Three essays on innovation networks, cluster policies and regional knowledge production

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Three essays on innovation networks, cluster policies and regional knowledge production

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I dedicate this dissertation to my loving parents...

Déclaration

L'université Jean Monnet n'entend ni approuver, ni désapprouver les opinions particulières du candidat : ces opinions doivent être considérées comme propres à leur auteur.

Alain N'Ghauran

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And the God of all grace, who called you to his eternal glory in Christ, after you have suffered a little while, will himself restore you and make you strong, firm and steadfast – 1 Peter 5:10

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Abstract

This dissertation presents three essays on innovation networks, cluster policies and regional knowledge production. Following the development of policies aiming at supporting innovation networks, especially cluster policies, this thesis intends to empirically test one of the theoretical foundations of these policies suggesting that the structure of innovation networks would have an impact on the knowledge production within regions. In doing so, it provides answers to a fundamental question from the geography of innovation literature and brings a new perspective to the analysis of cluster policies by evaluating them regarding their role for the structuration of innovation networks.

The first essay (Chapter 2) thus analyses the extent to which regional innovation is influenced by the structure of innovation networks. Although the development of policies supporting innovation networks suggests the existence of a potential relationship between the structure of innovation networks and knowledge production within regions, empirical evidence supporting this relationship is still scarce. Based from the French case, the results of Chapter 2 highlight the existence of this relationship, confirming that the structure of innovation networks has an impact on regional knowledge production. This result therefore reinforces the relevance of policies supporting innovation networks and underlines their importance for the optimisation of innovation networks. Building on this result, the second and third essays of the thesis (Chapters 3 and 4) propose an evaluation of cluster policies. These chapters stand out from the literature evaluating cluster policies by focusing on network failures.

Chapter 3 assesses the effects of cluster policies on the collaborative behaviour of cluster participants as well as their embeddedness in innovation networks. Based on a counterfactual analysis, this chapter addresses three main evaluation questions: do cluster policies make firms more collaborative? Do they encourage local ties? Do they induce network additionality? Although we found out some positive effects of French clusters on strengthening collaborations, the results also highlight the limits of clusters in enhancing the embeddedness of cluster participants within innovation networks.

As for Chapter 4, it takes on a regional dimension by analysing the effects of the French cluster policy on the overall structure of regional innovation networks. This chapter aims at assessing how cluster policies influence the structure of regional innovation networks according to network topologies that are considered to be beneficial for regional innovation. The spatial econometric methods used in this chapter help to identify the complex effects of cluster policies on regional innovation networks. The results suggest that the effects of cluster policies might vary according to the technological specialisation of regions. However, beyond those heterogeneous effects, the results point out that cluster policies may lead to a regional competition by strengthening the structure of innovation networks in some regions to the detriment of other regions.

Keywords:

Innovation networks, Cluster policies and Regional knowledge production, Evaluation.

Résumé

La présente thèse propose trois essais sur les réseaux d'innovation, les politiques de clusters et la production régionale de connaissances. Consécutivement au développement des politiques de soutien aux réseaux d'innovation, notamment des politiques de clusters, cette thèse entend tester empiriquement l'un des fondements théoriques de ces politiques selon lequel la structure des réseaux d'innovation aurait un impact sur la production d'innovation dans les territoires. Ce faisant, elle apporte des éléments de réponses à une question fondamentale en géographie de l'innovation et contribue à porter un nouveau regard sur les politiques de clusters en les évaluant au regard de leur rôle dans la structuration des réseaux d'innovation.

Le premier essai (Chapitre 2) analyse ainsi dans quelle mesure l'innovation régionale est influencée par la structure des réseaux d'innovation. Bien que le développement des politiques de soutien aux réseaux d'innovation laisse sous-entendre l'existence d'une potentielle relation entre structure de réseaux d'innovation et production de connaissances dans les territoires, les preuves empiriques de cette relation sont encore rares. Partant du cas français, les résultats du Chapitre 2 mettent en évidence l'existence de cette relation, confirmant ainsi que la structure des réseaux d'innovation a un impact sur la production régionale de connaissances. Ce résultat renforce donc la pertinence des politiques de soutien aux réseaux d'innovation et souligne leur importance pour l'optimisation des réseaux d'innovation. Partant de ce constat, le second et le troisième essais de la thèse (Chapitres 3 et 4) proposent une évaluation des politiques de clusters. Ces chapitres se démarquent de la littérature évaluant les politiques de clusters en mettant l'accent sur les défaillances de réseaux.

Le Chapitre 3 évalue ainsi les effets de la politique des pôles de compétitivité sur le comportement collaboratif de leurs membres ou adhérents ainsi que l'imbrication de ces derniers dans les réseaux d'innovation. En s'appuyant sur une analyse contrefactuelle, ce chapitre aborde trois principales questions d'évaluation : les politiques de clusters rendent-elles les entreprises plus collaboratives ? Encouragent-elles les liens locaux ? induisent-elles une additionnalité des réseaux ? Bien que les résultats mettent en exergue les effets positifs des pôles de compétitivité sur le renforcement des collaborations, les résultats soulignent également les difficultés des clusters français à renforcer la centralité de leurs membres au sein des réseaux d'innovation.

Le Chapitre 4 quant à lui s'inscrit dans une dimension régionale en analysant les effets de la politique des pôles de compétitivité sur la structure globale des réseaux régionaux d'innovation. Ce chapitre vise à évaluer comment les politiques de clusters influencent la structure des réseaux régionaux d'innovation selon des topologies de réseau considérées comme favorables à l'innovation régionale. Les méthodes d'économétrie spatiale mises en œuvre dans ce chapitre permettent de relever les effets complexes des politiques de clusters sur les réseaux régionaux d'innovation. Les résultats suggèrent que les effets des politiques de clusters varient en fonction de la spécialisation technologique des régions. Toutefois, au-delà de ces effets hétérogènes, les résultats soulignent que les politiques de clusters peuvent générer une certaine compétition régionale en renforçant la structure des réseaux d'innovation de certaines régions au détriment d'autres régions.

Mots clés :

Réseaux d'innovation, Politiques de clusters, Production régionale de connaissances, Production régionale d'innovation, Evaluation.

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1 General introduction

1.1 Innovation through collaboration and networks

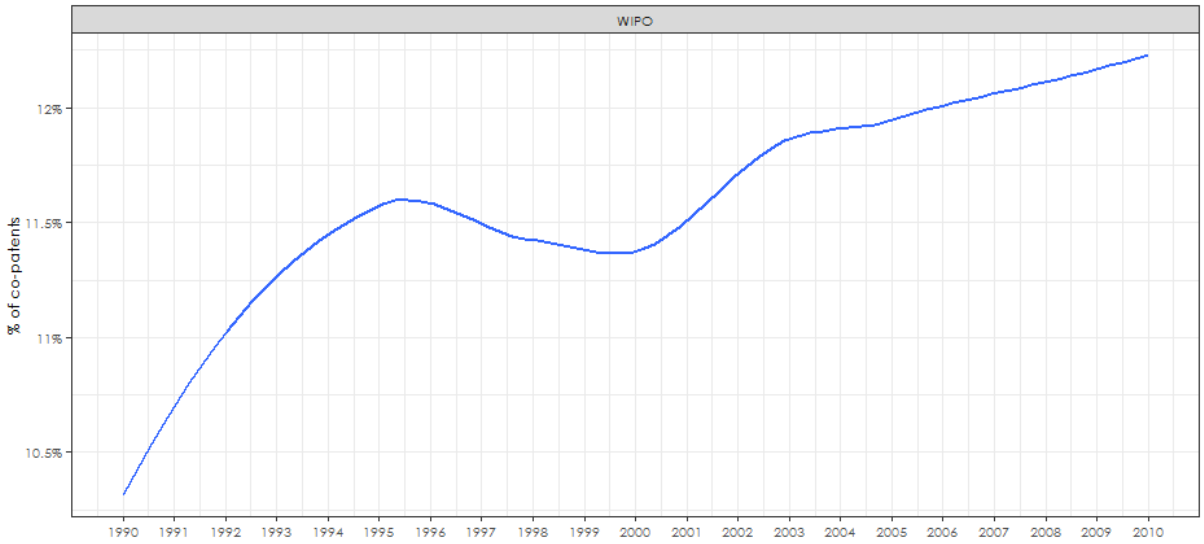
The role of innovation in growth and competitiveness is well-established today and policymakers, especially from advanced economies, are more and more committed to foster innovation by supporting public and private research and development (R&D) and broadly promote the emergence of knowledge-based economies. Public intervention for innovation has been justified for a long time by the existence of market failures suggesting that strict reliance on a market system would lead to under-investment in innovation activities, compared to the socially desirable level. Indeed, R&D projects can be expensive and involve investments with long pay-back times (Lerner et *al.*, 2011; Heher, 2006). In addition to the cost implications of R&D projects, the second brake on innovation relates to the fact that knowledge has characteristics of a public good that is both non-excludable and non-rivalrous (Arrow, 1962). This implies that returns on innovation cannot be fully appropriated because of knowledge spillovers which have the ability to diminish incentives to invest in R&D activities. These market failures are the traditional neoclassical justification for promoting innovation policies and they have as foundation the framework of the linear model of innovation (Schumpeter, 1912). This model analyses technological change as a linear process running from invention to innovation to diffusion. It can be illustrated by four kinds of activities: i) exploratory research and fundamental research, ii) applied research, iii) development and iv) production (Furnas, 1948). The linear model of innovation implies a set of activities which fan out from one another. Such a view of innovation process has led to the widespread implementation of direct innovation policies focusing on public R&D subsidies as well as indirect innovation policies focusing on tax incentives. Still today, R&D subsidies and tax incentives are among the most common innovation policies in OECD countries (Takalo et *al.*, 2012). The primarily goal of those policies is to stimulate private investment in R&D.

However, the linear conception has been strongly criticised by Kline and Rosenberg (1986) for example, who claim it distorts the reality of innovation in several ways. They proposed an interactive model of innovation (Chain-Linked Model) based on iterative fitting between the different stages of the innovation process (Kline and Rosenberg, 1986). This interactive conception of innovation processes has led to the development of new internal firm organisation models (intra-firm cooperation) as well as to a change of their relations with their surrounding environment (inter-firm cooperation). In this vein, Dosi (1988) stressed the need to see innovation as a process of experimenting and learning through which potential innovators need the capabilities and the know-how in order to make successful their researches and then

accomplish innovations. The acquisition of the needed capabilities and know-how can be reached through two complementary way: i) the potential innovator or firm can learn from its own experiences and accumulated knowledge or ii) through external knowledge sourcing, *i.e.* through cooperation with other actors and then learn from their experiences (Lundvall and Johnson, 1994). It is therefore acknowledged that the generation of technological know-how and innovations cannot be maximised when innovation processes are led by actors or organisations individually. Collaborations, indeed, allow partners to share the costs and the risk associated to research activities, to pool their knowledge and know-how, to obtain access to new markets and technologies (Kogut, 1989; Hagedoorn, 1993; Eisenhardt and Schoonhoven, 1996; Mowery et *al.*, 1998). Through collaboration, organisations can get access to external knowledge (directly – through bilateral collaborations, or not – through multilateral collaborations) given their position within collaboration/innovation/knowledge networks (Granovetter, 1985). Such networks, by pooling knowledge of partners from different scientific and technological areas may lead to disruptive innovations (Burt, 1992). They also facilitate trust between partners, increase the likelihood of successful collaborations (Coleman, 1988) and facilitate the internalisation of knowledge spillovers. Thus, both knowledge creation and diffusion are network-dependent activities (Cowan and Jonard, 2001; Autant-Bernard et *al.*, 2013). Janz et *al.* (2003), Van Leeuwen (2002) and Criscuolo and Haskel (2003), for instance, find evidence of a positive correlation between R&D collaborations and innovation performance, highlighting the importance of collaborative projects and therefore the necessity for organisations to be involved in innovation networks.

Given these many advantages, Scherngell and Barber (2009) describe collaborations as a "conditio sine qua non" for innovations which can now be considered as a panacea for success in R&D projects, either publicly funded or not. Considering co-patents – patents co-assigned by at least two organisations/assignees – as an indication of collaboration, Figure 1 illustrates the increasing importance of collaboration in innovation processes; the share of co-patents has grown from 1990 to 2010, rising from less than 10.5 percent to more than 12 percent. In absolute terms, the number of co-patents has increased by a factor of 10 over the same period *i.e.* from about 2,000 co-patents in the early 1990s to 20,000 in 2010.

Figure 1 Share co-patents granted by the World Intellectual Property Organization



Source: Author's own elaboration based on Morrison et al. (2017) data.

Beyond bilateral exchanges, the ability to be embedded in innovation networks has been considered to be one of the crucial ways to access external knowledge. Following this recognised importance of innovation networks, the use of social network analysis (SNA) in innovation studies were popularised in two main ways: (i) micro and (ii) regional or macro-levels studies. Within the micro level literature, in addition to the theoretical studies (Granovetter, 1985; Burt, 1992), the impact of social network position on innovation has been widely confirmed in empirical studies. In particular, the literature suggests that there is strong evidence about the role of firms' centrality on innovation as well as their absorptive capacity (Tseng et *al.*, 2016; Wei and Chen, 2019). However, regarding the regional or macro-level studies, although works on national and regional systems of innovation (see Freeman, 1987; Lundval, 1992) point out the importance of inter-actor relationships and more broadly of collaboration networks among organisations, the empirical literature is not clear on the degree to which innovation or collaboration networks influence the level of regional innovation (Fleming et *al.*, 2007; Bettencourt et *al.*, 2007; Lobo and Strumsky, 2008). This suggests the need for more empirical investigations to understand the relation between innovation networks and regional innovation. The first contribution of this PhD thesis lies in this perspective.

1.2 Rise of network-based innovation policies

Given the fundamental role of networks in fostering innovation production and diffusion, policymakers have seized on the idea that innovation is the result of complex relationships among organisations (firms, universities and public research institutes, etc.). This has led to the

development of collaboration or network-based innovation policies which put more emphasis on the structural, institutional and regulatory deficiencies leading to sub-optimal investment and networking in innovation activities. Such deficiencies are broadly referred to as system failures (Edler and Fagerberg, 2017). By encouraging collaborative innovation projects, and more broadly networking among organisations, network-based innovation policies have extended the scope of innovation policies beyond single-point interventions relating to individual research projects. At the European level, for instance, the majority of the Horizon 2020 budget is spent on supporting such collaboration (European Commission, 2018) and the European Union has been very active for several years in promoting collaborative innovation projects through its Framework Programmes (see Figure 2).

Figure 2 Collaborative projects in Framework Programmes

Source: European Commission (2018)

Network-based innovation policies and interventions are based on innovation theories or concepts such as the triple helix model of innovation (Etzkowitz and Leydesdorff, 1995), innovative milieus (Camagni, 1995), clusters (Porter, 1990). What all these concepts have in common is that they attribute the development of innovation not only to the innovative efforts (or on the characteristics) of individual organisations, but also – and even more important –, to the economic and institutional characteristics of the (local, regional, national or international) ecosystem in which they operate (Lundvall, 1992; Nelson and Rosenberg, 1993). They have moved the rationale for innovation policies from market failures to system failures by justifying public policies supporting innovation as interventions aiming at overcoming the imperfections in the innovation systems, *i.e.* system failures.

Several taxonomies were proposed to analyse and classify system failures within the framework of innovation systems (Arnold and Thuriaux, 2003; Woolthuis et *al.*, 2005, OECD, 2012). While defining system failures as the "*barriers to innovation that hinder the flow of knowledge and technology and reduce the overall efficiency of the system-wide R&D and innovation effort*",

the OECD (2012) identifies four main group of system failures: (i) framework failures, (ii) institutional failures, (iii) capability failures and (iv) network failures. Framework failures refer to global deficiencies in regulatory frameworks, business environment, cultural and social values, etc. that hamper R&D and innovation whereas institutional failures appear whenever institutions universities, research institutions are not able to efficiently perform their functions. In the triple helix model of innovation for example, institutional failures can be characterised, ceteris paribus, by the incapacity of universities to perform relevant basic research or/and to train a qualified workforce. Capability failures refer to actors' inability to act in their own best interests. Capability failures may come from many situations such as poor managerial capabilities, low technological skills, low absorptive capacity, etc. Finally, with regards to network failures, they refer to the insufficient and/or inefficient levels of networking and knowledge exchange between organisations. Given the now recognised importance of collaboration in innovation processes, network failures are fundamental issues for innovation systems which are today mainly tackled through network-based innovation policies (Cunningham and Ramlogan, 2016).

Following the development of network-based innovation policies, a growing body of literature aims at evaluating such policies. However, this literature has been so far mainly focused on input/output additionality (Falck et *al.*, 2010; Nishimura et Okamuro, 2011a; Bellégo and Dortet-Bernadet, 2014; Brossard et Moussa, 2014) in the sense that they analyse the effects of public interventions mostly on organisations innovation inputs (R&D expenditures) or on their outputs (productivity, patents, employment, etc.). Few research studies have examined the effects of such interventions regarding broader changes in the innovation system and the literature on this issue remains embryonic (Nishimura et Okamuro, 2011b; Cantner et *al.*, 2015; Giuliani et *al.*, 2016). This thesis aims to fill this gap by examining both the micro-level and macro-level effects of network-based innovation policies, with regards to network failures.

1.3 Research questions

1.3.1 Innovation networks and regional innovation

During the past two decades, the geography of innovation literature has provided a rich and detailed account of the underlying processes of regional innovation. One of the main questions in this literature is to find the necessary inputs for the production of knowledge and, more broadly, innovations at the regional level. This question has been extensively explored using the regional knowledge production function framework (Griliches, 1979) but studies considering innovation networks, *i.e.* their structure, as a determinant of regional innovation have only recently appeared in the literature (Fleming et *al.*, 2007; Bettencourt et *al.*, 2007; Lobo and

Strumsky, 2008; Breschi and Lenzi, 2016; Coffano et *al.*, 2017; Innocent et *al.*, 2019). So far, however, this literature is not clear about the effects of innovation networks on regional innovation. Therefore, before analysing the effects of network-based innovation policies, the current thesis starts with an analysis revisiting the regional knowledge production function (Charlot et *al.*, 2015) and empirically explores the role of innovation networks in regional innovation by answering the first research question:

Research Question 1: To which extent is regional innovation influenced by the structure of innovation networks?

1.3.2 Micro-level effects of network-based innovation policies

As discussed above, the development of network-based innovation policies results from the widely recognised benefits of collaborations and such policies aim at promoting collaborations and therefore organisations' involvement within innovation networks. Building on these considerations, the proposed micro-level evaluation of network-based innovation policies is based on the concept of behavioural additionality (Buisseret et *al.*, 1995) which has been associated with evolutionary rationales for innovation policies that focus on network failures (Amanatidou et *al.*, 2014). In the innovation policy evaluation literature, assessing behavioural additionality consists in attempting to understand the real difference (in that it would not have happened without the intervention) in the behaviour of the firm (Amanatidou et *al.*, 2014). Therefore, in contrast to input/output additionality, behavioural additionality analysis is an attempt to go beyond the input-output based approach and understand what is inside the "black box". Several scholars have investigated behavioural additionality in different evaluation exercises (e.g. Caloffi et *al.* ,2015; Wanzenböck et *al.*, 2013; Afcha Chavez, 2011; Nishimura and Okamuro, 2011; Teirlink and Spithoven, 2012; Antonioli et *al.*, 2014 and, more recently, Caloffi et *al.*, 2018) and the concept is understood in at least four different conceptualisations, namely: (i) as an extension of input additionality, (ii) as *one off* change in the behaviour related to R&D and innovation activities, (iii) as change in the persistent behaviour related to R&D and innovation activities and iv) as change in the general conduct of the firm with substantial reference to the building blocks of behaviour (Gök and Edler 2012). Although the above previous studies have succeeded in using relevant empirical designs, they did not tackle much the persistent behaviour changes. Indeed, while focusing on collaboration additionality, they neglect the key issue of actors' embeddedness within local and global networks. Thereby, our study falls in the third definition of behavioural additionality and complements the current empirical literature on the effectiveness of network-based innovation policies by answering the second research question:

Research Question 2: What are the effects of network-based innovation policies on firms' collaborative behaviour?

1.3.3 Macro-level effects of network-based innovation policies

The literature on innovation systems (Freeman, 1987; Lundval, 1992) suggests that a thriving regional or national innovation ecosystem requires not only individual capabilities, but also an effective level of collaboration among multiple actors at the macro level. Building on this consideration, it is worth looking at the extent to which network-based innovation policies shape regional innovation networks. In doing so, it is crucial to give special attention in considering the inherent interdependencies among regions due to cross-border collaboration. Indeed, as shown in the geography of innovation literature, knowledge does not stop flowing at territorial borders (Audretsch and Feldman 2004) since researchers and inventors cooperate across boundaries. Such cross-border collaborations and the other knowledge flows channels such as patent citations or labour mobility systematically create interdependence between regional innovation networks, making the regional innovation dynamics complex. Since changes in the structure of a region's innovation network would have an effect not only on that region (direct effect) but also on other regions (indirect effect), the effects of network-based policies of regional innovation networks may be revealing. While the micro-level evaluation places less emphasis on this interdependence, the macro-level evaluation will make it an important issue.

With regards to existing literature on the subject, studies trying to assess the effectiveness of network-based innovation policies with a global perspective on innovation networks (Larosse, 2001) remains scarce and far between. So far, the micro-level effects of network-based innovation policies have been the main focus of the policy evaluation literature. The third and last study of the thesis therefore attempts to fill this gap by answering the third research question:

Research Question 3: What are the effects of network-based innovation policies on the structure of regional innovation networks?

1.4 Research methodology and data

1.4.1 Research methodology

In order to address our research questions, we follow the recent innovation studies literature that already connects social network analysis (SNA) methods to innovation studies, especially those analysing collaboration between organisations or between individuals (Van der Valk and Gijsbers, 2010). In much of this literature, SNA methods have been applied extensively to depict

networks' characteristics and the methodological approach taken in this thesis follows this perspective. SNA methods and tools are implemented in all chapters primarily with the goal to compute outcome or explanatory variables.

Regarding estimation methods, we rely on quantitative methods including causal inference (Austin and Stuart, 2015) and spatial econometrics (LeSage and Pace, 2009). Relying on causal inference allows evidence-based conclusions to be drawn regarding the causal effects especially at the micro-level. At the regional level, spatial econometrics models allow to take into account the dependencies characterising innovation networks, and therefore direct and indirect effects. Spatial models have been proven to be strongly relevant to depict such complex mechanisms (Manski, 1993; Elhorst, 2010; Patuelli et *al.*, 2011; LeSgae, 2014). We therefore contribute to the literature by combining different methodologies, namely social network analysis, spatial econometrics and counterfactual analysis.

1.4.2 Data

Regarding the data, this thesis makes extensive use of patent data from the French patent office (INPI). Patent data have the advantage to signal the presence of R&D partners through co-patents. In this vein, engagement in collaborative projects is proxied by the intensity of co-invention and studies from the literature on the geography of innovation, make extensive use of co-invention network to proxy collaboration networks (Ter Wal, 2013). Throughout the different chapters of the thesis, the terms 'co-invention networks', 'collaboration networks' and 'innovation networks' are used interchangeably unless otherwise indicated.

We acknowledge the standard criticisms of patent data (Griliches 1990), especially their inability to capture all innovations, and therefore to fully capture innovation networks. However, patents are certainly one of the best data sources researchers can use for studying R&D collaboration. Patent data make it possible to geolocate the assignees and inventor addresses and therefore allow us to enrich social network analysis with spatial dynamics. Indeed, beyond the structural network topologies, the use of patent data allows us to depict de spatial structure of innovation networks and to quantify and measure regional innovation. Furthermore, patent data allow to classify regions in technological space and define their level of technological specialisation which is considered in the literature as correlated to regions' inventive performance.

Moreover, we claim that patent data remain among the most adequate for the purposes of our policy evaluation exercises since they provide us with external-to-the-policy network data which is necessary to build a counterfactual approach. The evaluation of network-based innovation policies regarding network failures can lead to relevant causal claims only by assessing the effects on broader innovation networks which are more likely to be representative

of all collaborations taking place within the ecosystem. Relying, for example, only on collaboration networks drawn from data on the projects supported by the policy data does not allow for observing counterfactual scenarios.

1.4.3 Policy under scrutiny: the French cluster policy

Research questions 2 and 3 are addressed in the context of the French cluster policy which is one of the most developed network-based policies in Europe.

Network-based innovation policies can take various forms (see Cunningham and Ramlogan, 2014 for a survey on policy instruments that enhance innovation through the activities of networks). Since Marshall (1890), it is widely acknowledged that geographical concentrations of firms and economic actors can generate positive effects on economic growth in specific territories. Following the development of the New economic geography (Krugman, 1991), which has brought to light new models that help to explain how and why agglomerations of industrial activity, clusters are probably one the most studied system among such geographical concentrations. According to the definition proposed by Porter (1998), a cluster is "*a geographical proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and externalities*". In the same vein, the term 'innovation cluster' refers to "*groupings of independent undertakings - innovative start-ups, small, medium and large undertakings as well as research organisations - operating in a particular sector and region and designed to stimulate innovative activity by promoting intensive interactions, sharing of facilities and exchange of knowledge and expertise and by contributing effectively to technology transfer, networking and information dissemination among the undertakings in the cluster*" (European Commission, 2006). Both definitions put emphasis on the two main patterns characterising clusters: spatial proximity and technological or cognitive proximity. Following the works of Porter (1990, 1998), clusters have been strongly associated with regional competitiveness and governments have adopted a range of cluster approaches at the national and regional levels. Nowadays, cluster policies have become an important component of the policymaker's toolbox, making them a relevant type of network-based innovation policies to investigate.

Chapters 3 and 4 focus on the French cluster policy which was launched in 2005 to raise the country's innovative capacity. This policy contributes to a broad industrial ambition in France aiming at a better combination of innovation and industry than in the past, within regions. Beyond data accessibility, our choice to focus on the French case was motivated by the fact that the French national cluster programme is among the most developed ones in the world, and the largest one in Europe (with a budget of 144 million euros). The French context is also highly relevant because it covers most types of cluster policy features: it targets both lagging

and leading regions and it relies on the three traditional roots of cluster policies: regional policy, science and technology policy and industrial/firm policy.

According to an official definition, a French cluster ("Pôle de compétitivité") "*brings together large and small firms, research laboratories and educational establishments, all working together in a specific region to develop synergies and cooperative efforts*"[1]. French clusters are therefore intended to actively support networking between firms, universities and research organisations mainly at the regional level (NUTS2), although clusters are also encouraged over time to increase networking between their participants (or members) and actors from others regions. In July 2005, the French government established 67 clusters in various fields (energy, mechanics, aerospace, transport, ICTs, health, environment, ecotechnology, etc.). After the creation of new ones and the merger of some of them over time, the number of clusters stood at 71 in 2014 and 56 today in various fields (energy, mechanics, aerospace, transport, ICTs, health, environment, ecotechnology, etc.). Cluster membership consists of an annual membership fee paid by establishment. In 2014, the 71 clusters had about 9,650 company-level participants (for 10,380 individual establishments) including 8,500 private firms and 1,150 public research organisations (DGE, 2017). Even though the French clusters are open to all firms no matter their size, the majority of private cluster participants are SMEs: in 2014, 75% of the participants were establishments owned by SMEs, 17% by mid-tier firms and 8% by large firms (DGE, 2017). The core activity of the clusters is to develop collaborative innovation projects, while integrating the potential economic benefits as early as possible (DATAR, 2004). Doing so, their priorities are focused on reinforcing the economic benefits of R&D projects and supporting firms' growth by offering collective and individual services related to access to financing, international development, the forecasting of companies' needs in terms of skills and individual assistance with the development of SMEs, including advice and tutoring.

The State support for clusters mainly takes the form of i) a partial financing of cluster governance structures, alongside local authorities and participants (public research organisations and firms), and ii) the granting of financial assistance to selected collaborative R&D projects emerging from clusters. Between 2005 and 2013, 1,313 collaborative R&D projects endorsed by clusters received public financing of €2.37 billion, including more than €1.45 billion granted by the French State through the Single Inter-Ministry Fund (FUI). However, despite these huge amounts of money allocations, the French cluster policy is not the most expensive area of state activity innovation policies. The national innovation support system is essentially based on indirect aids through the research tax credit (CIR), the cost of which amounted to €6.3 billion

[1] An establishment is defined as an independent production unit, physically located, but legally dependant of a firm/company.

in 2015, *i.e.* nearly 75% of the state's support for innovation, compared to 16.5% in 2000 (CNEPI, 2016). French clusters get their support mostly from financial instruments such as subsidies and they capture less and less public funding since their creation. Nevertheless, this does not call into question the importance of the clusters in the national innovation system since they are one of the major policy instruments (in terms of financial allocation) from the national innovation strategy designed to support collaborative R&D projects and local innovation ecosystems, particularly before the 2010s.

In terms of political orientations, the French cluster policy has evolved over time. The first phase of the policy (2005–2008) was essentially focused on structuring the clusters and the emergence of collaborative R&D projects within them. During this phase, the policymakers' aim was to propose to innovation actors a new model of carrying out R&D projects based on collaborations with other actors, particularly in co-located organisations. Clusters were, therefore, intended to act as incubators for collaborative R&D projects involving firms, universities and research organisations. Following the theoretical arguments in favour of strengthening collaborations between co-located organisations for economic growth, policymakers opted for a regional anchoring of clusters. This anchoring materialised in the adequacy between clusters' fields of specialisation and the economic sectors present in regions, as well as the research themes led by the regional public research actors. In order to support this vision, regional authorities were heavily involved from the beginning of the policy, particularly in terms of providing joint funding, alongside State financing. In addition to the strengthening of the local innovation ecosystem, the political will is to favour the national and international visibility of local actors. A distinction was made between world clusters, world vocation clusters and national clusters in order to support the participation in international projects (especially European projects) as well as the promotion of innovative local actors. To this respect, the cluster policy aims at helping cluster participants to hold more central positions within knowledge and innovation networks.

During the second phase of the policy (2009–2012), however, both the territorial and the international dimension have been revisited. The territorial anchoring of clusters has been relaxed to create synergies between them and all the other policies and actors supporting innovation both at national and local levels. The purpose of this new direction was to strengthen the consistency between innovation policies in France in order to build more relevant and resilient innovation ecosystems. This new strategy implied that clusters would be more open to long-distance collaborations and not only collaborations with regional actors. For policymakers, reinforcing the synergies between clusters must also be an inherent part of the cluster policy to avoid duplication of R&D efforts. Beyond the theoretical arguments supporting long-distance collaborations, the logic of optimising R&D efforts was even more

crucial in a significantly deteriorated economic context due to the economic crisis of 2008. The previous distinction between world clusters, world vocation clusters and national clusters has been removed but the political will to favour the national and international visibility of local actors has remained. Thus, networking of innovation stakeholders remained a main concern during the second phase of the cluster policy.

The following phase (2013–2018) built on the previous direction to reinforce collaborations between firms, universities and research organisations but the main objective of the clusters then became was to turn more towards their economic impact. This objective emerged from the recommendations of several evaluations of French clusters (Technopolis group et *al.*, 2012; Fontagné et *al.*, 2013; Ben Hassine and Mathieu, 2017) implemented by both practitioners and scholars. These studies revealed that the French cluster policy have had a positive effect on increasing innovation inputs (firms' R&D expenditures and employment of R&D staff). However, when it came to innovation outputs (granted patents, turnover, added value, employment, exports, etc.), evaluators found different results and, overall, there is little evidence of the positive effects of the policy on firms' performance. This lack of evidence has contributed to a growing scepticism towards the French clusters to the point where Ben Hassine and Mathieu (2017) refer to this as a "curse". In this context, evaluators were unanimous in recommending that the government continues funding clusters while looking for increases in their economic impacts.

The current context is also marked by the merger of some clusters and the co-endorsement of collaborative R&D projects by clusters. Previously organised into independent entities although maintaining close links, some clusters now tend to be increasingly structured around a single, unifying governance structure. In addition to policymakers' desire to encourage relations between clusters, this dynamic was also supported by the merging of certain French regions in 2016. Several clusters that were previously located in different regions have thus seen their scope of action becoming shared with other clusters. There is every indication that the future of French clusters would be marked by a greater openness towards (long-) distant collaborations, which implies cluster participants collaborating with actors that are not necessarily located within their region.

1.5 Overview of the chapters

1.5.1 Determinants of regional innovation: a network perspective

The first study conducted as part of the thesis aims to analyse the role of innovation networks as determinants of regional innovation outcomes within the framework of the regional knowledge production function. Since the seminal contribution made by Griliches (1979), the

analysis of the determinants of innovation has represented a core issue in the research area of the economics of innovation and technological change. This has been also debated in the literature of regional innovation systems, leading to the development over years of regional knowledge production functions (Charlot et *al.*, 2015). Chapter 1 contributes to this strand of literature by testing whether regions innovative outputs are influenced by the structure of innovation networks. This is a question of interest since most of network-based innovation policies, especially cluster policies, are implemented with the implicit assumption that better connections between innovation actors, and more broadly better innovation networks, results in a greater innovation output.

This study overcomes the main limits of most previous research which failed to systematically address both endogeneity issue and spatial dependencies at once (Fleming et *al.*, 2007; Bettencourt et *al.*, 2007; Lobo and Strumsky, 2008; Coffano et *al.*, 2017). Indeed, the geography of innovation literature has pointed out the spatial autocorrelation of innovation activities (Moreno et *al.*, 2005) and the endogenous structure of innovation networks (Breschi and Lenzi, 2016; Innocent et *al.*, 2019), making standard econometrics methods not relevant; but most of the previous literature only address either of these two challenges. Using a panel data of three periods and 94 NUTS3 French regions, we rely on an error component two stage least squares estimation (EC2SLS) combined with eigenvector spatial filtering in order to tackle both methodological challenges. The correction of endogeneity and the introduction of a spatial filter allow us to isolate the effects of network variables, which are otherwise, mainly captured by agglomeration variables. The results generally support the importance of the structure of innovation networks for regional innovation, similarly to recent previous research that control at least for spatial autocorrelation. Our results particularly stress the relevance of science-industry collaboration as well as the benefits of redundant links at the regional level, highlighting the importance of trust and reducing opportunism among local actors in order to boost regional innovation.

1.5.2 Effects of cluster policies on firms' collaborative behaviour

The second study conducted as part of the thesis analyses the micro-level effects of network-based innovation policies. It aims at providing a better understanding of the impact of clusters on the collaborative behaviour of their participants (behavioural additionality) as well as their embeddedness in collaboration networks (network additionality). There are few evaluations of cluster policies which analyse the behavioural additionality from a causal point of view. To the best of our knowledge, only Falck et *al.* (2010) have addressed this issue. Our study aims to contribute to this literature by combining counterfactual approaches and network analysis methods. Thus, the novel contribution of this chapter is that, unlike previous studies, it proposes

causal estimations based on (co-invention) network measures for assessing behavioural additionality of cluster policies. Moreover, the scope of this study is broader since it also tests for network additionality *i.e.* if cluster participants are qualitatively better embedded into networks of co-inventions than non- participants by holding globally more central positions.

We employ modern econometric methods of counterfactual analysis to uncover changes in the collaborative behaviour of cluster participants. The results obtained indicate a positive effect of cluster membership: cluster participants have significantly increased their tendency to be more engaged in collaborative projects. Over the studied period (2008-2020), cluster participants have increased their share of co-patents by approximately 4 percentage points as a result of being involved in cluster activities. Our results also indicate that this increase was much higher (more than 6 percentage points) for cluster participants who had little involvement in collaborative R&D projects prior to joining the clusters. Thus, the results provide evidence of the positive effect of French clusters in their support and leadership role, in that they were able to lead their participants to become more involved in collaborative R&D projects, regardless of whether they are publicly funded or not. However, despite this causal relationship between cluster membership and the enhancing of firms' collaborative behaviour, we found that the collaborative research projects carried out by cluster participants involved non-co-located partners. This suggests that French clusters had not significantly strengthened the establishment of collaborations between actors located in the same territory (NUTS2 region). Regarding the embeddedness of cluster participants in collaboration networks, we find no evidence for any significant effect of the French cluster policy mainly due to the presence of redundant links. From our results, it therefore appears that even though clusters positively affect the collaborative behaviour of their participants, their local anchoring *i.e.*, clusters' ability to reinforce links between co-located organisations, as well as the embeddedness of cluster participants in collaboration networks is not systematic.

