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Original Article

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

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Abstract

Whereas most collaboration-based innovation policies aim at fostering efficient ecosystems of innovation, evaluations of the behavioral impact of such policies remain few and far between. Relying on external-to-the-policy network data to build a counterfactual approach, this article 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.

JEL classification: O32, O38, D04

1. Introduction

The need for innovation actors to actively engage in collaboration and the benefits of the geographical concentration of firms and economic actors has largely contributed to the expansion of cluster policies across the world. By promoting collaboration, these policies aim not only at providing strong incentives to overcome suboptimal investment in collaboration but also at enhancing the local innovation ecosystem. The goal of cluster policies, therefore, goes beyond the mere desire to increase inter-organization collaboration and encompasses the construction of efficient knowledge networks.

Although social network analysis has long been concerned with analyzing the importance of network architecture on knowledge diffusion (Granovetter, 1985; Coleman, 1988; Burt 1992, 2008; Baum *et al.*, 2010), literature aiming to assess the effectiveness of cluster-based policies on network structure remains sparse[1] (Giuliani *et al.*, 2016; Calignano and Fitjar, 2017; Rothgang *et al.*, 2017; Lucena-Piquero and Vicente, 2019; Graf and Broekel, 2020).

1 A literature evaluating cluster policies (Falck et al., 2010; Martin et al., 2011; Mar and Massard, 2019; 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 largely overlooks behavioural additionality.

Indeed, in contrast to most subsidy-based policy evaluations, this literature does not employ a counterfactual analysis. It therefore sheds little light on the causal impact of cluster policies.

Combining program evaluation methods and social network analysis, this article contributes to this emerging literature. We are particularly interested in the impact of cluster policies on the intensity of collaborations, on their geographical scale and on the centrality of agents in the network. We study 116 establishments benefiting from the French cluster policy and construct a counterfactual sample of 931 establishments that are similar in terms of size, job structure, innovation, and industry. We match the data provided by the clusters with patent data from the French patent office (INPI - Institut National de la Propriété Intellectuelle) and individual company data. This combination of internal and external data is important. It allows us to assess the extent to which a cluster policy can change the features of an innovation network in comparison with what would have happened in the absence of the policy, while accounting for the fact that organizations which decide to join clusters are not necessarily comparable with those which do not. Our approach also departs from studies assessing the collaboration additionality of R&D subsidy policies (Afcha Chávez, 2011; Teirlinck and Spithoven, 2012; Antonioli *et al.*, 2014 and, more recently, Caloffi *et al.*, 2018). These survey-based approaches do not make it possible to obtain information about the network and therefore to address network additionality issues. Using external data also allow us to move from specific cluster case studies, often based on very few observations, to a broader cluster policy evaluation assessing the entire national cluster policy. We build innovation networks from patent co-invention data. This allows us to observe the features of both individual collaborations and the ego-network. We employ the latest econometric methods of counterfactual analysis to reveal changes in the collaborative and network behaviors of cluster participants.

The results obtained indicate that cluster membership has a positive effect: cluster participants significantly increase their tendency to be more engaged in collaborative projects. Over the studied period (2008–2010), cluster participants increased their share of co-patents by ~4.1 percentage points as a result of being involved in cluster activities. Our results also indicate that this increase was much higher (6.3 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 terms of providing support and leadership, 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 greater collaborative behavior, we found that the collaborative research projects carried out by cluster participants involved non-co-located partners. This suggests that French clusters have not significantly strengthened the establishment of collaborations between actors located in the same region (NUTS2 region). Regarding the embeddedness of cluster participants in collaboration networks, we found no evidence that the French cluster policy had had any significant effect, mainly due to the presence of redundant links. From our results, therefore, it appears that even though clusters positively affect the collaborative behavior of their participants, their local anchoring that is, clusters' ability to reinforce links between co-located organizations, as well as the embeddedness of cluster participants within collaboration networks is not systematic.

The remainder of this article is structured as follows. Section 2 recalls the rationale behind cluster policies and sets out the hypotheses tested in the article. Section 3 describes the characteristics of our dataset and Section 4 discusses our empirical strategy. The results are presented and discussed in Section 5. Finally, Section 6 draws some policy implications and proposes avenues for further research.

2. Rationales of cluster policies and resulting hypotheses

Based on the advantages of both R&D cooperation and favorable regional conditions such as Marshallian localization externalities (Asheim *et al.*, 2008) and sociocultural or institutional embeddedness (Rodríguez-Pose, 1998), cluster policies have ignited renewed interest and adaptations to an increasingly wide variety of contexts and countries.[2] According to the European Observatory for Clusters and Industrial Change (2019), the French cluster program is

2 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, and the Netherlands; OECD, 2010). More recently, the European Observatory for Clusters and Industrial Change (2019) stated that most EU countries implement a cluster policy and

one of the most developed, with the largest budget in Europe. In July 2005, the French government established 67 clusters in various fields including energy, mechanics, aerospace, transport, Information and Communication Technologies, health, environment, and ecotechnology. These clusters are non-profit organizations financed through public funding and members' contributions. Following the creation of new clusters and the merger of others over time, the number of clusters stood at 71 in 2014 and 56 today. Government support for the clusters mainly takes the form of (i) partial financing of cluster governance structures, alongside local authorities and members (public research organizations and firms), and (ii) granting of financial assistance to collaborative R&D projects emerging from clusters.[3] As is the case of most cluster policies, it aims at fostering collaboration between actors, with particular focus on 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."[4] Three interdependent dimensions of the cluster policies can therefore be identified, namely collaboration, geographical scope, and network. These are discussed below, with a particular focus on the specific goals of the French policy, from which we draw our main research hypotheses.

