Structural effects of cluster policies: Evidence from France

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Extended abstract - Very first draft

Background
Since the late 1990s, cluster policies have certainly been the most implemented innovation policies in Europe to support collaborations in R&D activities. The Basque Clusters Program with a dozen clusters (in progress since 1991), the Danish Clusters Program with 22 clusters (in progress since 2006) or the Competitiveness Clusters in France with 71 clusters (in progress since 2005) are some examples, among many others.

The classic arguments justifying public intervention in favour of innovation revolve around the will of public authorities to reduce the market failures limiting private investment in innovation activities. Indeed, high costs of the R&D activities, investments with long pay-back times, limited appropriability of returns on innovation, and other factors suggest that strict reliance on a market system will result in underinvestment in innovation, relative to the socially desirable level. These failures can still be used to justify public intervention for supporting network-based innovation policies especially clusters policies. However, this latter type of intervention mainly relies on network failures which can be described as the insufficient and/or inefficient levels of networking and knowledge exchange between organisations (Vicente, 2014).

Despite this dual incentive for cluster policies, most evaluations have been largely 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). In this literature, authors assess the effects of cluster policies on organisations innovation inputs (R&D expenditures) or on their outputs (productivity, patents, employment, etc.). Few research studies have examined the effects of cluster policies regarding network failures and the literature on this issue remains embryonic (Nishimura and Okamuro, 2011b; Giuliani et al., 2016; Cantner et al., 2017).

Given that cluster policies are primarily implemented to address network failures, it is necessary to evaluate how such policies influence the structuration of innovation networks.

Conceptual framework and research questions

Conceptual framework
In this paper, we study the effects of the French cluster policy on the structure of innovation networks during the period 2005-2010. Our goal is to identify how this policy has influenced the local (NUTS3) innovation networks in France. To the best of our knowledge, this is the first study to empirically evaluate a cluster policy regarding its effects on the structure of territorial innovation networks.

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Galaso (2018) argued that local social capital may be embedded in the network of relations connecting individuals. Accordingly, he proposed to identify local social capital with the network topologies that may generate externalities to local actors and strengthen local performance.

Following this reasoning, we identified four network configurations (topologies) that can foster innovation at the local level: embeddedness or connectivity, efficiency, resilience and geographical anchoring. Our analysis is focused on these topologies.

**Embeddedness**

Recent studies indicate 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; Giuliani, 2007). 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 (Nootenboom and Klein-Woolthuis, 2005).

**Efficiency**

As discussed above, collective learning is a prerequisite for innovative regions and takes place in networks with high connectivity. While such 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\(^1\) 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 and a short path length combines the advantages of efficiency and embeddedness. Fleming et al. (2007) have empirically demonstrated the positive effects of short path length and a high clustering coefficient on regional innovativeness.

However, it is worth noting that the literature reports divergent but complementary views about clustering since it implies redundant links (Scholten, 2006). While the Coleman’s closure argument stresses the importance of redundant links 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. We therefore consider that the absence of redundant links due to a low level of clustering between actors is not a systematic evidence of network inefficiency.

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\(^1\) The geodesic distance between two nodes in a network is the number of edges in a shortest path connecting them.
Resilience

Most of the previous studies exploring the relation between network structural properties and regional innovation were 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 resilience property in presence of hierarchy and disassortativity. 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.

Geographical anchoring

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, 2012). 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.

Research questions

Following the above discussion, four questions will be explored in this study:

Q1: Do cluster policies increase the connectivity in local innovation networks?

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

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

Q4: Do cluster policies reinforce and expand the geographical anchoring of local innovation networks?

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

Few comments on the French cluster policy

The French cluster policy was launched in 2005 to raise the innovative capacity of France. This policy is part of a large industrial ambition in France aiming at a better combination than in the past, of innovation and industry within territories. 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 therefore intended to actively support networking between establishments of firms, universities and research organisations mainly at the regional level (NUTS2). However, since 2009, clusters are also encouraged to increase networking between their members and actors from other regions.

Methodology

Step 1: Definition of local innovation networks and treatment intensity

Innovations networks are based on patent applications submitted to the French patent office (INPI) over the period 2002–2013. We use a three-year lag between the beginning of R&D projects and patent applications. 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: 1999–2001, 2002–2004, 2005–2007 and 2008–2010.

The local innovation networks for 94 NUTS3-regions (departments) were defined during each of these periods. This results in a set of 376 (94 \times 4) networks. The local innovation network of each department was built using all the patents involving at least one inventor belonging to the department. Therefore, the resulting networks is constituted by local but also non-local inventors. By construction, if present in a local innovation network, non-local inventors have at least one direct connection to local inventors (see Figure A).

Figure A: Local innovation network

Cluster members are unevenly distributed throughout the country. We therefore defined the treatment intensity for each department as the ratio of the number of cluster members 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 first two periods.