1.5.3 Effects of cluster policies on regional innovation networks

The third chapter provides empirical evidence supporting a theoretical foundation for the regional innovation system framework, specifically that the structure of innovation networks is important for regional innovation. Building on this evidence, this third and last study examines the effects of cluster policies on the structure of regional innovation networks. But, unlike Chapter 2, here we take a more global perspective by scanning changes in network structure at the regional level due to cluster policy. The study reported in the Chapter 3 aims at evaluating how cluster policies influence the structure of local innovation networks. The structure of innovation networks is analysed following four topologies that may prove to be beneficial for regional innovation according to the literature: (i) embeddedness or

connectivity, (ii) efficiency, (iii) resilience and (iv) the geographical anchoring of territorial innovation networks (Fleming and Frenken 2007; Ter Wal, 2013; Giuliani et *al.*, 2016; Crespo et *al.*, 2015).

While the most recent and relevant works in this area are essentially based on descriptive analyses of social networks (Rothgang et *al.* 2017; Töpfer et *al.*, 2017; Lucena-Piquero and Vicente, 2019) or on qualitative analyses (He et *al.*, 2013), our study presents a novelty of identifying three types of cluster policy effects: direct or locally bounded, indirect or associated neighbourhood spatial effects and the total cumulative effect resulting from the direct and indirect effects. Based on a panel data of four periods and 94 NUTS3 French regions (so called departments), we estimate spatial Durbin models allowing us to depict the complex mechanisms at play following the implementation of cluster policies. The results of this study are manifold. Overall, the main results highlight a positive total effect of clusters on the efficiency of regional innovation networks, especially for specialised departments. This finding supports the argument that regions' technological specialisation is a key factor for the success of cluster policies (Porter, 2000). However, regarding network resilience, evidence is found that clusters can tend to strengthen the assortative nature of innovation networks, especially in low specialised departments, resulting in a lower network resilience (Crespo et *al.*, 2015). With regards to networks' embeddedness and their geographical anchoring, we did not identify any significant total effect of the French cluster policy despite the presence of some direct positive effects. This suggests that cluster policies may lead to regional competition for the strengthening of innovation networks.

2 Determinants of regional innovation: a network perspective

This chapter is single authored by the PhD candidate.

Abstract

This study revisits the regional knowledge production function by considering the structure of innovation networks as a determinant of regional innovation outcomes. It aims at analysing the effects of particular structural properties of innovation networks on the inventive productivity of 94 NUTS3 French regions during the period 2005-2013. Using panel data, our empirical strategy is based on an error component two stage least squares estimation (EC2SLS) with eigenvector spatial filtering. Unlike previous studies, our specification allows to account for the presence of spatial autocorrelation and the endogeneity of network variables. The results highlight a positive effect of the intensity of science-industry collaboration as well as network clustering on regional innovation. However, we found no evidence for a significant effect of the internal and external social proximity on regional innovation, putting trust and science-industry links at the core of regional innovation processes at this territorial level.

2.1 Introduction

Since the seminal contribution made by Griliches (1979), the analysis of the determinants of innovation has represented a core issue in the research area of the economics of innovation and technological change. By introducing the concept of knowledge production function (KPF), Griliches (1979) raised an issue that has become increasingly important over the years: *what are the necessary inputs for the production of knowledge and, more broadly, innovations?* Following Griliches's contribution, research on the relationship between input and output of a knowledge production function has been explored in two different and somewhat separate strands of literature (Charlot et *al.*, 2015). The first strand of literature has its origins in the early work by Griliches himself (1979, 1986) and it consists of papers investigating the KPF within firms – micro-level. As for the second strand, it revisits the firm-level framework à la Griliches (1979, 1986) by investigating the knowledge production function at the regional level. What matters in this framework is the contribution of regional inputs to the generation of new local knowledge; this is referred to as regional knowledge production function (rKPF) and the present chapter is part of this literature.

During its development, the empirical literature of rKPF has so far gone through four major stages while remaining embedded into the geography of innovation literature and always providing new insights into the territorial determinants of innovation. The transition from KPF to rKPF was first made by aggregating the main determinants of innovation, *i.e.* human capital and the level of R&D investments performed by regional organisations (Jaffe, 1989; Acs et *al.*, 1992). The main limit of these first wave of studies on rKPF was their micro-level foundations. Indeed, they did not consider regional mechanisms linked to the role of neighbouring effects and agglomeration economies in the innovation process. Then, the next stage in disentangling the rKPF aimed at considering those regional mechanisms. The rationale for this consideration is twofold. First, knowledge that is produced in one region may spill over into another, influencing its innovative performance (Moreno et *al.*, 2005) since there is no reason to assume that knowledge stops flowing because of regional borders (Audretsch and Feldman, 2004). This has motivated the inclusion of spatially lagged terms of the determinants of innovation as well as other relevant additional sources of regional innovation in rKPF. Indeed, besides neighbouring effects, the greater proportion of a region's firms engaged in innovation activities might also give rise to agglomeration externalities which can push regional innovation upwards (Lobo and Strumsky, 2008). From the consideration of spatial neighbouring and agglomeration effects in the rKPF, it comes out that geographical proximity could facilitate a more rapid diffusion of knowledge and therefore influence regional innovation outcomes. However, scholars have also acknowledged the importance of other forms of proximity (cognitive, organisational, social, institutional, etc.) in knowledge diffusion. This has contributed to the use

of different forms of spatial weights matrix to capture proximity in the analysis of rKPF (Boschma, 2005; Maggioni et *al.* 2007; Miguélez and Moreno, 2013a, 2013b, 2013c; Hazir et *al.*, 2018). Finally, the fourth stage, which we consider to be ongoing, builds on the growing literature on social networks related to innovation, so-called innovation networks[2]. At this stage, structural properties of innovation networks are considered as important determinants of regional innovation and an increasing number of studies on innovation networks in a regional context are being observed (see Brenner et *al.*, 2011, 2013 for a survey). In this vein, some of these studies (Fleming et *al.*, 2007; Bettencourt et *al.*, 2007; Lobo and Strumsky, 2008; Miguélez and Moréno, 2013a, 2013b, 2013c; Breschi and Lenzi, 2016; Coffano et *al.*, 2017) integrate the structural properties of innovation networks as inputs within the rKPF in order to tackle one of the key questions in this literature, that is *whether regions innovative outputs are influenced by the quality and intensity of innovation networks*. Just as at the beginning of the rKPF, this recent research question draws on the progress made in micro level studies regarding innovation processes.

This strand of micro-level literature is based on the idea that innovation critically relies on the recombination of existing ideas or technological components in a novel manner (e.g., Nelson and Winter 1982; Fleming 2001). Therefore, occupying central and advantageous network positions in collaboration networks allows actors to access intangible external resources and then to become more innovative. This has been shown through many theoretical (Ahuja, 2000) and empirical (Gui et *al.* 2018) studies. For instance, focusing on patent co-authorship networks, scholars found out that central actors (using degree, betweenness or closeness measures of centrality) are likely to get first-hand information, and also enjoy controlling privileges over valuable information exchanged by their acquaintances (Nerkar and Paruchuri, 2005). Furthermore, the literature suggests that actors who occupy brokerage positions by bridging groups of otherwise disconnected actors (Burt, 1992) might have opportunities to make unique and valuable combinations of existing knowledge and also enhance their capability to generate fresh knowledge (McFadyen and Cannella, 2004; Audia and Goncalo, 2007). Regarding the structure of inventors' ego-networks, the literature is not conclusive because of a strong context-dependency (Walker et *al.* 1997; Gabbay and Zuckerman, 1998; Adler and Kwon, 2002), but it convincingly suggests the importance of both structural holes and closure (Coleman, 1988; Burt, 1992) which are now considered as two different complementary rather than competitive mechanism (Burt, 2000). Collaborations between industry and academia

[2] One should note that, in this literature, innovation networks are often proxied by patent co-authorship networks. Therefore, unless otherwise stated, the expressions "innovation network" and "co-invention network", are further used interchangeably.

have been studied in this literature as one of the aspects of open innovation. The literature suggests that these types of collaborations benefit both parties. Firms are granted with access to cutting-edge knowledge (Barnes et *al.* 2002) and expensive research infrastructure (Ankrah and AL-Tabbaa 2015). They can also profit from highly qualified human resources – researchers (Myoken, 2013). Universities, in return, mainly benefit from additional funding provided, from access to industry equipment or from licensing or patenting income (Barnes et *al.* 2002). Academic inventors often occupy central positions in networks, especially in science-based technologies, making them key players in innovation processes. Building on the results from these microlevel studies, scholars in the field of the geography of innovation are increasingly interested in the effects of the structure of innovation networks on regional innovativeness. Although the empirical literature addressing the effects of innovation networks on regional innovation outcomes within a rKPF is still in an embryonic stage, a number of findings have been put forward.

Early studies (Fleming et *al.*, 2007; Bettencourt et *al.*, 2007; Lobo and Strumsky, 2008) have shown a limited effect of the structural properties of innovation networks on regional innovation. Network structure turned out to be less important than the agglomeration of inventors in explaining regional innovation rates. However, the main limit of these studies is that they did not take into account the role of neighbouring effects and spatial autocorrelation which are believed to shape the output of a given region. Controlling for spatial autocorrelation in the design of the rKPF, Miguélez and Moreno (2013a, 2013b, 2013c) provided evidence supporting the influence of innovation networks on regional innovation. They showed that greater number of social ties among inventors and cross-regional linkages boost regional innovation capability but they acknowledged the potential inconsistency of their estimates due to endogeneity problems (Miguélez and Moréno, 2013a). The studies carried out by Araújo et *al.* (2019) and Innocenti et *al.* (2020) are also subject to this endogeneity problems. Breschi and Lenzi (2016) have examined the relative importance of agglomeration forces versus social networks on innovation using an instrumental variable framework in order to tackle the endogeneity of network variables. While their results do not contradict prior findings that agglomeration effects are important, they found that network properties also matter in regional innovation. Despite this promising result, their study did not take into account the potential presence of spatial spillovers in the specification of their rKPF. Thus, it appears that the literature faces two challenges: assessing the effects of innovation networks on regional innovation while dealing both with (i) the presence of spatial autocorrelation and (ii) the endogeneity of network variables.

The present chapter aims to contribute to the fourth stage of the development of the rKPF, looking at the effects of innovation networks on regional innovation outcomes and addressing

the two challenges above. We empirically assess the relationships between the structural properties of the co-invention network and regional innovation in NUTS-3 French regions. The presence of spatial autocorrelation and the endogeneity of network variables are addressed using an error component two stage least squares estimation (EC2SLS) with eigenvector spatial filtering. Our results suggest that the structure of innovation networks matter for regional innovation. In particular, the presence of dense cliques of regional inventors as well as a high level of science-industry collaboration have found to enhance the inventive productivity of regions.

The remainder of chapter is structured as follows. In the next section 2.2, we conceptually derive from the literature the research hypotheses to be tested. Section 2.3 describes how network variables are constructed. Section 2.5 presents the research design. In Section 5, the results are discussed, and the conclusions are presented in Section 2.6.

2.2 Innovation networks and regional innovation

There is a wide literature emphasising that the production of knowledge is highly concentrated in dense agglomerations (Capello 2009; Feldman and Kogler 2010; Foddi and Usai 2013; Maggioni et *al.*, 2015; Camagni et *al.*, 2016). One of the main explanations provided over the year by scholars is the importance of geographical proximity in reinforcing both knowledge production and diffusion (Feldman and Avnimelech, 2011). However, the panacea of geographical proximity has been questioned by a number of authors (see for example Breschi and Lissoni 2001; Howells 2002; Gertler 2003; Torre and Rallet 2005; Boschma 2005) who claim that simple co-location is neither a prerequisite nor a sufficient condition for collaboration (Boschma, 2005). Scholars have pointed out other forms of proximity that might affect innovative performance as well. Since the seminal work of Boschma (2005), it has been acknowledged that proximity is thereby not a purely spatial phenomenon, but also includes organisational, institutional, social and cognitive dimensions that might affect knowledge exchange at the regional level and therefore the innovative performance of regions.

Looking at the relative importance of geographical proximity compared to other forms of proximity, Autant-Bernard et *al.* (2007) claim that geographical proximity as such cannot be considered as the main determinant of spillover effects and, even within agglomerations, local clustering is rarely an "unintended" process. Findings and insights from different streams of research in regional studies, such as innovative milieus (Maillat, 1998), industrial districts (Becattini, 1979), regional clusters (Porter, 1990) or more recently EU's smart specialisation approach (McCann and Ortega-Argilés, 2014), also suggest that whatever the forms of proximity in play, social proximity tends to be a prerequisite for interactive learning since social relations strongly facilitate the exchange of tacit knowledge which is, by nature, much more

difficult to codify and hence to communicate and to trade through markets (Maskell and Malmberg, 1999). Furthermore, several authors point out the importance of social proximity for knowledge sharing, emphasising that social ties and trust can help organisations and individuals to collaborate and be more innovative (e.g., Boschma, 2005; Broekel and Boschma, 2012; Capone and Lazzeretti, 2018). In this vein, during the last two decades, the literature on the geography of innovation has embraced the view that a high concentration of actors, even belonging to the same sector, in an area is not enough to explain the innovative capacity of that area (Capello and Faggian, 2005). For such an area to be highly innovative, collective learning is a prerequisite and it implies a high level of social proximity among actors (Capello and Faggian, 2005). Thus, considering co-inventorship as a proxy for social ties (Breschi and Lissoni, 2009), a high level of social proximity among co-located inventors would therefore strengthen the innovativeness of the location by supporting a fast diffusion of information between local or internal inventors. This has been confirmed in previous studies by Miguélez and Moreno (2013a), Breschi and Lenzi (2016) and Coffano et *al.* (2017). Their findings suggest that when relatively few intermediaries separate inventors (*i.e.*, when internal social proximity is high), knowledge tends to diffuse more rapidly, and with less noise. Given the aforementioned discussion, we put forward our first research hypothesis:

Hypothesis 1*: Within a region's co-invention network, a high internal social proximity between local inventors will be positively associated with higher rates of invention in the region.*

For knowledge to be shared and used rapidly, the literature also suggests that the actors in the network should be locally clustered into cliques in which partners of partners are also frequently partners (Uzzi and Spiro, 2005; Schilling and Phelps, 2007). This idea originates from a still ongoing debate in the social network literature regarding the importance of cohesive subgroups of actors within networks (Wasserman and Faust, 1994; Watts and Strogatz, 1998). Within a network, cohesive subgroups can be considered as subsets of actors who tend to create tightly knit groups (*i.e.* cliques) characterised by a relatively high density of ties. Such dense cliques are said to promote trust, cooperation, and a more effective use of the acquired knowledge (Breschi and Lenzi, 2016). Indeed, when inventors are embedded in dense cliques, in which an actor's partners also collaborate with one another, they are able to monitor opportunistic behaviour by free-rider agents for example. In such context, high-quality collaborations can be easily achieved and lead to superior regional innovation capability. Another advantage resulting from the embeddedness of inventors in dense cliques is that it allows them to assess the authority, usefulness and reliability of information spread within the network (Schilling and Phelps, 2007). Being able to evaluate information and sources is all the more important, given the risks involved by R&D activities. Moreover, the persistence of such a cohesive dynamic over time inherently generates conformity and hence stimulates collective learning (Patacchini and

Venanzoni, 2014). Several empirical studies have established that the presence of local cliques characterised by a dense interaction among co-located inventors and regional innovation are correlated (Bettencourt et *al.* 2007; Breschi and Lenzi, 2016). These results allow us to raise our second research hypothesis:

Hypothesis 2*: Within a region's co-invention network, a high clique density will be positively associated with higher rates of invention in the focal region.*

Furthermore, a large part of the literature analysing the link between innovation performance and network structures identifies "small-world" networks as efficient networks for innovation production and diffusion (Kogut and Walker, 2001; Uzzi and Spiro, 2005; Fleming et *al.*, 2007; Schilling and Phelps, 2007). The combination of the two main properties of such networks (high clique density and social proximity; Watts and Strogatz, 1998) is said to boost innovation. Breschi and Lenzi, 2016 have empirically demonstrated the positive effects of this combination on regional innovativeness. We therefore put forward the following hypothesis:

Hypothesis 2a*: Within a region's co-invention network, a combination of high clique density and high internal social proximity between inventors will be positively associated with higher rates of invention in the focal region.*

Another strand of the literature points out that high clique density among co-located inventors could also hamper regional innovation. Indeed, while the Coleman's closure argument stresses the importance of redundant links or collaborations because they facilitate trust and reduce opportunism (Coleman 1988; 1990), Burt (1992) points out the advantages of structural holes which allow actors to have access to valuable and new resources. When local dense cliques imply redundant links between co-located inventors, this can lead to lock-in effects (Grabher, 1993) which hinders the inflow of new and non-redundant information into a region or a network of inventors (Granovetter, 1973; Grabher, 1993; Flache and Macy, 1996). Accessing to external knowledge, *i.e.* from other regions, therefore appears to be important for renewing the local knowledge base (Bathelt et *al.*, 2004; Hazir et *al.*, 2018) and collaboration between inventors from different regions is an effective vehicle for such interregional knowledge flows (Bell and Zaheer, 2007; Innocenti et *al.*, 2020). In other words, a high level of social proximity between local and external inventors is also necessary for supporting regional innovation capability and the geography of innovation literature has fully embraced the view that external links with other innovative regions may promote local innovation (Miguélez and Moreno, 2018) to the extent that local inventors have the absorptive capacity to effectively use the valuable external knowledge (Cohen and Levinthal, 1990; Tödtling and Trippl, 2005). In addition to having access to fresh external knowledge, local inventors can also have access to material or financial resources which are not available locally thanks to close links with

external inventors (Innocenti et *al.*, 2020). This is particularly true for inventors from regions with low internal resources dedicated to R&D and innovation. Indeed, Araújo et *al.* (2019) pointed out that those external links are essential for Brazilian regions that do not have auto sufficiency to innovate. Thus, building on the consideration that external sources of knowledge is likely to strengthen the inventive capability of local inventors, and therefore to foster regional inventive performance, we posit our third research hypothesis:

Hypothesis 3*: A high social proximity between inventors from a focal region and inventors in other regions (i.e. external social proximity) will be positively associated with higher rates of invention in the focal region.*

However, in order to efficiently spread external knowledge in the region, local inventors have to be in engaged in closer social ties (Cohen and Levinthal, 1990; Breschi and Lenzi, 2016). Thus, we would also expect that:

Hypothesis 3a*: A combination of high external and internal proximity will be positively associated with higher rates of invention in the focal region.*

Hypothesis 3b*: A combination of high external proximity and high clique density will be positively associated with higher rates of invention in the focal region.*

During the last decades, the role of universities in contributing to regional innovation has been the subject of intense academic political interest (see Lawton Smith, 2007 for a review). Nowadays, the importance of universities is fully recognised and they are known to contribute to regional innovation in multiple ways (Uyarra, 2008).

It is widely acknowledged that a core role of universities is to generate basic knowledge at the frontier of research and therefore acting as "knowledge factories" which can have a direct local economic impact (Stephan, 1996; Lach et *al.*, 2017). Over the years, the role of universities as producers of knowledge has gradually been transformed into that of producer-disseminator of knowledge. Indeed, the recent literature suggests that one important way universities and research institutions can benefit society beyond education is through an effective and enduring transfer of their knowledge and scientific research to firms which, in turn, can enhance innovation (García-Vega and Vicente-Chirivella, 2020) and thereby long-run economic growth (Mansfield, 1991). These dynamics are already underway, especially in advanced economies, and high-level relationships between universities and firms that can induce effective technology transfers take place through two main channels which are R&D contracting and cooperation (Perkmann and Walsh, 2007). The literature suggests that these two channels of knowledge transfer respond to different challenges at both firm and university levels (Cassiman et *al.*, 2010; Lucena, 2011; Vega-Jurado et *al.*, 2017). Scholars have stressed

the importance of R&D cooperation, which involves the sharing of both codified and tacit knowledge (Lane and Lubatkin, 1998; Almeida et *al.*, 2003), whereas R&D contracting, in general, mainly gives rise to codified knowledge flows between partners. Nevertheless, whatever the form of collaboration, it is generally expected an increase of firm innovativeness, and therefore regional innovation, following the strengthening of the science-industry collaboration.

Indeed, because of the lack of basic knowledge, there are some innovations that firms would not be able to develop on their own and potentially at a lower cost due to economies of scale and uncertainty. Mansfield (1991) illustrates this from the case of silicon and points out that the primary research on the organic compounds of silicon was motivated by the academic curiosity to find how similar silicon was to carbon and not by any commercial purpose (García-Vega and Vicente-Chirivella, 2020). Furthermore, even if firms are aware of the basic knowledge, they might lack the technical capabilities to effectively exploit this knowledge and then develop innovations. Such a need for industrial absorptive capacity can be satisfied through a regional innovative culture based on strong relationships between science and industry (Druilhe and Garnsey, 2000), especially in the context of high-technology activity (Grossetti, 1995). At the micro level, regular collaborations with academics also enable inventors to renew their knowledge base and open their mind to new possibilities, new products and new application areas. In this vein, science-industry collaboration can also preserve regions from technological lock-in and enhance regional inventive outcomes, as long as local inventors maintain close relations with universities (local or not) in various research fields. Hence, we put forward the following hypothesis:

***Hypothesis 4**: A high level of science-industry cooperation involving inventors from a focal region will be positively associated with higher rates of invention in the region.*

2.3 Measuring innovation and innovation networks

Although the theoretical idea that social networks and personal interactions affect the innovative productivity of regions is well established (Graf and Henning, 2009), it has only recently become amenable to direct empirical testing (Breschi and Lenzi, 2016). This chapter aims at contributing to this research area by investigating the effects of innovation networks on regional innovation outcomes. Following the recent contributions in this area (Breschi and Lenzi, 2016; Araújo et *al.* 2019; Innocenti et *al.* 2020), we rely on patent data as a source of relational data (*i.e.*, patent co-authorships) to proxy innovation networks. Relying on patent data as relational data has been popularised in the literature over the last years due to their usefulness in enabling to map and to analyse knowledge networks (Breschi and Lissoni 2004; Singh 2005; Ter Wal and Boschma 2009). In general, in such a framework, inventors are

considered as the nodes of the network, while the edges of the network connect pairs of co-inventors (nodes), *i.e.* the individuals who are designated as inventors in one or more patents.

To test our research hypotheses, we rely on patent applications made by French organisations to the French patent office (INPI). The shortcomings and limitations of patent data have been much discussed in the literature (Ter Wal and Boschma 2009) and scholars consistently point out two major caveats with respect to the use of such data. First, it is widely acknowledged that not all inventions are patented. Therefore, when using patent data, it should be kept in mind that patent data do not capture all collaborative processes at play. Although rarely specified in many studies, the use of patent data requires one to assume that the patent database used is representative of the collaboration occurring between all the inventors in a given geographic area. Second, patented inventions do not have the same market value (Giuri et *al.*, 2007) and economic impact (Griliches, 1990) since organisations, especially firms, patent to a large extent for strategic motives, such as building up a patent portfolio in order to improve their position in negotiations or their technological reputation (Verspagen and Schoenmakers, 2004). Yet despite these caveats, patents are still widely recognised as one the relevant indicators for proxying inventiveness as they present minimal standards of novelty, originality and potential profits, and as such are a good proxy for economically profitable ideas (Bottazzi and Peri 2003). One of the main advantages of patent data is that it allows to explore both network and geographic dimensions on innovation processes; this feature has strongly supported the development of patent-based studies in geography of innovation literature.

The INPI patent database we rely on covers the patenting activities between French organisations and therefore allows us to investigate the co-invention dynamics at the local, regional and national level. Interestingly, the dataset is disambiguated and make it possible to clearly distinguish every inventor. Moreover, as the addresses of the inventors and applicants are reported, patents can be allocated across French regions at the NUTS-3 level which is our level of analysis. Following Araújo et *al.* (2019), the geographical assignment of a patent to a particular NUTS-3 region requires that at least one inventor resides in the region. We used full counting of patents to assign them to (NUTS-3) regions instead of fractional counting since we here consider patents as ideas or pieces of knowledge and not for aggregation purposes to count and compare among regions (Ocampo-Corrales et *al.*, 2020). Thus, the level of regional innovation is proxied by the level of patenting activity of regional inventors, *i.e.* the number of patents they have co-authored.

Regarding the network dimension, we took advantage of opportunities offered by the use of patent data as a source of relational data. From our data, we defined a region's co-invention network as the connections or ties between all the inventors located in the same NUTS-3

regions. We refer to such connections as *internal* or *intraregional* collaborations and such a network as the *internal* or *intraregional* co-invention network. In the same vein, *external* or *interregional* collaborations are characterised by connections between inventors from different regions. Following Breschi and Lenzi (2016) and Araújo et *al.* (2019), we applied the tools of social network analysis and graph theory (Breschi and Lissoni, 2004; Singh, 2005) in order to defined the network variables needed to test our research hypotheses.

Internal social proximity

As formulated in our first research hypothesis, one of the indicators of interest is a measure of how close co-located inventors are, *i.e.* the social proximity within the internal co-invention network. The proposed measure of internal social proximity (ISP) is based on the connection intensity indicator proposed by Borgatti (2006) which is commonly referred to as in the network literature, as the average social distance weighted reach. It is computed as the average across all nodes (*i.e.*, inventors) in the network of the sum of the reciprocal social distances to all other nodes he can reach in the internal co-invention network:

$$ISP_i = \frac{\sum_{j=1}^{n_i} \sum_{\substack{k=1 \\ j \neq k}}^{n_i} \frac{1}{d_{jk}}}{n_i} \qquad [1]$$

where d_{ik} is the geodesic social distance (*i.e.*, the smallest number of intermediaries) that separates inventor j from inventor k in the internal co-invention network of a focal region i, and n_i is the number of inventors located in the region. The proposed measure therefore provides information on how the inventors are well-connected within one region, whether by direct connections or through intermediaries. The metric ranges between 0 (every inventor in a region is an isolate, *i.e.*, when she has no internal collaboration) and $n_i - 1$ (every inventor directly collaborates with every other inventor in the region – except herself).

Clique density

Again, following Araújo et *al.* (2019), we used the clustering coefficient to capture the existence of local cliques of inventors at the internal level, *i.e.* the extent to which the local collaborators of an inventor are also partners with one another. The clustering coefficient is therefore calculated from the inventor links within each region and identifies if the direct contacts of each inventor within the region are also interconnected. More formally, this is measured as follows:

$$CD_i = \frac{\sum_{j=1}^{n} \frac{2E_{(j)}}{C_D(j)[C_D(j)-1]}}{n_i} \qquad [2]$$

where $E_{(j)}$ represents the number of pairs of inventors that have shared links (co-inventions), forming a closed triad in region i and $C_D(j)$, the centrality degree of inventor j. A closed triad is formed when inventor j is linked to inventors k and l, with k and l already being connected. The clustering coefficient varies between 0 (no clustering, *i.e.* there are no closed paths of length two) and 1 (maximum clustering, *i.e.* all paths of length two are closed).

External social proximity

The measure of external social proximity is defined in a similar way as the internal social proximity, except that it focuses on external collaboration. Indeed, it aims at capturing the degree of openness of a focal region through the extent to which inventors in a NUTS-3 region have external links with inventors located in all the other French regions. The external social proximity is formally computed as follows:

$$ESP_i = \frac{\sum_{j=1}^{n_i} \sum_{h=1}^{n_h} \frac{1}{d_{jh}}}{n_i} \qquad [3]$$

where n_i denotes the number of inventors located in region i, n_h denotes the number of inventors located in other regions (*i.e.*, not located in region i), and d_{jh} denotes the geodesic social distance in the French global co-invention network between inventor j and inventor h. It is worth noting that the proposed measures of internal and external social proximity are not affected by the absolute size of the networks since they are weighted by the number of inventors within the region. Therefore, unlike measures that just consider the raw amount of internal and external connections of inventors (Fleming et *al.*, 2007; Lobo and Strumsky, 2008), our proposed measures are able to encompass both the size and the connectedness of the network, which are important aspects in explaining the knowledge flows, and to identify the region's propensity to establish internal or external connections (Araújo et *al.*, 2019).

Science-industry collaboration

Regarding our last research hypothesis, the measure of interest is intended to capture the intensity of cooperation between science and industry. The INPI patent database allows to identify patents that are co-assigned between a firm and a university or a public research organisation; such patents can be seen as science-industry collaborations (Ikeuchi et *al.*, 2017). Thus, we relied on this information to proxy the level of science-industry collaboration by the ratio of the number of co-inventions made through science-industry collaborations to the total number of inventions involving regional inventors:

$$SIC_i = \frac{CoInv_{SI_i}}{Inv_i} \quad [4]$$

where $CoInv_{SI_i}$ represents the number of co-inventions assigned by at least one firm and a public research organisation (as patent applicants or assignees) from region i and Inv_i, the total number of inventions from region i. SIC is therefore expressed as a share of the regional innovation outcomes, *i.e.* the number of inventions, and the higher the percentage, the more regional inventors are involved in science-industry collaborations.

2.4 Estimation strategy and data

2.4.1 Baseline model

Given the purpose of this study, which is to analyse the effects of innovation networks on regional innovation, the well-established Griliches's model of the knowledge production function (KPF) framework is applied at the regional level.

First used in the seminal studies of Griliches (1979) and Hausman et *al.* (1984) at the firm level, this framework was subsequently extended by Jaffe (1986, 1989) to the regional level. Since then, as depicted in the introduction, the regional KPF (rKPF) has undergone several improvements while remaining the standard tool for assessing the influence of regional innovation efforts on regional innovation output (Miguélez and Moreno, 2013a). A standard specification of this model is often expressed as follows:

$$Y = f(RD, HK, Z) \quad [5]$$

where Y is the regional innovation outcome of a given region, which depends on the level of regional R&D expenditures (RD) and the stock of human capital (HK) available for innovative activities. Z includes a number of time-variant variables that account for specific features of the region that might affect innovation outcomes. Following the related literature (Miguélez and Moreno, 2013a), it is assumed that the rKPF follows a multiplicative functional form:

$$Y_i = RD_i^{\alpha} \cdot HK_i^{\beta} \cdot Z_i^{\gamma} \cdot e^{\delta_i} \quad [6]$$

where e^{δ_i} stands for regional time-invariant fixed-effects that allow us to capture the unobserved time-invariant heterogeneity which is a critical determinant of the current spatial configuration of the economic and innovation activities across French NUTS-3 regions. The inclusion of fixed-effects in the model may arguably account for a sizeable part of the co-localisation of similar values of innovation variables in contiguous or proximate regions (Miguélez and Moreno, 2013a), but only to some extent.

In the present chapter we seek to shed some light on the extent to which regions innovative outputs are influenced by the structure of innovation networks. Following our research

hypotheses, we propose to expand the above standard model by modelling Z as a function of the following variables:

$$Z_i = g(ISP_i, CD_i, ESP_i, SIC_i, X_i) \quad [7]$$

where $ISP_i, CD_i, ESP_i, SIC_i$ are respectively the measures of the internal social proximity, clique density, external social proximity and the intensity of science-industry collaboration in region i. X is a set of control variables that account for agglomeration economies and regional technological specialisation.

Assuming that Equation [7] also follows a multiplicative functional form and inserting it into the logarithmic transformation of Equation [6] yields to the following empirical model, to which a well-behaved error term is now added, ε_i:

$$\begin{aligned}\ln(Y_{it}) = \alpha \cdot RD_{it-1} + \beta \cdot HK_{it-1} + \ \omega_1 \cdot ISP_{it-1} + \omega_2 \cdot CD_{it-1} + \omega_3 \\ \cdot ESP_{it-1} + \omega_4 \cdot SIC_{it-1} + \sum_h \omega_h \cdot \ln(X_{iht-1}) + \delta_i + \lambda_t \\ + \varepsilon_{it}\end{aligned} \quad [8]$$

The subscript t denotes time and right-hand side variables have been time-lagged one period $(t-1)$ to lessen endogeneity concerns. Time fixed-effects (λ_t) are also be added to account for any global shocks that may affect all the regions.

Despite the inclusion of regional fixed-effects (δ_i), the current operational model might fail to efficiently control for the spatial autocorrelation inherent to data describing innovation activities (Moreno et *al.*, 2005). The geography of innovation literature has pointed out the limits of standard econometrics methods (LeSage, 2014). Furthermore, lagging the explanatory variables may not fully rule out any potential correlation with the model error term Breschi and Lenzi (2016). This is particularly true for the network variables since network formation is known to follow an endogenous dynamic. We propose some improvements to the baseline model in order to account for the presence of spatial autocorrelation and the endogeneity of network variables.

2.4.2 Spatial filtering framework

Our approach to deal with spatial autocorrelation is using some spatial proxy variables extracted from the spatial weight matrix and added them as control variables to Equation [8]. This approach is known as eigenvector spatial filtering. The main idea behind spatial filtering procedures is that the studied variables (which are initially spatially correlated) are split into spatial and nonspatial components, which can then be employed in a conventional modelling framework. This conversion procedure requires the computation of spatial proxy variables, also

called "spatial filters". In this chapter, we employ the approach developed by Griffith (1996, 2000), which is briefly described below. The spatial filtering procedure is based on the computational formula of Moran's I (MI) statistic. It exploits eigenvector decomposition techniques, which consist in extracting the orthogonal and uncorrelated numerical components from a $N \times N$ (spatial weights) matrix (Tiefelsdorf and Boots 1995). Formally, these orthogonal components are the computed eigenvectors of the transformed spatial weights matrix:

$$\left(I - \frac{ll'}{N}\right) \cdot W \cdot \left(I - \frac{ll'}{N}\right) \qquad [9]$$

where I is the $N \times N$ identity matrix and l is an $N \times 1$ and vector of ones and l' its transpose. The N eigenvectors of the above matrix describe the full range of independent (mutually orthogonal and uncorrelated) map patterns, and their corresponding eigenvalues index the nature and degree of spatial autocorrelation portrayed by each eigenvector. The eigenvectors of the transformed matrix are computed, in sequence, to maximise the sequential residual MI values, while being uncorrelated with the preceding eigenvectors. In the framework of standard regression analysis, they can be interpreted as redundant information due to spatial interdependencies (Patuelli et *al.*, 2011).

As suggested by Patuelli et *al.* (2011), for model parsimony, it is not sensible to include all eigenvectors in the spatial filter. A relevant subset of "candidate" eigenvectors is selected from the N eigenvectors using a two-step procedure is used to identify a relevant subset of eigenvectors. First, eigenvectors are selected on the basis of their MI values exceeding some predefined minimum threshold; the common rule $MI/\max(MI) \geq 0.25$ is used (Patuelli et *al.*, 2011) to keep eigenvectors associated with strong spatial autocorrelation – this roughly corresponds to 5 percent of the variance being accounted for in the regression of a generic georeferenced variable Z on WZ (Griffith 2003). Then, a stepwise for linear regression can be used to select the significant eigenvectors. A linear combination of these eigenvectors is defined as spatial filter.

When applied to panel data analysis, eigenvector spatial filtering consists in four main steps (see Patuelli et *al.* 2011 for more details on the procedure). Below are the specifies of our setting.

- *Step 1: Computation of the eigenvectors from the spatial weights matrix*

Following Patuelli et *al.* (2011), we employ the C-coding scheme with the rook's definition of contiguity spatial weights matrix on W, an $N \times N$ nonnegative spatial weight matrix describing the connectivity structure between the $N = 94$ NUTS-3 French regions.

- *Step 2: Choice of a subset of candidate eigenvectors*

We first keep the set of eigenvectors with their corresponding eigenvalues greater or equal to 0.25.

- *Step 3: For each period, stepwise regression to test the statistical significance of the "candidate" eigenvectors*

The stepwise regression assumes a linear relationship between regional innovation outcome (Y) and the level of regional R&D expenditures (RD) and the stock of human capital (HK). In order to control for the presence of scale effects (Araújo et *al.*, 2019) we include GDP per capita and the number of the local population by the national population as control variables.

- *Step 4: The final spatial filter includes the set of eigenvectors which are common to all periods constitute*

We end up with a spatial filter that includes five significant (time-invariant) eigenvectors. Adding the obtained spatial filter to Equation [8] allows us to filter out spatially autocorrelated patterns and enables us to reduce the stochastic noise normally found in the residuals of standard statistical methods such as OLS. Moreover, Patuelli et al (2012) shows that the spatial filter also acts as a substitute for the individual or region fixed-effects and when employed as regressors, these eigenvectors may function as proxies for missing explanatory variables. Thus, substituting the regional fixed-effects (δ_i) in Equation [8] gives our final empirical model:

$$\ln(Y_{it}) = \alpha \cdot RD_{it-1} + \beta \cdot HK_{it-1} + \omega_1 \cdot ISP_{it-1} + \omega_2 \cdot CD_{it-1} + \omega_3 \cdot ESP_{it-1} + \omega_4 \cdot SIC_{it-1} + \sum_h \omega_h \cdot \ln(X_{iht-1}) + \sum_{k=1}^{5} \theta_k \cdot E_{ik} + \lambda_t + \varepsilon_{it} \quad [10]$$

where $\sum_{k=1}^{5} \theta_k \cdot E_{ik}$ is the obtained spatial filter and E_{ik} the selected eigenvectors. The main advantage of eigenvector spatial filtering compared to popular spatial econometrics models (Anselin et *al.* 2004) is that it identifies and isolates the stochastic spatial dependencies among georeferenced observations and then allow to apply conventional regression techniques as if these observations were independent (Griffith, 2009). Since our design also aims to control for the endogeneity of network variables, we opted for the use of eigenvector spatial filtering.