2.1 Cluster policy as a collaboration-based policy

The potential benefits of collaborative research are threefold (Hinloopen, 2001). First, by internalizing 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. Van Leeuwen (2002), Criscuolo and Haskel (2003), and Janz *et al.* (2003), for instance, found evidence of a positive correlation between R&D collaborations and innovation performance, highlighting the importance of collaborative projects. However, due to uncertainty and the asymmetry of information, organizations may interact poorly. This may hamper synergies, complementary know-how, creative problem solving and capacity sharing, and lead to the lack of a shared vision of future technological developments. This justifies the implementation of cluster policies that aim to encourage economic actors to engage in collaboration.

From this perspective, the French cluster policy provides incentives for collaborative research, through two types of tools[5]: direct R&D supports though the selection of projects involving different types of partners[6] and

compared the national cluster programmes in 20 EU countries and nine non-EU countries (USA, Brazil, Mexico, Israel, Taiwan, Singapore, China, Japan, and South Korea).

3 Note that the French cluster policy is not the most expensive area of state-funded innovation policies. The national innovation support system is essentially based on indirect aids through the research tax credit (*Crédit Impôt Recherche*), the cost of which amounted to €6.3 billion in 2015 that is, 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 have received 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 have been one of the major policy instruments (in terms of financial allocation) in 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 Companies (*Sociétés d'Accélération du Transfert de Technologies*) and the Technology Research Institutes (*Instituts de Recherche Technologique*) have also been implemented to support collaborative research, and strengthen science-industry collaboration and the transfer of technology.

4 It should be noted that in France, cluster members are actually firms' establishments where an "establishment" is defined as an independent production unit, with a physical location, but legally dependent upon 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 members while most of them are not.

5 In this respect, the French policy is fairly similar to the Japanese cluster policy. The German leading edge cluster competition also relies on these two tools.

6 Between 2005 and 2013, 1313 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).

non-financial support mainly targeted at small- and medium-sized enterprises (SMEs; training, partnership building, technical assistance, etc.). In order to benefit from these services, firms can choose to become members of the cluster, which involves paying an annual fee. These fees vary according to the size of the firms, from less than a thousand euros for very small firms to a tens of thousands of euros for larger ones. In 2014, the clusters had about 9650 company-level members (for 10,380 individual establishments) including 8500 private firms and 1150 public research organizations (Directorate General for Enterprise [DGE], 2017). Given these incentives, cluster policy participants would be more likely to be engaged in collaborative R&D projects than non-members, *ceteris paribus*. This behavioral change among the beneficiaries of the cluster policy should be observable in both their projects which are supported by the policy and in those which are not supported. Cluster policies should have a positive effect on the overall willingness of their members to collaborate, in 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 behavior of their members to hold true:

H1: Cluster policy participants are more engaged in R&D collaborations than non-participants

Very little evidence can be found on this issue in the literature. Studies considering the impact of public policies on collaborative behaviors have not looked at cluster policies but on regional, national, or international direct R&D support policies (Afcha Chávez, 2011; Teirlinck and Spithoven, 2012; Wanzenböck et al., 2013; Antonioli *et al.*, 2014; Caloffi *et al.*, 2015, 2018). Most of them point to the positive effects of financial support to R&D consortia on the intensity of collaboration or partner choices, although these effects do not occur systematically. Only Nishimura and Okamuro (2011) paid particular attention to cluster policies, also considering the role played by indirect coordination support. Their results point to the importance of such non-financial support for expanding R&D collaborations.

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 encourage local interactions. Since Marshall (1920), it has been agreed that the geographical concentrations of firms and economic actors can generate positive effects on economic growth in specific areas. It has also been shown, however, that proximity alone is not sufficient to achieve this. Proximity matters if it leads to a high level of interactions between actors (Autant-Bernard *et al.* 2013), enhancing the intensity of collaboration and knowledge flows between actors. As argued by Boschma (2005), these knowledge flows generate knowledge spillovers, innovation and, ultimately, regional growth.

For this reason, most cluster policies are implemented at the local level and put special emphasis 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 behavioral patterns and social interactions in the region. Lower levels of government, therefore, are needed to correct systemic dysfunctions linked to multi-level science, technology and innovation policies and they are in the best position to connect different stakeholders within the region. Sub-national government would also be able to tailor national and supra-national policies, guaranteeing consistency between the various directions taken by the region.

The French cluster policy was clearly built with this in mind and policymakers opted for a regional anchoring of clusters. This anchoring took the form of matching clusters' fields of specialization and the economic sectors present in the regions, as well as the research themes addressed by 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 national public financing. Thus, we put forward the following hypothesis:

H2: Cluster policy participants are more engaged in collaborations involving regional partners than non-participants

It is worth noting that this hypothesis does not imply that clusters are not also supposed to support collaboration with non-regional partners. Since most clusters are designed at a regional level, they are intended to support networking among regional organizations but also between regional and non-regional organizations. If cluster policy participants 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 regional anchoring of their members through collaborative innovation.

Although no specific assessment of the impact of cluster policies on local collaboration exists, some empirical evidence on this issue can be found that has taken into consideration other collaboration-based policies. Although analyzing the impact of the EU Framework Program on the intensity and geographical dimension of inter-regional collaborations, Scherngell and Lata (2012) observed that the effects of geographical distance and national borders 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 were more likely to cooperate with regional partners than extra-regional ones. The spatial scale of the collaborations induced by the policy therefore seems to be driven by the geographic scope of the policy.

