, and it has been run a simple t-tests on the differences. No statistically significant differences have been found between the treated and control group in terms of the above variables.

Unfortunately, the number of treated is very low: as showed in Table 16, there are less then 100 members of the poles which have received a subsidy. Estimates of the ATT have been obtained through the following equations:

$$ATT_{TFPfin\&pole} = \sum_{i \epsilon T} [(Y_{it_1} - Y_{it_0}) - \sum_{i \epsilon C} W_{ij} (Y_{jt_1} - Y_{jt_0})]\, w_i \tag{53}$$

$$ATT_{LPfin\&pole} = \sum_{i \epsilon T} [(Y_{it_1} - Y_{it_0}) - \sum_{i \epsilon C} W_{ij} (Y_{jt_1} - Y_{jt_0})]\, w_i \tag{54}$$

In equation (53) and equation (54) *T* stands for Treated group, *C* for non treated (Comparison) group, Y_{it_1} and Y_{it_0} are the outcomes of (treated) firm *i* after – and before – the programme time period, Y_{jt_1} and Y_{jt_0} are the outcomes of (non treated) firm *j* after – and before – the programme time period, *Wij* is the weight placed on comparison observation *j* for firm *i*, w_i account for the reweighting that reconstructs the outcome distribution for the treated sample. The effect of subsidies for poles' members on LP and TFP are positive and particularly high for mechanical firms and services firms, and positive but not particularly high for manufacturing firms. Estimates for mechanical and services firms are also statistically significant, both with a radius equal to 0.0005 and 0.0002.

Table 16 Estimation results of the third model (treatment: firms subsidized and members of the poles), with different Radius Matching (0.0005 and 0.0002 as radius), grouped by economic activities

	RADIUS 0.0005				RADIUS 0.0002			
	CS		NCS		CS		NCS	
	LP	TFP	LP	TFP	LP	TFP	LP	TFP
Mechanical firms	*0.532 (0.146)*	*0.456 (0.127)*	*0.676 (0.143)*	*0.561 (0.124)*	*0.590 (0.151)*	*0.516 (0.131)*	*0.652 (0.145)*	*0.544 (0.126)*
Treated	6	6	6	6	6	6	6	6
Control group	151	151	273	273	68	68	113	113
T-test	3.649	3.580	4.740	4.539	3.907	3.938	4.489	4.320
Manufacturing firms	*0.096 (0.073)*	*0.093 (0.077)*	*0.098 (0.073)*	*0.094 (0.077)*	*0.098 (0.073)*	*0.094 (0.077)*	*0.098 (0.073)*	*0.093 (0.077)*
Treated	29	29	29	29	29	29	29	29
Control group	2,434	2,434	2,619	2,619	1,263	1,263	1,343	1,343
T-test	1.314	1.210	1.346	1.228	1.336	1.223	1.339	1.206
Services firms	*0.241 (0.096)*	*0.230 (0.087)*	*0.240 (0.096)*	*0.228 (0.087)*	*0.250 (0.099)*	*0.245 (0.089)*	*0.250 (0.099)*	*0.244 (0.089)*
Treated	24	24	24	24	23	23	23	23
Control group	6,245	6,245	7,269	7,269	4,962	4,962	5,393	5,393
T-test	2.512	2.657	2.506	2.636	2.516	2.765	2.519	2.753

Legend:

NN = Nearest Neighbor

RM = Radius Matching

CS = Common Support

NCS = No Common Support

Standard errors in brackets

Source of Data: Author’s elaboration

3.3.4. Network effect

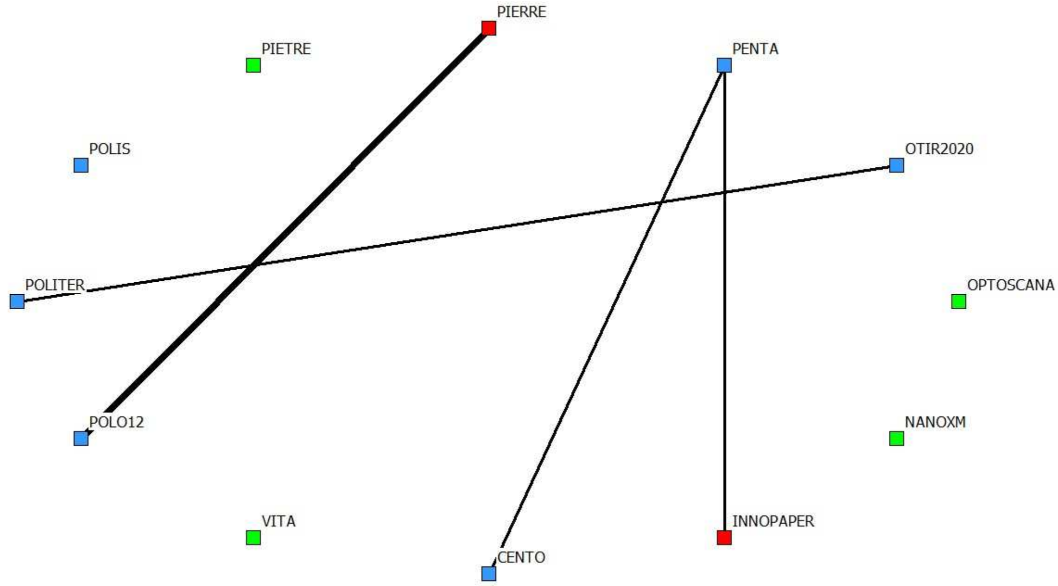
The last step of the analysis concerns the use of Social Network Analysis (SNA) to assess the impact of the innovation policies implemented by Tuscany Region. An econometric model which includes centrality indicator(s) can test whether a policy have had an impact on inter-organizational networks, which are in turn held responsible for the effectiveness of the programme (Giuliani and Pietrobelli 2011).

The effect of multiple policies can be additive or – on the contrary – a policy can interfere with another policy. As shown in the previous models, it seems that the *Poli di innovazione* have been effective in combination with the subsidies provided by the *Bando per l'acquisizione di servizi qualificati*, but, due to the lack of observations and the complexity in extracting their effective contribution from the total effect, the presence of a "*pole effect*" related to the connections of the poles is not totally verified.