2.4.3 Controlling for endogeneity

In order to control for the endogeneity of network variables, we adopted an instrumental variable approach using an "instrumental network" for innovation network. Our concern here is to find a network whose structural properties (i) are correlated with the endogenous variables of interest *i.e.* the structural properties of co-invention networks and (ii) have no direct effect on the regional innovation outcome (Stock and Watson, 2010). We suggest to use as "instrumental network" the network portrayed using establishments (firms' plants) as nodes, with

edges connecting pairs of establishments which belong to the same firm. Isolated nodes therefore represent mono-establishment firms.

The literature as pointed out the importance of organisational proximity for collaboration, especially for actors belonging to the same company group (Bartlett and Ghoshal, 1990). Building on this rationale, a very large part of collaborative activities and co-invention might involve inventors working in the same organisation; we therefore claim that the structure of establishment networks would shape and influence co-invention networks.

The variables used as instruments are computed using the same formulas than for ISP_i, CD_i, ESP_i. We also instrumented SIC_i using the ratio of the number of public research establishments to the number of establishments involved in R&D within a region. This choice is guided by the findings from the geography of innovation literature suggesting that colocation can increase the likelihood of collaboration. To rule out any simultaneity bias or potential direct effects on region patenting activities, all the instrumental variables have been time-lagged by two periods. We employ the error component two-stage least squares (EC2SLS) estimator proposed by Baltagi (1981) and expounded in Baltagi (2008).

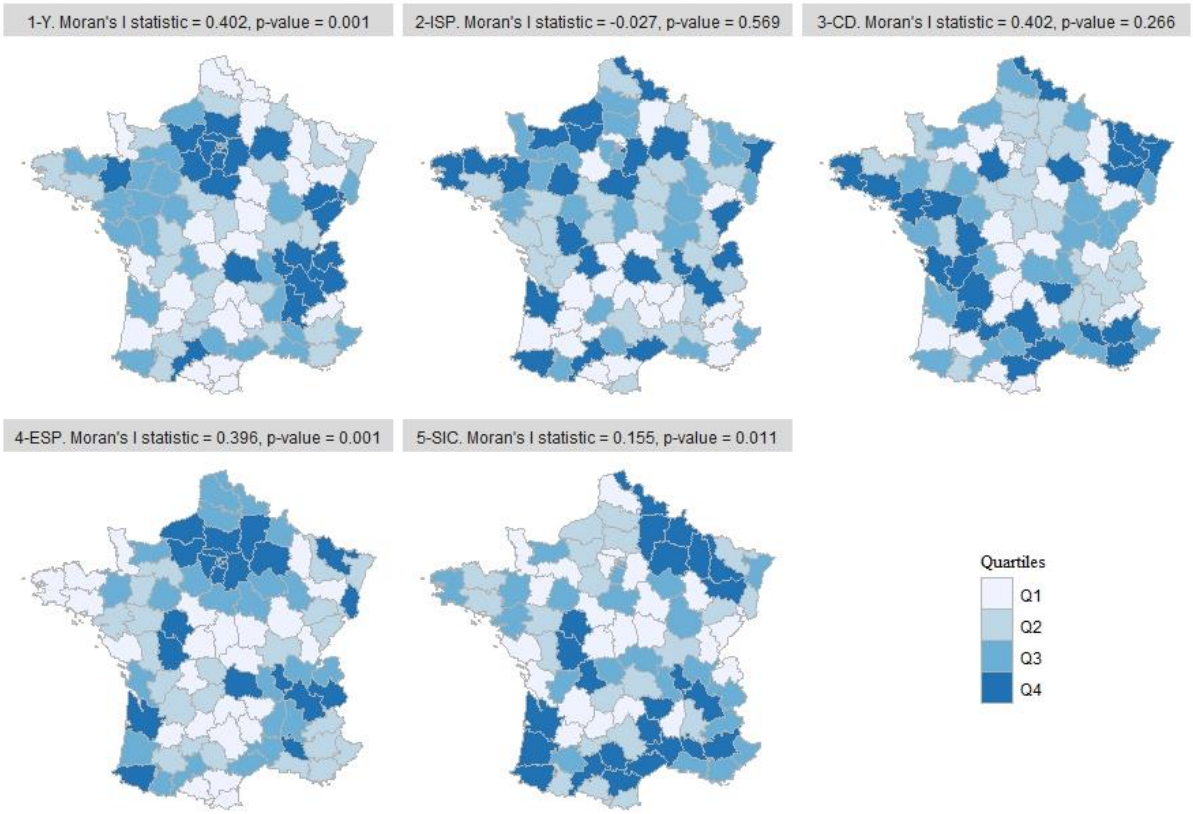
2.4.4 Data

Innovations networks are based on patent applications submitted to the French patent office (INPI) over the period 2005–2013. This time span was broken down into three three-year periods: 2002–2004, 2005–2007 and 2008–2010 and the internal and external regional innovation networks for the 94 metropolitan French NUTS3 regions (so called departments) are defined for each of these periods.

Our dependent variable (Y) was proxied with the number of patents per 100,000 inhabitants over the periods 2005–2007, 2008–2010 and 2011–2013. Following Breschi and Lenzi (2016) and Araújo et *al.* (2019), we also include several control variables in order to capture the importance of agglomeration economies for inventive activities as well as the local economic structures. Thus, the explanatory variables include a measure of R&D expenditures and of human capital at the regional level. We also control for regions economic wealth, technological specialisation, scientific publications, employment in industry and inventor density. For description of the variables, see A.1.2appendix A.1.1; appendices A.1.2 and A.1.3 present the descriptive statistics and the correlation matrix, respectively. All the explanatory variables, including the network variables, are lagged one period in order to lessen endogeneity problems due to system feedbacks (Miguélez and Moreno, 2013a; Innocenti et *al.* 2020); they are therefore defined for the periods 2002–2004, 2005–2007 and 2008–2010. A two-period time lag was used for the instrumental variables, *i.e.* for 1999-2001, 2002-2004 and

2005-2007. Figure 3 reports the spatial distribution of patent applications and network variables, averaged over all periods.

Figure 3 Outcome and network variables (averaged over all periods)



Unsurprisingly, the first map shows a significant and positive spatial autocorrelation of patent applications. This is in line with what the literature has highlighted regarding the concentration of innovation activities (Moreno et *al.*, 2005). We can see that the French patent production is highly concentrated in the NUTS-3 regions (also called departments) of Ile-de-France and Auvergne-Rhône-Alpes. Neighbouring departments also have a high level of patent applications, particularly the departments bordering on Ile-de-France, among them Loiret, Eure-et-Loir, Eure, Marne and Oise. A plausible explanation for this would be that these regions benefit from their geographical proximity to innovative regions by maintaining collaborations with inventors from these regions. This explanation is particularly relevant given the spatial distribution of the external social proximity (ESP). Indeed, the fourth map reveals that external collaborations mainly involve inventors located in the departments of Ile-de-France and Auvergne-Rhône-Alpes.

The fifth map depicts the spatial distribution of science-industry collaboration (SIC) and shows that this type of collaborations weakly involves inventors from Ile-de-France regions. Science-industry collaborations are more mobilised by inventors from the North-East and South regions.

Interestingly, it should be noted that regions such as Rhône and Isère stand out both for their strong involvement in external collaborations and for science-industry collaborations. These two regions also appear to be among the most dynamic in terms of internal social proximity (ISP), although this measure records a less significant spatial autocorrelation. We make the same observation for clique density (CD) although the South and West Coast regions seem to stand out from the other French regions. The low spatial autocorrelation of ISP and CD could be explained by the fact that, unlike the other indicators, ISP and CD are indicators capturing the structural properties of internal or intraregional co-invention networks.

2.5 Empirical results

Table 1 reports the estimates of standard panel data models. Following your research hypotheses, the models aim to show the relation between the innovation networks variables and the production of patents, while controlling for the effects of agglomeration economies for inventive activities.

Overall, coefficients on agglomeration variables are consistent with estimates in the literature. Results from the preferred random effects model (based on a Hausman test) show positive and significant effects of GDP, the stock of human capital as well as the share of employment in manufacturing industry on inventive productivity (Model 1, Table 1). However, we found no significant effect of R&D expenditures but the highly significant effect of the urban scale suggests that other agglomeration variables might still be capturing scale effects (Araújo *et al.*, 2019). Moreover, as discussed in Section 2.4, standard panel data models would fail to account for both the presence of spatial autocorrelation and the endogeneity of network variables. Models 2 to 5 report the second-stage regressions of the EC2SLS models, including spatial filter as covariate.

Table 1 Results of the panel estimations

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	**-4.296***	-4.419	-1.697	-3.612	-3.882
	(2.233)	(3.061)	(4.63)	(2.921)	(3.100)
R&D	0.057	**0.181*****	0.032	**0.184*****	**0.181*****
	(0.049)	(0.047)	(0.064)	(0.049)	(0.044)
HK	**6.066*****	**5.534*****	**6.101****	**5.523*****	**5.051*****
	(1.049)	(1.611)	(2.542)	(1.529)	(1.587)
GDP per capita	**0.581****	0.494	0.326	0.445	0.46
	(0.235)	(0.309)	(0.477)	(0.297)	(0.318)
Scientific publications	**0.103****	0.005	0.119*	-0.015	0.008
	(0.050)	(0.035)	(0.065)	(0.032)	(0.036)
Employment in manufacturing	**2.462****	0.408	1.574	-0.345	0.249
	(1.193)	(0.996)	(1.651)	(0.816)	(1.009)
Inventor density	-0.008	0.006	0.013	0.011	0.014
	(0.014)	(0.016)	(0.032)	(0.015)	(0.016)
Urban scale	**-18.174****	**-11.794***	-12.135	**-11.833***	**-12.182***
	(8.509)	(6.606)	(16.136)	(6.270)	(6.856)
Herfindahl index	-0.024	0.354	**-4.250*****	-0.096	-0.722
	(0.535)	(1.024)	(1.633)	(0.956)	(0.988)
RTA_Chemistry	-0.121	-0.103	**-0.346****	-0.149	**-0.222***
	(0.100)	(0.144)	(0.142)	(0.133)	(0.122)
RTA_Electrical Engineering	0.018	0.065	-0.012	-0.016	0.031
	(0.077)	(0.110)	(0.127)	(0.092)	(0.11)
RTA_Instruments	0.010	-0.095	**-0.266***	-0.102	-0.154
	(0.077)	(0.135)	(0.137)	(0.131)	(0.131)
RTA_Mechanical Engineering	0.186	0.1	0.289	0.1	0.16
	(0.122)	(0.174)	(0.252)	(0.173)	(0.169)
Internal social proximity (ISP)	**0.033****	-0.02	**1.490***	0.037	-0.004
	(0.013)	(0.059)	(0.890)	(0.064)	(0.061)
Clique density (CD)	-0.060	**0.746****	**0.875***	**0.699****	**0.686****
	(0.062)	(0.349)	(0.450)	(0.333)	(0.348)
External social proximity (ESP)	0.001	0.001	0.001	-0.0004	0.015
	(0.001)	(0.007)	(0.008)	(0.008)	(0.023)
Science-industry collaboration (SIC)	0.611	3.258	**8.691***	2.532	**5.937***
	(0.566)	(3.547)	(4.927)	(3.427)	(3.162)
E_{24}		**-1.035*****	**-1.266***	**-1.042*****	**-1.137*****
		(0.277)	(0.693)	(0.266)	(0.311)
E_{22}		**0.828*****	0.876	**0.806*****	**0.762*****
		(0.263)	(0.657)	(0.253)	(0.278)
E_{17}		**-1.533*****	**-1.547****	**-1.492*****	**-1.500*****
		(0.294)	(0.695)	(0.279)	(0.300)
E_{12}		**0.651****	0.483	**0.666*****	**0.695****
		(0.255)	(0.667)	(0.249)	(0.270)
E_{16}		**-0.792****	-0.81	**-0.816*****	**-0.718****
		(0.312)	(0.687)	(0.303)	(0.308)
ISP × CD			**-1.847***		
			(1.106)		
ISP × ESP				0.0003	
				(0.001)	
ESP × CD					-0.016
					(0.027)
Observations	282	282	282	282	282
R2	0.538	0.723	0.267	0.743	0.690
Adjusted R2	0.510	0.699	0.199	0.719	0.661
F Statistic	308.570***	740.548***	141.447***	805.665***	636.569***

Dependant variable: Patents per capita. *, **, *** refers to 90, 95% and 99% significance level. Heteroscedasticity-adjusted t-statistics are shown in parentheses. Model 1 is a random-effect (RE) model – a Hausman test suggested random over fixed effect. EC2SLS models include time-fixed effects (Models 2, 3, 4 and 5) and the spatial filter.

In these models, we found a positive and significant effect of clique density on the production of patents. This result supports our second hypothesis and confirms the importance for co-located inventors to be embedded in dense cliques in order to promote trust among them and

therefore supporting the collective learning taking place at the regional level. Such a local dynamic ends up by reinforcing the innovativeness of the regions. Bettencourt et *al.* (2007) and Araújo et *al.* (2019) found similar results and respectively concluded that US metropolitan areas and Brazilian regions with local networks characterising by the presence of cohesive groups would benefit from more knowledge diffusion because of trustful and reciprocal relationships resulting in positive effects on patenting activities.

Unlike the clique density, internal social proximity appears to be positive and significant only in one of the tested models (Model 3, Table 1). Although it is not the best model (based on R-squared), yet this indicates the importance of reducing the number of intermediaries separating local inventors in order to facilitate knowledge diffusion. This result also reinforces the evidence found by Fleming et *al.* (2007) suggesting that lower number of indirect ties, is related to the improvement of regional innovative performance. Interestingly, we found a negative and significant coefficient for the interaction term between the internal social proximity and clique density. This suggests that regions with a high level of social proximity and also converging toward a common and homogeneous set of knowledge through local dense cliques are likely to observe a negative effect on their innovativeness. Araújo et *al.* (2019) also found a negative effect of combining a high-level of internal social proximity with high clique density and Fleming et *al.* (2007) failed to demonstrate its positive effect on the innovative productivity within US regions. Therefore, despite having a positive effect on the regional innovative performance separately, regions that combine strong social proximity and high clique density may hamper innovative productivity. A possible explanation is that such regions may have experienced greater redundancy of knowledge and therefore lock-in effects from the combination of both network characteristics (Granovetter, 1973; Grabher, 1993; Flache and Macy, 1996).

As discussed in Section 2.2, having access to external knowledge is important to renew the regional knowledge base. We therefore hypothesised that external social proximity may have a positive effect on regional patenting activities by supporting the inflow of new and non-redundant information into a region or a network of inventors. However, we failed to confirm Hypothesis 3 since we found no significant effect of the external social proximity. The same result held when we interact the measures of internal and external social proximity. Broekel et *al.* (2015) and Breschi and Lenzi (2016) provide a plausible explanation for this result. They claim that intensive interregional collaborations may not necessarily enhance regional innovative outputs if regions have a poor knowledge infrastructure and a heavy dependence on external sources of knowledge. Because such regions are typically technologically dependent on others, they may intrinsically lack suitable conditions for the generation of innovation internally. Thus, the statistical non-significance of the external social proximity could be an indication of

a relative lack of inventive capacities in most on the NUTS-3 French regions or the lack of actors acting as knowledge brokers allowing regions to have access to valuable and new resources (Burt, 1992).

Turning to our Hypothesis 4, as expected the results indicate that science-industry cooperation matters in regional innovation. Indeed, we found a positive and significant effects of science-industry cooperation (Models 3 and 5, Table 1) suggesting that collaborations between inventors from industry and research organisations improve the inventive capacity of regions. This therefore supports the role of universities in knowledge production and diffusion. Interestingly, the effects of science-industry cooperation are often stronger than the effects of clique density. This could be an indication of the key role of universities in regional innovation and territorial development (Lawton Smith, 2007). However, given the non-significance of science-industry cooperation in some models, the relative importance against clique density has to be further investigated but this is out of the scope of this paper.

Regarding the control variables, the effects of human capital and R&D expenditures are found to be positive and significant. This is in line with the vast literature on the knowledge production function suggesting that R&D expenditures and human capital are key determinants of the regional innovation. However, most of the variables aiming at capturing the effects of agglomeration activities are not significant. We claim that this does not go against the previous findings suggesting the importance of agglomerative features on regional patenting productivity (Bettencourt et *al.* 2007; Lobo and Strumsky, 2008). Rather, this is evidence that the spatial filter included in the estimates have efficiently control for spatial autocorrelation and also act as robust fixed-effects (Patuelli et *al.*, 2012). This could also explain the limited effects of technological specialisation. Finally, the negative and significant effect of the urban scale is consistent with Araújo et *al.* (2019) estimates based on a spatial autoregressive model and suggesting that the greater the share of the local population by the national population, the lower the regional inventive performance in relative terms.

2.6 Conclusion

This chapter aims at contributing to the development of the regional knowledge production function – rKPF (Charlot et *al.*, 2015) by empirically assesses the relationships between the structural properties of the co-invention network and regional innovation in NUTS-3 French regions. Indeed, despite the acknowledged role of innovation networks, the empirical literature does not offer conclusive evidence on their importance for the inventive performance of regions (Breschi and Lenzi, 2016). Compared to previous studies (Fleming et *al.*, 2007; Bettencourt et *al.*, 2007; Lobo and Strumsky, 2008; Breschi and Lenzi, 2016; Coffano et *al.*, 2017; Araújo et *al.*, 2019; Innocenti et *al.*, 2020), our study constitutes a significant methodological

improvement by taking into account both the presence of spatial autocorrelation and the endogeneity of network variables. Whereas previous studies only address one of these problems at a time, our research design allows us to address them simultaneously.

The study analysed the inventive performance of regions over three three-year periods, from 2005 to 2013 and regional innovations networks have been constructed using patent applications submitted to the French patent office. To account for the presence of spatial autocorrelation and the endogeneity of network variables, we relied on an error component two stage least squares estimation (EC2SLS) with eigenvector spatial filtering. Overall, our results confirm the importance of the structure of local knowledge networks for regional innovation. In particular, we found that the inventive productivity of regions is consistently strengthened by network clustering, *i.e.* the presence of dense cliques of regional inventors, in which an actor's partners also collaborate with one another. This result confirms previous findings (Bettencourt et *al.*, 2007) and also stresses the importance of redundant links at the local or regional level and highlight the importance of trust and reducing opportunism among local actors in order to boost regional innovation. Nevertheless, our results indicate the combination of dense cliques and a strong level social proximity between regional inventors may hamper the innovative productivity of the region. Regions that exhibit such network characteristics are likely to suffer from technological lock-in effects (Grabher, 1993), especially if they are not able to get access to external sources of knowledge and to absorb and use this knowledge (Cohen and Levinthal, 1990). Another major finding is related to the role of science-industry collaboration. We found that the intensity of science-industry collaboration appears to be a key factor for enhancing regional inventive productivity. Our results indicate a positive effect of such collaborations on the inventive capacity of regions. This therefore supports the widely acknowledged idea that research institutions stand to benefit regions by transferring their knowledge and scientific research to firms which, in turn, can enhance innovation (García-Vega and Vicente-Chirivella, 2020) and thereby long-run economic growth (Mansfield, 1991). The study has also offered confirmatory results of the theory regarding the importance of agglomeration and scale effects (Breschi and Lenzi, 2016; Araújo et *al.*, 2019). Indeed, our results clearly confirm the importance of human capital and R&D as suggested by endogenous growth theorists (see Lucas, 1988; Romer, 1986, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1997); they also suggest significant effects of agglomerative features of regions studies (Lobo and Strumsky, 2008) but that significance may be sensitive to the presence of omitted variables describing the structures of local economies.

Two main policy implications can be derived from this study. First, the structure of innovation network matters for regional innovation. Thus, policymakers should not ignore this evidence when implementing innovation policies. Constantly monitoring the structure of the regional

innovation networks would make it possible to implement policies that make the most of network properties. The second policy implication is related to the complexity of tacking advantage of network properties. As illustrated by the induced negative effect from the combination of clustering and internal social proximity, policymakers should also be aware of the possible antagonistic effects resulting from the structure of innovation networks which can hamper the inventive capacity of regions. For example, a region that decides to strengthen collaboration between local actors should systematically ensure that those actors have sufficient links with actors from other regions and/or from academia in order to continually renew the regional knowledge base. Depending on the size of the region, some local key actors could act as gatekeepers or brokers (Burt, 1992), spanning structural holes in innovation networks and hence providing their region with access to new ideas. Building on these policy implications, the next two chapters will take a policy perspective and explore the relation between innovation policies and innovation networks.

Despite its strengths, our study shares the most important limitation with previous studies; that is, all of them rely on patent data. Indeed, as discussed in Section 2.3, proxying innovation networks by invention networks has some shortcomings among which the non-inclusion of other channels of knowledge flows. In our case, the results should be interpreted with some caution since the considered innovation networks do not include international links. We therefore follow Araújo et *al.* (2019) in claiming that future research could analyse innovation network in a more global perspective in order to provide new evidence on how innovations networks influence the innovative dynamics of regions but also of countries.

A.1 Appendices

A.1.1 Variable definitions and sources

Variable	Description	Source
Patents per capita	Patents per capita*(100,000) (log)	French National Institute of Industrial Property (INPI) database on patent applications.
R&D	R&D expenditures by private firms (log)	European Localized Innovation Observatory
HK	Human capital (HK). Average share of highly-qualified full-time equivalent employees (FTE) per year.	DADS database - French National Institute of Statistics and Economic Studies (INSEE)
GDP per capita	GDP per capita (log)	European Localized Innovation Observatory
Scientific publications	Number of scientific publications (log)	Web of Science (WOS)
Employment in manufacturing	Share of employment in manufacturing industry	Cambridge Econometrics
Inventor density	Number of inventors divided by the total area in square kilometres (log)	French National Institute of Industrial Property (INPI) database on patent applications.
Urban scale	Number of the local population by the national population	Cambridge Econometrics
Herfindahl index	Herfindahl index on 35 IPC classes	French National Institute of Industrial Property (INPI) database on patent applications.
RTA_Chemistry	Revealed technological advantage (RTA) index in seven broad technological areas (*i.e.*, chemistry, electrical engineering, instruments and mechanical engineering)	
RTA_Electrical Engineering		
RTA_Instruments		
RTA_Mechanical Engineering		
Internal social proximity	See Internal social proximity (ISP)	
Clique density	See Clustering coefficient (CD)	
External social proximity	See External social proximity (ESP)	
Science-industry collaboration	See Science-industry collaboration (SIC)	
IV_Internal social proximity	Main instrumental variable for ISP	FICUS-FARE database - French National Institute of Statistics and Economic Studies (INSEE)
IV_Clique density	Main instrumental variable for CD	
IV_External social proximity	Main instrumental variable for ESP	
IV_Science-industry collaboration	Main instrumental variable for SIC	

A.1.2 Descriptive statistics

	Patents per capita	R&D	HK	GDP per capita	Scientific publications	Employment in manufacturing	Inventor density	Urban scale	Herfindahl index	RTA_Chemistry	RTA_Electrical Engineering	RTA_Instruments	RTA_Mechanical Engineering
Period 1	**2005 - 2007**	**2002 - 2004**											
Mean	3.669	11.088	0.100	9.967	5.982	0.155	0.582	0.011	0.072	0.882	0.810	0.834	1.141
SD	0.704	1.766	0.047	0.209	2.216	0.050	3.073	0.008	0.033	0.349	0.503	0.292	0.320
Min	1.376	6.023	0.063	9.703	1.792	0.041	0.002	0.001	0.042	0.184	0.000	0.205	0.505
Max	5.622	15.075	0.375	11.114	10.885	0.256	26.190	0.043	0.284	1.951	2.918	1.541	2.206
Period 2	**2008 - 2010**	**2005 - 2007**											
Mean	3.746	11.224	0.101	10.064	6.169	0.144	0.568	0.011	0.086	0.846	0.773	0.901	1.078
SD	0.722	1.816	0.054	0.213	2.213	0.046	3.084	0.008	0.059	0.363	0.511	0.380	0.328
Min	2.206	2.814	0.054	9.801	1.609	0.038	0.001	0.001	0.041	0.000	0.000	0.172	0.463
Max	5.632	15.015	0.406	11.193	11.041	0.231	25.971	0.042	0.408	1.815	3.091	2.379	2.086
Period 3	**2011 - 2013**	**2008 - 2010**											
Mean	3.902	11.330	0.127	10.037	6.387	0.134	0.626	0.011	0.076	0.827	0.841	0.907	1.067
SD	0.716	1.800	0.048	0.242	2.198	0.042	3.483	0.008	0.033	0.389	0.476	0.375	0.313
Min	2.087	1.980	0.085	9.710	1.609	0.037	0.001	0.001	0.042	0.000	0.000	0.000	0.438
Max	5.816	15.051	0.414	11.268	11.240	0.217	30.067	0.041	0.188	1.995	2.657	2.193	1.865

	Internal social proximity	Clique density	External social proximity	Science-industry collaboration	IV_Internal social proximity	IV_Clique density	IV_External social proximity	IV_Science-industry collaboration
Period 1	**2002 - 2004**				**1999 - 2001**			
Mean	1.255	0.762	6.108	0.021	10.617	0.776	844.397	0.570
SD	1.387	0.277	5.597	0.020	10.569	0.070	644.871	0.432
Min	0.000	0.000	0.364	0.000	0.854	0.589	313.138	0.040
Max	11.530	1.000	24.524	0.111	47.565	0.983	3607.502	2.523
Period 2	**2005 - 2007**				**2002 - 2004**			
Mean	1.266	0.771	13.583	0.028	11.943	0.795	937.061	0.536
SD	1.358	0.273	13.705	0.033	11.488	0.063	708.324	0.476
Min	0.000	0.000	0.250	0.000	1.155	0.637	404.233	0.063
Max	11.294	1.000	53.929	0.286	57.129	1.000	4091.206	2.895
Period 3	**2008 - 2010**				**2005 - 2007**			
Mean	1.614	0.783	19.922	0.038	16.488	0.822	1218.720	0.295
SD	2.316	0.255	18.390	0.027	13.769	0.051	804.481	0.279
Min	0.000	0.000	0.535	0.000	1.474	0.718	485.080	0.041
Max	19.147	1.000	76.303	0.111	74.240	1.000	4693.238	2.181

A.1.3 Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	**Patents per capita**	1.000																				
2	**R&D**	0.760	1.000																			
3	**HK**	0.727	0.653	1.000																		
4	**GDP per capita**	0.657	0.598	0.855	1.000																	
5	**Scientific publications**	0.617	0.795	0.665	0.663	1.000																
6	**Employment in manufacturing**	-0.028	0.009	-0.352	-0.301	-0.305	1.000															
7	**Inventor density**	0.373	0.254	0.657	0.752	0.320	-0.302	1.000														
8	**Urban scale**	0.481	0.708	0.664	0.623	0.804	-0.289	0.431	1.000													
9	**Herfindahl index**	-0.159	-0.440	-0.195	-0.169	-0.380	0.099	-0.110	-0.396	1.000												
10	**RTA_Chemistry**	0.202	0.355	0.239	0.233	0.402	-0.278	0.155	0.344	-0.430	1.000											
11	**RTA_Electrical Engineering**	0.243	0.262	0.241	0.190	0.245	-0.222	0.125	0.191	-0.220	-0.134	1.000										
12	**RTA_Instruments**	0.139	0.217	0.238	0.180	0.329	-0.318	0.121	0.305	-0.313	0.086	0.189	1.000									
13	**RTA_Mechanical Engineering**	-0.079	-0.238	-0.193	-0.193	-0.384	0.414	-0.136	-0.322	0.508	-0.364	-0.558	-0.581	1.000								
14	**Internal social proximity**	0.439	0.449	0.289	0.266	0.474	0.028	0.021	0.318	-0.117	0.169	0.337	0.138	-0.256	1.000							
15	**Clique density**	0.153	0.368	0.081	0.097	0.296	0.057	0.009	0.214	-0.270	0.175	0.005	0.096	-0.079	0.135	1.000						
16	**External social proximity**	0.517	0.453	0.502	0.430	0.420	-0.159	0.223	0.371	-0.163	0.345	0.084	0.082	-0.140	0.453	0.044	1.000					
17	**Science-industry collaboration**	0.030	-0.015	0.093	0.058	0.183	-0.268	-0.024	0.066	0.034	0.213	0.054	0.336	-0.326	0.212	0.026	0.214	1.000				
18	**IV_Internal social proximity**	0.446	0.635	0.611	0.497	0.701	-0.308	0.201	0.877	-0.355	0.270	0.180	0.311	-0.319	0.294	0.179	0.387	0.094	1.000			
19	**IV_Clique density**	0.385	0.474	0.619	0.565	0.500	-0.234	0.480	0.559	-0.251	0.167	0.035	0.248	-0.147	0.133	0.139	0.377	0.039	0.515	1.000		
20	**IV_External social proximity**	0.521	0.515	0.811	0.748	0.568	-0.469	0.683	0.676	-0.245	0.247	0.209	0.254	-0.274	0.097	0.083	0.395	0.037	0.702	0.642	1.000	
21	**IV_Science-industry collaboration**	-0.161	-0.167	0.031	0.102	0.152	-0.439	0.203	0.155	-0.022	0.103	0.012	0.144	-0.199	-0.042	-0.138	-0.127	0.122	0.043	0.051	0.133	1.000

A.1.4 Instrument validity

	OLS – Dependant variable:			
	ISP	CD	ESP	SIC
Constant	0.833*** (0.146)	0.309 (0.197)	5.324*** (1.361)	0.025*** (0.002)
IV_Internal social proximity	0.042*** (0.008)			
IV_Clique density		0.581** (0.246)		
IV_External social proximity			0.008*** (0.001)	
IV_Science-industry collaboration				0.008** (0.004)
Observations	282	282	282	282
R2	0.086	0.019	0.156	0.015
Adjusted R2	0.083	0.016	0.153	0.011
Residual Std. Error (df = 280)	1.672	0.266	13.541	0.028
F Statistic (df = 1; 280)	26.474***	5.552**	51.706***	4.222**

*, **, *** refers to 90, 95% and 99% significance level

3 Assessing the collaboration and network additionality of innovation policies: a counterfactual approach to the French cluster policy

This chapter is co-authored with Corinne Autant-Bernard. The PhD candidate is the first author of the article.

Abstract

Whereas most collaboration-based innovation policies aim at fostering efficient ecosystems of innovation, evaluations of the behavioural impact of such policies remain few and far between. Relying on external-to-the-policy network data to build a counterfactual approach, this chapter addresses three main evaluation issues: do cluster policies make firms more collaborative? Do they encourage local ties? Do they induce network additionality? Focusing on French data, our results suggest that cluster policies may have difficulty in increasing the centrality of agents within knowledge networks.

3.1 Introduction

The need for innovation actors to actively engage in collaborations and the benefits of the geographical concentration of firms and economic actors have largely contributed to the expansion of cluster policies across the world. By promoting collaboration, these policies aim not only at giving strong incentives to overcome a sub-optimal investment in collaboration but also at enhancing the local innovation ecosystem. Gök and Elder (2012) refer to this as "behavioural additionality" in innovation policy. The goal of cluster policies goes therefore beyond the mere desire to increase inter-organisation collaboration: it encompasses the structuration of efficient knowledge networks.

However, the ability of public actors to shape firms' decision to create or delete alliances could be questioned. As stated by Tomasello *et al.* (2017), the process of network evolution is strongly path-dependent. Public incentives may therefore face difficulties to generate behavioural additionality. At the same time, the literature trying to assess the effectiveness of collaboration and network-based policies remains scarce and far between[3]. This literature developed along two lines. A first set of studies focuses on the policy impact on collaboration choices. They rely on surveys to identify the extent to which firms have increased the intensity of their collaboration or changed their type of partners. (Caloffi *et al.* ,2015; Wanzenböck *et al.,* 2013; Afcha Chavez, 2011; Nishimura and Okamuro, 2011; Teirlink and Spithoven, 2012; Antonioli *et al.,* 2014 and, more recently, Caloffi *et al.,* 2018). In spite of the relevance of the counterfactual approach used by most of these authors, these studies are quite limited in terms of their ability to deal with some important aspects of the cluster policies. While focusing on collaboration additionality, they neglect the key issue of the overall structure of the network. This network dimension of cluster policies has been investigated only recently by a second set of studies (Giuliani *et al.*, 2016; Calignano and Fitjar, 2017; Rothgang *et al.*, 2017; and Delio and Vicente, 2019). However, because these network studies do not rely on programme evaluation methods, they can hardly draw robust conclusions regarding cluster policies network additionality.

The key issue is thus to identify the extent to which the cluster policy has changed the innovation network features compared to what would have happened in the absence of the policy. This requires building a counterfactual network situation. This is the aim of this paper. As such, this chapter adds to the innovation policy evaluation literature by suggesting an original

[3] An evaluation literature on cluster policies (Falk et *al.* 2010; Martin et al, 2011; Nishimura and Okamuro, 2011) and more widely collaboration-based policies (Sakakibara, 1997; Branstetter and Sakakibarra, 2002; Hottenroot and Lopes-Bento, 2014) does exist. However, it focuses mainly on input and output additionality and neglect most of the time the behavioural additionality

approach combining programme evaluation methods and social network analysis. This is achieved by using internal and external data. "Internal" data refers to the cluster policy beneficiaries while "external" data covers both beneficiaries and non-beneficiaries. It should be noted that the survey-based studies referred above (Afcha Chavez, 2011; Caloffi *et al.* 2018, etc.) also rely on both internal and external data. However, surveys do not make it possible to obtain information about the network. In the surveys, firms are asked about the number of their collaborations or the features of their partners, but it is not possible to draw conclusions from these answers as to the overall network relationships between actors. In this paper, we suggest relying on network information.

More specifically, we use patent data to build a counterfactual analysis to investigate whether cluster participation leads to a change in the innovation process itself. This approach also allows us to move from specific cluster case studies, often based on very few observations, to a broader cluster policy evaluation. While survey-based approaches and most previous network studies focus on a single cluster, our methodology is conceived in order to evaluate the entire national cluster policy. Patent data are used to observe individual collaboration and ego-network features and they are combined with firm data in order to identify individual features.

We also add to the counterfactual evaluation literature by relying on recent evaluation technics. We combine Inverse Probability of Treatment Weighting (IPTW) with the double-difference approach. Both conventional and machine learning - based technics (McCaffrey *et al.*, 2004) are used to estimate the propensity score in order to build on the correct functional forms for each covariate and interactions between covariates (Stone and Tang, 2013). Following Bang and Robins (2005) and Kang and Schafer (2007), a doubly robust estimator of the average treatment effect is also provided to ensure that our estimator remains consistent if either the propensity score model or the outcome regression model is wrong. Finally, we rely on a method recently developed by Carnegie *et al.* (2016) to identify how much unmeasured confounding would produce a change in the conclusion of the study.

Our empirical analysis focuses on the French cluster policy which was launched in 2005 to raise the country's innovative capacity. We focus on the French case since this cluster is among the most developed one in the world, and the largest one in Europe (with a budget of 144 million euros). The French context is also highly relevant because it covers most types of cluster policy features: it targets both lagging and leading regions and it relies on the three traditional roots of cluster policies: regional policy, science and technology policy and industrial/firm policy. We consider as cluster policy participants firms that have paid cluster membership fees. In return, they receive support from the cluster in terms of training and assistance in setting up

collaborative R&D projects especially in partners' searching and networking. The final sample includes 1,047 establishments owned by private, for-profit organisations, including 116 treated establishments (cluster policy participants) and 931 controls.

This original database is then used to address three main evaluation issues: to what extent cluster policies push local actors to engage in collaborative R&D projects with other actors on the one hand, and with co-located partners on the other and whether this induces a change in actors' embeddedness within innovation networks. Focusing on firm data, this chapter addresses the key issue of the impact of the policy on the private sector engagement, which is acknowledged as a critical factor of success of such policies (OECD, 2007).