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

2.3 Cluster policy as a network-based policy

Collaboration-based innovation policies, and cluster policies in particular, do more than simply address market failures. As pointed out by the literature on innovation systems (for an overview, see Bleda and del Rio, 2013), systemic failures also arise in the innovation process. Systemic failures refer to structural, institutional, and regulatory deficiencies, which lead to suboptimal investment in innovation activities. One of the main structural deficiencies is insufficient and/or inefficient levels of networking and knowledge exchange between organizations. 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 reduce search and enforcement costs, firms tend to renew ties with past partners and form ties with their partners' partners. They are generally reluctant to form bridging ties despite their potential benefits, since brokering induces greater risk, uncertainty, and costs. Network failures may thus occur and 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 cost of switching or, in the case of monopolistic or high-tech markets, a lack of alternative partners, actors may be "locked into" their relationships, which may reduce both private and social benefits.

This requires public actors to prioritize socially distant ties. This can be achieved by creating opportunities for new encounters between firms or between firms and public research organizations. This can also be encouraged by enhancing the visibility of local actors, who can then be identified by potential partners.

The various types of services provided by clusters could contribute to this goal by helping local organizations to increase their network embeddedness (Martin and Sunley, 2003). For instance, the French cluster policy (and most other cluster policies) appoints brokers and intermediaries to organize coordination between actors. This should improve the ability of actors to identify relevant networks. Cluster policies also 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.

In this respect, an effective cluster policy is a policy that modifies the position of the funded firms within the network of its relationships, making it more central (Everett and Valente, 2016). Our third hypothesis therefore aims at investigating whether there is actually a cluster premium regarding the embeddedness of cluster policy participants within networks of co-inventions. We put forward the following hypothesis:

H3: Cluster policy participants are better embedded in knowledge networks than non-participants

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 Lucena-Piquero and

Vicente (2019) contribute towards this line of research. These network-based approaches provide us with precise insights into the evolution of the structural properties of the subsidized network, pointing, for instance, to the emergence of more central agents or more hierarchical relationships. They do not, however, allow us to draw robust conclusions regarding the causal impact of the cluster policy. Although only relying on the network of beneficiaries, comparison of the pre- and post-treatment periods is not sufficient to identify the role played by the policy. Comparing various industries, Tomasello *et al.* (2017), observed some universal properties in the structural dynamics of R&D networks. Most of the changes in the collaboration and network features may thus occur 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 new communication technologies is likely to induce changes for firms both within and outside clusters. In addition, firms that have chosen to join clusters 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 program evaluation methods. Our empirical strategy will be described in Section 4 after we have set out information on the data.

3. Data and outcome variables

As detailed below in Section 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 characterize the collaboration and network behavior 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, members receive support from the cluster in terms of training and assistance in setting up collaborative R&D projects especially with searching for and networking with partners. More precisely, clusters organize events to put their members in contact with partners in France and abroad, they provide them with support services for their innovation activities (monitoring, search for financing, etc.), they involve them in think tanks and technological project emergence groups, and provide lobbying and networking activities in order to join ambitious structuring projects. In order to assess the impact of the policies on the beneficiaries of R&D collaboration and network behavior, we need to observe the network of knowledge collaboration of both beneficiaries and non-beneficiaries. However, obtaining an exact list of organizations' 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 to 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 their use varies widely according to firm size and industries). However, patents remain one of the best indicators available to researchers for studying collaboration. By focusing on patent data, we put special emphasis on knowledge networks. This is consistent with the French cluster policy, the main goal of which is to reinforce R&D collaborations in order to strengthen local innovation ecosystems. Although patents are not the only output of R&D projects supported by cluster policies, the evaluation study ran by Erdyn, Technopolis and BearingPoint (2012) estimates 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 completed projects supported by this cluster, 107 led to the creation of one or more new products and 57 resulted in one or more patent applications. Patents thus appear as an important outcome of the French policy. Moreover, using patent data allow us to locate each invention and therefore to identify the spatial scope of collaborations.

However, other types of collaborations may result from cluster policies. Policy makers can try to encourage the various types of externalities likely to arise within clusters, such as input–output linkages, access to demand, and labor occupation linkages (Marshall, 1920). For instance, Delgado *et al.* (2014) show 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 that go 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.

3.1 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 3-year lag between the beginning of R&D projects and patent applications. The choice of this 3-year lag is justified by the average duration of Research & Development (R&D) projects supported by clusters through the FUI (Fonds Unique Interministériel), 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 3–5 years from the end of projects. Thus, within the FUI scheme, several clusters support R&D projects with an average duration of 3 years[7] 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 3-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 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 3-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 3-year periods: 2005–2007 and 2008–2010, which are respectively the pre- and post-treatment periods. Our treated population is, therefore, firms' establishments involved in clusters between 2008 and 2010, but not before 2008.

Primary patent data provide 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 organizations/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 that is, 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 organization employing each inventor following this assumption:

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

This assumption relies on the fact that the majority of inventors are employed by an organization (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 organization'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 8 km of their home (Baccaïni *et al.*, 2007). For employees whose workplace is not in their commune of residence, the

7 The duration of projects often varies between 24 and 48 months.

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 and Levy, 2016).

By combining both assumptions, we translate collaboration networks among organizations 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 article is on between-firm linkages only as we are interested in testing external collaborations facilitated by the cluster policy.

3.2 Characterizing 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 analyze the collaborative and network behavior 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 types of organizations (private or public) when computing these rates. Therefore, establishments' partners are not limited to establishments owned by private organizations. These rates are our outcome variables. The co-invention rate is formulated as follows:

$$co.invention\ rate_{i,t} = \frac{coinv_{i,t}}{inv_{i,\ t}}, \tag{1}$$

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 organization.

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:

$$intra.regional\ co.invention\ rate_{i,t} = \frac{intra.regional.coinv_{i,t}}{inv_{i,\ t}}, \tag{2}$$

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 organization.