SNA helps to test the effect of the network structure on the firm's performance. A clarification about the model which is going to be used is necessary: the dataset of the Innovation poles allows to identify which firms were included in 2011, but not their relationships. It is not possibile to create a map of the network based on the exchanges of resources among firms, but it is possibile to create a map of the network based on the exchanges among poles. The twelve poles have activated a large number of agents – employees and consultants – in the development of the knowledge and technological transfer system. Moreover, they have shared laboratories and incubators to support the diffusion of innovation and to stimulate innovative processes within enterprises. The more connections owned by a pole, the higher is the opportunity – for an enterprise – to access to knowledge and technological sharing.

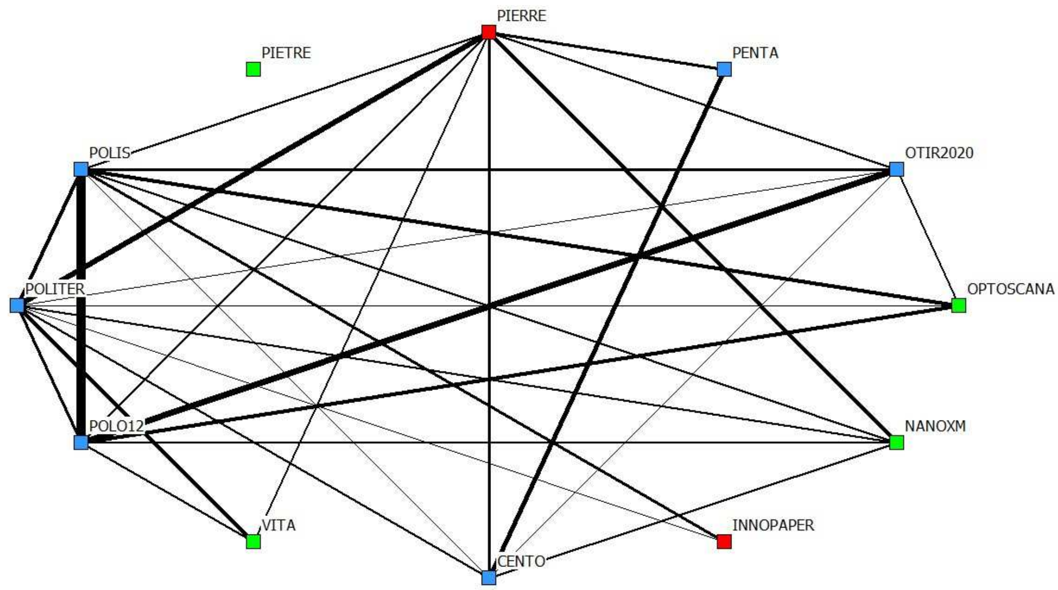
Figure 5, Figure 6, Figure 7, Figure 8 and Figure 9 illustrate the graphs of, respectively, the sharing of consultants, the sharing of employees, the sharing of laboratories, the sharing of incubators, and the sum of these networks. If a pole shares one of these elements with another pole, they have a linkage. Linkages are weighted by the number of shared elements (weights in Figure 9 are re-scaled for a better representation). Each pole is classified by its category (Table 4): blue squares are the poles which belong to the category 1, red squares are the poles which belong to the category 2, green squares are the poles which belong to the category 3.

Figure 5 Network of shared consultants among the twelve poles (line widths are based on tie strength)



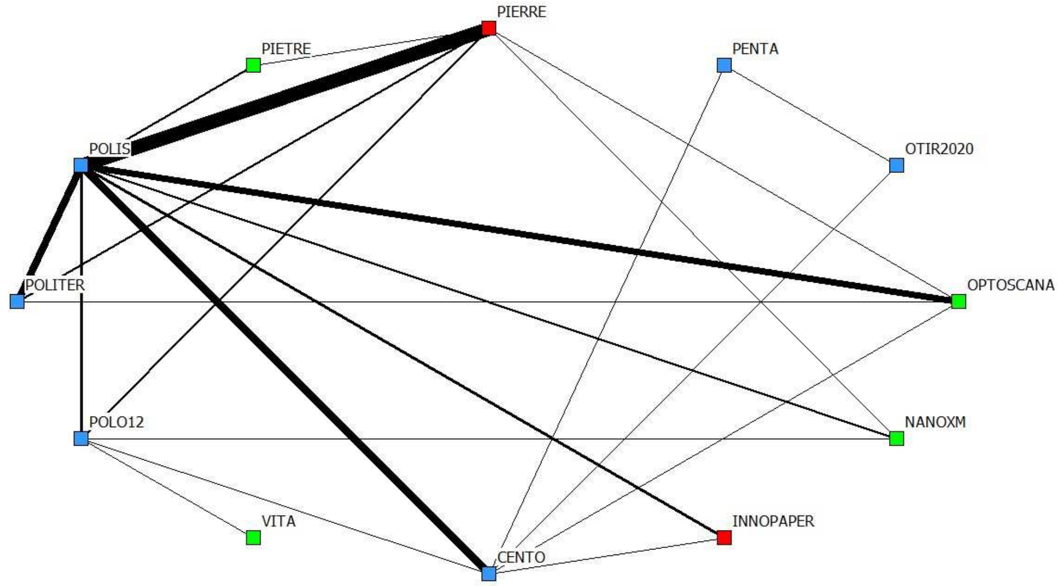
Source of Data: Author's elaboration

Figure 6 Network of shared employees among the twelve poles (line widths are based on tie strength)