Our empirical results support the existence of a positive and significant effect of cluster policy participation on organisations' collaborative behaviour. During the period under study (2008-2010), establishments benefiting from the cluster policy increased their participation in collaborative R&D projects by 4.1 percentage points as a result of being participants to French clusters, which is very high, given the low average propensity to co-invent. Our results also suggest that establishments with little or no prior experience in collaborative R&D projects before joining clusters experienced a greater impact, increasing their participation in collaborative R&D projects by 6.3 percentage points. However, we found no evidence that cluster policy participants were more engaged in collaborations involving co-located partners, suggesting that clusters have failed to strengthen local ties. Moreover, we found no evidence to support a network additionality resulting from the French cluster policy. Cluster policy participation did not increase establishments' embeddedness into collaboration networks. In sum, our findings support the positive collaboration additionality effect of cluster policies but provide little evidence of the effectiveness of the French cluster policy in improving actors' centrality and therefore tackling network failures.

The remainder of chapter is structured as follows. Section 3.2 recalls the rationale of cluster policies and sets out the hypotheses tested in the paper. Section 3.3 describes the characteristics of our dataset and Section 3.4 discusses our empirical strategy. The results are presented and discussed in Section 3.5. Finally, Section 3.6 concludes and proposes avenues for further research.

3.2 Rationales of cluster policies and resulting hypotheses

Based on the advantages of both R&D cooperation and favourable regional conditions such as Marshallian localisation externalities (Asheim *et al.*, 2006) and socio-cultural or institutional embeddedness (Rodriguez-Pose, 1998), cluster policies face a renewed interest and turns to

be adapted to an increasingly wide variety of contexts and countries[4]. According to the European Observatory for cluster and industrial change (2019), the French cluster programme is among the most developed one, with the largest budget in Europe. In July 2005, the French government established 67 clusters in various fields (energy, mechanics, aerospace, transport, ICTs, health, environment, ecotechnology, etc.). These clusters are non-profit organisation financed through public funding and participants' contributions. After the creation of new ones and the merger of some of them over time, the number of clusters stood at 71 in 2014 and 56 today. The State support for clusters mainly takes the form of i) a partial financing of cluster governance structures, alongside local authorities and participants (public research organisations and firms), and ii) the granting of financial assistance to collaborative R&D projects emerging from clusters[5]. As most cluster policies, it aims at fostering collaborations among actors putting special attention to their geographical scope. According to an official definition, a (French) cluster "*brings together large and small firms, research laboratories and educational establishments, all working together in a specific region to develop synergies and cooperative efforts*"[6]. This is because collaborations can be an effective way of reducing market failures associated with the innovation process and of creating innovation ecosystems which are likely to reduce network failures. Three interdependent dimensions of the cluster policies can therefore be identified, namely collaboration, geographical scope and network. They are discussed below, putting special attention to the specific goals of the French policy, in order to draw our main research hypotheses.

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[4] Although an exhaustive overview of such policies throughout the world does not exist, it seems that most countries support clusters. In its 2010 Science and Technology Outlook, the OECD reviewed a set of 18 countries implementing a national cluster policy (Argentina, Canada, Chile, Austria, Belgium, China, Columbia, Denmark, France, Germany, Greece, Ireland, Japan, New Zealand, Sweden, Belgium, Netherlands). More recently, the European Observatory for cluster and industrial change (2019) stated that most EU countries implement a cluster policy and compared the national cluster programmes in 20 EU countries and 9 non-EU countries (US, Brazil, Mexico, Israel, Taiwan, Singapore, China, Japan and South Korean).

[5] Note that the French cluster policy is not the most expensive area of state activity innovation policies. The national innovation support system is essentially based on indirect aids through the research tax credit (CIR), the cost of which amounted to €6.3 billion in 2015, *i.e.* nearly 75% of the state's support for innovation, compared to 16.5% in 2000 (CNEPI, 2016). French clusters get their support mostly from financial instruments such as subsidies (€2.37 billion between 2005 and 2013) and they capture less and less public funding since their creation. However, this does not call into question the importance of the clusters in the national innovation system since they are one of the major policy instruments (in terms of financial allocation) from the national innovation strategy designed to support collaborative R&D projects and local innovation ecosystems, particularly before the 2010s. Since 2010, several other policy instruments such as the Technology Transfer Accelerator Offices (SATT) and the Technology Research Institutes (IRT) have been implemented to also support collaborative research, the strengthening of science-industry collaboration and technology transfer.

[6] It should be noted that in France, cluster participants are actually firms' establishments where an "establishment" is defined as an independent production unit, physically located, but legally dependant of a firm. Several evaluations of the French cluster policy have been carried out by considering firms as treated units (Erdyn, Technopolis and BearingPoint, 2012; Fontagné et *al.*, 2013; Bellégo and Dortet-Bernadet, 2014; Ben Hassine and Mathieu, 2017). Such evaluations could lead to inconsistent results, particularly when only some firms' establishments are cluster participants while most of them are not.

3.2.1 Cluster policy as a collaboration-based policy

The potential benefits of collaborative research are threefold (Hinloopen, 2001). First, by internalising technological spillovers, collaborative research reduces the "free rider" problem. Second, cooperation makes it possible to combine complementary skills to reach the critical mass required to implement very large research projects. Third, risk pooling may also lead to an increase in private R&D activity. Scherngell and Barber (2009) thus describe collaborations as a *conditio sine qua non* for innovation. Several empirical findings confirm the expected positive results of R&D collaboration. Janz *et al.* (2003), Van Leeuwen (2002) and Criscuolo and Haskel (2003), for instance, find evidence of a positive correlation between R&D collaborations and innovation performance, highlighting the importance of collaborative projects.

However, due to uncertainty and asymmetric information, organisations may interact poorly. This may hamper synergies, complementary knowhow, creative problem solving and capacity sharing, and lead to the lack of a shared vision of future technology developments. This justify the implementation of cluster policies that aim to encourage economic actors to engage in collaboration in order to address market failures.

In this perspective, the French cluster policy provide incentives for collaborative research, through two types of tools[7]: direct R&D support though the selection of projects involving different types of partners[8] and non-financial support mainly targeted at SMEs (training, partnership building, technical assistance, etc.). In order to benefit from these services, firms have to become participants (also called members) of the clusters which involves paying fees. In 2014, the 71 clusters had about 9,650 company-level participants (for 10,380 individual establishments) including 8,500 private firms and 1,150 public research organizations (DGE, 2017). Even though the French clusters are open to all firms no matter their size, the majority of firms benefiting from the cluster policy are SMEs: in 2014, 75% of the participants were establishments owned by SMEs, 17% by mid-tier firms and 8% by large firms (DGE, 2017).

Cluster policy participants should, therefore, be more likely to be engaged in collaborative R&D projects than non- participants, *ceteris paribus*. This behavioural change among clusters policy beneficiaries should be observable both in their projects which are supported by the policy and in those which are not supported. Cluster policies should have a positive effect on

[7] To this respect, the French policy is quite similar to the Japanese cluster policy. The German leading-edge cluster competition also relies on these two tools.

[8] Between 2005 and 2013, 1,313 collaborative R&D projects endorsed by clusters received public financing of €2.37 billion, including more than €1.45 billion granted by the French State through the Single Inter-Ministry Fund (FUI).

the overall willingness of their participants to collaborate, on other words, cluster policy participants should be more open to collaborative innovation.

We therefore expect the following hypothesis concerning the effect of clusters on the collaborative behaviour of their participants to hold true:

***H1**: Firms benefiting from cluster policies are more engaged in R&D collaborations than the other firms*

Very few evidences can be found on this issue in the literature. Studies considering the impact of public policies on collaboration behaviours do not focus on cluster policies but on regional, national or international direct R&D support policies (Caloffi *et al.* ,2015; Wanzenböck *et al.,* 2013; Afcha Chavez, 2011; Teirlink and Spithoven, 2012; Antonioli *et al.,* 2014 and, more recently, Caloffi *et al.,* 2018). Most of them point to the positive effects of financial support to R&D consortia on collaboration intensity or partner choices, though these effects would not occur systematically. Only Nishimura and Okamuro (2011) put special emphasize on cluster policies considering therefore also the role played by indirect coordination support. Their results point out the importance of this non-financial support to expand R&D collaborations.

We therefore contribute to this literature by exploring the impact of the French cluster policy on collaborative behaviours. Contrary to past studies which rely on survey data, we suggest using systematic data (see Section 3.3) to avoid answer subjectivity and specific cluster case studies. We also include the spatial dimension to the analysis.

3.2.2 Cluster policy as a place-based policy

A second rationale for cluster policies is to enhance the concentration of economic activities, in order to favour local interactions. Since Marshall (1920), it has been agreed that geographical concentrations of firms and economic actors can generate positive effects on economic growth in specific territories. It has also been shown however that proximity by itself is not sufficient. Proximity matters if it leads to a high level of interactions between actors (Autant-Bernard *et al.* 2013), enhancing collaboration intensity and knowledge flows between actors. As argued by Boschma (2005), these knowledge flows generate knowledge spillovers, innovation and, finally, regional growth.

For this reason, most cluster policies are implemented at the local level and put special emphasize on local collaborations. According to Fernández-Ribas (2009), regional and local governments tend to have a better understanding of the formal and informal institutions that shape behavioural patterns and social interactions in the territory. Lower levels of administrations are, therefore, needed to correct systemic dysfunctions linked to multi-level STI policies and they are in the best position to connect different stakeholders within the territory.

Sub-national governments would also be able to tailor national and supra-national policies, guaranteeing the coherence between the various directions taken by the territory.

The French cluster policy was clearly built in this perspective, policymakers opting for a regional anchoring of clusters. This anchoring materialised in the adequacy between clusters' fields of specialisation and the economic sectors present in regions, as well as the research themes led by the regional public research actors. In order to support this vision, regional authorities were heavily involved from the beginning of the policy, particularly in terms of providing joint funding, alongside State financing.

However, note that the geographical scope of the French cluster policy has evolved over time, may be in reaction to the evolution of the proximity literature. This latter stated that other dimensions of proximity can influence collaborations (e.g. cognitive, organisational, social and institutional proximities) and too much proximity may also have negative impacts on innovation due to lock-in problems (Boschma, 2005), particularly in the case of geographical proximity where regional actors do not share a minimal degree of cognitive (technical) proximity (De Noni *et al.*, 2017).

The local dimension of the French cluster policy was particularly strong during the first phase of the policy (2005-2008) during which the policymakers' aim was to propose to innovation actors a new model of carrying out R&D projects based on collaborations with other actors, particularly in co-located organisations. This first phase was essentially focused on structuring the clusters and the emergence of collaborative R&D projects within them. During the second phase of the policy (2009–2012), both the territorial and the international dimension have been revisited. The territorial anchoring of clusters remained the core dimension, but the willingness to create synergies between them and all the other policies and actors supporting innovation both at national and local levels was added. The purpose of this additional direction was to strengthen the consistency between innovation policies in France in order to build more relevant and resilient innovation ecosystems. This new strategy implied that clusters would be more open to long-distance collaborations and not only collaborations with regional actors. For policymakers, reinforcing the synergies between clusters must also be an inherent part of the cluster policy to avoid duplication of R&D efforts. Beyond the theoretical arguments supporting long-distance collaborations, the logic of optimising R&D efforts was even more crucial in a significantly deteriorated economic context due to the economic crisis of 2008.

The current context is also marked by the merger of some clusters and the co-endorsement of collaborative R&D projects by clusters. Previously organised into independent entities although maintaining close links, some clusters now tend to be increasingly structured around a single, unifying governance structure. In addition to policymakers' desire to encourage relations

between clusters, this dynamic was also supported by the merging of certain French regions in 2016. Several clusters that were previously located in different regions have thus seen their scope of action becoming shared with other clusters. There is every indication that the future of French clusters would be marked by a greater openness towards (long-) distant collaborations, which implies cluster policy participants collaborating with actors that are not necessarily located within their region. Such a political orientation would potentially result in a decrease in local collaborations.

In this context of a progressive move towards a lower regional focus, one can wonder whether the French cluster policy succeeded to strengthen collaborations between regional actors. Thus, we put forward the following hypothesis:

***H2**: Firms benefiting from cluster policies are more engaged in collaborations involving regional partners than the other firms*

It is worth noting that this hypothesis does not imply that clusters do not support collaboration with non-regional partners. Since most clusters are designed at a regional level, they are intended to support networking among regional organisations but also between regional and non-regional organisations. If firms benefiting from the cluster policy are more engaged in co-inventions (with regard to the evolution of their inventive activity) with regional partners, we may conclude that clusters have succeeded in strengthening the territorial anchoring of their participants through collaborative innovation.

While no specific assessment of the impact of cluster policies on local collaboration exists, some empirical evidence on this issue can be found considering other collaboration-based policies. While analysing the impact of the EU Framework Programme on the intensity and geographical dimension of inter-regional collaborations, Scherngell and Lata (2013) observed that geographical distance and country border effects decrease over time. Due to the regional dimension of the data, they were, however, unable to implement a counterfactual analysis to properly assess the causality between the EU policy and the shape of collaboration networks. Conversely, based on concrete data and counterfactual analysis, Antonioli *et al.* (2014) found that regionally funded firms are more likely to co-operate with regional partners than extra-regional ones. The spatial scale of the collaborations induced by the policy seems, therefore, to be driven by the geographic scope of the policy.

Our investigation on the French cluster policy therefore build upon this literature to assess the impact of place-based policies using a counterfactual analysis. But it also goes beyond the mere analysis of the collaboration additionality, considering the structural effect of the policy on the R&D networks.

3.2.3 Cluster policy as a network-based policy

Collaboration-based innovation policies, and especially cluster policies, do more than simply address market failures. As pointed out by the literature on the innovation system (for an overview, see Bleda and Del Rio, 2013), systemic failures also arise in the innovation process. System failures refer to structural, institutional and regulatory deficiencies, which lead to sub-optimal investment in innovation activities. One of the main structural deficiencies is insufficient and/or inefficient levels of networking and knowledge exchange between organisations; these deficiencies are referred to as "network failures" and are an important component in the innovation policy agendas of regional, national and international institutions.

Following the seminal work by Granovetter (1985) several theoretical studies of network formation have pointed out that, in order to lower search and enforcement costs, firms tend to renew ties with past partners and form ties with their partners' partners. Consistent with these theoretical predictions, empirical studies find that firms collaborate more frequently and more intensely with a restricted set of partners (Baum et *al.* 2005). However, the key role of brokerage or clique-spanning ties within networks has also been stressed (Burt 1992, 2008). As stated by Baum, Cowan and Jonard (2010), innovation networks directly benefit from those ties that bridge structural holes providing « access to diverse information, technologies and markets, openings to broker the flow of information and resources among otherwise disconnected firms, and chances to control projects involving participants from different regions of the network » (Baum, Cowan and Jonard, 2010, p. 1). In their theoretical model, Baum, Cowan and Jonard, 2010 highlight that the ability to access complementary knowledge and therefore to create ties with distinct communities is more important for radical innovation than reinforcing collaborations with a small set of partners. Zaheer and Bell (2005) confirm this finding based on empirical evidence. They observe a positive relationship between structural hole position of a firm and innovation performance. However, brokering induces greater risk, uncertainty and costs. Consequently, firms are generally reluctant to form such bridging ties despite their potential benefits. System failures may thus lead to inefficiencies in the network structure (Woolthuis *et al.* 2005). Due to cultural, technological or geographical distance, a lack of bridging ties is likely to occur, which prevents access to new knowledge, complementary expertise and resources. Due to asset specificity, the existence of switching costs or, in the case of monopolistic or high-tech markets, a lack of alternative partners, actors may be "locked into" their relationships.

This requires public actors to favour socially distant ties. This can be achieved by creating opportunities for new meeting between firms or between firms and public research organisations. This can also be favoured by enhancing the visibility of local actors, which can

then be identified by potential partners. This is exactly the goal of the indirect tools implemented by clusters policies to support innovation.

The various types of services provided by clusters could contribute to this goal by helping local organisations to increase their network embeddedness (Martin and Sunley, 2003). For instance, most cluster policies appoint brokers and intermediaries to organise the coordination between actors. This should improve the ability of actors to identify relevant networks. It is also argued that cluster policies involve collective marketing of the region's industrial strengths. Raising awareness of local industrial specialisms makes local firms more likely to be asked to enter national and international partnerships and therefore to increase their centrality within knowledge networks. As argued by Martin and Sunley (2003), cluster policies should also identify weaknesses in existing cluster value chains and attract investors and businesses to fill those gaps. Such an attractiveness policy could strengthen the network positioning of local anchor firms by reinforcing their demand and supply links.

The French clusters policy clearly follow these goals. Both financial and non-financial supports provided by clusters managers are intended to actively support networking between firms, universities and research organisations. Specific services for networking building are provided. In addition to the strengthening of the local innovation ecosystem, the political will is to favour the national and international visibility of local actors. A distinction was made during the first phase of the policy between world clusters, world vocation clusters and national clusters in order to support the participation in international projects (especially European projects) as well as the promotion of innovative local actors. To this respect, the cluster policy aims at helping cluster policy participants to hold more central positions within knowledge and innovation networks. Although this distinction has been removed during the second phase of the policy, the political will to favour the national and international visibility of local actors has remained. Thus, networking of innovation stakeholders remained as a main concern during the second phase of the cluster policy. The recently launched call for applications concerning the selection of clusters for the forth phase (2019–2022) specifies that this phase will be designed from a more European perspective, in order to develop collaborative projects with European actors within the context of Horizon 2020 and Horizon Europe calls for tenders. This implies a stronger embeddedness of cluster policy participants into global innovation networks.

To this respect, an effective cluster policy is a policy that modifies the position of the funded firms in the network of its relationship, making it more centr*al.* In case a cluster policy increases the level of collaboration among actors already involved in past collaborations, the firm' centrality level would remain rather unchanged. Conversely in case policy incentives succeed to broaden the set of collaborators, then the centrality could increase, providing the firm with

a better access to local and global knowledge. Indeed, as stressed in recent social network literature (Everett and Valente, 2016) brokerage positions are strongly correlated with centrality. Increasing the ability of funded firms to connect previously unconnected agents (brokerage) thus modifies the network structure and favours knowledge diffusion. Our third hypothesis therefore aims at investigating whether there is actually a cluster premium regarding the embeddedness of firms benefiting from the cluster policy into networks of co-inventions. We put forward the following hypothesis:

***H3**: Firms benefiting from cluster policies are better embedded in knowledge networks than the other firms*

A recent literature addresses this network dimension of cluster policies by relying on social network analysis. Some recent papers by Giuliani *et al.* (2016), Calignano and Fitjar (2017) Rothgang *et al.* (2017) and Delio and Vicente (2019) belong to this line of research. These network-based approaches provide us with precise insights regarding the evolution of the structural properties of the subsidised network, pointing for instance to the emergence of more central agents or more hierarchical relationships. They do not allow however robust conclusions regarding the causal impact of the cluster policy to be drawn. While only relying on the network of beneficiaries, the pre- and post-treatment period comparison is not sufficient to identify the role played by the policy. Comparing various industries, Tomasello *et al.* (2017), observe some universal properties in the structural dynamics of R&D network. Most of the changes in the collaboration and network features may thus occurred even in the absence of the policy. The general trend towards a more collective innovation could, for instance, be observed in more spontaneous networks and not only within publicly-supported clusters. Similarly, the more global dimension of inter-firm collaboration supported by the new communication technologies is likely to induce changes for firms both within and outside clusters. Change in the relationships between science and industry and in between small and large firms may also evolve over time due to drivers other than cluster policies. In addition, firms that have chosen to enter the cluster may have specific features and innovation strategies that may explain some structural evolutions of their network which would have occurred even in the absence of the policy.

We therefore built a methodology allowing us to combine social network analysis and programme evaluation methods. To test hypotheses H1, H2 and H3 it would be insufficient to compare changes in the ability of cluster policy participants and non-participants to collaborate and to be embedded into networks. To estimate the causal effect of cluster membership, we need to account for the fact that organisations which decide to join clusters are not necessarily comparable to those which do not. Our empirical strategy will be described in Section 3.4 after setting out information on the data.

3.3 Data and outcome variables

As detailed below in Section 3.4, our empirical strategy consists in building a counterfactual approach in order to assess the existence of collaboration and the network additionality of the French cluster policy. This approach requires finding external-to-the-policy network data in order to outline the network of knowledge collaboration. This will allow us to characterise the collaboration and network behaviour of both beneficiaries and non-beneficiaries of the cluster policy. Beneficiaries of the cluster policy are those that have paid cluster membership fees. In return, participants receive support from the cluster in terms of training and assistance in setting up collaborative R&D projects especially in partners' searching and networking.

In order to assess the impact of the policies on the beneficiaries R&D collaboration and network behaviour, we need to observe the network of knowledge collaboration of both beneficiaries and non-beneficiaries. However, obtaining an exact list of organisations' collaborations is not straightforward. To the extent that these R&D projects lead to inventions, co-inventions can be considered as proxies for collaborations.

There are strong well-known limitations using patent data as a proxy for innovation activities (all innovations do not lead to a patent, all patents do not refer to an innovation, the value of patents can differ strongly and a strong heterogeneity occurs in their use according to firm size and industries). However, patents remain one of the best data sources researchers can use for studying collaboration. By focusing on patent data, we put special emphasis on knowledge networks. This is consistent with the French cluster policy whose main goal is to reinforce R&D collaborations in order to strengthen local innovation ecosystem. Even though patents are not the only output of R&D projects supported by cluster policies, the evaluation study ran by Erdyn, Technopolis and BearingPoint (2012) estimate that between 2008 and 2011 R&D projects supported by the French clusters policy would have led to the filing of nearly a thousand patents. One of the French clusters covered by our study, Images&Reseaux, provides online data on their projects output. Over the 203 achieved projects supported by this cluster, 107 have led to the creation of new product(s) and 57 have induced patent application(s). Patent thus appears as an important outcome of the French policy. Moreover, using patent data allows us to locate each invention and therefore to identify the spatial scope of collaborations.

However, other types of collaborations may result from cluster policies. Policymakers can try to favour the various types of externalities likely to arise within clusters such as input-output linkages, access to demand, labour occupation linkages (Marshall, 1920). Delgado *et al.* (2014) show for instance that industries located in clusters with dual specialization in innovation (patenting) and production (employment) grew faster in terms of innovation (patenting). This suggests that co-location of innovation and production matters for subsequent innovation and

facilitates a broad set of linkages, beyond knowledge linkages. It should therefore be kept in mind that cluster policies could foster collaboration between suppliers and buyers that may increase patenting but not necessary be reflected in co-invention among firms.

3.3.1 Building the network of collaboration

Co-invention networks (hereafter used interchangeably with "collaboration networks") are based on applications for patents submitted to the French patent office (INPI) over the period 2008–2013. We use a three-year lag between the beginning of R&D projects and patent applications. The choice of this three-year lag is justified by the average duration of R&D projects supported by clusters through the FUI, which is one of the main instruments for financing collaborative R&D projects from French clusters. In line with the vision of turning clusters into drivers of growth and competitiveness, the FUI mainly supports pre-competitive R&D projects aiming at placing new products and services on the market within three to five years from the end of projects. Thus, within the FUI scheme, several clusters support R&D projects with an average duration of three years[9] in order to target projects that are innovative but also "close to the market". Moreover, firms that are cluster policy participants are mainly industrial actors involved in more applied R&D projects. In this context, we consider this average duration of R&D projects supported through the FUI as being representative of the average duration of cluster policy participants' R&D projects. The choice of a three-year lag between the beginning of R&D projects and patent applications is also supported by previous studies on duration of R&D alliances (Phlippen and van der Knaap, 2007; Phelps, 2010).

When defining the pre- and post-treatment periods, we faced some challenges related to the short life span of firms' establishments. In order to have the largest sample of firms' establishments benefiting from the cluster policy, we considered 2008 as the date of treatment, and subscribers before 2008 were excluded from the sample. Considering the actual date of the cluster's creation, such as 2005, results in a small sample size, since clusters had few beneficiaries when they were established and many of those beneficiaries were young establishments for which information on the pre-policy period cannot be obtained. Based on a three-year lag between the beginning of R&D projects and patent applications, we then considered that patent applications between 2008 and 2013 were the result of projects that started during the 2005-2010 period. This time span was broken down into two three-year periods: 2005–2007 and 2008–2010, which are respectively the pre- and post-treatment periods.

[9] The duration of projects often varies between 24 and 48 months.

Our treated population is, therefore, firms' establishments involved in clusters between 2008 and 2010, but not before 2008.

Primary patent data provides us with information on applicants on the one hand and information on inventors on the other. Due to the multi-site nature of public or private organisations/firms (which are usually the patent applicants), the geographic addresses available on patent applications do not allow us to locate the places where inventions were actually made, *i.e.*, the locations of establishments which effectively carried the R&D projects. In order to identify these locations, we had to rely on two assumptions. Based on the distribution of patents between inventors and applicants during each period, we first identified the organisation employing each inventor following this assumption:

A1: an inventor belongs to an organisation when they file most of their patents with that organisation and that organisation alone.

This assumption relies on the fact that the majority of inventors are employed by an organisation (European Patent Office, 2011), which is usually, although not systematically, the patent applicant. We assume that the more an inventor's name appears in a set of patents (excluding co-patents) alongside a given applicant, the more likely this inventor is to be an employee of that applicant. Based on the addresses of inventors and establishments, we then identify the establishment employing each inventor following this second assumption:

A2: an inventor belongs to their organisation's establishment which is geographically closest to them.

Following Blomkvist *et al.* (2014), there are good reasons to assume that inventors live near their places of work, since they want their activities to remain within easy commuting distance of home (Zucker *et al.*, 1998). This assumption is highly plausible in the French context, since in 2004 for instance, half of all employees worked within eight kilometres of their home (Baccaïni *et al.*, 2007). For employees whose workplace is not in their commune of residence, the National Institute of Statistics and Economic Studies indicated that the distance between home and work increased by only 2 km between 1999 and 2013 (Coudène *et al.*, 2016).

By combining assumptions 1 and 2, we translate collaboration networks among organisations into collaboration networks among establishments, which allows for a more realistic geographical representation of collaboration networks. The final collaboration networks are therefore portrayed using nodes which represent establishments and edges connect pairs of nodes which are the co-inventors of at least one patent. Isolated nodes or establishments are patent owners which are not involved in any co-invention. Note that although these data treatment allowed us to identify linkages between establishments of the same firm, the focus

of this chapter is on between-firm linkages only as we are interested in testing external collaborations facilitated by the cluster policy.

3.3.2 Characterising individual collaboration and network features

Based on these collaboration networks, we can calculate the number of inventions and co-inventions of each establishment before and after joining clusters. Since the periods under study (2005–2007 and 2008–2010) are relatively short, it is important to analyse the collaborative and network behaviour of establishments with regard to their inventive activity over this timespan. For each establishment in the network, we calculated i) its co-invention rate (to test H1); ii) its intra-regional co-invention rate (H2) and iii) its degree centrality and betweenness centrality (H3) during the pre- and post-treatment periods.

The co-invention rate can be defined as the propensity of an establishment to be engaged in co-invention while the intra-regional co-invention rate is the propensity of an establishment to be engaged in co-invention with co-located partners. We take into account all type of organisations (private or public) when computing these rates. Therefore, establishments' partners are not limited to establishments owned by private organisations. These rates are our outcome variables. The co-invention rate is formulated as follows:

$$co.invention\ rate_{i,t} = \frac{coinv_{i,t}}{inv_{i,t}}, \qquad [11]$$

where $coinv_{i,t}$ and $inv_{i,t}$ are, respectively, the number of co-inventions and the total number of inventions (including co-inventions) of establishment i over period t, a dummy variable equal to 1 after the policy. $inv_{i,t}$ therefore, refers to the total number of inventions individually developed or not developed, while $coinv_{i,t}$ is the number of inventions developed by an establishment with at least one establishment from a different firm or organisation.

Building on the above definition of the co-invention rate, the intra-regional co-invention rate has as numerator only co-inventions involving at least one co-located establishment and is formulated as follows:

$$intra.regional\ co.invention\ rate_{i,t} = \frac{intra.regional.coinv_{i,t}}{inv_{i,t}}, \qquad [12]$$

where $intra.regional.coinv_{i,t}$ is the subset of co-inventions consisting of those involving at least one co-located establishment from a different firm or organisation.

In order to test the third hypothesis (H3), we rely on networks centrality measures. Following Broekel *et al.* (2015), we use the degree centrality and the betweenness centrality to respectively proxy the degree and the quality of establishment's embeddedness in innovation networks.

The degree centrality is a simple count of establishments' number of direct collaboration partners and therefore provides a quantitative expression of their local network embeddedness; Broekel *et al.* (2015) referred to this local embeddedness as *local centrality*. The degree centrality of a node i, for a given non-directed network $N := (V, E)$ with V nodes and E edges is denoted as:

$$C_D(i) = deg(i) \qquad [13]$$

Unlike the degree centrality, the betweenness centrality goes beyond establishments' direct collaboration. In the social network analysis literature, the "betweenness centrality" refers to the number of times a node lies on the shortest path between other nodes (Freeman 1987; Wasserman and Faust 1994). It therefore takes into account indirect ties and approximates the extent to which establishments act as "bridge" between other establishments in the network; Broekel *et al.* (2015) referred to this bridging position as *global centrality*. The betweenness centrality of a node i, for a given non-directed network $N := (V, E)$ with V nodes and E edges is defined as:

$$C_B(i) = \sum_{j \neq i \neq k} \frac{g_{jk}(i)}{g_{jk}} \qquad [14]$$

where, $g_{jk}(i)$ is the number of shortest paths connecting j and k passing through i and g_{jk} the total number of shortest paths connecting j and k.

After computing these four outcome variables from collaboration networks, we expanded the dataset by including characteristics from the DADS[10] database. We retrieved from this database the establishments' number of employees as well as their qualifications. The final sample included 1,047 establishments owned by private for-profit organisations[11]. These 1,047 private establishments included 116 which were treated (they had been cluster policy participants for at least one year between 2008 and 2010 and were not cluster policy participants before 2008), and 931 controls (non-cluster policy participants over the 2005–2010 period). Recall that beneficiaries are those firms' establishments that have paid cluster membership fees and benefit in return from the cluster assistance in partners' searching and networking. Conversely, non-cluster policy participants are establishments that are not participants of any of the cluster built by the policy. In order to avoid bias due to indirect policy

[10] The DADS database is administered by the French National Institute of Statistics and Economic Studies (INSEE). It provides employment information on the French directory of firms' establishments. Geographic information (address) from the DADS database was complemented with data from the free online business directory www.societe.com.

[11] Our final dataset only contains establishments with complete information *i.e.*, those that have no missing data in the DADS database.

effect between establishments of the same firm, all the establishments from firms which have at least one participant establishment are excluded from the control sample. We thus only consider establishment within firms that are never treated.

3.3.3 *Beneficiaries vs non-beneficiaries' characteristics*

All the baseline characteristics as well as the outcome variables before benefiting from the cluster policy are listed in Table 2, along with their mean and standard deviation, and their proportions (for categorical variables) in both populations.

Table 2 Baseline characteristics of treated and control subjects in the original sample

	Cluster policy participants:	
	No	**Yes**
Variable	**(N = 931)**	**(N = 116)**
Size	216.73 (493.09)	401.84 (629.14)
Highly-qualified employees	0.26 (0.25)	0.30 (0.21)
Number of inventions	11.40 (32.17)	23.37 (88.68)
Technological intensity		
High-technology	43 (4.6%)	17 (14.7%)
Knowledge-intensive services (KIS)	184 (19.8%)	21 (18.1%)
Less knowledge-intensive services (LKIS)	105 (11.3%)	6 (5.2%)
Low technology	81 (8.7%)	14 (12.1%)
Medium-high technology	325 (34.9%)	41 (35.3%)
Medium-low technology	193 (20.7%)	17 (14.7%)
Firm's type of establishment		
Large enterprises	302 (32.4%)	34 (29.3%)
Micro enterprises	23 (2.5%)	3 (2.6%)
Intermediate-sized enterprises	345 (37.1%)	48 (41.4%)
Small and medium-sized enterprises	261 (28.0%)	31 (26.7%)
Region		
Alsace	25 (2.7%)	1.0 (0.9%)
Aquitaine	31 (3.3%)	3 (2.6%)
Auvergne	18 (1.9%)	1.0 (0.9%)
Basse-Normandie	16 (1.7%)	2.0 (1.7%)
Bourgogne	23 (2.5%)	6 (5.2%)
Bretagne	47 (5.0%)	3 (2.6%)
Centre	36 (3.9%)	5 (4.3%)
Champagne	25 (2.7%)	4 (3.4%)
Franche-Comté	22 (2.4%)	4 (3.4%)
Haute-Normandie	22 (2.4%)	3 (2.6%)
Ile-de-France	233 (25.0%)	27 (23.3%)
Languedoc	14 (1.5%)	3 (2.6%)
Limousin	3 (0.3%)	1.0 (0.9%)
Lorraine	22 (2.4%)	2.0 (1.7%)
Midi-Pyrénées	27 (2.9%)	6 (5.2%)
Nord	33 (3.5%)	3 (2.6%)
Normandie	3 (0.3%)	1.0 (0.9%)
Pays-de-la-Loire	58 (6.2%)	4 (3.4%)
Picardie	35 (3.8%)	1.0 (0.9%)
Poitou-Charente	29 (3.1%)	2.0 (1.7%)
Provence-Alpes-Côte d'Azur	31 (3.3%)	7 (6.0%)

Variable	Cluster policy participants: No (N = 931)	Yes (N = 116)
Rhône-Alpes	178 (19.1%)	27 (23.3%)
OUTCOMES		
Co-invention rate	0.04 (0.14)	0.05 (0.13)
Intra-regional co-invention rate	0.02 (0.09)	0.02 (0.08)
Degree centrality	2.43 (5.22)	2.10 (4.65)
Betweenness centrality	1301.33 (5107.99)	2492 (174498.06)

Note: Continuous variables are represented as mean and standard deviation (in parentheses), while dichotomous variables are represented as N (%).

From Table 2, there was not too much difference between the treated and control groups regarding their co-invention rate and their intra-regional co-invention rate before the treatment. Regarding the centrality measures, cluster policy participants had less direct ties compared to non-participants (degree centrality) but they have acted more as "bridges" between other establishments in the collaboration network (betweenness centrality). Treated establishments also had partially different background characteristics from controls before joining clusters. Indeed, cluster policy beneficiaries are much larger establishments in terms of the number of employees than controls. They also have a higher proportion of highly-qualified employees and are much more present in high-technology sectors. Overall, these differences may reflect a selection bias that should be addressed before making any causal inference.

3.4 Empirical strategy

3.4.1 Econometric approach

Our objective is to identify the average mean effect of treatment (on the treated – ATT) on the co-invention rate, the intra-regional co-invention rate and the centrality (degree and betweenness) of cluster policy participants. Following Rubin's causal model (Rubin, 1974), finding a reliable estimate for the counterfactual state, *i.e.*, the outcome if participants had not participated in the programme, is the primary task of any evaluation study. This way of defining treatment effects is often referred to as the "potential outcomes approach" (Rubin, 1978, 1980). The main challenge of such an evaluation is to find a reliable estimate for the counterfactual state, *i.e.* the outcome if cluster policy beneficiaries had not joined the clusters (*i.e.* if they had not paid the membership fees and therefore were not involved in the policy actions). For any establishment i, the causal effect of Z on Y is:

$$Y_i(Z = 1, X) - Y_i(Z = 0, X), \qquad [15]$$

where X includes any influence on Y other than the treatment Z. However, we can never observe this causal effect directly because we cannot simultaneously observe the same unit with and without the treatment condition. The estimation procedure used in this chapter is

based on the combination of Inverse Probability of Treatment Weighting (IPTW) with the double-difference approach.

3.4.2 Estimation procedure

One of the main challenges in observational studies is unbalanced baseline characteristics across comparison groups; constructing a credible counterfactual group to capture what would have happened to participating units had they not participated is therefore crucial to draw causal estimates. The causal inference literature provides various procedures to be followed (Imbens and Wooldridge, 2009). The Inverse Probability of Treatment Weighting (IPTW) is one of those procedures. It aims at creating a pseudo-population of both treated and control groups, with the same covariate distribution. Treated and control units are weighted in order to balance covariate distribution in both groups. By doing this, IPTW mimics a randomised experiment (Austin and Stuart, 2015).

As a propensity score method, IPTW is based on the propensity score which is defined as the subject's probability of treatment selection, conditional on observed baseline covariates *i.e.*, $e(X) = P(Z = 1|X)$. Given the relatively small sample size at our disposal we chose to rely on IPTW since it includes all study units unlike other propensity score methods based on matching which select some matched treated and controls and discards others. We propose a formal set of balance diagnostics that check the reliability of the weighting procedure.

In our setting, propensity scores were estimated using a probit regression and we refer to this model as the "simple specification of propensity score model":

$$P(Z = 1|X_i) = \Phi\left(\sum_{k=0}^{K} \beta_k X_{ik}\right), \qquad [16]$$

where Z_i is a treatment indicator, taking values of 1 for the treated and 0 for the untreated; X is a vector of K number of observed measures that predict the probability of joining clusters for each establishment i. β denotes a set of coefficients that estimates the relationship between the covariates and the probability of being cluster policy participants, under the cumulative normal distribution Φ.