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:

$$C_D(i) = \deg(i) \tag{3}$$

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:

$$C_B(i) = \sum_{j \neq i \neq k} \frac{g_{jk}(i)}{g_{jk}} \tag{4}$$

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[8] database. We retrieved from this database the establishments' number of employees as well as their qualifications. The final sample included 1047 establishments owned by private for-profit organizations.[9] These 1047 private establishments included 116 which were treated (they had been cluster policy participants for at least 1 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 member of any of the cluster built by the policy. In order to avoid bias due to indirect policy 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 Beneficiaries versus non-beneficiaries' characteristics

All the baseline characteristics as well as the outcome variables before benefiting from the cluster policy are listed in Table 1, along with their mean and standard deviation, and their proportions (for categorical variables) in both populations.

From Table 1, 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 with 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.

4. Empirical strategy

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 that is, the outcome if participants had not participated in the program, 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 that is, 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:

$$Y_i(Z = 1, X) - Y_i(Z = 0, X), \tag{5}$$

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

8 The DADS database (Déclaration annuelle des données sociales) is administered by the French National Institute of Statistics and Economic Studies. It provides employment information on the French directory of firms' establishments. Geographic information (address) from the DADS database was supplemented with data from the free online business directory *www.societe.com*.

9 Our final dataset only contains establishments with complete information that is, those that have no missing data in the DADS database.

Table 1. Baseline characteristics of treated and control subjects in the original sample

Variable	Cluster policy participants	
	No ($N = 931$)	Yes ($N = 116$)
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%)
SMEs	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%)
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 (174,498.06)

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

estimation procedure used in this article is based on the combination of Inverse Probability of Treatment Weighting (IPTW) with the double-difference approach.

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 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 randomized 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 that is, $e(X) = P(Z = 1|X)$. 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":

$$P(Z = 1|X_i) = \Phi\left(\sum_{k=0}^{K} \beta_k X_{ik}\right), \tag{6}$$

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 generalized boosted models (GBMs). 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 *et al.*, 2017) to estimate the propensity score by modeling:

$$g(X_i) = logit(e(X_i)) = \log\left(\frac{e(X_i)}{1 - e(X_i)}\right), \tag{7}$$

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 generalized boosted-regression modeling 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 generalized 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:

$$w_i = Z_i + \frac{(1 - Z_i)e_i(X)}{1 - e_i(X)}, \tag{8}$$

Equation (8) 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 1000 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 standardized mean difference (SMD) to assess the balance in baseline characteristics between treated and control groups (Austin and Stuart, 2015; Caloffi *et al.*, 2018). Although there is no consensus as to what value of a SMD can be considered as an indication of imbalance, several authors have suggested that a SMD 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 randomized 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:

$$\left(\overline{Y}_{i(Z=1),\ t=1} - \overline{Y}_{i(Z=1),\ t=0}\right) - \left(\overline{Y}_{i(Z=0),\ t=1} - \overline{Y}_{i(Z=0),\ t=0}\right) \tag{9}$$

We base our estimation procedure on the first difference that is, 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:

$$\Delta Y_i = Y_{i,\ t=1} - Y_{i,\ t=0} = \alpha + \delta_{ATT} Z_i + \varepsilon_{i,t} \tag{10}$$

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):

$$\hat{\delta_{ATT}} = \frac{\sum_{i=1}^{n} Z_i \Delta Y_i}{\sum_{i=1}^{n} Z_i} - \frac{\sum_{i=1}^{n} (1 - Z_i)\Delta Y_i e(X_i)/(1 - e(X_i))}{\sum_{i=1}^{n} (1 - Z_i) e(X_i)/(1 - e(X_i))}, \tag{11}$$

4.3 Control variables

The literature on cluster policy evaluation suggests that qualitative methods could be a better approach for evaluating behavioral additionality (Falck *et al.*, 2010). This is partially due to the fact that changes in establishments' behavior could also come from their participation in subsidized 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).[10] This measure is a dummy variable constructed as follows:

$$collaborative\ establishment_{i,t=0} = \begin{cases} Yes,\ if\ co.invention\ rate_{i,t=0} > 0 \\ No,\ otherwise \end{cases} \tag{12}$$

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, FP is likely to affect firms' collaborative behavior 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 FP during the post-policy period (2008–2010)[11]:

10 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 members to be more likely to receive subsidies for collaborative R&D projects (Broekel et al., 2015) and therefore being more collaborative.

11 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 behavior.

$$FP_{i,t=1} = \begin{cases} Yes, \ if \ establishment's \ firm \ participate \ in \ FP \\ No, \ otherwise \end{cases} \tag{13}$$

We extended our response model from Equation (10) to take into account establishments' collaborative behavior before joining clusters and their participation to FP 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 behavior, 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 (WLSs) regressions and heteroskedasticity robust standard errors. We provide a counterfactual assessment of both collaboration and network behavior additionality. A robustness check and a sensitivity analysis to "unmeasured confounding" are provided in Supplementary Appendix. We conclude from this analysis that unmeasured confounding would not produce significant change in the conclusion of the study.

5. Empirical results

5.1 Propensity score results and balancing the sample

As explained in Section 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 that is, the probit regression, achieved the best balance in baseline covariates (see Supplementary Appendix Table SA6 and Figures 2 to 7). Therefore, the results presented in this section are based on that model.

Before presenting the treatment effect results, let us start by analyzing the results of the probit regression estimating the treatment assignment. Table 2 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 organizations doing research. Bellégo 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 member.

Results of the propensity score model also reveal that establishments of micro-enterprises, and 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.[12]

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 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.