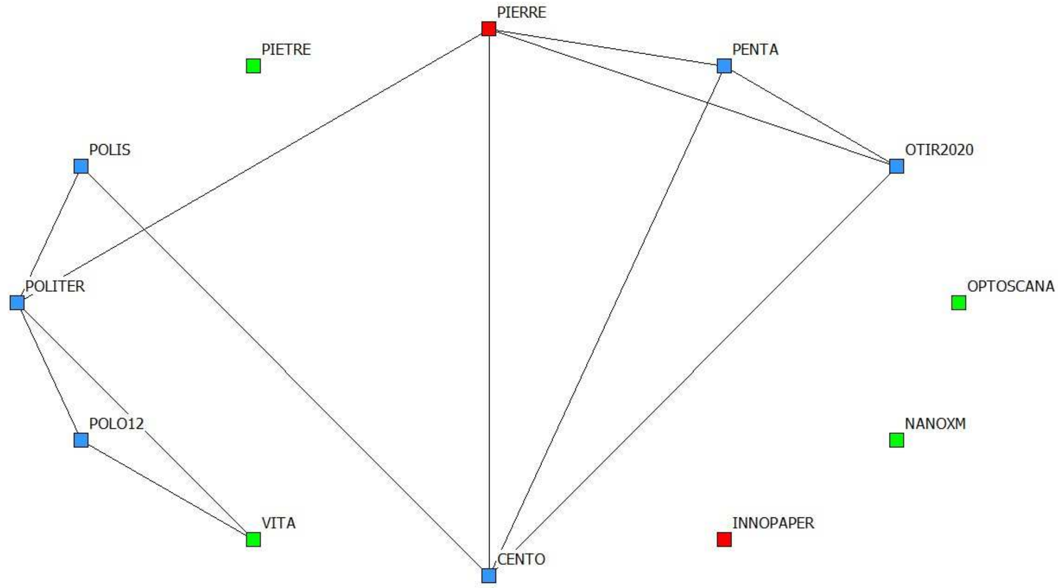
Source of Data: Author's elaboration

Figure 7 Network of shared laboratories among the twelve poles (line widths are based on tie strength)



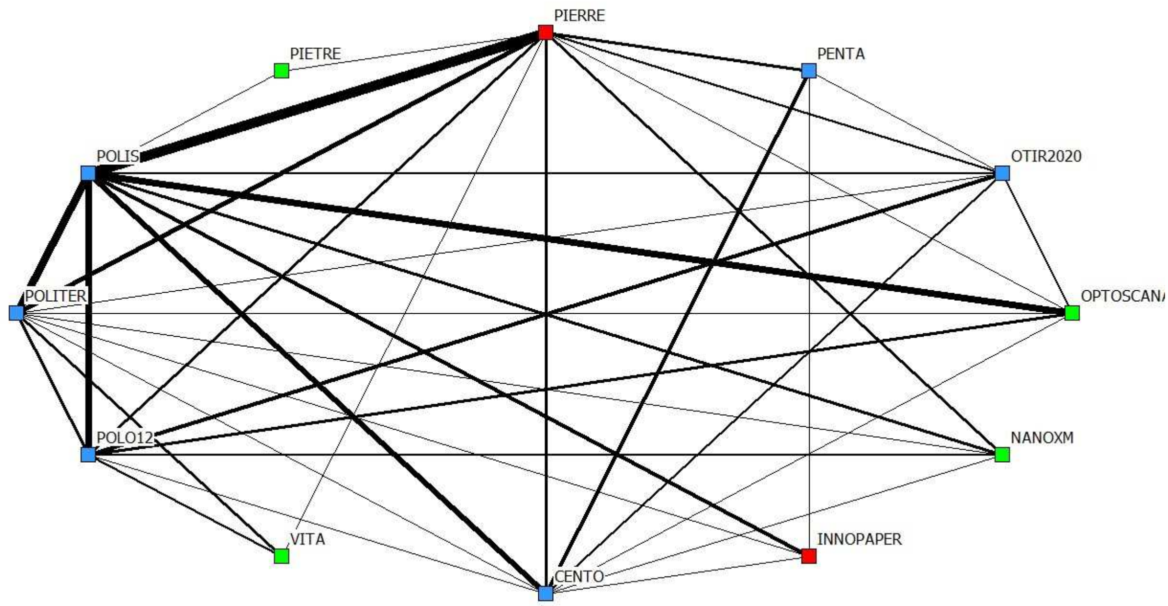
Source of Data: Author’s elaboration

Figure 8 Network of shared incubators among the twelve poles (line widths are based on tie strength)



Source of Data: Author’s elaboration

Figure 9 Network of total connections – consultants, employees, laboratories, incubators – among the twelve poles (line widths are based on tie strength)



Source of Data: Author’s elaboration

The adjacency matrices of the different networks have been created computing the number of consultants, employees, laboratories, and incubators in common to each couple of poles – and the sum of these sharings for the total network. Weights have been used to highlight the strenght of the relationships: they are equal to zero in some cases, while in others they are very relevant (Appendix B). The intensity of the relationships depends on two factors:

- the dimension of the pole (bigger poles in terms of human resources or infrastructures are more likely to share their assets with others),
- the sector(s) of activity (poles which belong to a similar sector are more likely to share their assets because of a common vision, and a common “*language*”).

Five centrality measures have been computed for these networks: degree, Bonacich power (beta-centrality), closeness, eigenvector and betweenness (Table 17, Table 18, Table 19, Table 20,

Table 21). Values have been normalized. For each firm, these variables take the value of the centrality measure computed for the pole they belong to. In case of multiple memberships – firms had the opportunity to join more than one pole, even if a threshold[5] was imposed in 2011 – it has been assigned the value of the pole with the best score.