Step 2: Outcomes variables

A set of 10 outcome variables were selected in order to characterise the four network topologies of interest. The selection of these outcome variables is based on how well they describe the selected topologies on the one hand, and how well-established they are in the literature on the other. All the variables were computed from the local innovation networks defined in Step 1. This yields a panel data set that spans four periods.
Table 1  Outcome variables

<table>
<thead>
<tr>
<th>Network topology</th>
<th>Outcome variables</th>
<th>Definition and rationale</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Embeddedness</td>
<td>Density</td>
<td>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 (Monge et al., 2008). This may lead to a reduction of the risk of adopting collaborative solutions to an increase in trust and cooperation. Moreover, information in dense networks can flow more easily than in sparse or fragmented networks.</td>
<td>Wasserman and Faust (1994)</td>
</tr>
<tr>
<td></td>
<td>Fragmentation index</td>
<td>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. Fragmentation therefore occurs when two nodes belong to different, unconnected components of the network.</td>
<td>Giuliani et al., 2016 Ter Wal, 2013</td>
</tr>
<tr>
<td></td>
<td>Share of the network’s main component</td>
<td>The share of the network’s main component is the ratio of 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.</td>
<td>Cantner and Graf, 2006 Casper, 2007 Fleming and Frenken, 2007 Ter Wal, 2013</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Clustering coefficient ratio</td>
<td>The large clustering coefficient displayed by small-world networks is 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 (Granovetter, 1985; Coleman, 1988)</td>
<td>Uzzi and Spiro, 2005 Ter Wal, 2013</td>
</tr>
</tbody>
</table>

2 For details on the computation of outcome variables, please see the references.
<table>
<thead>
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<th>Outcome variables</th>
<th>Definition and rationale</th>
<th>References</th>
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<tbody>
<tr>
<td></td>
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<td>which in turn promotes collaboration and facilitates risk sharing, resource pooling, and information diffusion.</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>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.</td>
<td></td>
</tr>
</tbody>
</table>
| (average) Path length ratio | Low path length increases network connectivity, and so it makes easier knowledge circulation and transmission. Fleming et al.(2007) showed that a decrease in a network’s average path length increases network connectivity and also improves network members’ average innovation performance. | Uzzi and Spiro, 2005  
Ter Wal, 2013 |
|                  |                   | 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. |            |
| 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. | Crespo et al. (2014; 2015) |
|                  |                   | 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. |            |
|                  | 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... | Crespo et al. (2014; 2015) |
**Network topology** | **Outcome variables** | **Definition and rationale** | **References**
---|---|---|---
| | | 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. 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. | Ter Wal, 2013

**Geographical anchoring**

| | **Share of local inventors** | This is the ratio of the number of local (NUTS3) inventors to the number of inventors in the network. This indicates the strengthening the local anchoring of the network. | Ter Wal, 2013
| | **Share of regional inventors** | This is the ratio of the number of regional (NUTS2) inventors, but not local, to the number of inventors in the network. This indicates the degree of openness of the network towards regional actors. | Ter Wal, 2013
| | **Share of national inventors** | This is the ratio of the number of national (but not local and regional) inventors to the number of inventors in the network. This indicates the degree of openness of the network towards national (non-regional) actors. | Ter Wal, 2013
Step 3: Econometric specification

Our econometric specification consists of a series of panel regressions (fixed effects, time fixed effects or random effects). The choice of the relevant model was based on several statistical tests (Hausman test, unit root test, Breusch-Pagan test, etc.).

Our control variables include the local (NUTS3) GDP; the internal R&D expenditures; the amount of subsidies received from local and regional authorities (essentially from regions and departments); the amount of subsidies received from national authorities (from diverse French ministries, national agencies) and the amount of subsidies received from the European Commission.

Besides these control variables, we also considered a group variable to take into account the heterogeneity of the French departments in terms of absorptive capacity and innovation. This group variable relied on a typology developed by the European localized innovation observatory (EuroLIO) and is based on more than 30 variables, mostly recorded in 2011, characterising the economy, attractivity, employment, innovation, demography and quality of life in French departments. This typology is based on a cluster analysis in two stages: hierarchical cluster analysis and k-means cluster analysis. The defined groups are described as follows:

- **Group 3**: This group is composed of three departments (with the following zip codes: 75, 78 and 92). These departments differ from other French departments in terms of size, population density, wealth and their strong knowledge-based society nature.

- **Group 2**: This group is composed of the departments with the following zip codes: 6, 13, 31, 33, 34, 38, 44, 59, 62, 67, 69, 76, 77, 91, 93, 94 and 95. They are almost comparable to departments from the Group 3 but with a lower population density.