12 According to the Directorate General for Enterprise (DGE, 2017), in 2014, 87% of cluster member firms are SMEs, half of which (53%) are micro-enterprises (employing fewer than 10 people).

Table 2. Propensity score model (simple specification)

	Probit	
	Coefficient (SE)	Marginal effect (SE)
Constant	−3.553 (0.653)***	
Log (size)	0.292 (0.052)***	0.041 (0.007)
Highly qualified employees	3.555 (0.971)***	0.505 (0.139)
Highly qualified employees^2	−3.576 (1.166)***	−0.508 (0.170)
Number of inventions	0.002 (0.001)	0.000 (0.000)
Firm's type of establishment, compared with large enterprises		
Micro enterprises	1.501 (0.424)***	0.440 (0.181)
Intermediate-sized enterprises	0.222 (0.154)	0.033 (0.025)
Small- and medium-sized enterprises	0.614 (0.193)***	0.106 (0.041)
Technological intensity, compared with high-technology		
KIS	−0.526 (0.235)**	−0.060 (0.021)
LKIS	−0.630 (0.289)**	−0.063 (0.019)
Low technology	−0.307 (0.257)	−0.036 (0.025)
Medium-high technology	−0.609 (0.217)***	−0.077 (0.025)
Medium-low technology	−0.617 (0.239)***	−0.068 (0.021)
Regional dummies	Considered	
Aldrich-Nelson R^2	0.1	
McFadden R^2	0.1	
Cox-Snell R^2	0.1	
Nagelkerke R^2	0.2	
Likelihood Ratio Chi^2 (33 variables)	100.1	
Prob > Chi^2	0.0	
Log-likelihood	−314.5	
Deviance	628.9	
Akaike information criterion (AIC)	696.9	
Bayesian information criterion	865.4	
Number of observations	1047	

Note: Statistical significance: $^{**}P < 0.05$, and $^{***}P < 0.01$.

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 1 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 neutralizing 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 1, our weighting process based on propensity scores from the probit model (simple specification) considerably improves balance in the sample. Even though the non-parametric GBM 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.

5.2 Effect of French clusters and discussion

Table 3 shows that cluster policy participants exhibit, on average, an increase of about 0.034 that is, 3.4 percentage points, in their co-invention rate. After controlling for participation in the FP and the pre-policy behavior of establishments towards collaboration, the effects of cluster policy participation on establishments' co-invention rate rises to

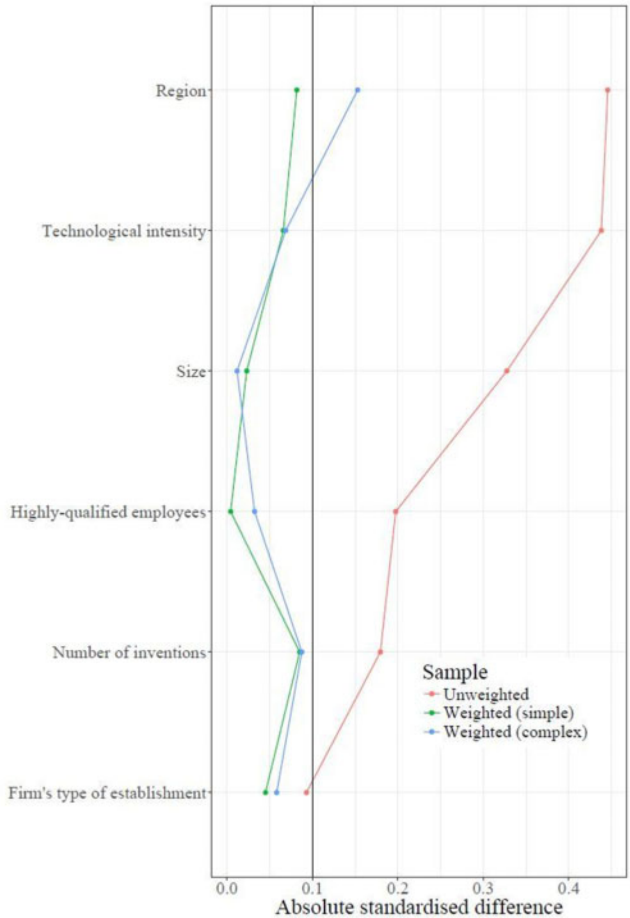

Figure 1. Balance in baseline characteristics according to the sample specification.

0.041 that is, 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 behavior. This result provides evidence for a behavioral 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 criticized regarding their input and output additionality (Duranton, 2011; Vicente, 2014), this result supports the ability of cluster policies to influence collaborative behavior.

When compared with 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 Chávez (2011) or by several studies focusing on regional supports to R&D collaboration (Afcha Chávez, 2011 in Spain; Tierlinck 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-subsidized 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 (Table 3). 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 Supplementary Appendix) reveals that our result is not highly sensitive to the presence of unmeasured

Table 3. Effects on collaboration and intra-regional collaboration

Dependent variable:	Change in co-invention rate				Change in intra-regional co-invention rate			
	WLS (1)	Survey-weighted (robust SE) (1')	WLS (2)	Survey-weighted (robust SE) (2')	WLS (3)	Survey-weighted (robust SE) (3')	WLS (4)	Survey-weighted (robust SE) (4')
Constant	0.002 (0.008)	0.002 (0.007)	0.027 (0.008)***	0.027 (0.008)***	0.0004 (0.005)	0.0004 (0.005)	0.007 (0.005)	0.007 (0.006)
Treatment	0.034 (0.011)***	0.034 (0.019)*	0.041 (0.011)***	0.041 (0.018)**	0.009 (0.007)	0.009 (0.011)	0.010 (0.007)	0.010 (0.010)
Collaborative establishment = *Yes*	–	–	−0.127 (0.013)***	−0.127 (0.026)***	–	–	−0.022 (0.008)***	−0.022 (0.022)
FP = *Yes*	–	–	0.038 (0.017)**	0.038 (0.022)*	–	–	−0.011 (0.011)	−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
AIC		387.957		293.631		−570.477		−575.201
Residual SE	0.085		0.081		0.054		0.054	
F statistic	9.230***		37.605***		1.521		3.419***	

Note: Statistical significance: $^{*}P < 0.10$, $^{**}P < 0.05$, and $^{***}P < 0.01$.