Table 17 Centrality measures (consultants network)

Pole	Degree	Bonacich Power	Closeness	Eigenvector	Betweenness
Optoscana	0.091	0.025	0.333	0.000	0.000
Innopaper	0.182	5.997	0.367	0.707	0.000
Otir2020	0.182	0.166	0.355	0.000	0.000
Scienze della Vita	0.091	0.025	0.333	0.000	0.000
Pietre Toscane	0.000	0.000	0.333	0.000	0.000
Penta	0.273	8.483	0.379	1.000	0.018
Polis	0.000	0.000	0.333	0.000	0.000
Nanoxm	0.091	0.025	0.333	0.000	0.000
Cento	0.182	5.997	0.367	0.707	0.000
Pierre	0.182	0.166	0.355	0.000	0.000
Polo12	0.182	0.166	0.355	0.000	0.000
Politer	0.182	0.166	0.355	0.000	0.000
Mean	0.137	1.768	0.350	0.201	0.002

Source of Data: Author's elaboration

Table 18 Centrality measures (employees network)

Pole	Degree	Bonacich Power	Closeness	Eigenvector	Betweenness
Optoscana	0.455	2.846	0.524	0.336	0.000
Innopaper	0.273	1.536	0.478	0.181	0.000
Otir2020	0.636	3.974	0.611	0.469	0.019
Scienze della Vita	0.364	2.195	0.524	0.259	0.000
Pietre Toscane	0.091	0.003	0.250	0.000	0.000
Penta	0.273	1.310	0.458	0.154	0.000
Polis	0.818	4.671	0.688	0.551	0.093
Nanoxm	0.545	3.521	0.579	0.415	0.004
Cento	0.636	3.664	0.611	0.432	0.057
Pierre	0.818	4.551	0.688	0.536	0.127
Polo12	0.727	4.257	0.647	0.502	0.044
Politer	0.909	4.974	0.733	0.586	0.147
Mean	0.545	3.125	0.566	0.368	0.041

Source of Data: Author's elaboration

[5] Three poles, but sometimes it has not been respected.

Table 19 Centrality measures (laboratories network)

Pole	Degree	Bonacich Power	Closeness	Eigenvector	Betweenness
Optoscana	0.455	3.925	0.579	0.463	0.045
Innopaper	0.273	2.165	0.524	0.255	0.000
Otir2020	0.273	1.106	0.440	0.129	0.000
Scienze della Vita	0.182	0.894	0.407	0.105	0.000
Pietre Toscane	0.273	2.371	0.478	0.280	0.000
Penta	0.273	1.106	0.440	0.129	0.000
Polis	0.818	6.045	0.786	0.713	0.321
Nanoxm	0.364	3.261	0.524	0.385	0.000
Cento	0.636	3.992	0.688	0.469	0.367
Pierre	0.636	4.951	0.611	0.584	0.094
Polo12	0.545	4.131	0.647	0.487	0.227
Politer	0.364	3.217	0.500	0.380	0.000
Mean	0.424	3.097	0.552	0.365	0.088

Source of Data: Author’s elaboration

Table 20 Centrality measures (incubators network)

Pole	Degree	Bonacich Power	Closeness	Eigenvector	Betweenness
Optoscana	0.000	0.000	0.250	0.000	0.000
Innopaper	0.091	0.007	0.250	0.000	0.000
Otir2020	0.364	5.037	0.379	0.595	0.000
Scienze della Vita	0.273	1.593	0.355	0.184	0.000
Pietre Toscane	0.091	0.007	0.250	0.000	0.000
Penta	0.364	5.037	0.379	0.595	0.000
Polis	0.273	2.830	0.393	0.333	0.027
Nanoxm	0.000	0.000	0.250	0.000	0.000
Cento	0.455	5.698	0.393	0.673	0.045
Pierre	0.455	5.881	0.423	0.694	0.136
Polo12	0.273	1.593	0.355	0.184	0.000
Politer	0.455	3.621	0.423	0.423	0.191
Mean	0.258	2.609	0.342	0.307	0.033

Source of Data: Author’s elaboration

Table 21 Centrality measures (total network)

Pole	Degree	Bonacich Power	Closeness	Eigenvector	Betweenness
Optoscana	0.636	3.536	0.688	0.417	0.000
Innopaper	0.455	2.101	0.611	0.247	0.009
Otir2020	0.727	3.787	0.733	0.446	0.021
Scienze della Vita	0.364	1.805	0.579	0.213	0.000
Pietre Toscane	0.273	1.225	0.55	0.144	0.000
Penta	0.455	2.055	0.611	0.242	0.009
Polis	0.909	4.310	0.846	0.508	0.107
Nanoxm	0.545	3.012	0.647	0.355	0.000
Cento	0.909	4.410	0.846	0.520	0.065
Pierre	1.000	4.525	0.917	0.533	0.177
Polo12	0.818	4.124	0.786	0.486	0.038
Politer	0.909	4.38	0.846	0.516	0.083
Mean	0.667	3.273	0.722	0.386	0.042

Source of Data: Author's elaboration

Correlations between these measures are illustrated in Appendix C. The finding that central network positions are associated with power has been widely demonstrated, because actors in central positions have access to – and control over – relevant resources (Krackhardt and Brass 1994). To assess the network position effect on the economic performance of the enterprises, it has been estimated a quantile regression model in which the independent variable is a measure of centrality [6] and the dependent variable is a measure of performance.

The population is composed by the firms which have received a subsidy (first treatment), in order to test whether a membership to a central pole has an additive effect on subsidized firms or not. The dependent variable and the independent variable have been created as follows.

Controlling for correlations between centrality measures of the different networks, it has emerged that these variables are highly correlated. To avoid multicollinearity problems in the quantile regression model, it has been chosed to concentrate on a single measure using the estimated value of closeness centrality from the total network (Figure 9), instead of the closeness centralities of the different networks (Table 21). Closeness centrality emphasizes

[6] Firms which do not belong to a pole have a closeness centrality equal to zero.

the independence of the actors and is linked to their ability to easily access informations, power and influence in the network (Prell 2012). This variable has been rescaled, according to the distribution of the qualified services values. Due to the absence of firm-level data, this transformation is a sort of “*distance attribution*” in order to detect which firms have been more connected – in terms of amount of the subsidies – with their poles: firms which belong to the same pole but have received different amount of subsidies to purchase qualified services (from the pole) have a different value of closeness centrality.