Models developed using probit regression may not produce the best propensity scores (Dehejia and Wahba, 1999; Olmos and Govindasamy, 2015). Following the recent development of machine learning techniques applied to causal analyses, McCaffrey *et al.* (2004) also suggested an alternative approach to estimating propensity scores using Generalised Boosted Models (GBM). GBMs are multivariate nonparametric techniques that recursively partition the data for each covariate and predict treatment assignment based on

decision trees. GBMs use the "forward stagewise additive algorithm" (Abdia, 2017) to estimate the propensity score by modelling:

$$g(X_i) = logit\big(e(X_i)\big) = \log\left(\frac{e(X_i)}{1 - e(X_i)}\right), \qquad [17]$$

where X is the vector of covariates and $e(X)$ the propensity score. McCaffrey *et al.* (2004) argued that GBMs are particularly suited to estimating propensity scores in the presence of a large number of pre-treatment covariates and also when covariates are non-linearly related with the treatment assignment. The main advantage of this approach over a simple specification of treatment assignment mechanism is that generalised boosted-regression modelling builds on the correct functional forms for each covariate and interactions between covariates, that are not fully specified in a simple specification such as a probit regression (Stone and Tang, 2013). We estimated another set of propensity scores using a generalised boosted model and refer to this model as the "complex specification of propensity score model".

By using two propensity score models, we aim to compare (and then select) the one that achieves the best balance in terms of baseline covariates between treated and control groups. Moreover, a high correlation between the propensity scores obtained in both specifications would suggest a good specification of the probit regression.

To estimate the ATT, the weight w_i for each establishment is defined as:

$$w_i = Z_i + \frac{(1 - Z_i)e_i(X)}{1 - e_i(X)}, \qquad [18]$$

Equation [18] leads to weights of 1 for treated and $\frac{e_i(X)}{1-e_i(X)}$ for controls. Two weighted samples are then created based on estimated propensity scores from the simple and complex specifications. All the estimates involving each of these weighted samples are actually based on 1,000 bootstrapped samples and large weights have been truncated in order to guarantee the stability of the procedure (Elze *et al.*, 2017). We rely on the standardised mean difference (SMD) to assess the balance in baseline characteristics between treated and control groups (Austin and Stuart, 2015; Caloffi *et al.*, 2018). While there is no consensus as to what value of a standardised mean difference can be considered as an indication of imbalance, several authors have suggested that a standardised mean difference in excess of 0.1 may be indicative of meaningful imbalance in a covariate between treated and control subjects (e.g. Normand *et al.*, 2001; Mamdani *et al.*, 2005; Austin and Stuart, 2015).

Despite its ability to mimic randomised experiments, IPTW alone is not sufficient for an unbiased estimate of the ATT, since time-invariant unobserved characteristics may still contribute to

selection bias. Therefore, we rely on the double-difference framework which is based on a comparison of treated and controls before and after the intervention to control for those unobservable characteristics. The difference-in-differences (DD) estimator is defined as the difference in average outcome of the treatment group minus the difference in average outcome in the control group before and after treatment. The estimate is constructed as follows:

$$\left(\bar{Y}_{i(Z=1),t=1} - \bar{Y}_{i(Z=1),t=0}\right) - \left(\bar{Y}_{i(Z=0),t=1} - \bar{Y}_{i(Z=0),t=0}\right) \quad [19]$$

We base our estimation procedure on the first difference *i.e.*, the difference between two time points as a dependent variable. The second difference comes from our treatment variable. Our response model is therefore defined as follows:

$$\Delta Y_i = Y_{i,t=1} - Y_{i,t=0} = \alpha + \delta_{ATT} Z_i + \varepsilon_{i,t} \quad [20]$$

where ΔY_i is the change in the outcome of interest, δ the coefficient of interest (treatment effect) and α the time trend. One should note that this estimate of the treatment effect with propensity score weighting is also the difference between the weighted means of the outcome for treated and untreated establishments (Imbens, 2004):

$$\widehat{\delta_{ATT}} = \frac{\sum_{i=1}^{n} Z_i \Delta Y_i}{\sum_{i=1}^{n} Z_i} - \frac{\sum_{i=1}^{n} (1 - Z_i) \Delta Y_i e(X_i)/(1 - e(X_i))}{\sum_{i=1}^{n} (1 - Z_i) e(X_i)/(1 - e(X_i))}, \quad [21]$$

3.4.3 Control variables

The literature on cluster policy evaluation suggests that qualitative methods could be a better approach for evaluating behavioural additionality (Falck *et al.*, 2010). This is partially due to the fact that changes in establishments' behaviour could also come from their participation in subsidised R&D projects, not just from the cluster policy. However, it is not straightforward to identify which establishments have received any support for collaborative R&D projects before the policy given the large number of funding schemes available. Nevertheless, one can assume that establishments receiving this kind of support are those that show some interest in collaborative R&D projects. In order to differentiate these establishments from others, we propose a qualitative measure, $collaborative\ establishment_{i,t=0}$, identifying which establishments are interested in collaborative projects during the pre-policy period (2005-2007)[12]. This measure is a dummy variable constructed as follows:

[12] It should be noticed that this variable would be biased if computed during the post-policy period since a cluster premium would exist allowing cluster participants to be more likely to receive subsidies for collaborative R&D projects (Broekel et *al.*, 2015) and therefore being more collaborative.

$$collaborative\ establishment_{i,t=0} = \begin{cases} Yes, if\ co.invention\ rate_{i,t=0} > 0 \\ No, otherwise \end{cases} \quad [22]$$

In order to better address this attributability challenge, we also consider establishments' participation to the EU's Framework Programme (FP). Indeed, as a key policy instrument to support medium- to large-sized collaborative research projects in Europe, Framework Programme is likely to affect firms' collaborative behaviour and therefore to confound the effect of the French cluster policy. We generated a dummy variable specifying whether or not an establishment has participated to a project under the Framework Programme during the post-policy period (2008-2010)[13]:

$$FP_{i,t=1} = \begin{cases} Yes, if\ establishment's\ firm\ participate\ in\ FP \\ No, otherwise \end{cases} \quad [23]$$

We extended our response model from Equation [20] to take into account establishments' collaborative behaviour before joining clusters and their participation to Framework Programme during the treatment period.

To sum up, in our econometric specification, we combine IPTW with the double-difference approach; by doing this we are able to identify the treatment effects in a selection on observables and unobservables context (Imbens and Wooldridge, 2009). Such a specification relies on two main identification assumptions. On the one hand, we assume that the establishment's treatment only affects its behaviour, not that of other establishments; this assumption is known as the Stable Unit Treatment Value Assumption (SUTVA). On the other hand, our specification relies on the Parallel Trend Assumption which requires that in the absence of treatment, the difference between cluster policy participants and non-participants is constant over time.

The treatment effect is estimated using weighted least squares regressions and heteroskedasticity robust standard errors. We provide a counterfactual assessment of both collaboration and network behaviour additionality. A robustness check and a sensitivity analysis to "unmeasured confounding" are provided in appendix. We conclude from this analysis that unmeasured confounding would not produce significant change in the conclusion of the study.

[13] Given the reasoning used in the generation of the variable "collaborative establishment", it already includes the information on participation in EU's Framework Programme before the policy (2005-2007). We therefore limit ourselves to generating the variable "FP" only for the treatment period and used it as an explanatory variable in the response model in order to control for a potential effect of the Framework Programme on establishments' collaborative behaviour.

3.5 Empirical results

3.5.1 Propensity score results and balancing the sample

As explained in Section 3.4, the objective of IPTW analyses is to first create a weighted sample in which the distribution of the confounding variables is the same between treated and control groups. In our analysis, propensity scores resulting from the simple specification *i.e.*, the probit regression, achieved the best balance in baseline covariates (see appendix A.2.1). Therefore, the results presented in this section are based on that model.

Before presenting the treatment effect results, let us start by analysing the results of the probit regression estimating the treatment assignment. Table 3 shows the coefficients and marginal effects of the probit estimation to derive the propensity score for being a cluster policy beneficiary. The general conclusion of this model is that results are in line with previous findings about firms' participation in cluster policies.

First, the size of the establishment is positively correlated to joining a cluster. This is not a surprising relationship, since larger establishments are likely to have more resources, especially human resources, dedicated to R&D activities and they are, therefore, likely to be among the most active organisations doing research. Bellego and Dortet-Bernadet (2014) also found the same relation when estimating the probabilities of firms joining French clusters. This relationship is complemented with a positive marginal effect of the establishment's share of highly-qualified employees. Beyond the fact that the larger establishments tend to join clusters, establishments with highly-qualified employees are also likely to join clusters. However, this relationship is limited by a negative quadratic effect of highly-qualified employment on the probability of being cluster participant.

Results of the propensity score model also reveal that establishments of micro-enterprises, and small- and medium-sized enterprises (SMEs) were more likely to join clusters than large firms' establishments. This finding is in line with the rationale behind the French cluster policy, which tends to provide much greater support to establishments that have greater difficulty innovating. Typically, the subsidy rate for collaborative R&D projects which are supported by a French cluster is always higher for SMEs than for large companies. Furthermore, public statistics on the composition of French clusters show that they are mainly composed of SMEs[14].

A sectorial effect can be observed in joining clusters. The propensity score model indicates that establishments in high-technology industries were more likely to join clusters. Ben Hassine and Mathieu (2017) also found the same result when estimating the probabilities of firms joining

[14] According to Directorate General for Enterprise (DGE, 2017), in 2014, 87% of cluster participants are SMEs, half of which (53%) are micro-enterprises (employing fewer than ten people).

French clusters. Indeed, this result is strongly in line with the aim of the French cluster policy, which is to mainly support industrial activities with a significant technological component.

Table 3 Propensity score model (simple specification)

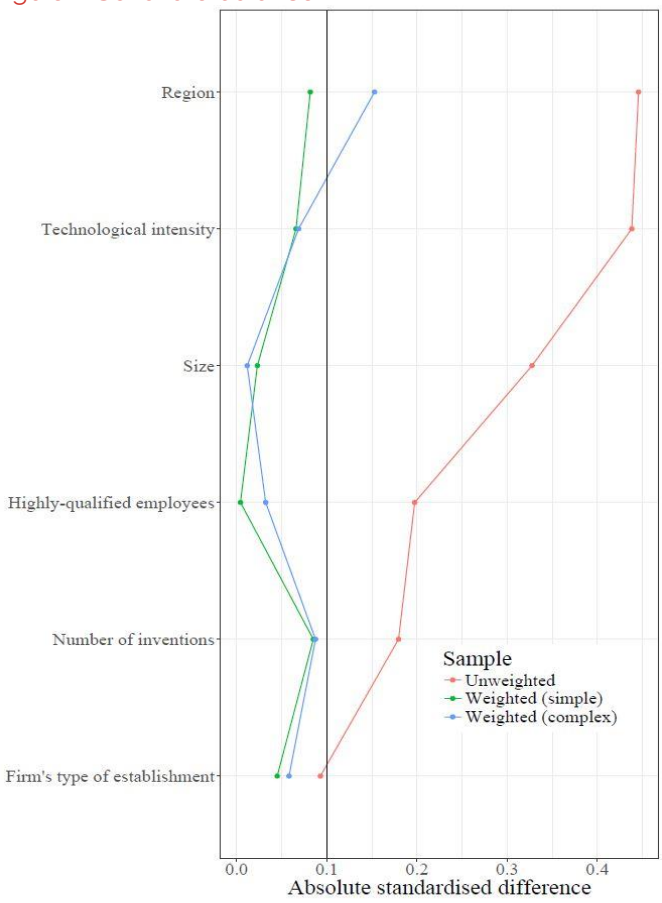
	Probit	
	Coefficient (Std. Error)	Marginal effect (Std. Error)
Constant	-3.553***	
	(0.653)	
log(Size)	0.292***	0.041
	(0.052)	(0.007)
Highly-qualified employees	3.555***	0.505
	(0.971)	(0.139)
Highly-qualified employees²	-3.576***	-0.508
	(1.166)	(0.170)
Number of inventions	0.002	0.000
	(0.001)	(0.000)
Firm's type of establishment, compared to large enterprises		
Micro enterprises	1.501***	0.440
	(0.424)	(0.181)
Intermediate-sized enterprises	0.222	0.033
	(0.154)	(0.025)
Small and medium-sized enterprises	0.614***	0.106
	(0.193)	(0.041)
Technological intensity, compared to High-technology		
Knowledge-intensive services (KIS)	-0.526**	-0.060
	(0.235)	(0.021)
Less knowledge-intensive services (LKIS)	-0.630**	-0.063
	(0.289)	(0.019)
Low technology	-0.307	-0.036
	(0.257)	(0.025)
Medium-high technology	-0.609***	-0. 077
	(0.217)	(0.025)
Medium-low technology	-0.617***	-0.068
	(0.239)	(0.021)
Regional dummies	Considered	
Aldrich-Nelson R-sq.	0.1	
McFadden R-sq.	0.1	
Cox-Snell R-sq.	0.1	
Nagelkerke R-sq.	0.2	
LR Chi2 (33 variables)	100.1	
Prob > Chi2	0.0	
Log-likelihood	-314.5	
Deviance	628.9	
AIC	696.9	
BIC	865.4	
Number of observations	1047	

Note: Statistical significance: *p< 0.10, **p< 0.05, ***p< 0.01

We found no evidence that the number of inventions is a determining factor for an establishment to join a cluster. This could seem counterintuitive, since Table 2 clearly shows the gap between treated subjects and controls regarding their number of inventions. Our view on this is that the number of inventions can be perceived as an output of establishments' R&D activities. In this vein, after controlling for factors such as the size of establishments or their sector, we end up by neutralising a potential effect of the number of inventions on the probability of joining clusters. This variable is, however, retained in the propensity score model since, otherwise, the propensity score model would not allow to balance the "number of inventions" between the treated and the controls.

As shown in Figure 4, our weighting process based on propensity scores from the probit model (simple specification) considerably improves balance in the sample. Even though the nonparametric generalised boosted model failed to balance the treated and controls as regards "Region", it performs fairly well and its resulting propensity scores and those obtained with the probit regression are highly correlated (>90%). This is an indication of the relevance and reliability of the simple specification of the propensity score model.

Figure 4 Covariate balance



3.5.2 *Effect of French clusters and discussion*

Table 4 shows that firms benefiting from the cluster policy exhibit, on average, an increase of about 0.034 *i.e.*, 3.4 percentage points, in their co-invention rate. After controlling for participation in the Framework Programme and the pre-policy behaviour of establishments towards collaboration, the effects of cluster policy participation on establishments' co-invention rate rises to 0.041 *i.e.*, 4.1 percentage points. This indicates a positive and significant effect of the French cluster policy on the co-invention rate of the beneficiaries and therefore on their collaborative behaviour. This result provides evidence for a behavioural additionality effect of the French cluster policy and therefore confirms the positive impact of the clusters, since they have been able to encourage their beneficiaries to become more involved in collaborative R&D projects. In a context where cluster policies are often criticised regarding their input and output additionality (Vicente, 2014; Duranton, 2011), this result supports the ability of cluster policies to influence collaborative behaviour.

Table 4 Effects on collaboration and intra-regional collaboration

	Dependent variable:							
	Change in co-invention rate				**Change in intra-regional co-invention rate**			
	WLS	Survey-weighted (robust Std. Error)	WLS	Survey-weighted (robust Std. Error)	WLS	Survey-weighted (robust Std. Error)	WLS	Survey-weighted (robust Std. Error)
	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
Constant	0.002	0.002	0.027***	0.027***	0.0004	0.0004	0.007	0.007
	(0.008)	(0.007)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)
Treatment	0.034***	0.034*	0.041***	0.041**	0.009	0.009	0.010	0.010
	(0.011)	(0.019)	(0.011)	(0.018)	(0.007)	(0.011)	(0.007)	(0.010)
Collaborative establishment = *Yes*	-	-	-0.127***	-0.127***	-	-	-0.022***	-0.022
			(0.013)	(0.026)			(0.008)	(0.022)
FP = *Yes*	-	-	0.038**	0.038*	-	-	-0.011	-0.011
			(0.017)	(0.022)			(0.011)	(0.014)
Observations	1047	1047	1047	1047	1047	1047	1047	1047
R^2	0.009		0.098		0.001		0.010	
Adjusted R^2	0.008		0.095		0.0005		0.007	
Log Likelihood		-191.978		-142.815		287.239		291.600
Akaike Inf. Crit.		387.957		293.631		-570.477		-575.201
Residual Std. Error	0.085		0.081		0.054		0.054	
F Statistic	9.230***		37.605***		1.521		3.419***	

Compared to previous studies, we thus confirm for the French case positive findings obtained on other contexts by Nishimura and Okamuro (2011) for Japanese clusters, by Afcha Chavez (2011) or by several studies focusing on regional supports to R&D collaboration (Afcha Chavez,

2011 in Spain; Tierlink and Spitoven, 2012 in Belgium and Caloffi et *al.*, 2018 in Italy). In addition to these studies, our results suggest that the policy may increase collaboration even beyond the only financial incentives since the participation in co-inventions encompasses non-subsidised projects.

The robustness of the significant effect on the co-invention rate is tested using a doubly robust estimation procedure. The doubly robust estimate of the average treatment effect is 0.041636, with a standard error of 0.0175. This estimate is close to that obtained previously with a non-doubly robust estimator (see appendix A.2.2). This is a desirable result because it shows that the effect is not sensitive to the specification of the response model. Moreover, the sensitivity analysis (see appendix) reveals that our result is not highly sensitive to the presence of unmeasured confounders since the current effect would change only if a confounder with a strong relationship with the treatment or the outcome variables (especially on the outcome variable).

It is also worth noting that the estimated average treatment effect is not only due to the increase in the co-invention rate of some treated subjects, especially those already engaged in co-inventions before joining clusters. It also results from an increase in the number of treated establishments engaged in co-inventions (from 32 during the pre-treatment period to 41 during the post-treatment period; and 23 treated subjects which were engaged in co-inventions during both periods). Furthermore, this effect is not exclusively the result of an increase in co-inventions between cluster policy participants alone. During the post-treatment period, 17% of cluster policy participants were engaged in co-inventions with other cluster policy participants and 9.3% of non-participants were also engaged in co-inventions with cluster policy participants.

Regarding the control variables, we observed a positive and significant relationship between participation in the Framework Programme projects and establishments' co-invention rate. As expected, this provides evidence as to the role of the EU Framework Programme in affecting firms' collaborative behaviour through the support of collaborative R&D projects between organisations across Europe. Interestingly, we observe a negative and significant correlation between the collaborative behaviour of establishments before joining clusters and the change in their co-invention rate. Establishments which were already engaged in collaborative R&D projects before joining clusters tend to increase their co-invention rate to a smaller extent compared to establishments with little or no prior experience in collaboration. This unexpected result suggests that the positive average effect on the co-invention rate might hide some heterogeneity between establishments depending on their willingness to collaborate. We will have more to say on that in the next sub-section.

As discussed above, cluster policy participation has a positive and significant effect on establishments' co-invention rate. However, we observed no significant effect on the intra-regional collaboration. This suggests that although clusters have effectively supported their beneficiaries in participating in collaborative projects, a very small proportion of these collaborations involve organisations from the region to which cluster policy participants belong. While recent literature on geography of innovation suggests that interregional collaborations should not be supported at the expense of intraregional collaborations (De Noni *et al.*, 2017), our results reveal that the French cluster policy has not significantly strengthened the establishment of collaborations between organisations located in the same region. This result could be explained by the fact that the studied period partially covers the second phase of the cluster policy (2009-2012) during which interregional collaborations were encouraged. It would seem that the strengthening of interregional collaborations has been to the detriment of intra-regional collaborations. This could be damaging for innovation, since collaborations with proximate partners are those who favours most the innovative output (Hazir and Autant-Bernard, 2016).

Table 5 Effects on network embeddedness

	Dependent variable:							
	Change in Degree centrality				**Change in betweenness centrality**			
	WLS	Survey-weighted (robust Std. Error)	WLS	Survey-weighted (robust Std. Error)	WLS	Survey-weighted (robust Std. Error)	WLS	Survey-weighted (robust Std. Error)
	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
Constant	0.450***	0.450***	0.489***	0.489***	1016.805*	1016.805**	1637.882***	1637.882
	(0.128)	(0.122)	(0.138)	(0.167)	(562.105)	(427.030)	(607.430)	(1133.184)
Treatment	-0.182	-0.182	-0.144	-0.144	-1453.501*	-1453.501	-1475.578*	-1475.578
	(0.180)	(0.332)	(0.180)	(0.319)	(792.859)	(1546.029)	(791.003)	(1518.176)
Collaborative establishment = *Yes*	-	-	-0.574***	-0.574	-	-	-679.494	-679.494
			(0.210)	(0.565)			(924.600)	(2365.502)
FP = *Yes*	-	-	0.772***	0.772	-	-	-3978.360***	-3978.360
			(0.290)	(0.788)			(1278.741)	(5892.672)
Observations	1047	1047	1047	1047	1047	1047	1047	1047
R^2	0.001		0.013		0.003		0.014	
Adjusted R^2	0.00002		0.010		0.002		0.011	
Log Likelihood		-3097.736		-3091.552		-11881.370		-11875.710
Akaike Inf. Crit.		6199.472		6191.103		23766.730		23759.420
Residual Std. Error	1.369		1.362		6022.362		5995.646	
F Statistic	1.025		4.477***		3.361*		4.908***	

Furthermore, we observed no significant effect on network embeddedness variables, namely the degree centrality and the betweenness centrality (Table 5). To this regard, our results differ from past studies on cluster policies which tend to conclude on the improvement of the network properties. Giuliani *et al.* (2016), evaluating a cluster development programs in the electronics cluster in Argentina observe a reduction in the number of isolated firms together with a higher polarisation and centralisation of the network. In the French context, Delio and Vicente (2019) find that the structure of the Aerospace Valley cluster has moved from a highly-hierarchical structure, centralised around a couple of long-established oligopolistic companies, to a more democratic, less assortative, and multipolar structure, involving the entry of SMEs to the elite part of the network. However, these past studies do not control for confounding factors as they focus on the network of treated units only. Using a counterfactual analysis to evaluate cluster policies, and moving from case studies to systematic analysis of a National cluster programme, our findings suggest that the change in the network structure over time results more from a global dynamic of collaborative R&D networks than from the specific incentives induced by cluster policies.

There are several possible interpretations for this result. The French cluster policy failed to strengthen the embeddedness of cluster policy participants into networks of co-inventions. Since we previously found a positive and significant effect of cluster membership on the co-invention rate (Table 4), this insignificant effect on network embeddedness could be explained by the fact that cluster policy beneficiaries collaborate with almost the same partners in their different projects. This could result from the specific period of observation which encompasses the 2008 crisis. During an economic recession, nearby firms that are engage in long-term collaborations may be more willing to pool resources and share the risk with a small set of firms[15]. To this regard, public incentives to increase their collaborations may have led to reinforcing past collaborations instead of having new collaborators. However, an analysis over a longer and different period of time would be necessary to validate this hypothesis. Another interpretation might be found in the interaction between cluster and FP policies. It might be the case that the cluster policy participants which face an increase in their centrality are those who participate in FP. As such, the French cluster would produce an indirect effect on centrality by encouraging FP participation. This indirect effect goes beyond the scope of this paper, but it would represent an interesting avenue for further research. The absence of a centrality effect may also result from a strong heterogeneity of the cluster policy effect on network positioning of innovating firms. This is investigated more thoroughly in the next sub-section. Finally, the

[15] We owe this point to one of the anonymous reviewers.

French cluster policy may also increase the size of the network, allowing new actors to enter the invention network. The centrality of historical actors could therefore be reduced. This interpretation is in line with our previous result, pointing to a higher impact on collaborations for those firms which were not involved in co-inventions before their cluster participation. In any case, our results corroborate those obtained by Broekel *et al.* (2015) for spontaneous clusters, in showing that the effects of cluster policy participation on organisations' embeddedness in collaboration networks are not systematic.

3.5.3 Treatment heterogeneity

There are good reasons to believe that the positive average effect on the co-invention rate might hide some heterogeneity between establishments depending on their pre-policy behaviour towards collaboration. Such a heterogeneity has already been highlighted in few previous studies on collaboration-based policies (Afcha Chávez, 2011; Teirlinck and Spithoven, 2012). In our case, following the negative effect of the pre-policy period collaborative behaviour of an establishment (Table 4), one would expect a different effect on establishments which were engaged in collaborations and establishments with little or no experience in collaboration before joining clusters. To test for such a heterogeneous treatment effect, we estimated the response models stratified by the pre-policy behaviour of establishments towards collaboration (*collaborative establishment*) and formally tested for effect heterogeneity (Table 6). The same analysis was also run for the local collaboration rate and our two measures of centrality. However, these measures do not provide any significant coefficient. Only the co-invention rate results are therefore reported in Table 5. The results obtained for the other dependent variables are available upon request.

In addition to the positive effect of cluster policy participation on the co-invention rate initially observed (Table 4), Table 6 indicates that this increase is much higher for policy participants which were weakly involved in collaborative R&D projects before joining the clusters. Those establishments have increased their co-invention rate by more than 6 percentage points as a result of participating in the cluster policy, while the effect of cluster policy becomes insignificant for establishments which were engaged in collaborations before joining clusters. Although still confirming the positive impact of French clusters in improving the collaborative behaviour of organisations, this result reveals that this impact is more likely to be on establishments with little or no experience in collaboration before joining clusters. The absence of significant effect observed on establishments which were already engaged in collaborations before joining clusters may suggest that those establishments do not necessarily join clusters with the goal to expanding their network of partners. They are more likely to be interested in other cluster premiums such as the access to R&D subsidies (Broekel *et al.*, 2015).

Table 6 Treatment heterogeneity

Change in co-invention rate		
	WLS	Survey-weighted (robust Std. Error)
	(1)	(1')
Constant	0.0003	0.0003
	(0.008)	(0.007)
FP = *Yes*	0.016	0.016
	(0.018)	(0.022)
Treatment × Collaborative establishment = *No*	0.063***	0.063***
	(0.012)	(0.020)
Treatment × Collaborative establishment = *Yes*	-0.042**	-0.042
	(0.017)	(0.041)
Observations	1047	1047
R^2	0.042	
Adjusted R^2	0.039	
Log Likelihood		-174.130
Akaike Inf. Crit.		356.259
Residual Std. Error	0.084	
F Statistic	15.235***	

Note: Statistical significance: *p< 0.10, **p< 0.05, ***p< 0.01. We also tested for effect heterogeneity for the other outcome variables, namely intra-regional co-invention rate, degree centrality and betweenness centrality; we still did not observe any significant treatment effects.

3.6 Conclusion

This chapter aimed to investigate the extent to which cluster policies favour collaboration and induce network additionality. Focusing on the French national cluster policy and on the collaborative behaviour of cluster policy participants during the period 2008-2010, the aims were threefold: H1) to assess whether firms benefiting from the cluster policy are more engaged in co-inventions, and especially, H2) with co-located organisations and H3) to assess whether policy beneficiaries are more embedded in networks of co-inventions. We combined the Inverse Probability of Treatment Weighting (IPTW) with a difference-in-difference estimator in order to address the causal effects of cluster policy participation on firms' establishments. Though the results remain somehow specific to the French context, this policy is among the most intensive one in the world, France being the country which devotes the highest budget in Europe to a National cluster programme. We can therefore believe that this policy provides a relevant field experiment to assess the potential impacts of national cluster policies. Our empirical findings confirm that such policies can significantly enable their beneficiaries to be

more engaged in co-inventions: on average, French cluster participants increased their co-invention rate by 4.1 percentage points as a result of their membership. Notably, the policy had a greater impact upon establishments with little or no experience in collaboration before joining clusters, leading to an increase in their co-invention rate of 6.3 percentage points. However, we found no evidence that firms benefiting from the cluster policy were more engaged in co-inventions involving co-located partners, implying that the French cluster policy failed to reinforce intra-regional collaboration. Regarding the embeddedness of cluster policy participants in networks of co-inventions, we also find no evidence for any significant effect of the cluster policy. In summary, we confirmed hypothesis H1, but failed to confirm hypotheses H2 and H3. This suggests, on the one hand, that firms benefiting from the cluster policy, especially those with little or no prior experience in collaborations, have become more open to collaboration but not necessarily with regional actors. On the other hand, cluster policy participants did not show a stronger embeddedness into networks of co-inventions than non-participants, either quantitatively (by increasing the number of direct partners) or qualitatively (by acting more as "bridge" between other establishments). French clusters were thus able to tackle network failures during the studied period, but only partially.

We therefore confirm the results obtained for other collaboration-based policies (regional support to R&D collaboration) in various countries regarding the ability of public incentives to generate collaboration additionality (Afcha Chavez, 2011; Nishimura and Okamuro, 2011; Caloffi et al, 2018, 2011). We also provide specific insights regarding the lack of local impact (H2) of cluster policies, at least in France. And more importantly, we call into question the conclusions of previous studies regarding the ability of cluster policies to improve the overall structure of collaborative R&D networks (H3). This criticism of past results relies on the mobilisation of a counterfactual sample, allowing a better identification of the causal relationships between the public incentives to R&D collaboration and the evolution of network properties over time.

Therefore, whereas the actors' positions within networks have been proved to be strongly correlated to the actors' level of performance, the various types of services provided by clusters to favour network embeddedness do not necessarily contribute to this go*al.* Clusters are not sufficient tools, at least in the short run, to improve the ability of actors to identify relevant networks, or conversely to raise awareness of local industrial specialisms in order to make local firms more likely to be asked to enter national and international partnerships and therefore to increase their centrality within knowledge networks. Our results may also suggest, following Martin and Sunley (2003), that more attention should be devoted to identifying and attracting investors and businesses likely to fill the gaps in existing cluster value chains in order to strengthen the network positioning of local anchor firms by reinforcing their demand and

supply links. Nevertheless, it should be noted that our findings do not call into question the relevance of clusters for firm growth and regional development. Indeed, clusters may still be important factors in achieving these goals but not necessarily through the intensification of collaborations between regional actors. By supporting long-distance collaboration which is also required to improve regional innovation capacity (Boschma, 2005), clusters continue to contribute to regional development. They can also contribute to the growth of firms through training activities for skills development (Giuliani *et al.*, 2016).

The main point of this study is that the local anchoring of clusters *i.e.*, their ability to reinforce links between co-located organisations, as well as the embeddedness of cluster policy beneficiaries in collaboration networks is not systematic. This claim has a number of policy implications that especially concern the design and evaluation of cluster policies. It first raises the question of the theoretical framework in which cluster policies are designed and the extent to which such policies differ from other policy instruments supporting innovation. Although it is widely accepted that collaboration-based innovation policies, especially cluster policies, not only deal with market failures but also with systemic failures (Uyarra and Ramlogan, 2012), the evaluation of cluster policies is still largely focused on their contribution towards tackling market failures. We argue that the lack of studies focusing on the impact of cluster policies from a systemic failures perspective is often due to the lack of a clear theory-based design of such policies regarding the systemic failures they are supposed to tackle. Our results highlight the importance for policymakers of clearly defining the network failures and, more broadly the systemic failures they want to tackle while designing cluster policies. Otherwise, it would be difficult to assess the impacts of clusters beyond input and output additionality. When systemic failures can be assessed, they highlight the structural effects of cluster policies. For instance, our study stresses that cluster policies do not necessarily strengthen local collaborations. Policymakers should therefore be careful not to encourage long-distance collaborations to the detriment of local ones, given the complementary roles of both forms of collaboration (De Noni *et al.*, 2017). They should also encourage cluster actors to become more embedded in collaboration networks and to go beyond simple bilateral collaborations with the same partners. Such incentives could take the form of a stronger support to cluster policy participants to find new local, national or foreign partners. As pointed out previously by Vicente (2014), it is clear that new opportunities for cluster policies exist through surgical incentives for R&D collaborations tackling network failures.

Despite the above findings, our study has some shortcomings which also open avenues for future research. First, our results relate to a relatively short period and therefore should be corroborated by further empirical analyses over a longer period. Such analyses could also be based on collaboration data collected directly from establishments or firms, although this may

be a resource-intensive methodological exercise. However, this would be all the more relevant since collaborative R&D projects do not necessarily lead to co-patenting and given the importance of informal collaboration in R&D activities. Future research may also extend our study by exploring further structural effects of cluster policies, such as science-industry collaborations, since they are increasingly perceived as a means of enhancing knowledge transfers from research institutions to industry. Finally, it should be noted that the analyses carried out in this chapter lead to aggregated results that do not necessarily reflect the situation in each (French) cluster individually. Although this study makes it possible to draw overall conclusions, essentially based on average effects, a more detailed analysis of each cluster – involving qualitative methods – could reveal some differences.

A.2 Appendices

A.2.1 Absolute standardised mean differences (SMD) in baseline characteristics after weighting

	Weighted sample (simple specification)			Weighted sample (complex specification)		
	Cluster participants:		**SMD**	**Cluster participants:**		**SMD**
Variable	**No (N = 114.79)**	**Yes (N = 116)**		**No (N = 96.05)**	**Yes (N = 116)**	
Size	417.81 (754.70)	401.84 (629.14)	**0.023**	409.89 (737.55)	401.84 (629.14)	**0.012**
Highly-qualified employees	0.30 (0.21)	0.30 (0.21)	**0.004**	0.30 (0.21)	0.30 (0.21)	**0.032**
Number of inventions	17.43 (43.46)	23.37 (88.68)	**0.085**	17.26 (43.62)	23.37 (88.68)	**0.087**
Technological intensity			**0.066**			**0.069**
High-technology	15.5 (13.5%)	17.0 (14.7%)		12.7 (13.2%)	17.0 (14.7%)	
Knowledge-intensive services (KIS)	19.4 (16.9%)	21.0 (18.1%)		16.9 (17.6%)	21.0 (18.1%)	
Less knowledge-intensive services (LKIS)	7.1 (6.2%)	6.0 (5.2%)		5.8 (6.1%)	6.0 (5.2%)	
Low technology	13.5 (11.8%)	14.0 (12.1%)		10.8 (11.3%)	14.0 (12.1%)	
Medium-high technology	42.2 (36.8%)	41.0 (35.3%)		34.6 (36.1%)	41.0 (35.3%)	
Medium-low technology	17.0 (14.8%)	17.0 (14.7%)		15.2 (15.8%)	17.0 (14.7%)	
Firm's type of establishment			**0.045**			**0.058**
Large enterprises	33.8 (29.5%)	34.0 (29.3%)		30.5 (31.7%)	34.0 (29.3%)	
Micro enterprises	3.8 (3.3%)	3.0 (2.6%)		2.1 (2.2%)	3.0 (2.6%)	
Intermediate-sized enterprises	46.6 (40.6%)	48.0 (41.4%)		37.9 (39.4%)	48.0 (41.4%)	
Small and medium-sized enterprises	30.5 (26.6%)	31.0 (26.7%)		25.6 (26.6%)	31.0 (26.7%)	
Region			**0.082**			**0.153**
Alsace	0.9 (0.8%)	1.0 (0.9%)		0.6 (0.6%)	1.0 (0.9%)	
Aquitaine	2.3 (2.0%)	3.0 (2.6%)		1.7 (1.8%)	3.0 (2.6%)	
Auvergne	1.2 (1.0%)	1.0 (0.9%)		0.9 (1.0%)	1.0 (0.9%)	
Basse-Normandie	2.1 (1.8%)	2.0 (1.7%)		1.2 (1.3%)	2.0 (1.7%)	
Bourgogne	6.4 (5.6%)	6.0 (5.2%)		5.8 (6.1%)	6.0 (5.2%)	
Bretagne	2.8 (2.4%)	3.0 (2.6%)		2.1 (2.2%)	3.0 (2.6%)	

	Weighted sample (simple specification)			Weighted sample (complex specification)		
	Cluster participants:		**SMD**	**Cluster participants:**		**SMD**
	No	**Yes**		**No**	**Yes**	
Variable	**(N = 114.79)**	**(N = 116)**		**(N = 96.05)**	**(N = 116)**	
Centre	4.4 (3.8%)	5.0 (4.3%)		3.1 (3.2%)	5.0 (4.3%)	
Champagne	5.0 (4.3%)	4.0 (3.4%)		3.2 (3.3%)	4.0 (3.4%)	
Franche-Comté	3.5 (3.1%)	4.0 (3.4%)		2.8 (2.9%)	4.0 (3.4%)	
Haute-Normandie	3.3 (2.8%)	3.0 (2.6%)		2.7 (2.8%)	3.0 (2.6%)	
Ile-de-France	26.8 (23.3)	27.0 (23.3)		25.3 (26.4)	27.0 (23.3)	
Languedoc	2.7 (2.4%)	3.0 (2.6%)		2.1 (2.2%)	3.0 (2.6%)	
Limousin	0.8 (0.7%)	1.0 (0.9%)		0.6 (0.7%)	1.0 (0.9%)	
Lorraine	1.9 (1.6%)	2.0 (1.7%)		1.9 (1.9%)	2.0 (1.7%)	
Midi-Pyrénées	6.3 (5.5%)	6.0 (5.2%)		5.1 (5.3%)	6.0 (5.2%)	
Nord	3.0 (2.6%)	3.0 (2.6%)		2.6 (2.8%)	3.0 (2.6%)	
Normandie	1.1 (0.9%)	1.0 (0.9%)		0.4 (0.4%)	1.0 (0.9%)	
Pays-de-la-Loire	4.1 (3.5%)	4.0 (3.4%)		3.8 (3.9%)	4.0 (3.4%)	
Picardie	0.9 (0.8%)	1.0 (0.9%)		0.8 (0.9%)	1.0 (0.9%)	
Poitou-Charente	1.8 (1.6%)	2.0 (1.7%)		2.0 (2.1%)	2.0 (1.7%)	
Provence-Alpes-Côte d'Azur	6.6 (5.8%)	7.0 (6.0%)		5.0 (5.2%)	7.0 (6.0%)	
Rhône-Alpes	27.0 (23.5%)	27.0 (23.3%)		22.3 (23.2%)	27.0 (23.3%)	

A.2.2 *Robustness check: doubly robust estimation*

A mis-specified propensity model may lead to a wrong estimator for δ_{ATT}. For an estimator of average treatment effect, double robustness means that the estimator remains consistent if either the propensity score model or the outcome regression model is wrong (but not both). Doubly robust propensity score methods rely on dual modelling of both the treatment assignment mechanism and the response to provide unbiased estimates if either the propensity score model or the outcome model is correct (Imbens and Wooldridge, 2009). Although several doubly robust estimators have been proposed (e.g. Bang and Robins, 2005; Kang and Schafer, 2007), the estimate for the average treatment effects can be formulated as follows:

$$\widehat{\delta_{DR}} = n^{-1}\sum_{i=1}^{n}\left[\frac{Z_i\Delta Y_i}{e(X_i)} - \frac{Z_i - e(X_i)}{e(X_i)}m_1(X_i)\right] - n^{-1}\sum_{i=1}^{n}\left[\frac{(1-Z_i)\Delta Y_i}{1-e(X_i)} - \frac{Z_i - e(X_i)}{1-e(X_i)}m_0(X_i)\right], \quad [24]$$

where $m_1(X_i)$ and $m_0(X_i)$ are respectively postulated models for the true regressions $E(\Delta Y|Z=1,X)$ and $E(\Delta Y|Z=0,X)$. This estimator may be viewed as taking each term from the inverse weighted estimator and "augmenting" it by a second term, hence the name "augmented inverse propensity weighted" (AIPW), which is often given to doubly robust estimation in IPTW analyses. Following Bang and Robins (2005) and Kang and Schafer (2007), our double robust estimation consists of a regression estimation of propensity score weighted means using the propensity score as covariates, followed by an estimation of the difference between weighted means with Equation [19]. For an introduction to AIPW estimation see Glynn and Quinn (2010).

