

The French cluster policy put to the test with differences-in-differences estimates

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Abstract:

There is an abundant literature on innovative clusters but the incidence of cluster policies is hardly ever assessed. We assemble a panel of 94 French regions for 1997-2008 and use difference-in-differences regressions to evaluate the cluster policy that is being implemented in France since 2004-2005 in some of these regions. We obtain a positive, significant but rather small impact on patenting.

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1. Introduction

An important research effort has been devoted to the study of innovative clusters, considering geographical concentrations of innovative actors as particularly efficient sources of knowledge production (Malmberg and Power, 2005, OECD, 2011). The general idea of this literature is that agglomeration externalities can amplify the social benefits of R&D, thereby leading some cities, regions and even nations to acquire a technological competitive advantage (Porter, 1998). Captivated by this idea, policy makers have tried to design various kinds of cluster policies to support innovation and regional development. In parallel, the empirical literature on clusters sought to identify the agglomeration economies that best support innovation in the long run. It mainly focused on the specialisation/diversity controversy (Beaudry and Shiffauerova, 2009, Duranton, 2011), debating whether regional innovation, productivity and growth are better supported by the geographical concentration of firms belonging to similar industries or by the agglomeration of dissimilar ones. This controversy evolved recently though, when some authors found that successful innovative regions diversify into new activities that remain related to their existing industrial specialties (Boschma and Frenken 2011).

These studies may help policy makers to design their cluster policies, but they do not answer a fundamental question: do cluster policies really enhance innovation? Indeed the literature provides very few *ex post* assessments of cluster policies, especially regarding their impact on innovation. There are many case studies of successful clusters like Silicon Valley or Baden-Württemberg (see e.g. OECD, 2009), but these clusters emerged naturally, not from cluster initiatives. Three exceptions, however, are the differences-in-differences studies by Nishimura and Okamuro (2011), Falck et al. (2010) and Martin et al. (2011). The former evaluates a cluster policy implemented in Japan in 2001 and the two others assess the incidence of cluster policies implemented in France and Germany in 1999². Cluster policies are rarely assessed because they are often small-scale and short-lived initiatives implemented on non-randomly selected territories. It is therefore difficult to realize before/after comparisons of ‘treated’ and ‘non-treated’ territories. However, the French government launched in 2004 a policy named “Politique des Pôles de compétitivité” that fulfills the requirements for a difference-in-differences evaluation. Indeed, all the 94 metropolitan NUTS3 regions (the so-called French “Départements”) could respond to the calls for tender, but only part of them obtained the treatment. It is therefore possible to build control groups with the non-treated regions. Selection into the treatment was certainly not random, but one can control for the characteristics that influenced it as well as the outcome of interest (regions’ innovation). Moreover, this policy has not been abandoned since then, which means that we have a long enough perspective to detect its effects on innovation, if they do exist.

The aim of this paper is to provide the first difference-in-differences evaluation of the French “Competitiveness clusters” initiative. Section 2 describes this policy. Section 3 presents the method and the econometric results. Section 4 concludes.

2. The French cluster policy since 2004

The French “Competitiveness Clusters” program was launched in 2004, and the selected regions started to receive the ‘treatment’ in 2005. The French Ministry of Economics granted the official label “Pôle de compétitivité” to an initial list of 66 clusters in 2005. It granted five new cluster labels in 2007, removed six clusters and replaced them by six others in 2010. Therefore, since 2007, there are 71 officially branded “Pôles de compétitivité”. Because our

² Note however that, contrary to Falck et al. (2010) and the present study, Martin et al. (2011) assess the impact of the 1999 French cluster initiative on productivity, not on innovation.

observation period ends in 2008, we use the cluster list of year 2007. Among these officially supported clusters, seventeen have been granted a “*world-class cluster*” label (“*Pôles de compétitivité mondiaux ou à vocation mondiale*”) and are more strongly supported. For all clusters, the treatment consists in enduring fiscal, financial and institutional support to the cluster members, which are firms, research centres and education institutions specialized in similar activities or technologies. Two conditions are required to receive the treatment: collaboration and co-localization³. These criteria determined the selection into the program but they also determine since then the intensity of the treatment for the regions that have been selected. The two main financial aids take the form of tax cuts and public project funds. Firms belonging to a “Pôle” and located in predefined R&D zones –a restrictive list of municipalities for each cluster– did not pay any corporate income tax during their first three years of positive net income and only paid 50% of the taxes during the following two years. This tax exemption was suppressed in 2009 however. In addition, members of a cluster are exempted from social security contributions for the R&D employees. The project funding side of the program is also rather ambitious. The members of a “Pôle” are granted project funds by the FUI (“Fond Unique Interministériel”) when they set up collaborative R&D projects. The FUI distributed nearly 1.5 billion Euros between 2005 and 2011. These funds are complemented by subsidies provided by local authorities and other national agencies (OSEO, ANR, etc.).