Table 22 Correlations between the different closeness centralities of the consultants network, the employees network, the incubators network, and the laboratories network

	Consultants	Employees	Incubators	Laboratories
Consultants	1			
Employees	0.9882	1		
Incubators	0.9858	0.9924	1	
Laboratories	0.9696	0.9825	0.9717	1

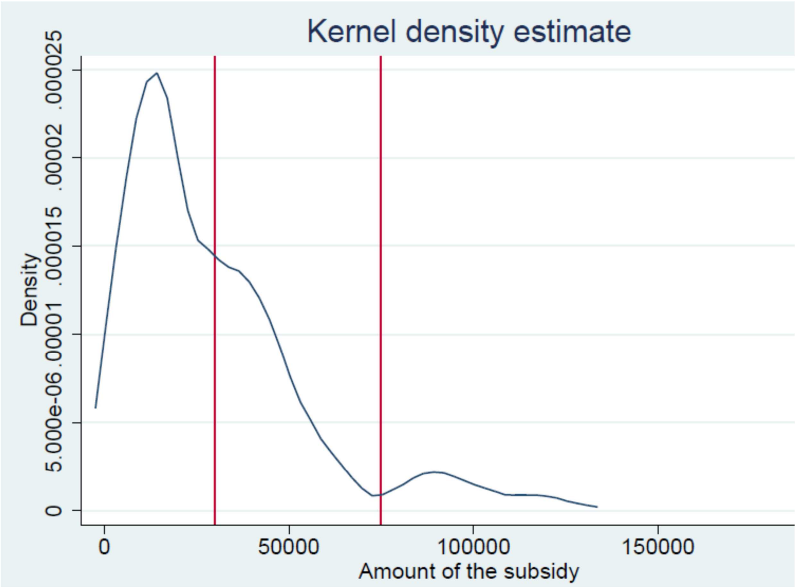
Source of Data: Author’s elaboration

To rescale closeness centrality, they have been identified two levels of discontinuity using the estimated probability density function of the variable which identifies the amount of the subsidies received by firm *i* (Figure 10). The rescaled closeness centrality for each firm *i* is the original closeness centrality weighted by a scalar which depends on its location respect to the discontinuity levels:

$$IC_i = C_i * wt_i \tag{55}$$

where IC_i is the rescaled closeness centrality of firm *i*, C_i is the original closeness centrality of firm *i*, and wt_i is a scalar which takes value 0.33 if the total amount of subsidies received by firm *i* is lower than 30,000 euro, takes value 0.66 if the total amount of subsidies received by firm *i* is between 30,000 and 75,000 euro, and takes value 1 if the total amount of subsidies received by firm *i* is greater than 75,000 euro.

Figure 10 Kernel density estimator (estimated probability density function) of the total amount of subsidies: red lines indicate the discontinuity values of 30,000 and 75,000 euro



Source of Data: Author's elaboration

The dependent variables used for the quantile regression model are the net values of the differences of TFP and LP for each firm *i*. From the pre-post differences of TFP and LP for each firm *i* they have been subtracted the pre-post differences means of TFP and LP for the firms which compose the counterfactual created using the radius matching (with radius equal to 0.0005 and equal to 0.0002):

$$Y_{i_{TFPa}} = (TFP_{i_{post}} - TFP_{i_{pre}}) - (\overline{TFP}_{c_{post}} - \overline{TFP}_{c_{pre}}) \quad \text{if radius=0.0005} \tag{56}$$

$$Y_{i_{LPa}} = (LP_{i_{post}} - LP_{i_{pre}}) - (\overline{LP}_{c_{post}} - \overline{LP}_{c_{pre}}) \quad \text{if radius=0.0005} \tag{57}$$

$$Y_{i_{TFPb}} = (TFP_{i_{post}} - TFP_{i_{pre}}) - (\overline{TFP}_{c_{post}} - \overline{TFP}_{c_{pre}}) \quad \text{if radius=0.0002} \tag{58}$$

$$Y_{i_{LPb}} = (LP_{i_{post}} - LP_{i_{pre}}) - (\overline{LP}_{c_{post}} - \overline{LP}_{c_{pre}}) \quad \text{if radius=0.0002} \tag{59}$$

where Y_i is the outcome for firm *i* (*a* and *b* indicate which kind of radius has been used to identify the counterfactual: respectively, 0.0005 and 0.0002), $TFP_{i_{post}}$ and $LP_{i_{post}}$ are the Total Factor Productivity and the Labor Productivity of firm *i* in the post treatment period, $TFP_{i_{pre}}$ and $LP_{i_{pre}}$ are the Total Factor Productivity and the Labor Productivity of firm *i* in the pre treatment period, $TFP_{c_{post}}$ and $LP_{c_{post}}$ are the mean Total Factor Productivity and the mean Labor Productivity of the counterfactual of firm *i* in the post treatment period,

$TFP_{c_{pre}}$ and $LP_{c_{pre}}$ are the mean Total Factor Productivity and the mean Labor Productivity of the counterfactual of firm *i* in the pre treatment period. Every firm *i* has been matched with a group of firms which belong to the same sector (mechanical, manufacturing, and services).

After defining the dependent variable and the independent variable, it has been possibile to estimate the effect of the closeness centrality on the performance of the firms. Quantile regression (Koenker and Basset, 1978) has been used to estimate this effect. The quantile regression approach is a methodology to estimate the regression coefficients at different quantiles of the distribution of the response variable; it is more robust to non-normal errors and outliers compared to OLS, and it allows to consider the impact of a covariate on the entire distribution of the dependent variable, not merely on its conditional mean.

They have been created four quantile regression model, one for each outcome estimated in equation (56), (57) , (58) , and (59):

$$Y_{TFPa} = \alpha_\tau + \beta_\tau IC + \epsilon_\tau \quad \text{where } \tau = 0.33, 0.50, 0.66, 0.75, 0.90 \tag{60}$$

$$Y_{LPa} = \alpha_\tau + \beta_\tau IC + \epsilon_\tau \quad \text{where } \tau = 0.33, 0.50, 0.66, 0.75, 0.90 \tag{61}$$

$$Y_{TFPb} = \alpha_\tau + \beta_\tau IC + \epsilon_\tau \quad \text{where } \tau = 0.33, 0.50, 0.66, 0.75, 0.90 \tag{62}$$

$$Y_{LPb} = \alpha_\tau + \beta_\tau IC + \epsilon_\tau \quad \text{where } \tau = 0.33, 0.50, 0.66, 0.75, 0.90 \tag{63}$$

where τ indicates the quantile, and for each τ the estimated coefficient β illustrates the variation of the τ-quantile of the outcome (Y_{TFPa}, Y_{LPa}, Y_{TFPb}, Y_{LPb}).