In our application of doubly robust estimation with propensity score as covariates, postulated models $m_1(X_i)$ and $m_0(X_i)$ are based on the recommendation from Bang and Robins (2005), which suggests adding to the regressions the inverse of the propensity score and the inverse of "1 minus the propensity score". Therefore, $m_1(X_i)$ and $m_0(X_i)$ are fitted to the outcomes of treated and control establishments using:

$$m_1(X_i) = \Delta Y_{i(Z=1)} = \beta_0 + \beta_1\frac{1}{e(X_{i(Z=1)})} + \beta_2\frac{1}{1-e(X_{i(Z=1)})} \quad [25]$$

$$m_0(X_i) = \Delta Y_{i(Z=0)} = \beta_0 + \beta_1\frac{1}{e(X_{i(Z=0)})} + \beta_2\frac{1}{1-e(X_{i(Z=0)})} \quad [26]$$

Since the propensity scores are known for the entire sample, the above regressions are used to obtain predicted values $\Delta\widehat{Y_{i(Z=1)}}$ and $\Delta\widehat{Y_{i(Z=0)}}$ but only for treated establishments, since the estimate of interest is the ATT. The doubly robust estimator of the ATT is obtained with Equation

[19] using predicted outcomes $\Delta\widehat{Y_{i(Z=1)}}$ and $\Delta\widehat{Y_{i(Z=0)}}$ instead of observed outcomes $\Delta Y_{i(Z=1)}$ and $\Delta Y_{i(Z=0)}$, respectively.

A.2.3 Sensitivity analysis

In the field of causal inference, sensitivity analysis generally refers to approaches that assess the sensitivity of causal estimates to the presence of unmeasured confounders. This is sometimes referred to as sensitivity to "unmeasured confounding" or to "hidden bias" (Rosenbaum, 2002). Sensitivity analyses aim to address a lack of confidence in the assumption, commonly invoked with observational data, that all confounders have been measured (Carnegie *et al.*, 2016). In this vein, the objective of our sensitivity analysis is to identify how much unmeasured confounding would produce a change in the conclusion of the study.

We rely on a method developed by Carnegie *et al.* (2016) for sensitivity analysis where the relationship between a single confounding variable U, treatment Z and outcome ΔY are manipulated through a simulation to identify how large these relationships need to be for the treatment to become nonsignificant. This method consists in evaluating changes to the treatment effect and its p-value for a set of values of two sensitivity parameters.

Let us denote ζ^Z as the sensitivity parameter quantifying the relationship between U and Z, while $\zeta^{\Delta Y}$ quantifies the relationship between U and ΔY. This method is a five-step process implemented as follows (Leite, 2016):

1. Define sensitivity parameters based on the observed data. Multiple values should be selected for both ζ^Z and $\zeta^{\Delta Y}$, which results in a matrix of combinations of values.

2. For each pair of values of ζ^Z and $\zeta^{\Delta Y}$ and the vector of observed values of ΔY, Z, and X, simulate U from the conditional distribution of U given ΔY, Z, and X.

3. Fit the response model with Z, X, and U as predictors and obtain the treatment effect and its standard error.

4. Repeat Steps 2 and 3 for k iterations with the same pair of sensitivity parameters, and average the treatment effects across iterations. The standard error is obtained by squaring the sum of the within-replication and between-replication variances.

5. Select another pair of sensitivity parameters and repeat Steps 2 to 4.

In our implementation of this method, the response model is fitted the same way as in the doubly robust estimation *i.e.*, with the inverse of the propensity score and the inverse of "1 minus the propensity score" as covariates. Changes in treatment effects, given the coefficients on U, are shown in the table below. The coefficients on the confounding variable U reflect the strength of the relationships between U and the treatment Z on the one hand, and between

U and the outcome ΔY on the other. Therefore, conclusions from the sensitivity analysis result from an evaluation of the coefficients on the confounding variable compared to the estimated coefficients obtained from the regression of ΔY on Z and X and from the regression of Z on X.

Changes in treatment effect on the co-invention rate, given the coefficients on an unmeasured confounding U

$\zeta^{\Delta Y}$ \ ζ^{Z}	**-2.85**	**-2.221**	**-1.592**	**-0.962**	**-0.333**	**0**	**0.925**	**1.554**	**2.183**	**2.812**
0	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
0.034	0.061	0.060	0.059	0.053	0.046	0.041	0.028	0.023	0.021	0.019
0.067	0.083	0.081	0.076	0.067	0.052	0.041	0.015	0.005	0.001	-0.001
0.101	0.104	0.101	0.093	0.081	0.058	0.040	0.003	-0.014	-0.021	-0.024
0.135	0.126	0.121	0.112	0.092	0.061	0.045	-0.011	-0.033	-0.043	-0.047
0.168	0.151	0.143	0.130	0.107	0.075	0.043	-0.031	-0.052	-0.067	-0.073
0.202	0.173	0.165	0.147	0.128	0.077	0.049	-0.045	-0.076	-0.091	-0.100
0.236	0.200	0.187	0.175	0.146	0.093	0.048	-0.065	-0.103	-0.121	-0.130
0.269	0.233	0.218	0.202	0.165	0.100	0.055	-0.095	-0.135	-0.154	-0.164
0.303	0.270	0.255	0.221	0.188	0.119	0.064	-0.125	-0.171	-0.193	-0.211

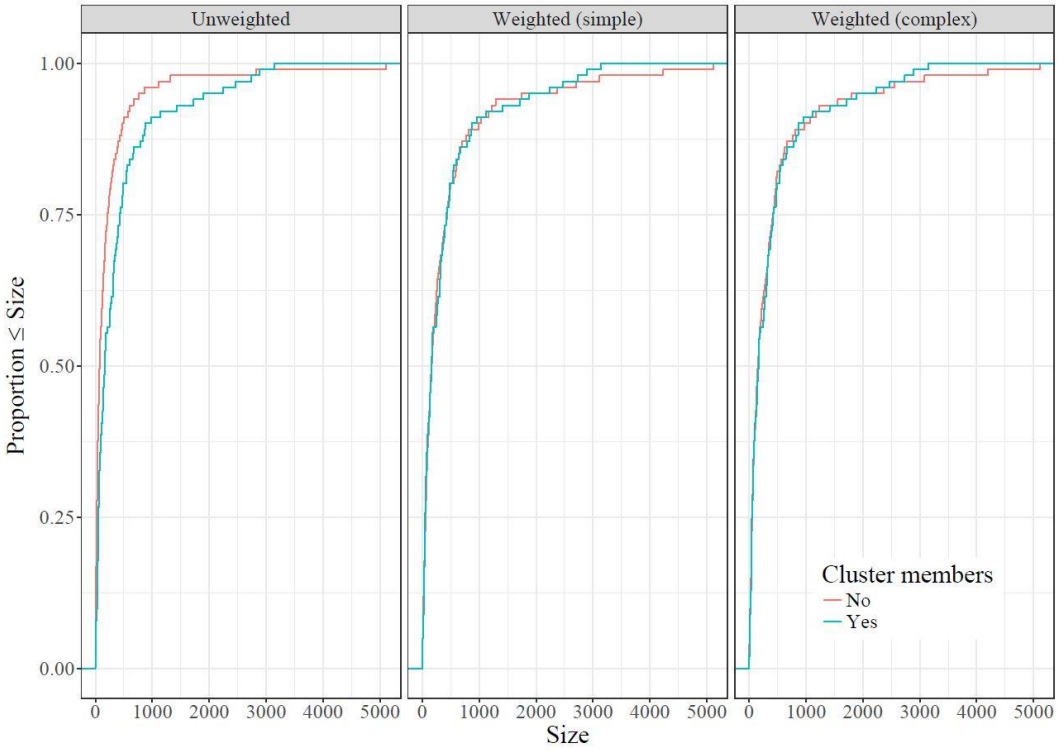
The sensitivity analysis indicates that even in the presence of an unmeasured confounder which explains up to 10% of the variation of ΔY (but which does not affect Z), the estimate of the average treatment effect would remain almost constant and significant.

A.2.4 Variable definitions and sources

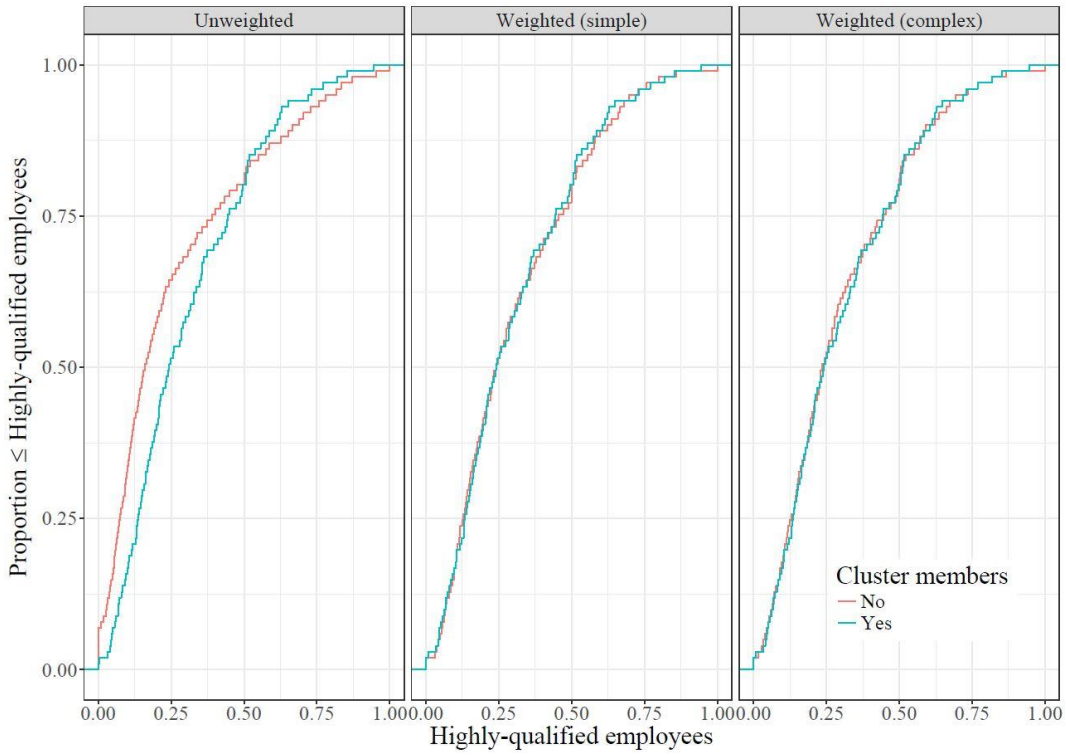
Variable	Description	Source
Number of inventions	Number of patents	French National Institute of Industrial Property (INPI) database on patent applications. The database is publicly available at: https://data.enseignementsup-recherche.gouv.fr/explore/dataset/fr-esr-brevets-france-inpi-oeb/information/?
Co-invention rate	Propensity of an establishment to be engaged in co-invention. The co-invention rate is defined as the ratio of the number of co-inventions, with establishments from different firms or organisations, over the total number of the establishment's inventions (including co-inventions)	
Intra-regional co-invention rate	Propensity of an establishment to be engaged in co-invention with co-located partners. The intra-regional co-invention rate is defined as the ratio of the number of co-inventions, including at least one co-located establishment from a different firm or organisation, over the total number of the establishment's inventions (including co-inventions)	
Degree centrality	Number of establishments' direct collaboration partners	
Betweenness centrality	Number of times an establishment lies on the shortest path between other establishments	
Size	Average 12-month full-time equivalent employees (FTE)	DADS database. The database is provided by the French National Institute of Statistics and Economic Studies (INSEE) under general conditions of use
Highly-qualified employees	Average share of highly-qualified full-time equivalent employees (FTE) per year. Share of highly-qualified employees is defined as the ratio of full-time equivalent highly-qualified employees over the establishment's12-month FTE.	
Firm's type of establishment	Type of firm to which an establishment belongs	
Region	French region where an establishment is located	
Technological intensity	Establishments' technological level based on NACE code – divisions of Rev. 2. Match between NACE codes and technological levels	EUROSTAT aggregations of manufacturing based on NACE Rev. 2, available at https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf
Treatment	Dummy variable indicating treatment assignment, taking the value of 1 for treated establishments (cluster participants for at least for one year from 2008 to 2010 and non- participants before 2008) and 0 for controls (non-cluster participants)	Cluster membership database. The database is provided by the Directorate-General Enterprise (DGE)
Participation in Framework Programme (FP)	Dummy variable indicating whether firms (and then establishments) participate in Framework Programme's projects starting during the post-treatment period	Contracts and participation database on Framework Programme's projects. The database is provided by the Ministry of Higher Education, Research and Innovation
Collaborative establishment	Dummy variable indicating whether the *co-invention rate* during the pre-treatment period is greater than zero	See source of *co-invention rate*

A.2.5 Balance in baseline characteristics after weighting

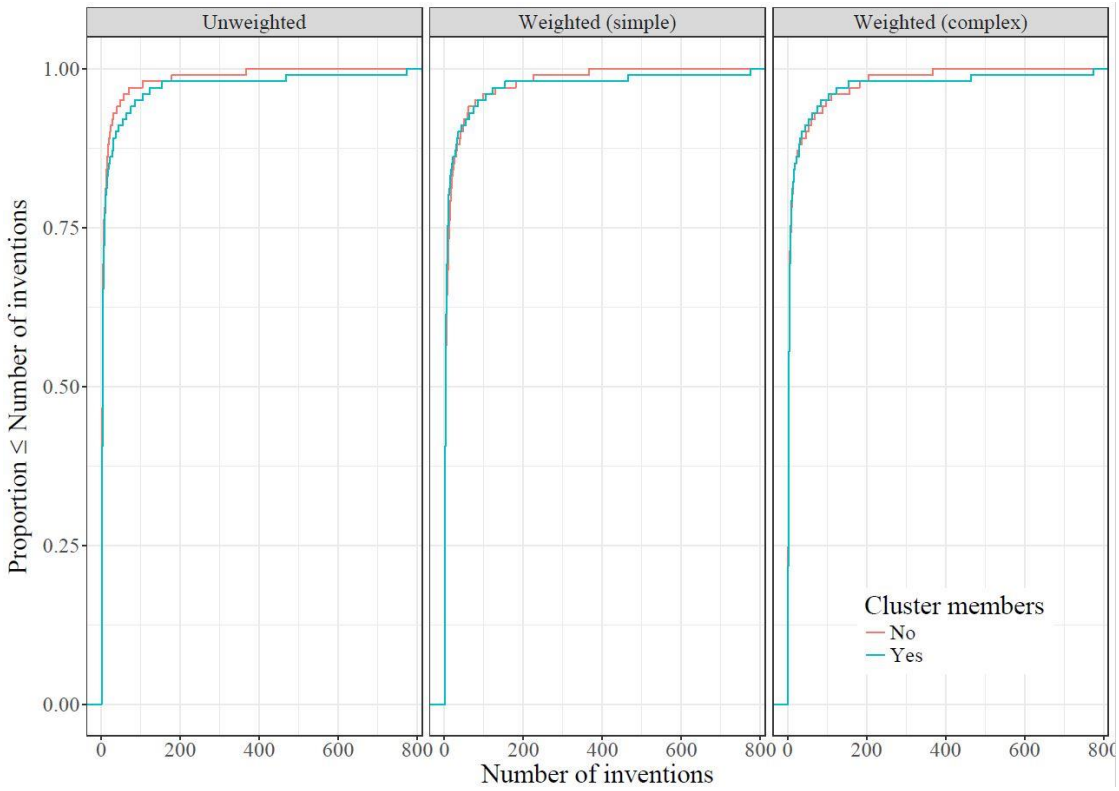
A.2.5.1 Balance in baseline characteristics after weighting: cumulative distribution of size



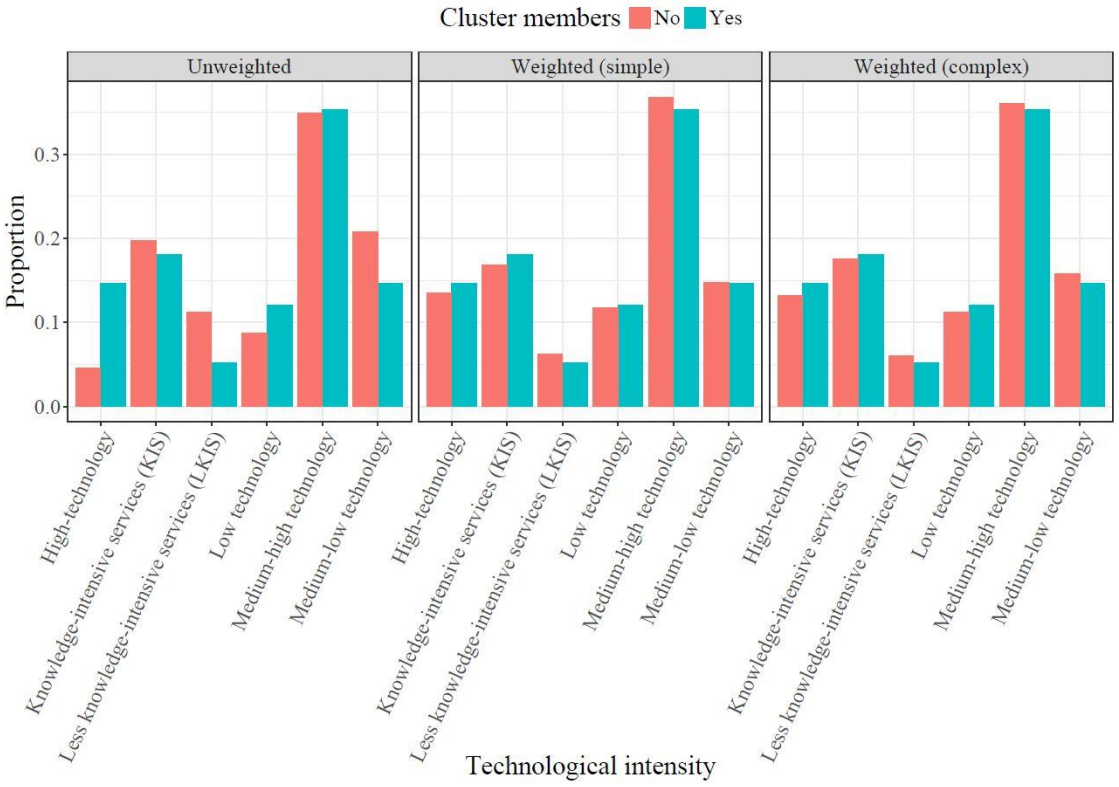
A.2.5.2 Balance in baseline characteristics after weighting: cumulative distribution of highly-qualified employees



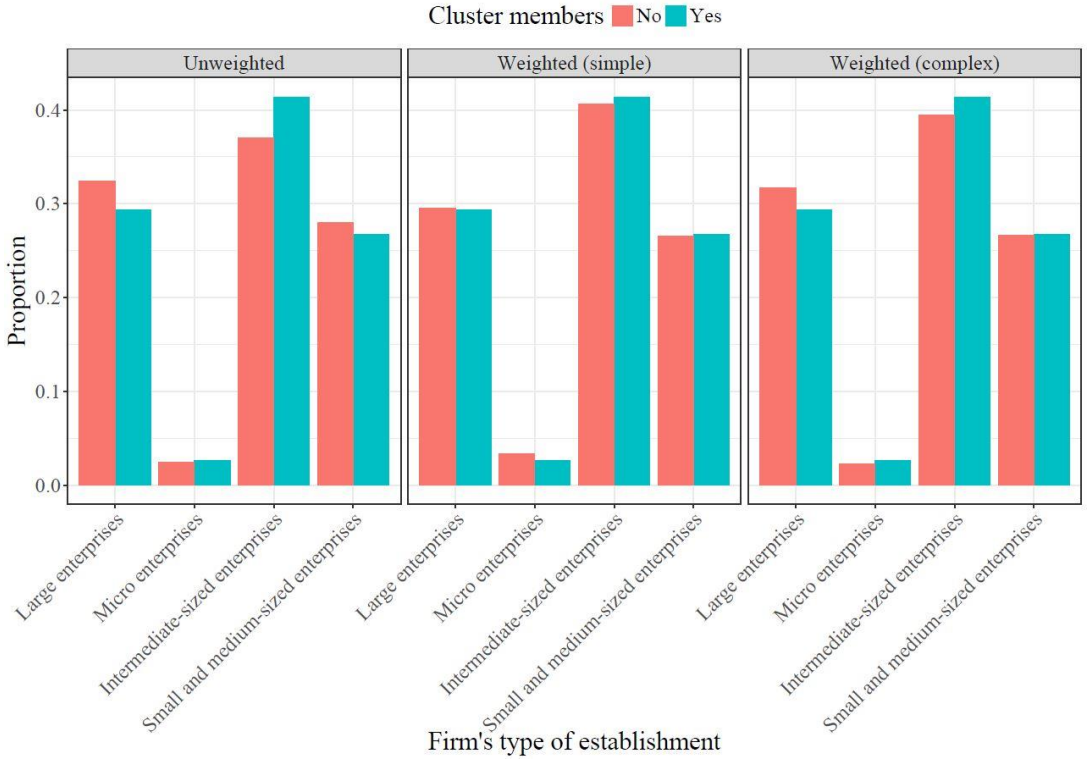
A.2.5.3 Balance in baseline characteristics after weighting: cumulative distribution of number of inventions



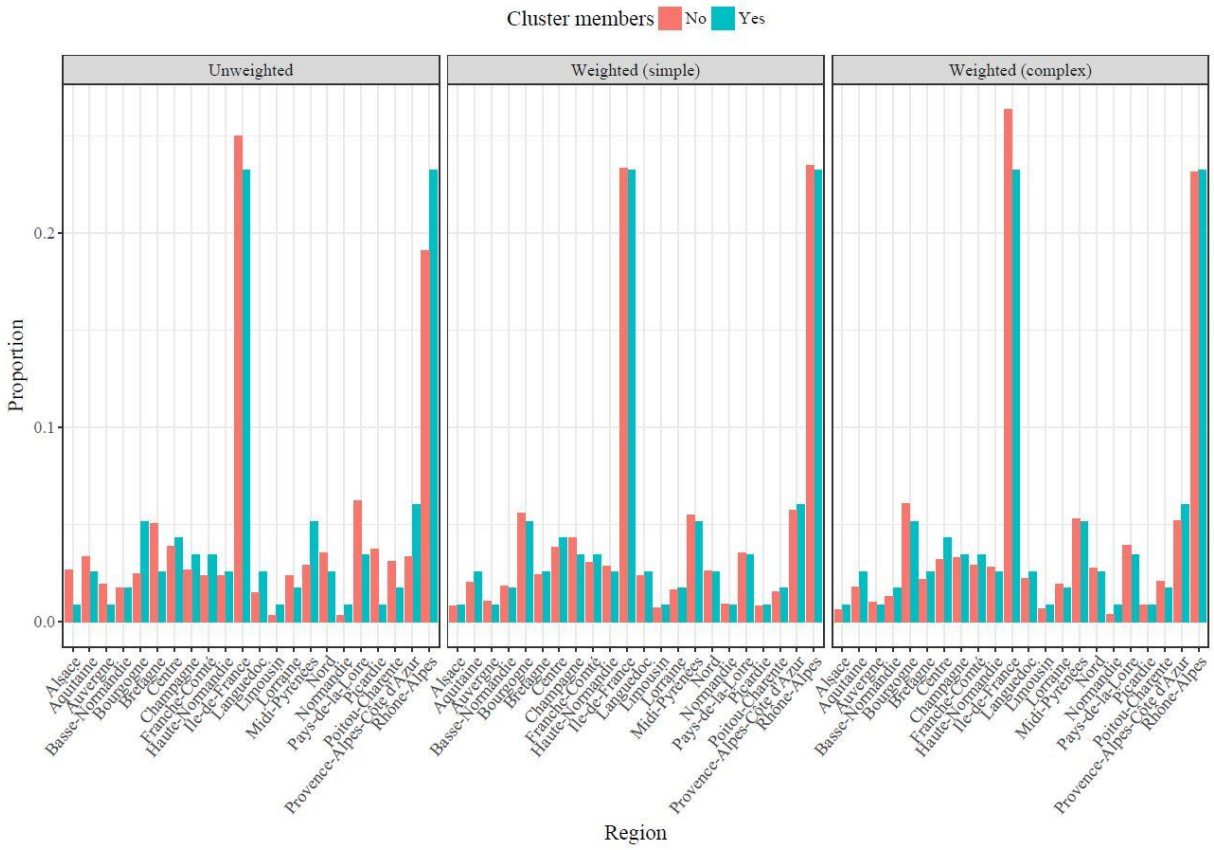
A.2.5.4 Balance in baseline characteristics after weighting: technological intensity



A.2.5.5 Balance in baseline characteristics after weighting: firm's type of establishment



A.2.5.6 Balance in baseline characteristics after weighting: region



4 Effects of cluster policies on regional innovation networks: Evidence from France

This chapter is co-authored with Corinne Autant-Bernard. The PhD candidate is the first author of the article.

Abstract

Despite the growing body of literature evaluating cluster policies, it still remains difficult to establish conclusively their structural effects on regional innovation networks. Focusing on the French cluster policy during the period 2005-2010, this study aims at evaluating how cluster policies influence the structure of local innovation networks following network topologies that may be beneficial for regional innovation. Based on a panel data of four periods and 94 NUTS3 French regions, we estimate spatial Durbin models, allowing us to identify direct, indirect and total effects of cluster policies. The results suggest that cluster policies can result in both positive and negative total effects on the structure of local innovation networks depending on regions' technological specialisation. Beyond the heterogeneous effects, the results also highlight that cluster policies may lead to a regional competition for the strengthening of innovation networks. This finding echoed previous research pointing out the possible 'beggar-thy-neighbour' effects of cluster policies.

4.1 Introduction

Since the development of the regional innovation system (RIS) framework (Doloreux and Parto, 2005) it has been widely acknowledged that a region's innovative output is not only the result of actors' individual efforts but it is also strongly influenced by the quality and intensity of regional innovative networking (Doloreux, 2002; Graf and Henning, 2009). The recognition of the importance of interactions between innovation actors has greatly contributed to the development of public policies aiming at strengthening knowledge networks. Such interventions are referred to as innovation network policies and defined by Cunningham and Ramlogan (2016) as "*measures aimed at promoting or sustaining the linkage of firms and/or knowledge producers where the activities concerned are centred on a specific technological or problem-oriented topic for the primary purpose of knowledge and information sharing*". In this context, innovation network policies are justified, at least in part, by the insufficient and/or inefficient levels of linkage and knowledge exchange between organisations. They differ in this sense from traditional innovation policies, focused on the provision of research and development (R&D) funding, which are generally based on the market failures argument. Although also providing funds for the implementation of R&D projects, primarily collaborative projects, innovation network policies are intended to go further by tackling the systemic failures rather than just market failures, thus highlighting the significance of actors as well as the relationships between them. Such interventions are of crucial importance at the regional level since the set of relationships between actors constitute a relational capital allowing regions to act as innovative milieus (Camagni, 1995) and maintain a long-term competitiveness thanks to collective learning (Capello and Faggian, 2005). Aware of this, policymakers have, for several years now, supported measures to strengthen regional innovation networks and cluster policies have become an important component of their toolbox in this respect (Cunningham and Ramlogan, 2016; Uyarra and Ramlogan, 2016). As pointed by Cunningham and Ramlogan (2016), innovation network policies differ from clusters in that they are not necessarily geographically co-located; co-location is therefore the primary criterion differentiating innovation network policies from cluster policies. As innovation network policies, cluster policies are also expected to strengthen the structure of innovation networks, but especially at the territorial or regional level.

Although clusters are regarded as important instruments to strengthen regional innovation networks, most evaluations of cluster policies are focused on market failures (Falck et *al.*, 2010; Nishimura et Okamuro, 2011a; Bellégo and Dortet-Bernadet, 2014; Brossard et Moussa, 2014; Braune et *al.*, 2016). The effects of cluster policies on the structure of innovation networks have yet to be fully evaluated in the literature. In the debate to which extent public interventions are effective, the "additionality" question – *i.e.* the results that would not have been realised by

the private sector without the public instrument, e.g. subsidies, tax credits, innovation network policies – takes a central place (Larosse, 2001). Following this additionality perspective, the cluster evaluation literature falls into three streams: input and output additionality, behavioural additionality and systemic additionality.

Looking at the input and output additionality of cluster policies, and more broadly of innovation network policies, is the most common form of evaluation undertaken in the literature (Sakakibara, 1997; Branstetter and Sakakibara, 2002; Hottenroot and Lopes-Bento, 2014; Bellégo and Dortet-Bernadet, 2014; Brossard et Moussa, 2014; Braune et *al.*, 2016). This kind of assessment essentially consists in estimating additional inputs (primarily R&D expenditure and human capital) and comparing the outputs (economic growth, productivity, patents, etc.) of actors that received and did not receive support from clusters. This way of evaluating cluster policies seems to be a pure legacy of the linear innovation model in which innovation (output) is largely a straightforward outcome of research and development activities (input). This approach has therefore been criticised for being limited since regional innovation policies do not only aim at increasing the amount of resources that actors invest in innovation and/or their innovative outputs. As stated above, such interventions also aim at changing actors' behaviour by promoting and sustaining the linkage and knowledge exchange between them. In this vein, the Organisation for Economic Co-operation and Development (OECD) has recommended to consider behavioural additionality in econometric studies (Georghiou and Clarysse, 2006).

Thus, a growing literature is attempting to understand and evaluate the difference in actors' behaviour resulting from innovation network policies and cluster policies, *i.e.* the behavioural additionality of these policies (e.g. Clarysse et *al.*, 2009; Falck et *al.*, 2010; Nishimura and Okamuro, 2011b; Giuliani et *al.*, 2016; Rothgang et *al.*, 2017; Töpfer et *al.*, 2017)[16]. The main goal of this literature is to test the ability of policy interventions to stimulate learning processes that result in changes in actors' behaviour. In the specific case of cluster policies or regional innovation policies, scholars explore organisations' collaboration patterns (Antonioli et *al.*, 2014; Caloffi et *al.*, 2015; Caloffi et *al.*, 2017), thus considering the latter as the units of analysis. Although such micro level analyses provide insightful results on how organisations change their behaviour when participating in innovation network policies, they do not provide a macroeconomic overview of how innovation networks are structured following the

[16] Several different terms are used in the literature to refer to behavioural additionality (collaboration additionality, network additionality, etc.); this can be particularly confusing for readers that are not familiar with this literature. No matter what term is used to describe behavioural additionality, they all have their roots in the Buisseret et *al.* (1995) definition which made it clear that behavioural additionality covers changes in organisation/actor behaviour that result from public support. Nevertheless, despite the growing use of the concept of behavioural additionality in the cluster literature, the definition and theorisation of the concept still needs further work (Gök and Edler, 2012) to allow for meaningful comparisons and the development of evidence-based policy recommendations.

microeconomic changes observed in the behaviour of organisations. Assessing the overall structure of innovation networks is all the more important given that the sum of individual additional results cannot assess appropriately the emergence of system effects (Bellandi and Caloffi, 2010).

Questions regarding additionality at the network and/or regional level are tackled in a third strand of the cluster evaluation literature (e.g. Bellandi and Caloffi, 2010; He et *al.*, 2013; Ter Wal, 2013; Rothgang et *al.* 2017; Töpfer et *al.*, 2017; Lucena-Piquero and Vicente, 2019). Studies from this strand of research start from the premise that innovation network policies are primarily designed to strengthen innovation networks and build on the theoretical work on the link between network structures and innovation performance. In this vein, scholars have drawn attention to how the whole structure of innovation networks evolves as a result of innovation network policies. Larosse (2001) refers to this kind of additionality as systemic additionality to stress the fact that innovation network policies aim at changing the system. Despite the relevance of this type of evaluation, systemic additionality is rarely addressed in the literature. The most recent and relevant works in this area are essentially based on descriptive analyses of social networks[17] (Rothgang et *al.* 2017; Töpfer et *al.*, 2017; Lucena-Piquero and Vicente, 2019) or on qualitative analyses (He et *al.*, 2013). Moreover, most of these studies rely on information about the collaborative projects supported by clusters. Since the key issue is to estimate the "additionality" of cluster policies, we claim that using such data source is not relevant to assess systemic additionality because the whole structure of the systems or innovation networks is not considered.

This chapter aims to contribute to this third strand of literature by filling these gaps. Compared to previous studies, instead of describing innovation networks directly from projects supported within clusters, we rely on patent data to get closer to the actual structure of local (NUTS3) innovation networks. Then, we empirically assess the effects of cluster policy on those networks – *i.e.* the changes in the structure of innovation networks resulting from the policy. We focus on the French cluster policy over the period 2005-2010. Based on a literature review, we summarised the structural changes under scrutiny in four network topologies: embeddedness or connectivity, efficiency, resilience and geographical anchoring. Due to the spatial interactions induced by local networks, our empirical strategy relies on spatial Durbin models applied to panel data of four periods and 94 NUTS3 French regions (called departments). We also tested for effect heterogeneity across departments according to their level of technological specialisation. Our econometric specification allows us to identify three types of

[17] In this strand of literature, innovation networks are usually proxied by social networks (in which nodes can represent inventors, organisations, etc.).

cluster policy effects: direct or locally bounded, indirect or associated-neighbourhood spatial effects and the total cumulative effect resulting from the direct and indirect effects. Our results indicate a positive total effect of the French cluster policy on the efficiency of local innovation networks by increasing the small-world nature of those networks, especially in the case of highly specialised departments. However, regarding network resilience, we found an adverse effect of the policy on the structure of innovation networks in low specialised departments. In those departments, the policy has contributed to strengthen collaboration but mostly between central actors of the networks, leaving aside peripheral actors. Finally, we found no significant total effects on network embeddedness and the regional anchoring of networks even though some direct positive effects have been observed. This suggests the existence of territorial competition resulting from cluster policies. Besides contributing to close a research gap, this chapter also has a rather interesting and meaningful implication for policymakers. It does not only show evidence that cluster policies can positively or negatively affect the structure of innovation networks depending on the regional level of specialisation, but also suggests that the strengthening of innovation networks in some territories as a result of cluster policies could be to the detriment of other territories.