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 FP projects and establishments' co-invention rate. As expected, this provides evidence as to the role of the EU FP in affecting firms' collaborative behavior through the support of collaborative R&D projects between organizations across Europe. Interestingly, we observe a negative and significant correlation between the collaborative behavior 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 with 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 Section 5.3.

As discussed earlier, 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 organizations from the region to which cluster policy participants belong. Although recent literature on geography of innovation suggests that inter-regional 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 organizations 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 inter-regional collaborations were encouraged. It would seem that the strengthening of inter-regional collaborations has been to the detriment of intra-regional collaborations. This could be damaging for innovation, since collaborations with proximate partners are those who favors most the innovative output (Hazır *et al.*, 2018). 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).

Furthermore, we observed no significant effect on network embeddedness variables, namely the degree centrality and the betweenness centrality (Table 4). 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 polarization and centralization of the network. In the French context, Lucena-Piquero and Vicente (2019) find that the structure of the Aerospace Valley cluster has moved from a highly hierarchical structure, centralized 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 program, 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 3), this insignificant effect on network embeddedness could be explained by the fact that cluster policy beneficiaries collaborate with almost the same

Table 4. Effects on network embeddedness

Dependent variable								
	Change in degree centrality				Change in betweenness centrality			
	WLS (1)	Survey-weighted (robust SE) (1')	WLS (2)	Survey-weighted (robust SE) (2')	WLS (3)	Survey-weighted (robust SE) (3')	WLS (4)	Survey-weighted (robust SE) (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		−11,881.370		−11,875.710
AIC		6199.472		6191.103		23,766.730		23,759.420
Residual SE	1.369		1.362		6022.362		5995.646	
F statistic	1.025		4.477***		3.361*		4.908***	

Note: Statistical significance: $^*P < 0.10$, $^{**}P < 0.05$, and $^{***}P < 0.01$.

Table 5. Treatment heterogeneity

Change in co-invention rate		
	WLS (1)	Survey-weighted (robust SE) (1')
Constant	0.0003 (0.008)	0.0003 (0.007)
FP = *Yes*	0.016 (0.018)	0.016 (0.022)
Treatment × collaborative establishment = *No*	0.063 (0.012)***	0.063 (0.020)***
Treatment × collaborative establishment = *Yes*	−0.042 (0.017)**	−0.042 (0.041)
Observations	1047	1047
R^2	0.042	
Adjusted R^2	0.039	
Log likelihood		−174.130
AIC		356.259
Residual SE	0.084	
F statistic	15.235***	

Note: 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.

[and]Statistical significance: $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

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.[13] 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 article, 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 Section 5.3. Finally, the 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 organizations' embeddedness in collaboration networks are not systematic.

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 behavior towards collaboration. Such an 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 behavior of an establishment (Table 3), 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 behavior of establishments towards collaboration (*collaborative establishment*) and formally tested for effect heterogeneity (Table 5). 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.

13 We owe this point to one of the anonymous reviewers.

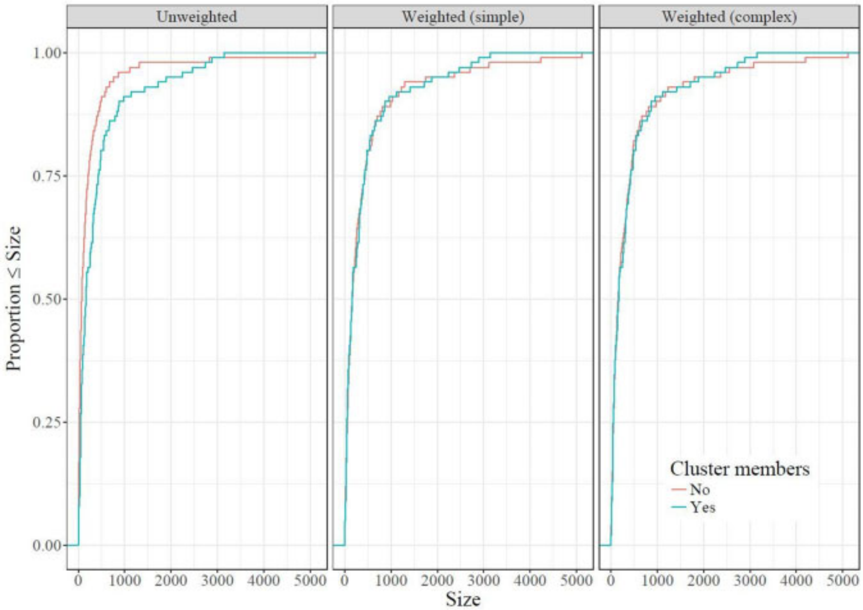

Figure 2: Balance in baseline characteristics after weighting: cumulative distribution of size