Table 23 Estimation results of the equations (60), (61), (62), (63)

Dep. var.	Y_{TFPa}	Y_{LPa}	Y_{TFPb}	Y_{LPb}
IC				
q(0.33)	0.0427	0.130	0.120	0.291**
	(0.0999)	(0.114)	(0.239)	(0.128)
q(0.50)	0.140	0.170	0.232	0.135
	(0.107)	(0.109)	(0.174)	(0.122)
q(0.66)	0.187*	0.302**	0.297**	0.149
	(0.112)	(0.144)	(0.125)	(0.103)
q(0.75)	0.283	0.216	0.240	0.254
	(0.196)	(0.162)	(0.195)	(0.173)
q(0.90)	0.793**	0.620	0.869***	0.550
	(0.392)	(0.441)	(0.305)	(0.373)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source of Data: Author's elaboration

Five quantiles have been choosed in order to test whether the centrality of a pole on a group of firms instead of another. It appears that the impact of the poles centrality is quite homogeneous: always positive e increasing in the top part of the distribution. It seems that the effect is more emphasized for the most productive firms. The null hypothesis is that the growth rates of the outcome (TFP or LP) do not differ at each quantile across different levels of centrality: this hypothesis is rejected for both the TFP of quantiles 0.66 and 0.90 and the LP of quantile 0.66 (radius matching equal to 0.0005)[7], showing a particularly positive situation for enterprises at the top level.

These results mean that members of the *Poli di innovazione* have experienced on average an higher productivity gain respect to the firms which did not become members of the poles, and that being involved in a pole which is central – in terms of shared consultants, shared employees, shared laboratories, and shared incubators – is particularly convenient.

[7] And for the LP of quantile 0.33 (radius matching equal to 0.0002), which have also a large positive coefficient – compared to the other quantiles.

Conclusions

The aim of this thesis is to assess the effect of an integrated system of innovation policies on the economic performances of Tuscan small and medium enterprises. Evaluation methods (matching and difference-in-differences) are used in combination with Social Network Analysis (SNA) in order to detect the effectiveness of these policies.

Tuscany Region subsidized R&D activities through the call for tender *Bando per l'acquisizione di servizi qualificati* and the creation of the *Poli di innovazione* (Innovation poles). In the first case, a direct financing for purchasing qualified services was given to innovative projects; in the second case, firms were encouraged to join local networks composed of services centres, universities, private research centres, laboratories, and incubators. The *Bando per l'acquisizione di servizi qualificati* was active from 2008 to 2013, while the *Poli di innovazione* were active from 2011 to 2014. Regional goals were focused to support innovation activities and networking between small and medium enterprises. The novelty of this research lies in the object of study and the evaluation approach: Tuscany Region integrated two different policies in order to support the innovation process, using a mixed top down/bottom up approach which has never been studied before. Moreover, this research is a first attempt to use SNA data in order to assess potential network's effect on the performances of the enterprises.

The analysis uses Total Factor Productivity (TFP) and Labor Productivity (LP) as measures of performance. For each firm, TFP is estimated using the Levinsohn and Petrin approach, which – differently from the classical OLS estimates of production functions – uses intermediate inputs as a proxy for productive shocks. LP is estimated using the ratio between value added and the number of employees per year. TFP and LP trends have been observed in the two-year period 2009-2010 and the two-year period 2012-2013: 2011 has been chosed as "*treatment year*", because poles started to operate in that year – and their members started to apply to the call for tender using the benefit deriving from their membership.

A combination of propensity score matching and difference-in-differences (DID) method is used to estimate the effect of these policies. Propensity score matching reduces the bias due to confounding variables that could be found in the estimate of the treatment effect; DID uses a before-after comparison across groups to estimate the treatment effect. This methodology addresses endogeneity and provides more accurate estimates: matching controls for the selection bias restricting the DID estimates to a sub-sample of actors based on a set of observable characteristics. Radius Matching has been chosed as algorithm of matching, but they have been used two measures of radius (0.0005 and 0.0002) in order to control for counterfactual groups with different dimensions.

Individually, the two policies have achieved different results. Considering the first treatment – firms which have received the R&D subsidies – the mechanical firms have experienced on average the highest productivity gain towards the end of the period of subsidization, compared to manufacturing firms and services firms which have received the subsidization. On average, the TFP and the LP of the mechanical firms which have been subsidized are around 10-15% higher than the mechanical firms which have not been subsidized, while manufacturing firms and services firms which have been subsidized have had a performance – in terms of TFP and LP increase – of nearly 10% higher than the firms which have not been subsidized. Both using a radius equal to 0.0005 or equal to 0.0002 does not produce (totally) different results. Estimates are statistically significant for mechanical firms and manufacturing firms. These results are coherent with the purpose of the Tuscany Region, whose focus was on supporting the innovative process of small and medium enterprises belonging to the traditional manufacturing sector.

Considering the second treatment – firms which have become members of the *Poli di innovazione* – the services firms which have joined the poles have experienced on average – compared to the firms which did not become members of a pole – a 10% increase of TFP and LP (statistically significant). Mechanical firms have experienced a positive increase which is halved respect to the firms which have received the R&D subsidies, while manufacturing firms have experienced a negative increase: both these results are not statistically significant. The results of this policy are completely different from the results of the *Bando per l'acquisizione di servizi qualificati*: the services firms have had more benefits from the membership to the *Poli di innovazione*, while the mechanical firms and the manufacturing firms have had more benefits from the R&D subsidies.

Considering the third treatment – members of the poles which have been subsidized – it is interesting to notice that the combined effect of these policies is particularly effective for mechanical firms, which have experienced a 50-60% increase in the TFP and the LP. Also for services firms the estimated results are strongly positive and statistically significant, but the dimension of the population – less than 100 firms which have received a R&D subsidy during their poles' membership – lead to assume a careful interpretation of the effect of the (combined) policies.