The remainder of the chapter is organised as follows. Section 4.2 reviews the literature on the characterisation of innovation networks and derives our research questions. Section 4.3 describes the data and explains the estimation techniques. Section 4.4 discusses the findings and interprets the structural effects of the French Cluster policy. A final section 4.5 concludes and derives policy recommendations.

4.2 Literature review and research questions

As outlined in the introduction, by fostering relationships between actors, cluster policies aim at providing a strong social/relational capital allowing regions to act as innovative milieus (Camagni, 1995). But the real challenge is how to measure such a social capital, especially when it is considered as a collective resource (Coleman, 1990). Starting from a conceptualisation of social capital at the local level, Galaso (2017) proposes to identify local social capital with the network topologies that may positively influence local performances. While making this proposition, Galaso (2017) points out that local social capital is not the network itself, but certain topological properties of the local network that may facilitate the appearance of positive externalities. Following this approach, we provide a literature review of network topologies that may prove to be beneficial for regional innovation and set out our research questions.

4.2.1 Network topologies for regional innovation

The literature on the geography of innovation has embraced the view that a high concentration of actors, even belonging to the same sector, in an area is not enough to explain the innovative capacity of that area (Capello and Faggian, 2005). For such an area to be innovative, collective learning is a prerequisite since it implies a high level of cultural proximity (sense of belonging, interaction capacity and common values) among local actors (Capello and Faggian, 2005). This cultural proximity is reflected in a strong network embeddedness, which is the extent to which actors are linked to third parties in the network (Raub and Weesie, 1990). Network embeddedness can be assessed through the overall network connectivity which is expressed as the proportion of node pairs in a network that can reach one another thanks to the existence of a network path between them (Ter Wal, 2013). Connectivity is also known to facilitate knowledge spillovers since a network with high connectivity allows knowledge to flow through direct and indirect linkages (Nooteboom and Klein-Woolthuis, 2005). Wanzenböck *et al.* (2019) provide empirical evidence of the positive effect of R&D network embeddedness on innovation performances at the EU level. Accordingly, the first research question is as follows:

***Q1**. Do cluster policies increase the embeddedness in local innovation networks?*

While highly connected networks can make regions more innovative, they are not necessarily efficient. Indeed, even though networks with high connectivity allow knowledge to flow, an efficient knowledge circulation depends on the geodesic distance between actors in the network. The larger the geodesic distance between any two actors, the weaker the linkage between these actors, resulting in a smaller likelihood that they will interact with each other. The geodesic distance has, therefore, strong implications for trust building, knowledge transfer and spillovers diffusion. A large part of the literature analysing the link between innovation performance and network structures identify small-world networks as efficient networks for innovation production and diffusion (Kogut and Walker, 2001; Uzzi and Spiro, 2005; Fleming et *al.*, 2007; Schilling and Phelps, 2007). The combination of the two main properties of such networks (high clustering and low average path length; Watts and Strogatz, 1998) is said to boost innovation. A small-world network with a high clustering coefficient (nodes sharing common partners tend also to be directly connected together) and a short path length (average social distance between any pair of nodes) combines the advantages of efficiency and embeddedness. Clustering facilitate trust and reduce opportunism (Coleman 1988; 1990) while short path length ensures the existence of structural holes which allow actors to have access to valuable and new resources (Burt; 1992). Fleming et *al.* (2007) have empirically demonstrated the positive effects of short path length and a high clustering coefficient on regional innovativeness. Therefore, the second research question is stated as follows:

Q2. *Do cluster policies reinforce the efficiency of local innovation networks?*

Most of the previous studies exploring the relation between network structural properties and regional innovation focused on innovation performance considering innovation production and diffusion. However, in a context characterised by faster technological cycles and increasing turbulence in the economic environment, efficient innovation networks can also be sensitive to external shocks and exhibit fragility properties (Crespo et *al.*, 2014). Network resilience therefore appears as an important feature allowing innovative regions to regulate the trade-off between path dependency and adaptability (Pike et *al.*, 2010; Simmie and Martin, 2010). In this vein, Crespo et *al.* (2014) argued that innovation networks can exhibit a resilience property in presence of hierarchy (existence of a core/periphery structure in the network) and disassortativity (tendency of weakly connected agents to create ties with highly connected agents). Hierarchical networks allow to set up compatibility and interoperability among the different components of the network in order to reduce system dysfunctions and enhance knowledge diffusion within the network. Disassortative networks limit the redundancy of knowledge flows and also allow the exploration or exploitation of new ideas emerging from either the core or the periphery on the network. The third research question is therefore formulated as:

Q3. *Do cluster policies reinforce the resilience of local innovation networks?*

During the recent years, several studies have investigated the effects of network geographical anchoring on innovation. This literature mainly focuses on the influence of network openness on regional performance and overall, findings do not give primacy to any form of relation either distant or local since both have advantages for regional innovation. On the one hand, some authors claim that distant relations have a positive influence in regional innovative performance because they bring new ideas into the region to avoid redundancy and lock-in (Bathelt et *al.*, 2004; Breschi and Lenzi, 2016). On the other hand, other studies (Boschma 2005; D'Este et *al.*, 2013) present evidence suggesting that local collaborations facilitate and strengthen network embeddedness especially when local actors share a common knowledge base with diverse but complementary capabilities. To sum up, the findings from this strand of literature indicate that local and distant relationships have a complementary role in enhancing regional innovation. Broekel (2012) and De Noni et *al.* (2017) summarised this by pointing that a balance between local and distant collaboration is required to support regional innovation. Accordingly, the fourth and last research question can be stated:

Q4. *Do cluster policies reinforce the geographical anchoring of innovation networks?*

We sought to answer these four questions using the case of the French cluster policy.

4.2.2 *French cluster policy*[18]

In the early 2000s, innovation policy has become a major public concern and French government officials have nurtured the ambition to create a better combination than in the past, of innovation and industry within territories. The period 1999 to 2008 saw the development of policy instruments designed on the one hand to develop cooperation between actors and on the other hand to enhance the valorisation of public research (Lallement and Harfi, 2016). It is in this context that the French cluster policy was launched in 2005 to raise the innovative capacity of France. According to an official definition, a (French) cluster "*brings together large and small firms, research laboratories and educational establishments, all working together in a specific region to develop synergies and cooperative efforts*". French clusters are intended to actively support networking between firms, universities and research organisations mainly at the regional (NUTS2) level even though clusters were also encouraged over time to increase networking between their participants and actors from others regions. From those networking activities come out collaborative R&D projects and then innovation and regional growth. The French cluster policy therefore appears an interesting and relevant case study to address our research questions.

From 2005 to 2010, 71 competitiveness clusters from various fields (energy, mechanics, aerospace, transport, ICTs, health, environment, ecotechnology, etc.) have been supported by the French authorities. The State support for clusters mainly takes the form of (i) a partial financing of cluster governance structures, alongside local authorities and participants (public research organisations and firms), and (ii) the granting of financial aids to collaborative R&D projects coming out of clusters. Between 2005 and 2013, 1,313 collaborative R&D projects endorsed by clusters received public financing of €2.37 billion, including more than €1.45 billion granted by the French State through the Single Inter-Ministry Fund (FUI). Clusters are also financed from membership fees. In return, participants receive support from the cluster in terms of training and assistance in setting up collaborative R&D projects especially in partners' searching and networking.

4.3 Data and methodology

As mentioned in the previous sections, this study aims at assessing the (additional) effects of cluster policies on the structure of local innovation networks. This requires to find first external-to-the-policy data in order to define the local innovation networks and then to rely on relevant network measures characterising the four topologies of interest.

[18] A more detailed description of the French cluster policy is provided in the general introduction.

4.3.1 Data

The relational capital of a territory is an intangible asset that cannot be directly measured (Capello and Faggian, 2005). Recent empirical advancements in the geography of innovation literature, however, have shown that patent data allow us to measure, although not exhaustively, an important component of relational capital which is cooperation among inventors (Ter Wal and Boschma, 2009). These contributions suggest that co-inventorship networks can be considered as a proxy for local networks of collective learning (Ter Wal, 2013). Following this research line, we propose to reconstruct co-inventorship networks based on patent data to proxy innovation networks. Innovation networks were therefore based on patent applications submitted to the French patent office (INPI) over the period 2002–2013. We used a three-year lag between the beginning of R&D projects and patent applications[19]. By doing this, we considered that patent applications submitted between 2002 and 2013 result from R&D projects that started during the 1999-2010 period. This time span was broken down into four three-year periods around 2005 *i.e.*, two pre-policy periods: 1999–2001, 2002–2004 and two post-policy periods 2005–2007, 2008–2010.

The local innovation networks for 94 NUTS3-regions (so called departments) were defined during each of these periods. This results in a set of 376 (94×4) networks. Innovation networks are portrayed using nodes which represent inventors and edges connect pairs of nodes which are the co-inventors for at least one patent. Isolated nodes are inventors which are not involved in any co-invention. The local innovation network of each department was built using all the patents involving at least one inventor belonging to the department; therefore, it can be seen as an aggregation of the ego-networks of local inventors. This implies that local innovation networks are constituted by local but also non-local inventors[20]. If present in a local innovation network, non-local inventors have at least one direct connection to at least one local inventor (as illustrated in appendix A.3.1).

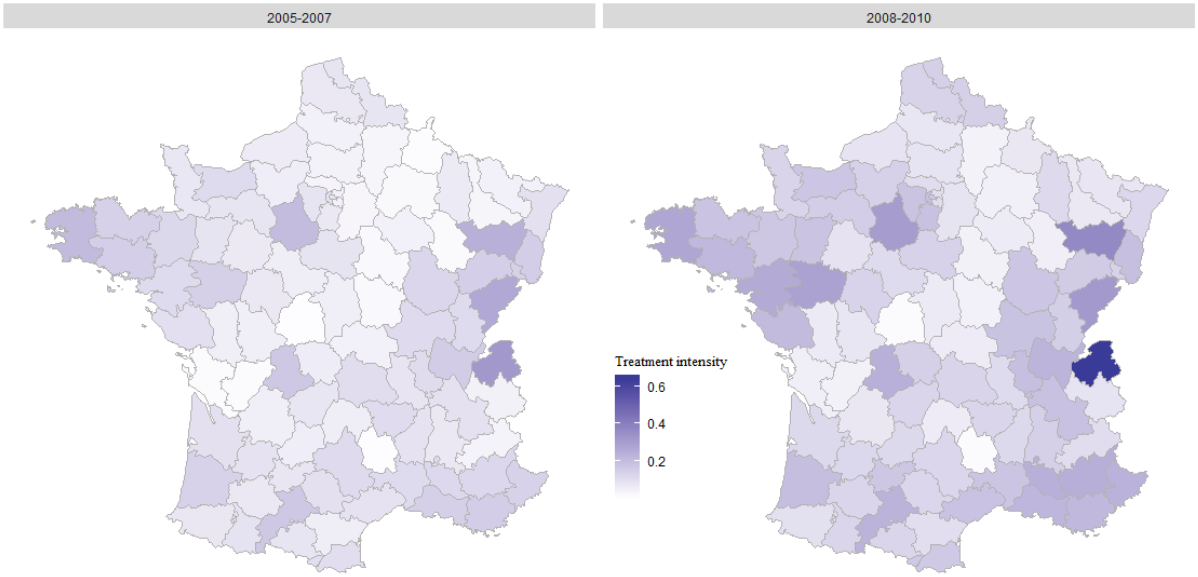
Cluster participants are unevenly distributed throughout the country. We therefore defined the treatment intensity for each department as *the ratio of the number of cluster participants located in the department to the number of establishments involved in R&D activities and also located in the department*. Since the policy started in 2005, the treatment intensity is zero for all the departments during the pre-treatment periods (1999–2001 and 2002–2004). During the first post-treatment period (2005-2007), the average treatment intensity per department was

[19] The choice of this three-year lag is justified by the average duration of R&D projects supported by clusters through the FUI, which is one of the main instruments for financing collaborative R&D projects from French clusters.

[20] The inventor-disambiguated patent data we relied on – which are provided by the French patent office – only include applicants and inventors with a French address. The dataset is freely accessible at https://data.enseignementsup-recherche.gouv.fr/explore/dataset/fr-esr-brevets-france-inpi-oeb

about 8.8%, meaning that 8.8% of establishments involved in R&D activities in the French departments were cluster participants. That average has almost doubled (14.6%) over the second post-treatment period (2008-2010). Not surprisingly, and as shown in Figure 5, these averages hide a strong heterogeneity between departments even though there has been little change in the spatial distribution of cluster participants between both periods.

Figure 5 Treatment intensity (during the post-treatment periods)



Indeed, some departments have a share of cluster participants – treatment intensity – well above the averages; this is particularly the case for departments from the western (e.g. Finistère, Maine-et-Loire, Loire-Atlantique), southern (e.g. Alpes-Maritimes, Haute-Garonne), and eastern (e.g. Haute-Savoie, Doubs, Vosges) parts of the country. Three of them stand out for being in the top 3 on both periods: Haute-Savoie, Doubs and Vosges. These regions are known to be medium-sized departments with a high industrial specialisation. Haute-Savoie hosts the Arve Valley whose expertise in precision machining has been developed from the region's clock and watch making industry during the 19th century. The Arve Valley's expertise is nowadays recognised throughout the world and precision machining in the Haute-Savoie department accounts for 30% of its GDP and 70% of total French sales for this sector. Regarding the Doubs department, since the 17th century it has been shaped by the watchmaking industry thanks to an internationally recognised know-how in the various stages of watch manufacture. Following the watchmaking crisis of the 1970s and 1980s, the department has gradually diversified its industrial base towards microtechnology and is now considered as one of the leading French territories in the field of microengineering. Finally, the Vosges, often referred to as the "Wood Valley" is the leading French department for the volume of wood production (over 1 million m³ per year). The wood industry has always occupied an important place in the

local economy and the department is home to a complete wood-based industry, ranging from timber harvesting to primary and secondary manufacturing (construction and high-end furnishings). To date, the department hosts more than 1,000 establishments and 13,000 jobs in the wood industry as well as the only public engineering school in France specialising in technologies related to wood and natural fibres. Most of the other departments having a high treatment intensity are also characterised by a certain level of industrial specialisation, although in smaller extent than those already mentioned. This descriptive analysis confirms the close link between the treatment intensity and territorial specialisation.

A set of nine outcome variables were selected in order to characterise the four network topologies of interest, namely embeddedness, efficiency, resilience and geographical anchoring. The selection of such a number of indicators or outcome variables is explained by the fact that the network topologies under scrutiny are complex and cannot be consistently assessed on the basis of a single network indicator. Therefore, for each network topology, at least two outcome variables are used for its characterisation as it is usual in the empirical network literature[21]. The selection of those variables is based on how well they describe the selected topologies on the one hand, and how well-established they are in the theoretical and empirical literature on the other (Table 7).

All these outcome variables were computed for the 376 local innovation networks. This yields a panel data set that spans four periods. Two important methodological issues must be discussed here. Firstly, most studies on innovation or even social networks focus on the network's main component to provide network indicators. This is because most of these indicators require direct or indirect connexions between nodes to be computed. This is for instance the case for the average path length ratio. The focus on the main component induce an important bias (in our case the main component of the 94 local networks often gathers less than 10% of the total number of nodes). To overcome this difficulty, we only considered and averaged the lengths of the existing paths and set the mean degree in the neighbourhood of isolated nodes to zero (Crespo et *al.* 2014). This allows us to take into account all the information regarding the local networks. In addition, network indicators could be very sensitive to the network size. This is all the more important to control for this size effect when it comes to compare the properties of networks involving a very different number of actors. To this aim, as soon as size matters, we define our network indicators as a ratio of the observed value in the observed network to the value obtained for a random network of equal size.

[21] Four different indicators of centrality are for instance used by Calvó-Armengol, Eleonora Patacchini, Yves Zenou (2009) to analyse peer effects in education or by Mastrobuoni and Patacchini (2012) to study mafia networks.

Table 7 Outcome variables[22]

Network topologies	Outcome variables	Description	Theoretical references	Empirical references
1- Embeddedness	Density	Density represents the proportion of possible relationships in the network that are actually present. This is the ratio of the number of edges to the number of possible edges. It is a well-established statistic in the literature and high levels of density are supposed to generate a belonging/camaraderie collective feeling in social networks. This may lead to a reduction of the risk of adopting collaborative solutions thanks to an increase in trust and cooperation. Moreover, information in dense networks can flow more easily than in sparse or fragmented networks.	Wasserman and Faust (1994)	Giuliani et *al.*, 2016
	Fragmentation index	Fragmentation occurs when two nodes belong to different, unconnected components of the network. The fragmentation index is the ratio of the number of components to the number of nodes. It indicates the degree to which some nodes are disconnected from the network and is defined as the proportion of node pairs that cannot reach each other.	Wasserman and Faust (1994)	Giuliani et *al.*, 2016 Ter Wal, 2013
	Share of the network's	The largest component of connected nodes in a network is referred to as the main component. The share of the network's main component is the ratio of	Wasserman and Faust (1994)	Cantner and Graf (2006)

[22] For more details on the mathematical formulation of the variables, the reader is referred to the cited literature and references therein.

Network topologies	Outcome variables	Description	Theoretical references	Empirical references
	main component	number of nodes in the main component to the total number of nodes in the network. This is the percentage of nodes present in the main or largest component. The higher the number of nodes present in the main component, the more a collective learning process is assumed to take place within the network.		Casper (2007) Fleming and Frenken (2007) Ter Wal (2013)
2-Efficiency	Clustering coefficient (ratio)	The large clustering coefficient displayed by small-world networks describes a tendency of closure *i.e.* nodes that share neighbours are often also directly connected to each other. It is widely acknowledged that network closure generates trust which in turn promotes collaboration and facilitates risk sharing, resource pooling, and information diffusion. The clustering coefficient ratio is defined as the ratio of the observed clustering coefficient to the clustering coefficient of a random network of equal size and density. It indicates the extent to which the observed clustering coefficient differs from the value expected in comparable random network.	Granovetter (1985) Coleman (1988) Uzzi and Spiro (2005)	Ter Wal (2013)
	Average Path length (ratio)	Low path length increases network connectivity, and so it makes easier knowledge circulation and transmission. A decrease in a network's average path length increases network connectivity which in turn can improve network nodes performance.	Uzzi and Spiro (2005)	Fleming et *al.* (2007) Ter Wal (2013)

Network topologies	Outcome variables	Description	Theoretical references	Empirical references
		The path length ratio is defined as the ratio of the observed average path length to the average path length of a random network of equal size and density. It indicates the extent to which the observed average path length differs from the value expected in comparable random network.		
3-Resilience	Hierarchy	The presence of hierarchy in a network is reflected by an unequal distribution of degrees. Crespo et *al.* (2015) argued that in hierarchical networks, core actors have enough power to coordinate the whole network and lead the systemic technological process while peripheral ones can bring complementary modules to that process. The level of network hierarchy is considered as the slope of the degree distribution, *i.e.* the relation between nodes degree and their rank position.	Borgatti and Everett (1999)	Crespo et *al.* (2014; 2015)
	Assortativity	Hierarchical networks are relevant structures mainly for network coordination. However, even though it is crucial to have key actors coordinating a local innovation network, the degree of openness among the core and the periphery of the network also matters. Crespo et *al.* (2014) point out the necessity for the different hierarchical levels to be connected in order to avoid redundancy of knowledge flow and also to allow the exploration or exploitation of new ideas from either the core or the periphery. They referred to this tendency of nodes in a network to connect with other nodes as assortativity (also called homophily).	McPherson et *al.* (2001)	Crespo et *al.* (2014; 2015)

Network topologies	Outcome variables	Description	Theoretical references	Empirical references
		A network is assortative when nodes are preferentially connected with other nodes that have a similar degree, *i.e.* high-degree nodes tend to interact with high-degree nodes, and low-degree nodes with low-degree nodes. On the contrary, a network is disassortative when high-degree nodes tend to interact with low-degree nodes, and conversely. The level of assortativity or disassortativity of networks is reflected by the degree correlation: it is the slope of the relation between nodes' degree and the mean degree of their local neighbourhood.		
4- Geographical anchoring	Share of local links	This is the ratio of the number of edges among local (NUTS3) inventors to the number of edges in the network. This indicates the strengthening the local anchoring of the network.	Boschma (2005)	Ter Wal (2013)
	Share of regional links	This is the ratio of the number of edges between local (NUTS3) and regional (NUTS2) inventors to the number of edges in the network. This indicates the degree of openness of the network towards regional actors.	Boschma (2005)	Ter Wal (2013)

Figure 6 Spatial distribution of the outcome variables (averaged over the pre-treatment periods

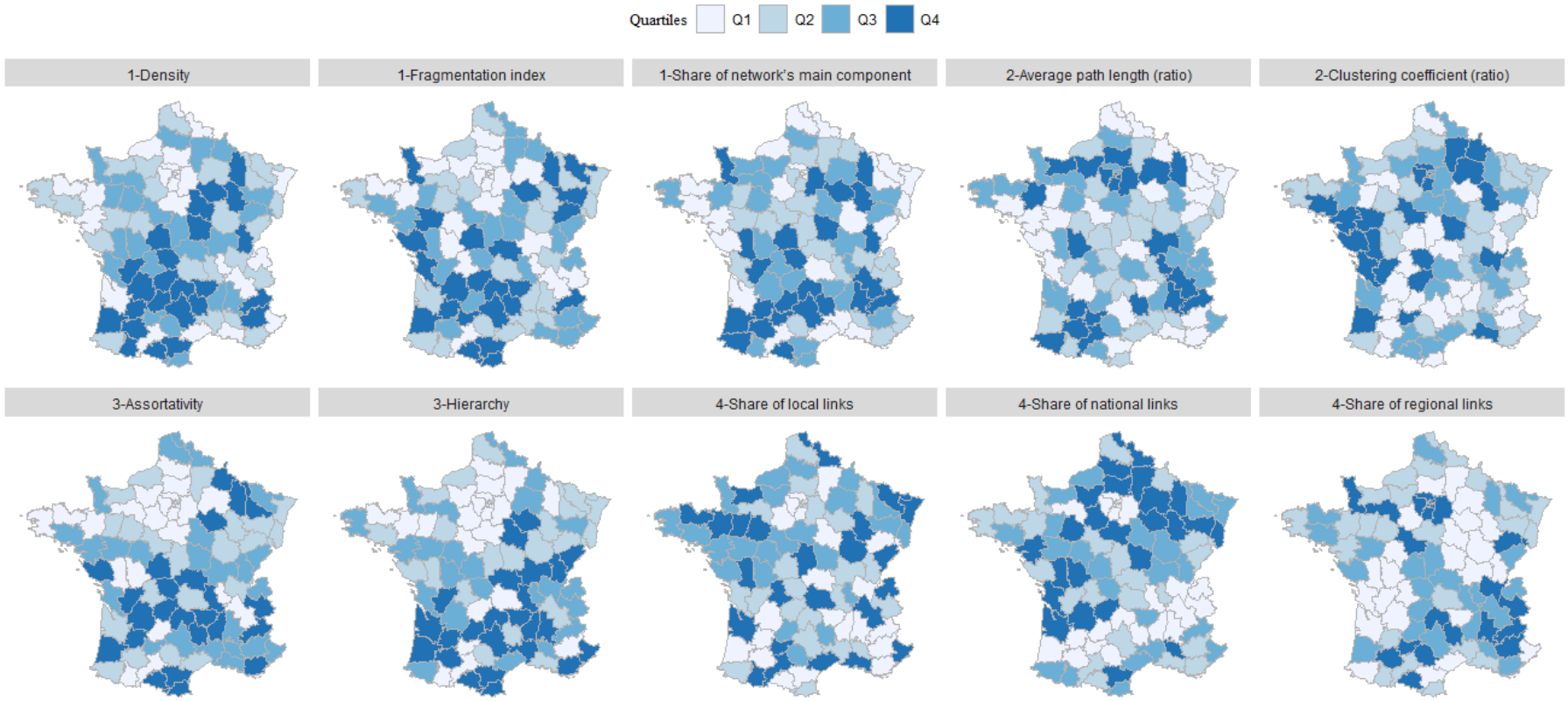


Figure 6 shows the spatial distribution of the outcome variables, averaged over the pre-treatment periods. Looking at the variables characterising network embeddedness (the first topology – 1), we can see that most of the dense innovation networks with a large main component were fragmented before the implementation of the cluster policy. The few exceptions are Haute-Vienne, Vienne, Saône-et-Loire and Somme which therefore could be considered as some of the most connected local innovation networks since they were also dense but less fragmented compared to the other networks. The tendency for dense networks to be fragmented could be explained by the existence of several technological areas within departments; each area being developed by different communities of actors. In this vein, cluster policy implemented in such diversified departments is likely to strengthen network fragmentation, especially with multi-thematic clusters.

Regarding the efficiency (second topology – 2) of local innovation networks during the pre-policy periods, it turns out that most of the small-world networks (*i.e.* networks characterised by high clustering coefficient and low average path length) were essentially those of west coast departments, namely Morbihan, Loire-Atlantique, Vendée and Charente-Maritime. Although there were also other departments (Ardennes, Bouches-du-Rhône, etc.) having the "small-worldness" property, small-world networks were not the most prevalent situation in French departments even in innovative territories such as the Paris area, Rhône and Haute-Garonne. Within innovation networks from those departments, the high level of clustering was very often coupled with a high average path length. By reducing path length, the cluster policy would make local innovation networks more efficient.

Furthermore, during the pre-policy periods, local innovation networks were also not resilient to the extent that as hierarchical structure was very often coupled with assortativity (third topology – 3). Therefore, even though there were core actors able to coordinate local innovation networks, those actors tended to collaborate with each other. There were, of course, some exceptions, mainly among small to medium-sized departments such as Lot, Finistère, Marne, Orne, and Vienne. It is worth noting the growing and innovative department that is Rhône was one of these exceptions.

Finally, two main patterns are seen regarding the geographical anchoring (fourth topology – 4) of innovation before the implementation of the French cluster policy. On the one hand, one can notice the central position of the Paris area especially the NUTS2-region Île-de-France. Actors from this region strongly interact with each other and also act as key partners for actors from neighbouring regions. Thus, departments close to Île-de-France tended to have a high share of national links and low level of regional or local links. On the other hand, departments with high shares of interaction at the local (NUTS3) and regional (NUTS2) levels were clustered

in space: the northwest part of the country for local links and southeast for regional links. Such spatial clustering suggests the presence of interdependencies between innovation networks.

4.3.2 *Model*

The purpose of this study is to evaluate the effects of cluster policies (treatment) on the structure of local innovation networks (outcome variables). Conventional econometric models used to analyse cross-sectional and panel data assume that statistical units are independent of one another. Since local innovation networks can involve non-local actors, we acknowledge that there is a systematic dependency between departments with respect to the structure of their innovation network. Such a spatial dependence clearly appears from the spatial distribution of our dependent variables reported in appendix (figure 3). Spatial econometrics provide a natural tool to investigate such interdependencies. Empirical models from the spatial econometrics' literature deal with three different types of interactions (Manski, 1993; Elhorst, 2010):

- endogenous interaction, when the dependant variable of an agent or a geographical area depends on the dependant variables of its neighbours;
- exogenous interaction, when the dependant variable of an agent or a geographical area depends on the observable characteristics (independent variables) of its neighbours;
- spatial dependencies in the residuals due to unobserved characteristics.

A full model with the three types of interactions can take the form:

$$Y = \alpha\iota_N + \rho WY + X\beta + WX\theta + u, \qquad [27]$$
$$u = \lambda Wu + \varepsilon$$

We assume that the error term ε follows a multivariate normal distribution of with a mean of zero and a variance of $\sigma^2 I_n$, where I_N is an $N \times N$ identity matrix. β is the vector of parameters associated to each explanatory (treatment and control) variable, ρ measures the endogenous interaction effects (referred to as spatial autoregressive coefficient) and θ the exogenous interaction effects. λ captures the spatial correlation effect of errors known as spatial autocorrelation coefficient. Interdependencies are introduced in the model through W, an $N \times N$ nonnegative spatial weight matrix based on contiguity of the N departments. Non-zero elements in the ith row and the jth column of W indicate that department i and j are neighbours; the main diagonal elements are zero and rows are normalised so elements of each row sum to unity. ι_N is a constant term vector associated with the parameter α to accommodate situations where the vector Y does not have a zero mean value. The three

types of interactions are considered in this model through spatial lags terms for the outcome or dependent variable; the explanatory variables and the disturbances are respectively represented by WY, WX and Wu. Even though there is no obstacle to estimating this full model (Equation [27]), most empirical studies consider one or two types of interactions[23].

In order to choose which interaction(s), and therefore, which model has to be considered, LeSage (2014) suggested to regional scientists to consider only two models: the Spatial Durbin Error Model (SDEM) or the Spatial Durbin Model (SDM) since the other spatial models are special cases of either the SDEM model or the SDM model (see Elhorst, 2010 for a survey on spatial models specification).

$$Y = \alpha\iota_N + X\beta + WX\theta + u,$$
$$u = \lambda Wu + \varepsilon \qquad [28]$$

$$Y = \alpha\iota_N + \rho WY + X\beta + WX\theta + \varepsilon \qquad [29]$$

Equations [28] and [29] respectively depict the SDEM and SDM models. As can be seen from both equations, the SDM model explicitly takes into account the endogenous and exogenous interactions, unlike the SDEM model which considers spatial correlation of the covariates and the error term. LeSage (2014) recommended to use a SDEM model when the research question reflects local spillovers, *i.e.* a situation in which one can assume that endogenous interaction is not present. Given the substantive aspects of our research questions as well as the structure of our data, this is not a plausible assumption. Indeed, local innovation networks involve both local and non-local actors, implying a systematic interdependence in the structure on innovation networks from different areas. In this contest, we are in the case of global spillovers and, as argued by LeSage (2014), the most relevant spatial model to choose is the SDM model[24]. Moreover, though the error term in Equation [29] could be further divided into spatially structured and random errors, therefore taking the form of Equation [27], ignoring spatial dependence in the disturbances, if present, will only cause a loss of efficiency in the estimates which will remain unbiased and consistent (LeSage and Pace, 2009; Elhorst, 2014a). Besides this empirical motivation, the choice of a SDM model is also theoretically relevant in that previous research has found that an effective way to reduce omitted variable bias is to estimate a

[23] Making the model identifiable actually requires one to assume that neighborhood matrices W are not identical for all the three types of spatial interactions. The most common solution in the spatial econometrics literature consists in eliminating one of the three forms of spatial correlation represented by parameters ρ, θ and λ.

[24] LeSage (2014) also states that networks represent one situation that may involve global spillovers, supporting our choice for the SDM.

spatial Durbin models (Autant-Bernard and LeSage, 2011; Fingleton and Le Gallo, 2012) and therefore to avoid misleading causality inference often pointed out in spatial models (Halleck Vega and Elhorst, 2015)

We therefore consider a spatial panel Durbin model specified as:

$$Y_{it} = \alpha\iota_N + \rho\sum_{j=1}^{N} W_{ij}Y_{jt} + X_{it-1}\beta + \sum_{j=1}^{N} W_{ij}X_{ijt-1}\theta + \varepsilon_{it} \qquad [30]$$

where i is an index for the cross-sectional dimension (spatial units), with $i = 1; \ldots; N$, and t is an index for the time dimension (time periods), with $t = 1; \ldots; T$. The subscript $t-1$ is introduced in all the regressors in order to make clear that they have been time-lagged one period. Equation [30] can be extended with department and time fixed effects:

$$Y_{it} = \mu_i + \lambda_t + \rho\sum_{j=1}^{N} W_{ij}Y_{jt} + X_{it-1}\beta + \sum_{j=1}^{N} W_{ij}X_{ijt-1}\theta + \varepsilon_{it} \qquad [31]$$

Our dependent variable Y corresponds to the overall properties of the network (embeddedness, efficiency, resilience and geographical anchoring). The model is thus estimated separately for each of our nine outcome variables. Our main explanatory variable is the intensity of the cluster policy within the area, *i.e.* the treatment. To rule out potential bias and possible competing hypothesis, we introduce control variables at the network, territorial, and technological specialisation levels. As mentioned above, all the explanatory variables, as well as the treatment, are lagged one period in order to lessen endogeneity problems due to system feedbacks.

The number of nodes in the network is included (nb_nodes) as it is usual in network properties analysis. Even though our indicators are built in such a way that they avoid to be directly driven by the network size, one cannot exclude that some network properties could still be influenced by size. A larger network may for instance face more hierarchy or allow a more international anchoring thanks to the higher visibility/reputation acquired by some actors.

Moreover, based on the literature on collaboration ties formation, actors are more likely to enter networks if the benefits they expect to get from the collaboration exceed the cost of forming or maintaining ties (Jackson and Wolinski, 1996). As for the specific case of R&D collaboration networks, one main condition to benefit from network participation is to hold sufficient absorptive capacities. This is a pre-requisite to be able to access and assimilate external knowledge made available through direct and indirect ties. This absorptive capacity is defined by both the amount of internal knowledge already accumulated and the diversity of this knowledge (Cohen and Levinthal, 1989). While this analysis stems from individual processes of knowledge, it has been widely transposed to the firm and regional level. Recent

work on regional knowledge production shows for instance that innovation networks differ between regions that produce specialised and diversified knowledge (Van der Wouden and Rigby, 2019). This implies that the structure of a territory's innovation network is correlated with its level of technological specialisation.

Following the absorptive capacity theory, we therefore consider that local network properties for each of our 94 NUTS3 regions depend on the total research capacities and on the degree of knowledge diversity. Research capacities are proxied by the total amount of R&D expenditure in the area ($dird$). We also include local GDP to (gdp) to control more widely for the significant disparity in size and the state of the local economy. We expect positive impacts on network embeddedness, efficiency and resilience. The impact on the geographical anchoring is less obvious. A high level of local R&D and economic activity may favour local interactions, but it can also favour collaboration with more distant partners as it ensures a higher ability to benefit from leading edge knowledge.

Diversity of local knowledge is accounted for by introducing the Krugman Specialisation Index (KSI). KSI measures the distance between the distributions of patent shares in a department and at the country level. More precisely, this relative measure of specialisation considers a department to be specialised if the distribution of its patenting activities across technological fields[25] differs from the average distribution observed at the country level. The Krugman specialisation index takes value zero if department i has a patents distribution identical to the rest of the country, indicating that department i is not specialised, and takes a maximum value of 2 if it has no technological fields in common with the rest of the country, reflecting strong sectoral specialisation; the higher the KSI, the greater the regional specialisation. A negative effect of this variable is expected on network embeddedness, since, according to the absorptive capacities, a more diversified industrial structure would favour collaborations and therefore lead to more connected networks. The impact on network efficiency is less clear: on the one hand, most specialised areas could be more likely to exhibit high clustering coefficients due to the presence of technological communities. On the other hand, social proximity (clustering for instance) could be required to counterbalance the lack of information and confidence that could arise is case of diversity.

In order to identify the proper effect of the Cluster policy, we also need to control for the other public support to private R&D. Direct R&D subsidies allocated to local companies are therefore introduced as regressors. There are indirect R&D policies as well in France. The Research Tax

[25] Technological fields are based on the aggregation of the International Patent Classification (IPC) codes, proposed by the World Intellectual Property Organization (Schmoch, 2008). This classification aggregates IPC codes into 35 technological fields.

Credit is the most important one in terms of financial amounts but we do not include it here. It is not conditioned on any form of collaboration among firms or between science and industry. It has therefore no reasons to induce any direct specific change in the innovation network. Moreover, as it is proportional to the amount of R&D, it would not add a lot to our R&D expenditure variable. Regional, national and international direct supports are for their part often conditioned on collaborative behaviours. This is especially the case at the EU level where almost all tools are based on collaboration. We therefore expect significant impact of such subsidies on the network properties. The impact on the geographical features would of course depend on the level at which the subsidy policy is implemented. We therefore distinguish the local amount of regional, national and EU subsidies. We introduce three variables:

sub_region (subsidies received from local authorities, *i.e.*, essentially regions and departments); sub_nat (total of the subsidies received from various French Ministries, *i.e.*, national subsidies) and sub_cee (European subsidies received from the European Commission). The rationale behind distinguishing between local, national and European subsidies is due to the fact that these subsidies have different objectives depending on donors' policy choices and are therefore likely to have different effects on the structure of innovation networks. For example, European subsidies, particularly received under the Framework Programmes, are more oriented towards strengthening international cooperation than subsidies granted by local authorities or national administrations.