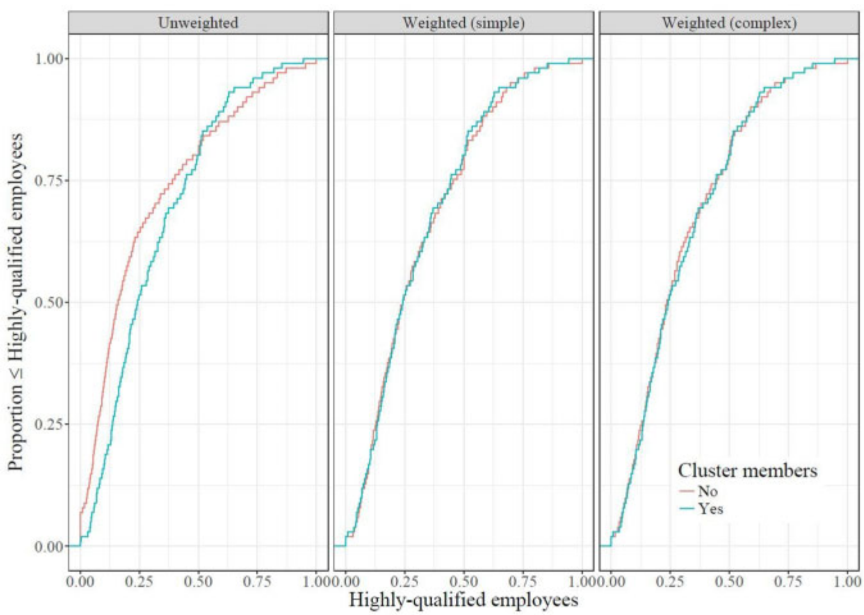

Figure 3: Balance in baseline characteristics after weighting: cumulative distribution of highly-qualified employees

In addition to the positive effect of cluster policy participation on the co-invention rate initially observed (Table 3), Table 5 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

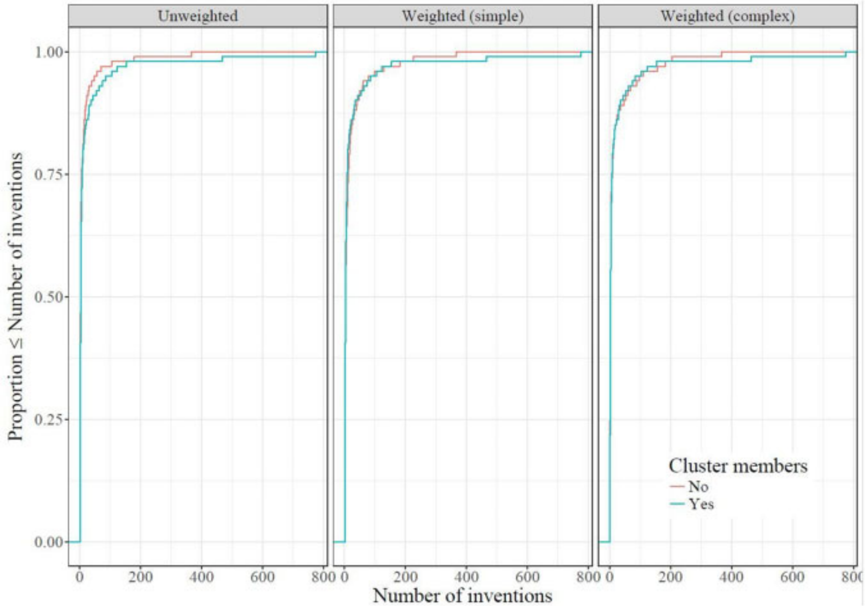

Figure 4: Balance in baseline characteristics after weighting: cumulative distribution of number of inventions

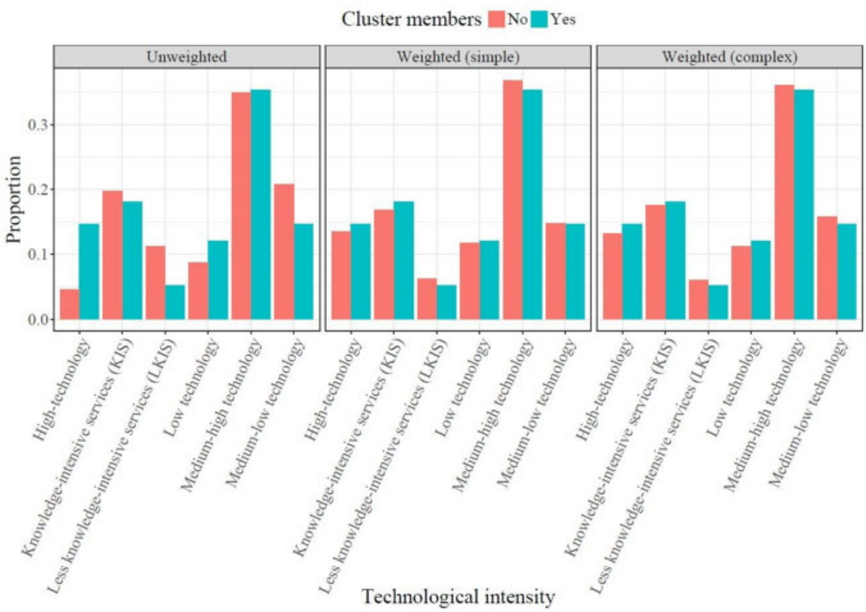

Figure 5: Balance in baseline characteristics after weighting: technological intensity

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 behavior of organizations, 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