To assess the network effect of the *Poli di innovazione* on the performance of the SME, Social Network Analysis (SNA) has been used as evaluation method. Performance results of the firms which have received the R&D subsidies have been related to the centrality – in terms of shared consultants, employees, laboratories, and incubators – of their membership pole. As measures of performance, they have been choosed the differences between the net values of TFP and LP for each firm which has received the R&D subsidy and the net mean values of TFP and LP of each counterfactual group of firms selected using the above different radius matching. Due to the lack of data, no informations about the relationships between firms were available, but the closeness centrality of a pole has been used as a proxy of its ability to operate as a "*bridge*" between different organizations and facilitate the innovation process. A rescaled measure of closeness centrality – based on the total amount of subsidies received by the members of the poles – has been used in a quantile regression model in order to understand if being central is a benefit or not. Quantile regression has been choosed because of the dataset: around 200 firms do not belong to a pole, while around 60 firms belong to – at least – one pole, i.e. this distribution could affect an ordinary least squares regression. Furthermore, a quantile regression is more robust to non-normal errors and outliers, and provides a richer characterization of the data, allowing to consider the impact of a covariate on the entire distribution of the outcome variable, not merely its conditional mean.

It has emerged that if a firm belong to a central pole it experiences a positive gain in terms of TFP and LP increase, but the increase is decisively high – and statistically significant – only for the firms which already have the best performances of TFP and LP increase. Five quantiles have been choosed in order to test whether the centrality of a pole on a group of firms instead of another, and it has been discovered that over the quantile (0.66) the "*pole effect*" is relevant and almost statistically significant, except for the LP estimated with the second radius matching (0.0002). It means that members of the *Poli di innovazione* have experienced on average an higher productivity gain respect to the firms which did not become members of the poles, and that being involved in a pole which is central – in terms of shared consultants, shared employees, shared laboratories, and shared incubators – is convenient.

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Appendix A

List of the qualified services

Type	List of services
A. First level qualified services (*Servizi qualificati di primo livello*)	A.1 - Servizi di audit e assessment del potenziale A.2 - Studi di fattibilità di primo livello
B. Specialized qualified services (*Servizi qualificati specializzati*)	B.1.1 - Servizi di supporto alla innovazione di prodotto nella fase di concetto B.1.2 - Servizi di supporto all'introduzione di nuovi prodotti B.1.3 - Servizi tecnici di progettazione per innovazione di prodotto e di processo produttivo B.1.4 - Servizi tecnici di sperimentazione (prove e test) B.1.5 - Servizi di gestione della proprietà intellettuale B.1.6 - Ricerca tecnico-scientifica a contratto B.1.7 - Servizi di supporto all'innovazione dell'offerta B.2.1 - Servizi di supporto al cambiamento organizzativo B.2.2 - Servizi di miglioramento della efficienza delle operazioni produttive B.2.3 - Gestione della catena di fornitura o supply chain management B.2.4 - Supporto alla certificazione avanzata B.2.5 - Servizi per l'efficienza energetica B.2.6 - Servizi per l'efficienza ambientale B.2.7 - Servizi di supporto all'innovazione organizzativa mediante gestione temporanea di impresa (Temporary management – TM) B.3.1 - Supporto alla introduzione di innovazioni nella gestione delle relazioni con i clienti B.3.2 - Supporto allo sviluppo di reti distributive specializzate ed alla promozione di prodotti B.3.3 - Servizi di valorizzazione della proprietà intellettuale B.4.1 - Servizi qualificati specifici per la creazione di nuove imprese innovative

	– B.4.1.1 - Pre-incubazione – B.4.1.2 - Incubazione – B.4.1.3 - Accompagnamento commerciale e accelerazione B.4.2 - Servizi qualificati specifici a domanda collettiva – B.4.2.1 - Marchi collettivi – B.4.2.2 - Tracciabilità dei prodotti – B.4.2.3 - Certificazione di filiera – B.4.2.4 - Logistica e supply chain management – B.4.2.5 – Reti distributive e gestione delle relazioni con i clienti – B.4.2.6 - Temporary management – B.4.2.7 – Supporto alla costituzione di Organizzazioni interprofessionali e alla progettazione dei servizi connessi
C. Internazionalization services (*Servizi all’internazionalizzazione*)	C.1.1 - Partecipazione a fiere e saloni internazionali C.1.2 - Creazione di uffici o sale espositive all’estero C.1.3 - Realizzazione di nuovi centri di assistenza tecnica post-vendita all’estero C.1.4 - Realizzazione di nuove strutture logistiche all’estero di transito e di distribuzione internazionale di prodotti C.2.1 - Servizi promozionali C.2.2 - Supporto specialistico all’internazionalizzazione C.2.3 - Supporto all'innovazione commerciale per la fattibilità di presidio su nuovi mercati

Source of Data: Tuscany Region

Appendix B

Adjacency matrices of the graphs representing the different networks (consultants, employees, laboratories, incubators, and their sum) created by the *Poli di innovazione*.

Adjacency matrix of the network of shared consultants

	Optoscana	Innopaper	Otir 2020	Scienze della Vita	Pietre Toscane	Penta	Polis	Nanoxm	Cento	Pierre	Polo 12	Politer
Optoscana	1	0	0	0	0	0	0	0	0	0	0	0
Innopaper	0	20	0	0	0	1	0	0	0	0	0	0
Otir2020	0	0	18	0	0	0	0	0	0	0	0	1
Scienze della Vita	0	0	0	2	0	0	0	0	0	0	0	0
Pietre Toscane	0	0	0	0	0	0	0	0	0	0	0	0
Penta	0	1	0	0	0	39	0	0	1	0	0	0
Polis	0	0	0	0	0	0	0	0	0	0	0	0
Nanoxm	0	0	0	0	0	0	0	1	0	0	0	0
Cento	0	0	0	0	0	1	0	0	17	0	0	0
Pierre	0	0	0	0	0	0	0	0	0	3	3	0
Polo12	0	0	0	0	0	0	0	0	0	3	3	0
Politer	0	0	1	0	0	0	0	0	0	0	0	2