Furthermore, it is widely acknowledged that there is no "one size fits all" policy. To this regard, an important concern for national cluster programs evaluation is to identify whether the policy is more efficient under certain contexts. Grillitsch and Asheim (2018) argued that the ability of place-based policies to foster knowledge networks and local dynamics greatly depends on the initial local industrial structure. Cluster policies would therefore have different effects depending on the level of specialisation of regions. In order to test this hypothesis, the Krugman Specialisation Index was used to proxy the level of technological specialisation for each department during the pre-policy period (1999-2004). The recommended approach to assessing treatment effect heterogeneity is to model the statistical interaction between the treatment and individual characteristics that define subgroups of the population. Departments were therefore divided into two subgroups based on the median KSI value: departments with a KSI below the median are defined as *low specialised departments (KSI1)* and departments with a KSI above the median as *highly specialised departments (KSI2)*.

To investigate treatment effect heterogeneity across the two groups of departments we extended our baseline model (Equation [31]) by allowing an interaction between the treatment intensity and dummy variables indicating the level of specialisation (low/ highly

specialised departments). This allowed us to examine the effect of cluster policies given the level of regional technological specialisation. This issue is all the more important in the French context where the national cluster policy has been recently reoriented towards a more reduced number of clusters, more diversified due to merging, often at the benefice of the largest and more diversified areas.

Finally, it is worth making a few observations regarding the model's interpretation. Unlike least-squares approaches, in the SDM model the derivative of y_i with respect to the kth explanatory variable x_{ik} usually does not equal β_k, and the derivative of y_i with respect to x_{jk} (for $j \neq i$) usually does not equal 0. This can be seen by rewriting Equation [30] in vector form:

$$Y_t = \alpha\iota_N + \rho W Y_t + X_{t-1}\beta + WX_{t-1}\theta + \varepsilon_t \qquad [32]$$

Which implies that:

$$Y_t = (I_N - \rho W)^{-1}\alpha\iota_N + (I_N - \rho W)^{-1}(X_{t-1}\beta + WX_{t-1}\theta) + (I_N - \rho W)^{-1}\varepsilon_t \qquad [33]$$

It follows that the matrix of partial derivatives of the dependent variable with respect to the kth explanatory variable in the different departments (say, x_{1k} for $i = 1; \ldots; N$) at a particular point in time t is:

$$\left[\frac{\partial Y}{\partial x_{1k}} \quad . \quad \frac{\partial Y}{\partial x_{Nk}}\right]_t = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix}_t = (I_N - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & . & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & . & w_{2N}\theta_k \\ . & . & . & . \\ w_{N1}\theta_k & w_{N2}\theta_k & . & \beta_k \end{bmatrix} \qquad [34]$$

Assuming that the spatial weight matrix is constant over time, the matrix on the right-hand side of Equation [34] is independent of the time index t (Elhorst, 2014a). These calculations are therefore equivalent to those presented in LeSage (2008) and LeSage and Pace (2009) for cross-sectional setting. The only major difference in the panel setting is computational in that given the dimension of the data in a panel (NT), a block diagonal matrix $I_T \otimes W$, whose diagonal blocks are the spatial weight matrix is used instead of the spatial weight matrix itself (Piras, 2014).

The average of the diagonal elements of the matrix resulting from the right-hand side of Equation [34] is labelled by LeSage (2008) as the *average direct effect/impact*. This is the impact of changes in the ith observation of variable k, averaged over the N departments. For example, let's consider k is the treatment variable *i.e.* the cluster policy, the average direct effect provides a summary measure of the impact of the treatment of department i on its own innovation network. The average effect on department i resulting from changes in the treatment of other departments is referred to as *average indirect effect/impact*. This is the average of either the row sums or the column sums of the non-diagonal elements of the matrix

resulting from the right-hand side of Equation [34]. LeSage (2008) also defined the *average total effect/impact* as the average total cumulative effect, *i.e.*, the sum of the *average direct effect* and the *average indirect effect*[26]. The estimations of different effects are performed under the Lee-Yu correction (Lee and Yu, 2010a; 2010b) using the MATLAB routines *sar_panel_FE* and *panel_effects_sdm*, made available by Elhorst (2014b), to estimate spatial Durbin models.

4.4 Empirical results and discussion

Research questions were formulated in the second section (4.2) following four network topologies that are beneficial for regional innovation: embeddedness or connectivity, efficiency, resilience and geographical anchoring. This section comments on the results of the estimation of Equation [31] with and without the interaction between the treatment intensity and dummy variables indicating the level of specialisation. Furthermore, as noted in Section 4.3.2, the SDM model estimates cannot be interpreted as partial derivatives in the typical regression model fashion. We therefore turn to the summary measures of direct, indirect and total effects presented in Table 8 to Table 11. The full set of partial derivatives or coefficients are available upon request.

There is a positive and significant direct effect of the French cluster policy on the density of innovation networks. However, the total effect is not significant. This suggests that reinforcing cluster policies in neighbouring departments might cancel out the positive direct effects on density and therefore on the embeddedness of local innovation networks. We also found that the policy has increased the fragmentation of innovation networks in low specialised departments. This total effect is mostly comprised of the indirect effect suggesting that reinforcing cluster policies in neighbouring departments increase the fragmentation of the innovation networks of low specialised departments. This could be explained by the fact that because of the cluster policy, the local innovation networks of low specialised departments get divided into several specialised components, *i.e.*, groups of connected actors sharing similar or related specialisation. This is in line with previous studies suggesting that cognitive proximity is an important, and perhaps even the most important determinant in R&D collaboration (Nooteboom et *al.*, 2007; Boschma and Frenken, 2010; Broekel, and Boschma, 2016). Overall, the results are rather mixed and there is no clear evidence supporting that the French cluster policy has reinforced the embeddedness of local innovation networks.

[26] In what follows, the word 'average' will be omitted when referring to the different types of effects for sake of clarity.

Table 8 Marginal effects of SDM for network embeddedness

		Density		Fragmentation index		Share of the network's main component	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Direct effects							
	nb_nodes	0.000	0.000	0.000	0.000	0.000**	0.000***
	gdp (log)	-0.035*	-0.028	0.222**	0.174*	-0.059	-0.040
	dird (log)	0.002	0.002	-0.014	-0.010	-0.005	-0.002
	sub_region (log)	0.000	0.000	0.000	0.000	0.000	0.000
	sub_nat (log)	-0.003***	-0.003***	0.010***	0.010***	-0.007***	-0.008***
	sub_cee (log)	0.000	0.000	-0.002*	-0.002*	0.001	0.001
	KSI	0.020***		-0.055*		0.065**	
	treatment_int	0.024*		-0.057		0.057	
	treatment_int * KSI1		0.026*		-0.049		0.048
	treatment_int * KSI2		0.031		-0.105		0.123
Indirect effects							
	nb_nodes	0.000	0.000	0.000*	0.000*	0.000	0.000*
	gdp (log)	-0.019	-0.039	-0.007	-0.098	-0.126	-0.240
	dird (log)	-0.008	-0.007	-0.052*	-0.043	0.022	0.022
	sub_region (log)	-0.001	-0.001	0.001	0.002	-0.003	-0.003
	sub_nat (log)	0.001	0.001	0.010	0.009	-0.013*	-0.013*
	sub_cee (log)	0.000	0.000	-0.001	-0.001	0.004*	0.004*
	KSI	-0.003		0.018		0.084	
	treatment_int	-0.017		0.239		-0.219	
	treatment_int * KSI1		-0.005		0.381**		-0.070
	treatment_int * KSI2		-0.044		0.113		-0.460**
Total effects							
	nb_nodes	0.000	0.000	0.000*	0.000**	0.000	0.000
	gdp (log)	-0.054	-0.067	0.215	0.076	-0.185	-0.281
	dird (log)	-0.007	-0.005	-0.066**	-0.053*	0.017	0.020
	sub_region (log)	-0.001	-0.001	0.001	0.002	-0.003	-0.003
	sub_nat (log)	-0.002	-0.002	0.020**	0.019**	-0.020**	-0.021**
	sub_cee (log)	0.000	0.000	-0.003	-0.003	0.005*	0.005*
	KSI	0.016		-0.037		0.149**	
	treatment_int	0.007		0.182		-0.163	
	treatment_int * KSI1		0.021		0.332*		-0.022
	treatment_int * KSI2		-0.012		0.007		-0.337*

Note: Statistical significance: *p< 0.10, **p< 0.05, ***p< 0.01

Regarding network efficiency, the French cluster policy had a negative total effect on the average path length in the innovation networks of all departments. This suggests an increase in network connectivity due to the cluster policy, making knowledge diffusion easier. This negative total effect on the average path length is more significant for highly specialised departments. In addition to the reduction of the average path length, highly specialised departments have also experienced a significant increase of their network's cluster coefficient due to the cluster policy (total effect). The cluster policy has therefore contributed to the reinforcement of the network efficiency in highly specialised departments. The small-world nature of the local innovation networks of those departments has been reinforced through the decrease of the average path length and the increase of the cluster coefficient. A complementary qualitative analysis has shown that specialised departments are essentially departments in which production and agricultural activities are predominant and whose innovation networks are relatively small compared to those of low-skilled departments. It therefore appears that the structuring effects of French clusters, in terms of network efficiency, are more observable in specialised regions. This may question the recent reorientation of the

French cluster programme towards big clusters, often located in the largest and more diversified areas. Thus, much more than the number of actors present in innovation networks, regional specialisation constitutes a key factor for the success of cluster policies. This finding therefore provides strong support for innovation network policies which support regional growth by building around existing place-based capabilities; besides cluster policies, such policies also include smart specialisation strategies (Balland et *al.*, 2018) for example.

Table 9 Marginal effects of SDM for network efficiency

		Log Clustering coefficient (ratio)		**Average path length (ratio)**	
		Model 1	Model 2	Model 1	Model 2
Direct effects					
	nb_nodes	0.000	0.000	0.000***	0.000***
	gdp (log)	6.521*	8.157**	0.199	0.136
	dird (log)	0.033	-0.147	0.010	0.015
	sub_region (log)	0.016	0.001	0.000	0.000
	sub_nat (log)	0.149	0.153	0.002	0.003
	sub_cee (log)	-0.089**	-0.086**	0.001	0.000
	KSI	-0.659		-0.042	
	treatment_int	-0.244		0.157	
	treatment_int * KSI1		-1.731		0.162
	treatment_int * KSI2		3.237		0.078
Indirect effects					
	nb_nodes	0.000	0.000	0.000	0.000
	gdp (log)	0.515	6.238	-0.480	-0.598
	dird (log)	-0.671	-1.220	0.122**	0.130**
	sub_region (log)	0.044	-0.006	-0.004	-0.002
	sub_nat (log)	0.328	0.325	-0.040**	-0.040**
	sub_cee (log)	-0.147	-0.130	0.021***	0.020***
	KSI	-0.187		0.087	
	treatment_int	5.350		-0.710**	
	treatment_int * KSI1		-0.159		-0.544
	treatment_int * KSI2		12.140*		-0.883**
Total effects					
	nb_nodes	0.000	0.001	0.000	0.000
	gdp (log)	7.036	14.395*	-0.281	-0.462
	dird (log)	-0.638	-1.367	0.132**	0.145**
	sub_region (log)	0.060	-0.005	-0.004	-0.003
	sub_nat (log)	0.477	0.478	-0.038**	-0.038**
	sub_cee (log)	-0.237**	-0.215**	0.021***	0.021***
	KSI	-0.846		0.044	
	treatment_int	5.106		-0.552*	
	treatment_int * KSI1		-1.890		-0.381
	treatment_int * KSI2		15.377**		-0.805*

Note: Statistical significance: *p< 0.10, **p< 0.05, ***p< 0.01

With respect to network resilience, we found that the French cluster policy has strengthened the assortative nature of the innovation networks for all departments, increasing the tendency of high-degree actors to interact with each other. Although the strengthening of collaborations between innovation actors is an advantage, the resilience of innovation networks also requires the strengthening of collaboration between core and peripheral actors in order to limit potential redundancy in knowledge flows and to allow the exploration of new ideas by peripheral actors and their exploitation by core actors (Cattani and Ferriani, 2008). The French cluster policy has not led to this, especially in low specialised departments for which we found a more significant positive effect on network assortativity. This result could be explained by the

fact that most of the calls for collaborative projects managed by French clusters are competitive in nature. These "winners-take-all" competitions have probably contributed to the strengthening of collaborations "between winners". To sum up, we found no evidence that the policy has contributed to make the local innovation networks more resilient, and even worse it has contributed to the reinforcement of collaboration between core actors, leaving peripheral actors on the margins.

Table 10 Marginal effects of SDM for network resilience

		Hierarchy		Assortativity	
		Model 1	Model 2	Model 1	Model 2
Direct effects					
	nb_nodes	0.000	0.000	0.000	0.000
	gdp (log)	-0.305*	-0.355*	-0.032	-0.106
	dird (log)	-0.021	-0.011	-0.011	-0.007
	sub_region (log)	-0.001	-0.001	-0.002*	-0.002
	sub_nat (log)	-0.012**	-0.013**	0.000	0.000
	sub_cee (log)	0.004*	0.004*	0.001	0.001
	KSI	0.032		0.001	
	treatment_int	0.093		0.049	
	treatment_int * KSI1		0.099		0.104
	treatment_int * KSI2		0.049		-0.115
Indirect effects					
	nb_nodes	0.000	0.000	0.000	0.000
	gdp (log)	-0.413	-0.603*	-0.223	-0.349
	dird (log)	-0.047	-0.044	-0.034	-0.013
	sub_region (log)	-0.006	-0.005	-0.005	-0.003
	sub_nat (log)	-0.002	-0.002	0.014	0.013
	sub_cee (log)	0.002	0.002	-0.005	-0.006
	KSI	0.198		0.016	
	treatment_int	0.033		0.554***	
	treatment_int * KSI1		0.326		0.677***
	treatment_int * KSI2		-0.337		0.437*
Total effects					
	nb_nodes	0.000	0.000	0.000	0.000
	gdp (log)	-0.719**	-0.958**	-0.255	-0.454
	dird (log)	-0.068	-0.055	-0.045	-0.020
	sub_region (log)	-0.007	-0.005	-0.007*	-0.005
	sub_nat (log)	-0.015	-0.015	0.014	0.014
	sub_cee (log)	0.006	0.006	-0.004	-0.004
	KSI	0.230*		0.017	
	treatment_int	0.126		0.603***	
	treatment_int * KSI1		0.425		0.781***
	treatment_int * KSI2		-0.289		0.322

Note: Statistical significance: *p< 0.10, **p< 0.05, ***p< 0.01

Finally, these are the findings on the effects on the geographical anchoring. At the local level, we found that the French cluster policy has a negative and significant total effect on the strengthening of collaborations between local actors from low specialised departments. This result is not intuitive since we would expect from place-based interventions such as cluster policies to strengthen collaboration between co-located actors (Bučar and Rissola, 2018) but

there are two possible explanations to this result. Firstly, low specialised departments suffering from a lack of innovative capabilities do not have a critical mass of innovative actors that would allow strategic collaborations to be formed at the local level very often. The second explanation of this result is related to the fact that some low specialised departments do not necessary suffer from a lack of innovative capabilities (for instance the western Paris region). The decrease of local collaboration in this type of departments could be the result of the involvement of local innovative actors in partnership with regional or national actors. This result is consistent with the observation made by Bernela and Levy (2017) on French clusters. While focusing on publicly-supported R&D projects, they find no impact of the geographical proximity on the likelihood that two partners interact within a collaborative project.

Table 11 Marginal effects of SDM for network geographical anchoring

		Share of local links		**Share of regional links**	
		Model 1	Model 2	Model 1	Model 2
Direct effects					
	nb_nodes	0.000**	0.000*	0.000	0.000
	gdp (log)	0.410***	0.348**	-0.115	0.091
	dird (log)	-0.017	-0.021	0.013	0.017
	sub_region (log)	-0.001	-0.002	0.001	0.000
	sub_nat (log)	0.010***	0.003	-0.007**	0.002
	sub_cee (log)	-0.002**	-0.001	0.001	-0.001
	KSI	-0.045		-0.036	
	treatment_int	-0.036		0.112*	
	treatment_int * KSI1		-0.148		0.129
	treatment_int * KSI2		-0.065		0.160
Indirect effects					
	nb_nodes	0.000***	0.000	0.000**	0.000
	gdp (log)	-0.123	0.261	-0.023	-0.110
	dird (log)	-0.017	0.034	0.004	-0.021
	sub_region (log)	0.003	0.004	-0.001	0.001
	sub_nat (log)	0.001	-0.009	0.001	0.008
	sub_cee (log)	-0.003	-0.004	0.005**	0.001
	KSI	-0.044		0.037	
	treatment_int	-0.041		0.016	
	treatment_int * KSI1		-0.387		-0.142
	treatment_int * KSI2		-0.090		-0.270
Total effects					
	nb_nodes	0.000*	0.000	0.000	0.000
	gdp (log)	0.287	0.609**	-0.138	-0.020
	dird (log)	-0.035	0.014	0.016	-0.004
	sub_region (log)	0.001	0.002	0.000	0.001
	sub_nat (log)	0.010	-0.006	-0.006	0.011
	sub_cee (log)	-0.005*	-0.005	0.006**	0.000
	KSI	-0.089		0.002	
	treatment_int	-0.077		0.129	
	treatment_int * KSI1		-0.535**		-0.013
	treatment_int * KSI2		-0.155		-0.110

Note: Statistical significance: *p< 0.10, **p< 0.05, ***p< 0.01

At the regional level, we found for all departments a positive and significant direct effect of the policy on the strengthening of regional collaboration. However, the total effect while remaining positive is no longer significant, suggesting that the strengthening of collaboration between actors from the same region is mitigated by their involvement in partnership with actors from other regions, and vice-versa. Indeed, this result is balanced with the complementary trend observed at the national level where the negative direct effects of the policy on the strengthening of national or interregional collaboration are also no longer significant when we look at the total effects. These findings highlight the existence of competition effects between regions since the benefits of strengthening the cluster policy in one region can be moderated by the intensity of the clustering in neighbouring regions. These competition effects may also explain the non-significance of the positive total effects on the density of local innovation networks. While assessing the German 'leading-edge cluster competition' policy, Lehmann and Menter (2018) found a similar result. Their result suggests that neighbouring cluster regions could suffer from the increased attractiveness of the promoted clusters.

4.5 Concluding remarks and policy implications

Clusters have emerged as important policy instruments in the past decades, requiring evidence to support them. Yet despite the growth of a body of literature evaluating cluster policies, the changes in the structure of innovation networks resulting from cluster policies remain unclear. The research conducted here has sought to empirically assess the structural effects of cluster policies by extending the spatial Durbin model to panel data. We investigated the effects of the French cluster policy on the structure of local innovation networks following four network topologies that may prove to be beneficial for regional innovation, namely embeddedness or connectivity, efficiency, resilience and geographical anchoring. Network embeddedness was defined as the overall network connectivity while network efficiency refers to the "small worldness" of innovation networks. With regard to network resilience, it characterises hierarchical and disassortative innovation networks; network geographical anchoring was assessed through their tendency to include links involving local, regional and national actors. Several conclusions related to each of these topologies can be drawn from this study.

Essentially, the results highlight a positive total effect of cluster policies on the efficiency of local innovation networks, especially in the case of highly specialised departments. By increasing the small-world nature of innovation networks from such departments, the policy has facilitated the establishment of collaborations and knowledge diffusion. In diversified regions which have achieved a critical mass in several specializations and which host major universities and

research centres, the additional effect induced by cluster policies on innovation networks is weak. This finding supports the argument that regions' technological specialisation is a key factor for the success of cluster policies (Porter, 2000). Indeed, even though a high degree of specialisation could make regions more prone to exogenous shocks, policymakers should ensure that there is a minimum degree of specialisation in a region before implementing a cluster policy in that region.

Despite these positive effects, cluster policies can lead to negative effects. The results indicate an adverse effect of cluster policies on the structure of innovation networks, especially in low specialised departments. In those departments, the French cluster policy has strengthened collaboration but mostly between central actors of the networks. This suggests that the reinforcement of collaboration between core and peripheral actors is not a systematic outcome of cluster policies. It is therefore crucial for policymakers to setup the right mechanisms to support such type of collaborations in order to reinforce the resilience of innovation networks. Though the underlying mechanisms need further exploration, recent studies suggest that implementing outreach actions in order to encourage collaboration between central and peripheral actors might be more effective than imposition of policy requirements (Rossi et *al.* 2016).

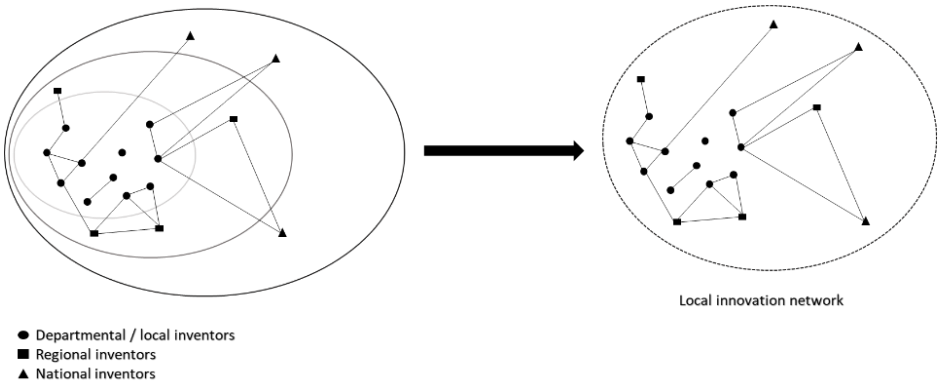
With respect to networks' embeddedness and their geographical anchoring (local, regional or national), our results do not allow us to identify any significant total effect of the French cluster policy. Although some direct positive effects have been observed on network density or on the regional anchoring of networks, the total effects are not significant. These results highlight the existence of a certain form of regional competition resulting from cluster policies. When a cluster is established within a region, the latter benefits from positive effects on its innovation network through the strengthening of collaborations between the innovation actors, particularly between local and regional actors in the case of the French cluster policy. However, those positive effects could be modified (increased, cancelled out or reduced) if clusters are also established within the other regions, in particular the neighbouring ones. Such competition may reinforce regional inequalities. Accordingly, as also pointed out by Lehmann and Menter (2018), the possible 'beggar-thy-neighbour' effects of cluster policies should be considered by policymakers when designing cluster policies. In practice, this would mean, for example, to evaluate *ex-ante* the impacts of implementing or strengthening a cluster policy within a region on neighbouring regions.

Although this study provides interesting results, it has some limitations that should be considered. As in the previous chapter, one main limit is related to the fact that patent data do not capture all collaborative processes. Therefore, our results should be corroborated by further empirical

analyses using primary data from surveys on collaborations. It should also be noted that the analyses carried out in this study lead to aggregated results that do not necessarily reflect the effects of each (French) cluster individually. Although this study makes it possible to draw overall conclusions, essentially based on average effects, a more detailed and qualitative analysis of each cluster and region could reveal some differences. Still at the methodological level, we also acknowledge that our results do not establish in-depth causal effects, opening the floor for future research in this direction. But despite these limitations, this study could serve as an insightful starting point for further investigations of the structural effects of cluster policies.

A.3 Appendices

A.3.1 Representation of local innovation network



A.3.2 Descriptive statistics of the control variables

Control variables	N	Mean	St. Dev.	Min	Max
nb_nodes	376	719.96	1,164.559	5.000	6,749
gdp (log)	376	16.351	0.879	14.234	19.028
dird (log)	376	11.194	1.715	5.599	15.144
sub_region (log)	376	2.318	5.311	-6.908	10.085
sub_nat (log)	376	7.824	2.394	-6.908	13.456
sub_cee (log)	376	3.924	4.958	-6.908	10.265
KSI	376	0.661	0.237	0.243	1.835

A.3.3 Correlation matrix of the control variables

		1	2	3	4	5	6	7
1	nb_nodes	1.000						
2	gdp (log)	0.727	1.000					
3	dird (log)	0.665	0.855	1.000				
4	sub_region (log)	0.276	0.407	0.441	1.000			
5	sub_nat (log)	0.587	0.739	0.813	0.471	1.000		
6	sub_cee (log)	0.434	0.647	0.753	0.364	0.676	1.000	
7	KSI	-0.480	-0.763	-0.748	-0.353	-0.654	-0.579	1.000

A.3.4 Subgroups of departments, based on KSI median value during the pre-policy period

Low specialised departments (KS1)	Ain; Alpes-Maritimes; Ardèche; Bouches-du-Rhône; Calvados; Charente-Maritime; Corrèze; Côte-d'Or; Drôme; Eure-et-Loir; Finistère; Gard; Haute-Garonne; Gironde; Hérault; Indre-et-Loire; Isère; Loir-et-Cher; Loire-Atlantique; Loiret; Maine-et-Loire; Manche; Meurthe-et-Moselle; Morbihan; Moselle; Nord; Oise; Pas-de-Calais; Bas-Rhin; Haut-Rhin; Rhône; Saône-et-Loire; Haute-Savoie; Paris; Seine-Maritime; Seine-et-Marne; Yvelines; Tarn; Tarn-et-Garonne; Var; Vienne; Yonne; Essonne; Hauts-de-Seine; Seine-Saint-Denis; Val-de-Marne; Val-d'Oise
Highly specialised departments (KSI2)	Aisne; Allier; Alpes-de-Haute-Provence; Hautes-Alpes; Ardennes; Ariège; Aube; Aude; Aveyron; Cantal; Charente; Cher; Côtes-d'Armor; Creuse; Dordogne; Doubs; Eure; Gers; Ille-et-Vilaine; Indre; Jura; Landes; Loire; Haute-Loire; Lot; Lot-et-Garonne; Lozère; Marne; Haute-Marne; Mayenne; Meuse; Nièvre; Orne; Puy-de-Dôme; Pyrénées-Atlantiques; Hautes-Pyrénées; Pyrénées-Orientales; Haute-Saône; Sarthe; Savoie; Deux-Sèvres; Somme; Vaucluse; Vendée; Haute-Vienne; Vosges; Territoire de Belfort

5 General conclusion

Innovation has been extensively studied over the last decades both by scholars and practitioners. Since Solow (1957), it is agreed that technological change and innovation are major driving forces behind growth and competitiveness. Furthermore, it has become increasingly recognised in the literature that knowledge spillovers may have an important impact on innovation processes and regional economic development. The analysis of the determinants of innovation has therefore become a crucial issue in the field of economics of innovation. This analysis deals with the production of innovation within organisations as well as territories or regions. The main analytical framework used to answer related questions is the knowledge production function (KPF) which relates the inputs or determinants of innovation to the output which is the production of innovation. In regional science, this function (regional knowledge production function – rKPF) has seen many advances both in terms of modelling methods and the types of inputs considered within the function. Since the recognition of the positive effects of collaboration on innovation, researchers and practitioners have widely acknowledged the importance of collaborative or innovation networks on the innovativeness of regions. However, the theoretical and empirical arguments in favour of the potential effects of innovation networks on regional innovation are not yet clearly established in the literature due to the complex mechanisms that characterise these networks. Policymakers are showing a growing interest in policies aiming at supporting collaborative innovation but the empirical evidence on the effects of innovation networks is scarce and still inconclusive. In Europe, for example, the European Commission notes that most European countries have implemented cluster-specific policies and programmes (20 out of 29 European sample countries according to the report from the European observatory for cluster and industrial change, 2019).

In light of the above, this dissertation has presented three essays on innovation networks, cluster policies and regional knowledge production. Our overall contribution can be summed up in the following points.

5.1 Theoretical contributions

Public intervention in favour of innovation is generally justified by neoclassical arguments. Indeed, the relatively high costs of research and development (R&D) activities, coupled with the uncertainty about the results of these activities and the limited ownership of innovations are factors that suggest that strict reliance on a market system would lead to under-investment in innovation, compared to the socially desirable level. In this vein, public policy instruments supporting innovation are generally designed with the aim to reduce a set of market failures

limiting private investment in innovation activities. This vision is now shared by most public interventions implemented to support innovation but given the benefits of collaborative innovation, the rationale of network-based innovation policies such as cluster policies has been extended and supporting collaboration has become a major concern for policymakers. However, the design (and the evaluation) of network-based policies is still focused on supporting collaboration with a view to reducing market failures (especially in order to internalise spillover effects) even though other benefits of collaboration can be expected (direct but also indirect access to knowledge, reduction of opportunistic behaviour, etc.). The implementation and evaluation of innovation policies should consider these benefits and identify the conditions that need to be met for them to take place. It is therefore in this context that this thesis has raised the importance of considering the structural properties of innovation networks. For example, while the Coleman's closure argument stresses the importance of redundant links or collaborations because they facilitate trust and reduce opportunism (Coleman 1988; 1990), Burt (1992) points out the advantages of structural holes which allow actors to have access to valuable and new resources. Both arguments are now considered as two different complementary rather than competitive mechanism. However, the risk and costs associated with bridging positions prevent them to be spontaneously created in sufficient numbers by the agents. Similarly, institutional distance may hamper collaborations between science and industry, leading to a suboptimal level of science-industry knowledge flows. Hence, there is a need for network-based policies to improve the overall structure of the networks. Indeed, we showed that network failures – which refer to the insufficient level of interaction between innovation actors and to the inefficiency of the networks characterising these interactions – are not just conceptual ideas but actual brakes that can hamper innovation especially at the regional level.

Thus, while the literature focuses mainly on public incentives for collaboration, there is a real need to take into account network failures as well. By assessing the contribution of cluster policies on the reinforcement of interactions between innovation actors on the one hand and on the structure of innovation networks on the other, the thesis contributes to put network failures at the centre of cluster actions. Indeed, the results of second and third essays (Chapters 3 and 4) show that the role of clusters can go beyond the neoclassical view concerning the role of public intervention to support innovation.

Thus, from a theoretical point of view, we claim that taking network failures into account in the design and analysis of innovation policies is crucial; the mere strengthening of collaborations does not necessarily result in optimal innovation network structures.

5.2 Empirical contributions

The structure of innovation networks matters for regional innovation: The first essay (Chapter 2) analyses the contribution of some structural properties of innovation networks to the production of innovation at the regional level (NUTS-3). To do so, the regional knowledge production function is revisited in order to respond to the main methodological limit of previous studies which failed to simultaneously take into account spatial autocorrelation and the endogeneity of the structural properties of innovation networks. By addressing this limit, we propose to shed light on the theoretical debate concerning the contribution of innovation networks. It emerges from this analysis that the structure of innovation networks matters for regional innovation. In other words, the inventiveness of a territory does not only depend on the internal human and financial resources mobilised for innovation; it also depends on the structure of the links among innovators. The analysis underlines in particular the importance of science-industry collaboration and points out the need to strengthen trust between co-located innovators through redundant interactions between them. Public interventions oriented in this direction are therefore necessary; this reinforces the relevance of cluster policies.

The role of cluster policies for enhancing innovation networks: Regarding cluster policies in particular, this thesis reveals that such policies have the potential to change the structure of innovation networks and therefore to tackle network failures. Our results overall suggest that while increasing the level of collaboration, cluster policies may not necessarily improve the structure of innovation networks, suggesting that only considering the strengthening of collaboration is not sufficient to maximise the impact of cluster policies. Thus, the design and evaluation of such policies should also consider network failures since increasing collaborations do not necessarily leads to most efficient networks.

The second essay (Chapter 3) assesses the effect of the French cluster policy on the collaborative behaviour of cluster participants (firms that have paid cluster membership fees) as well as their integration into innovation networks, over the period 2008-2010. Econometric methods of counterfactual analysis have been used to compare cluster participants to non-participants. The results obtained indicate a positive effect of the policy since cluster participants have significantly increased their co-invention rate, *i.e.* their propensity to be involved in collaborative research and development (R&D) projects. Over the studied period, cluster participants increased the share of collaborative projects by more than 4 percentage points and this result is strongly attributable to their membership. Our results also indicate that this increase was much higher for cluster participants who were weakly involved in collaborative R&D projects before joining clusters (approximately 6 percentage points). However, although the clusters have effectively supported companies in their participation in

collaborative projects, a very small proportion of these collaborations concern partnerships between co-located establishments. Furthermore, the involvement of cluster participants in collaborative projects has not resulted in the reinforcement of their embeddedness in innovation networks, indicating a certain redundancy of collaborations involving cluster participants.

The last essay (Chapter 4) examines the structural effects of the cluster policy. We were particularly interested in the impact of this policy on the structure of regional innovation networks over the period 2005-2010. We relied on spatial Durbin models in order to control for the interdependencies between regions. The conclusions of this study are multiple. Overall, the results highlight that the regions that have improved most their innovation networks from the policy are regions with areas of technological specialisation. For less specialised regions, the results indicate that the policy has mainly strengthened collaboration between the most central actors in the networks, excluding peripheral actors. This is an indication that the presence of agents spanning the structural holes is not systematic. Beyond these heterogeneous effects, we found out that cluster policies may lead to regional competition for the strengthening of innovation networks to the extent that strengthen the structure of innovation network in a region may weaken those of its neighbours.

5.3 Policy implications

Regarding the policy implications, we claim that market failures should no more be considered as the only motivation for innovation, especially in the case of cluster policies. Policymakers should not ignore the fact that the structure of innovation matters. From our point of view, this is all the more important for cluster policies (and more broadly for network-based policies) given that these policies are often implemented as structural and non-cyclical policies, with the aim of driving persistent behavioural changes and innovation dynamics.

- In this vein, we recommend a constant monitoring of the structure of the innovation networks in order to deeply understand how innovations actors behave when it comes to establishing collaborations. This will allow policymakers to implement relevant innovation policies, especially at the regional/local level.

To our knowledge, very few French territories have committed to this exercise. When it is the case, it is part of a wider operational approach of territorial technological intelligence. Nevertheless, we acknowledge that taking advantage of this awareness is not a straightforward task given the complexity dynamics characterising innovation networks. Based on the results of this thesis, policymakers should consider the following points:

- The effects of the structure of innovation networks on territories depend on the level of specialisation of that territories. Thus, the monitoring and analysis of regional innovation network should be undertaken with regard to the industrial evolution of the region as well as its degree of technological specialisation. This will enable policymakers to identify and address the most important network failures specific to their territory at a given time.
- A region's innovativeness is also influenced by the structure of innovation networks of other regions. This implies that local policymakers should also monitor the innovation networks of other regions, especially that of neighbouring regions. Indeed, our results show that there is competition between geographically close regions to strengthen their innovation networks. The French cluster policy, for example, has strengthened the structure of innovation networks in some regions to the detriment of those of their neighbours.
- Given the positive effect of reinforcing collaboration between co-located organisations, we claim that interregional or international collaboration, although important, should not be encouraged to the detriment of local and regional collaboration. Each of these forms of collaboration should receive special attention from policymakers. This is particularly important in France since the cluster policy tended to strongly reinforce collaborations between central actors.
- Although this is now widely recognised, our results pointed out the importance of science-industry collaborations. Policymakers should therefore continue the efforts undertaken in this direction while positioning them within a network perspective.

5.4 Limits and future research

The use of patent data is certainly one of the main limitations of the three studies as patents do not capture all the collaborative initiatives taking place between innovation actors. In other words, the innovation networks considered represent only an observable dimension of the interactions between actors. Analyses based on other types of data (surveys, data from social media networks, etc.) could help to deepen our understanding of innovation networks and their contributions. The inclusion of international collaborations would also contribute to this objective. In the same vein, while only science-industry collaborations have been investigated in the thesis, other types of collaboration, in particular collaborations between small and large enterprises as well as intra- or inter-sectoral collaborations are also important to understand the role of innovation networks and therefore for the implementation of network-based innovation policies.

Three avenues for future research can be drawn from the dissertation. Firstly, this thesis makes interesting methodological contributions, in particular through the articulation of social network

analysis and counterfactual evaluation methods, and by using various spatial analysis methods to account for the indirect spatial effects of public policies. Future research could therefore draw on this work to analyse the role of innovation networks and the impact of network-based innovation policies in other contexts in order to corroborate the conclusions we had made. Secondly, the articulation of innovation networks with other types of networks (commercial and financial interactions, labour mobility, etc.) will also shed new light on the spatial dynamics of collaborative innovation. This is all the more important because such networks would shape in some extent the structure of innovation networks. Last but not least, the theoretical literature is not conclusive yet about the characterisation of network properties as well as their implication for regional innovation. Theoretical future works should therefore pay particular attention to strengthening our understanding of the properties of networks that are beneficial to innovation depending on the context.

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