- **Group 4**: This group is composed of the departments with the following zip codes: 2, 3, 4, 5, 7, 8, 9, 10, 12, 15, 16, 18, 19, 23, 24, 28, 32, 36, 39, 41, 43, 46, 47, 48, 50, 52, 53, 55, 58, 61, 65, 70, 71, 79, 80, 81, 88, 89 and 90. These departments are characterised by a high share of industrial employment and agricultural occupations. They also exhibit patterns of industrial specialisation.

- **Group 1**: This group is composed of the departments with the following zip codes: 1, 11, 14, 17, 21, 22, 25, 26, 27, 29, 30, 35, 37, 40, 42, 45, 49, 51, 54, 56, 57, 60, 63, 64, 66, 68, 72, 73, 74, 82, 83, 84 and 85. They are considered as departments having the average profile of a French department. They are a little more urbanised (compared to departments from the Group 4), less affected by agricultural occupations and are generally closer to the coast.

In our different panel regressions, we are interested in the effects of the French cluster policy for each group of departments.

**Preliminary results**

As we expected, the preliminary results suggest a strong heterogeneity in the effects of the French cluster policy. The following table summarises the results:

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3 These preliminary results are based on robust standard errors (i.e. heteroskedasticity consistent coefficients).
### Table 2  Summary of the preliminary results

<table>
<thead>
<tr>
<th>Network topology</th>
<th>Outcome variables</th>
<th>Model</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Embeddedness</td>
<td>Density</td>
<td>Fixed effects</td>
<td>• Positive and significant effects on Groups 2 and 3</td>
</tr>
<tr>
<td></td>
<td>Fragmentation index</td>
<td>Random effects</td>
<td>• Negative and significant effects on Groups 1, 2, 3 and 4</td>
</tr>
<tr>
<td></td>
<td>Share of the network’s main component</td>
<td>Fixed effects</td>
<td>• Positive and significant effects on Group 2</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Clustering coefficient ratio</td>
<td>Fixed effects</td>
<td>• Negative and significant effects on Group 1</td>
</tr>
<tr>
<td></td>
<td>(average) Path length ratio</td>
<td>Time fixed effects</td>
<td>• No significant effect on any Group</td>
</tr>
<tr>
<td>Resilience</td>
<td>Hierarchy</td>
<td>Fixed effects</td>
<td>• Positive and significant effects on Group 3</td>
</tr>
<tr>
<td></td>
<td>Assortativity</td>
<td>Time fixed effects</td>
<td>• No significant effect on any Group</td>
</tr>
<tr>
<td>Geographical</td>
<td>Share of local inventors</td>
<td>Time fixed effects</td>
<td>• Positive and significant effects on Group 3</td>
</tr>
<tr>
<td>anchoring</td>
<td>Share of regional inventors</td>
<td>Fixed effects</td>
<td>• Positive and significant effects on Groups 1 and 4</td>
</tr>
<tr>
<td></td>
<td>Share of national inventors</td>
<td>Time fixed effects</td>
<td>• Positive and significant effects on Group 4</td>
</tr>
</tbody>
</table>

### Conclusions

**Q1:** The French cluster policy has increased the connectivity in all the local innovation networks. However, local innovation networks of knowledge-based and densely populated departments (Groups 3 and 2) show a stronger increase of their connectivity due to the policy, compared to other departments.

**Q2:** We found no evidence that the French cluster policy has increased the small-world nature of local innovation networks. Nevertheless, the policy has significantly reduced the tendency of closure in the departments from Group 1 (i.e. departments having the average profile of a French department). In other words, the policy has contributed to the reduction of redundant links in the innovation networks of those departments. Overall, we have no systematic evidence of network inefficiency induced by the cluster policy.

**Q3:** We found no evidence that the French cluster policy has increased the assortative nature of local innovation networks. This means that, highly connected actors do not interact more with less connected ones as a result of the cluster policy. This is true for all the French departments. However, the policy has significantly increased the hierarchy in the local innovation networks for departments from Group 3 (i.e. knowledge-based and densely populated French departments). Innovation networks from those departments are getting more core-periphery networks implying the emergence of key
actors which are able to coordinate the local innovation networks. Since we did not observe a strengthening of the links between the core and the periphery for all the networks, we cannot confirm the positive effect on the resilience of local innovation networks but we support a partial resilience effect on departments from Group 3.

Q4: The French cluster policy has reinforced the local anchoring of the local innovation networks for departments from Group 3. Their innovation networks involved more local actors as a result of the cluster policy. The policy has had the opposite effect on departments from Groups 1 and 4. The local innovation networks for departments from Group 1 have been spatially extended to include more regional actors. The same effect is observed on the local innovation networks for departments from Group 4 (i.e. departments with a high share of industrial employment and agricultural occupations) but here, the innovation networks have been also extended to include more national actors, i.e. actors from a different regions.

Limitations and future research
Despite these promising preliminary results, our analysis is still subject to a potential bias due to a spatial or network dependence among the departments. Models accounting for this dependence are under investigation and policy implications will be drawn after the final results.

Indicative references