Adjacency matrix of the network of shared employees

	Optoscana	Innopaper	Otir 2020	Scienze della Vita	Pietre Toscane	Penta	Polis	Nanoxm	Cento	Pierre	Polo 12	Politer
Optoscana	29	0	3	0	0	0	6	0	0	0	6	1
Innopaper	0	24	0	0	0	0	4	0	0	0	0	1
Otir2020	3	0	44	0	0	0	4	0	1	3	10	1
Scienze della Vita	0	0	0	26	0	0	0	0	0	2	2	6
Pietre Toscane	0	0	0	0	22	0	0	0	0	0	0	0
Penta	0	0	0	0	0	25	0	0	7	4	0	0
Polis	6	4	4	0	0	0	55	3	1	2	14	5
Nanoxm	0	0	0	0	0	0	3	25	2	6	2	2
Cento	0	0	1	0	0	7	1	2	34	4	0	2
Pierre	0	0	3	2	0	4	2	6	4	56	2	8
Polo12	6	0	10	2	0	0	14	2	0	2	37	4
Politer	1	1	1	6	0	0	5	2	2	8	4	82

Adjacency matrix of the network of shared laboratories

	Optoscana	Innopaper	Otir 2020	Scienze della Vita	Pietre Toscane	Penta	Polis	Nanoxm	Cento	Pierre	Polo 12	Politer
Optoscana	14	0	0	0	0	0	11	0	1	1	0	1
Innopaper	0	4	0	0	0	0	4	0	1	0	0	0
Otir2020	0	0	6	0	0	1	0	0	1	0	0	0
Scienze della Vita	0	0	0	2	0	0	0	0	0	0	1	0
Pietre Toscane	0	0	0	0	3	0	2	0	0	1	0	0
Penta	0	0	1	0	0	3	0	0	1	0	0	0
Polis	11	4	0	0	2	0	100	3	12	25	4	15
Nanoxm	0	0	0	0	0	0	3	4	0	1	1	0
Cento	1	1	1	0	0	1	12	0	12	0	1	0
Pierre	1	0	0	0	1	0	25	1	0	23	2	3
Polo12	0	0	0	1	0	0	4	1	1	2	9	0
Politer	1	0	0	0	0	0	15	0	0	3	0	17

Adjacency matrix of the network of shared incubators

	Optoscana	Innopaper	Otir 2020	Scienze della Vita	Pietre Toscane	Penta	Polis	Nanoxm	Cento	Pierre	Polo 12	Politer
Optoscana	0	0	0	0	0	0	0	0	0	0	0	0
Innopaper	0	1	0	0	0	0	0	0	0	0	0	0
Otir2020	0	0	1	0	0	1	0	0	1	1	0	0
Scienze della Vita	0	0	0	2	0	0	0	0	0	0	1	1
Pietre Toscane	0	0	0	0	1	0	0	0	0	0	0	0
Penta	0	0	1	0	0	1	0	0	1	1	0	0
Polis	0	0	0	0	0	0	1	0	1	0	0	1
Nanoxm	0	0	0	0	0	0	0	0	0	0	0	0
Cento	0	0	1	0	0	1	1	0	3	1	0	0
Pierre	0	0	1	0	0	1	0	0	1	2	0	1
Polo12	0	0	0	1	0	0	0	0	0	0	1	1
Politer	0	0	0	1	0	0	1	0	0	1	1	3

Adjacency matrix of the network of shared consultants, employees, laboratories, and incubators

	Optoscana	Innopaper	Otir2020	Scienze della Vita	Pietre Toscane	Penta	Polis	Nanoxm	Cento	Pierre	Polo 12	Politer
Optoscana	44	0	3	0	0	0	17	0	1	1	6	2
Innopaper	0	49	0	0	0	1	8	0	1	0	0	1
Otir2020	3	0	69	0	0	2	4	0	3	4	10	2
Scienze della Vita	0	0	0	32	0	0	0	0	0	2	4	7
Pietre Toscane	0	0	0	0	26	0	2	0	0	1	0	0
Penta	0	1	2	0	0	68	0	0	10	5	0	0
Polis	17	8	4	0	2	0	156	6	14	27	18	21
Nanoxm	0	0	0	0	0	0	6	30	2	7	3	2
Cento	1	1	3	0	0	10	14	2	66	5	1	2
Pierre	1	0	4	2	1	5	27	7	5	84	7	12
Polo12	6	0	10	4	0	0	18	3	1	7	50	5
Politer	2	1	2	7	0	0	21	2	2	12	5	104

Source of Data: Author’s elaboration

Appendix C

Correlations between centrality measures of the different networks (consultants, employees, laboratories, incubators):

- Degree centrality

	Consultants	Employees	Incubators	Laboratories
Consultants	1			
Employees	0.7878	1		
Incubators	0.8677	0.9186	1	
Laboratories	0.6900	0.9550	0.8690	1

- Bonacich Power centrality

	Consultants	Employees	Incubators	Laboratories
Consultants	1			
Employees	0.2929	1		
Incubators	0.4582	0.8454	1	
Laboratories	0.3475	0.9045	0.6902	1.0000

- Eigenvector centrality

	Consultants	Employees	Incubators	Laboratories
Consultants	1			
Employees	0.2679	1		
Incubators	0.4356	0.8439	1	
Laboratories	0.3299	0.9036	0.6871	1

- Betweenness centrality

	Consultants	Employees	Incubators	Laboratories
Consultants	1			
Employees	-0.0428	1		
Incubators	-0.0288	0.8635	1	
Laboratories	-0.0387	0.7401	0.4452	1

Source of Data: Author’s elaboration

Correlations between centrality measures of the total network

	Degree	Bonacich	Closeness	Eigenvector	Betweenness
Degree	1				
Bonacich	0.9981	1			
Closeness	0.9938	0.9936	1		
Eigenvector	0.9981	1.0000	0.9935	1	
Betweenness	0.8069	0.7748	0.7642	0.7749	1

Source of Data: Author's elaboration