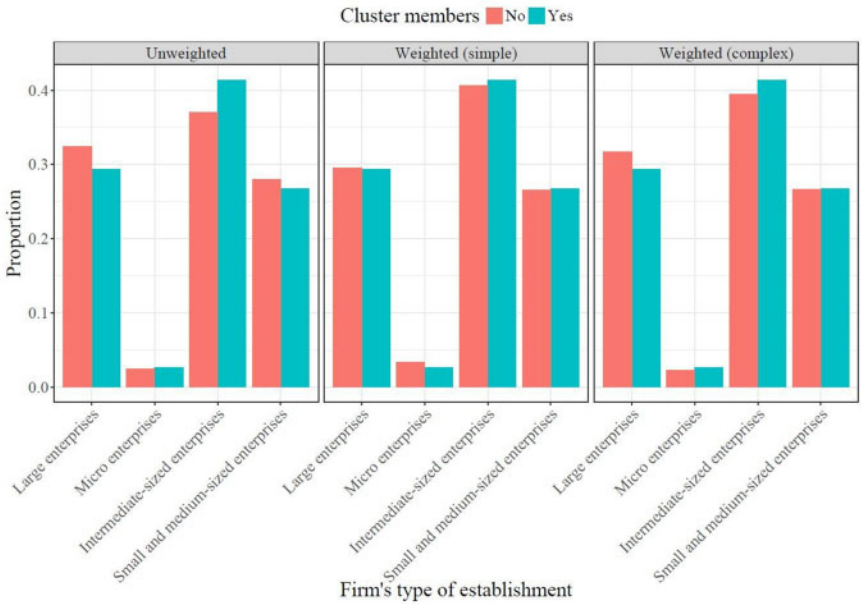

Figure 6: Balance in baseline characteristics after weighting: firm's type of establishment

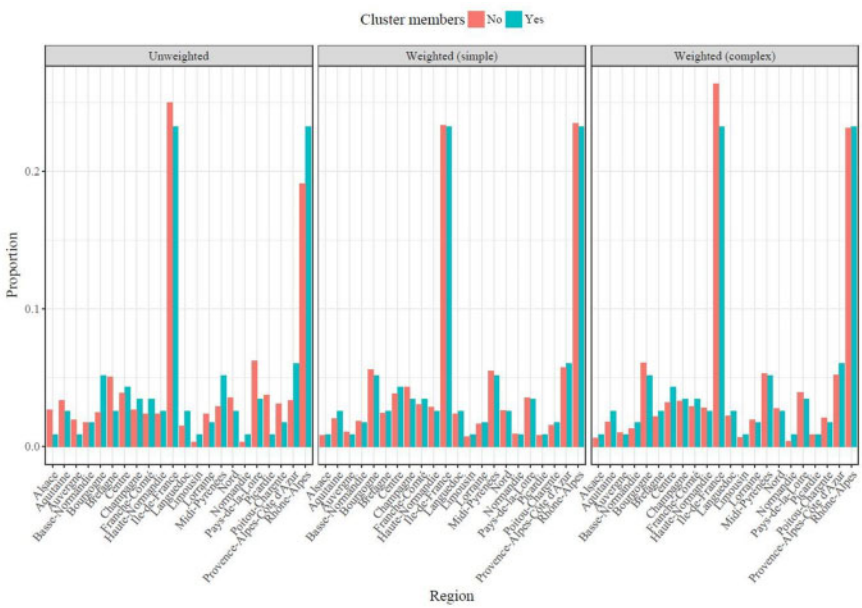

Figure 7: Balance in baseline characteristics after weighting: region

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).

6. Conclusion

This article aimed to investigate the extent to which cluster policies favor collaboration and induce network additionality. Focusing on the French national cluster policy and on the collaborative behavior of cluster policy participants during the period 2008–2010, our 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 organizations, and (H3) to assess whether policy beneficiaries are more embedded in networks of co-inventions. We combined the IPTW with a DD estimator in order to address the causal effects of cluster policy participation on firms' establishments. Though the results remain somewhat specific to the French context, this policy is one of the most intensive in the world, as France has the highest budget in Europe set aside for a national cluster program. We can, therefore, consider this policy to provide a relevant field experiment to assess the potential impacts of other national cluster policies.

The main point of this study is that the local anchoring of clusters that is, their ability to reinforce links between co-located organizations, as well as the embeddedness of cluster policy beneficiaries in collaboration networks is not systematic. Indeed, our empirical findings suggest, on the one hand, that firms benefiting from the cluster policy, especially those with little or no prior experience in collaborations, become more open to collaboration, albeit not necessarily with regional actors. On the other hand, cluster policy participants did not show stronger embeddedness into networks of co-inventions than non-participants, either quantitatively (by increasing the number of direct partners) or qualitatively (by acting as "bridge" between other establishments).

Therefore, while actors' positions within networks have been proven to be strongly correlated to the actors' level of performance (Zaheer and Bell, 2005; Baum *et al.*, 2010), the various types of services provided by clusters to promote network embeddedness do not necessarily contribute towards this goal, at least in the short term.

This claim has a number of policy implications particularly concerning 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 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 aim to tackle when designing cluster policies. If this is not the case, it will 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 stronger support to cluster policy participants with finding new local, national, or foreign partners or, conversely, raising awareness of local industrial specialisms in order to make local firms more likely to be asked to enter national and international partnerships. For instance, following Martin and Sunley (2003), 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. Moreover, a systematic evaluation of the various tools to promote such network embeddedness should be performed. It remains, for instance, unclear whether the financial incentives offered to R&D collaborations perform better than the indirect support provided within clusters. Moreover, this indirect support encompasses a plurality of ways of linking innovation actors to one another. Substantial work remains to be done to identify the most effective methods. The creation of places for the co-production of knowledge would perhaps be more likely to remove the obstacles to sharing of knowledge than encounters arising from standard events (visits, conferences, or training) organized by the clusters.

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 of time 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 these are increasingly perceived as a means of enhancing knowledge transfers from research institutions to industry. Finally, it should be noted that the analyses presented in this article lead to aggregated results that do not necessarily reflect the situation in each individual (French) cluster. 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.

Supplementary Data

Supplementary materials are available at *Industrial and Corporate Change* online.

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