Contrary to the previous French cluster initiative of 1999 studied by Martin et al. (2011), this program does not appear to be particularly focused on industrial specialization. By the way, the mean comparison tests displayed in Appendix 2 show that the treated regions do not have a significantly different level of specialization compared to the non-treated ones. Therefore, it is not a cluster policy in the sense of encouraging territorial specialization. However, it can be considered as a genuine cluster policy because it creates incentives for neighboring organizations to collaborate for R&D activities, and also because it can attract young innovative firms in specific R&D zones wherein they will be able to obtain exemptions of taxes and social security charges. Consequently, this program offers the opportunity to test the joint effect of clustering and collaboration.

Each “Pôle de compétitivité” is officially tied up to a single NUTS2 region. For example the cluster “Finance Innovation” is formally located in Ile-de-France. A few clusters however can be associated to several NUTS2 regions. For instance, the cluster “Aerospace Valley” is officially a partnership between Aquitaine and Midi-Pyrénées. Be that as it may, the geographical targeting of the tax cuts and project funds is actually much narrower than this: for each cluster, a decree of the Ministry of Economics and Finance establishes a restrictive list of the municipalities that will be able to receive the tax support. Members of a cluster have to be located in one of these municipalities to be able to receive the tax credit, but a cluster participant that is not located there can still obtain the project funds of the FUI. Finally, if the geographical boundaries of a cluster are officially large, they are in reality much narrower. We obtained information on the localization of the cluster members from the Industry Directorate General (DGCIS). This information reveals that 80% to 100% of the establishments and employees of each cluster are located in two or three NUTS3 sub-regions. The other cluster members are generally scattered on the whole French territory. We therefore consider that the regions benefiting from the program are only those that contain a significant number of cluster members, that is to say the three main NUTS3 regions of each cluster. We

³ These conditions are stated in the text of the initial call for tender, which can be read at http://competitivite.gouv.fr/documents/commun/Politique_des_poles/1ere_phase_2005-2008/Premiere_labellisations_des_poles/cahier_des_charges_poles.pdf.

localize the treatment in accordance with the distribution of the cluster’s workforce between these three NUTS3 regions. If a NUTS3 sub-region hosts one third of the cluster’s total labor force, we consider that it receives a treatment dose of 0.33. To measure precisely the treatment intensity, one must also take into account that a NUTS3 sub-region can obtain several cluster labels if it is located in a NUTS2 region that has won several calls for tender. For instance, the NUTS2 region Midi-Pyrénées actually received three “Pôles de compétitivité”. This is a second source of variation of the intensity of the treatment across regions. Since then, our policy incidence variable will be a weighted count of the number of “Competitiveness clusters” obtained by treated regions: we localise each cluster in the three NUTS 3 regions where its workforce is mainly located. We then sum up the total number of clusters present in each region, weighting each cluster by the share of its total workforce employed in the considered region. Eventually, among our 94 NUTS3 regions, 72 are endowed with at least a piece of cluster but only 28 receive a “World-class cluster” label and the corresponding program. On average, NUTS3 regions obtain 0.48 clusters, with a maximum number equal to 3.27 in the “Rhône” region.

3. Method and results

To obtain the difference-in-differences estimator of the impact of the cluster policy on regional innovation, we first estimate the following equation:

(Equation 1)

$$\log(pat_int_{it}) = \alpha + \beta treatment_after_{it} + \gamma after_t + \delta treated_i + \varepsilon_{it}$$

where:

- pat_int_{it} is the total number of patents *per capita* filed by region i at year t ,
- $treatment_after_{it}$ is a crossed variable equal to the weighted number of “competitiveness clusters” granted to region i multiplied by a dummy equal to 1 from 2005 to 2008,
- $after_t$ is a dummy equal to 1 from 2005 to 2008,
- $treated_i$ is a dummy equal to 1 if region i has been granted a “competitiveness cluster”,
- ε_{it} is the usual idiosyncratic error term.

Appendix 1 describes the variables and the data sources. The estimates are implemented over the 94 French metropolitan NUTS3 regions (“Département Français”) between 1997 and 2008. We have to account for the fact that within-region autocorrelation and between-regions heteroskedasticity may produce biased standard errors (Bertrand et al., 2001). We therefore use Huber-White standard-errors clustered at the region level throughout.

Provided that the identification conditions are fulfilled, OLS estimates of the coefficient β deliver the difference-in-differences estimator of the impact of the “Competitiveness clusters” policy on patenting activity. Indeed, β is equal to the difference:

$$E(pat_int_{treated}^{after} - pat_int_{treated}^{before}) - E(pat_int_{non\ treated}^{after} - pat_int_{non\ treated}^{before})$$

The identification of this incidence coefficient would be straightforward if treated regions had been selected randomly, that is to say in a fashion warranting that treated and non-treated regions have the same characteristics. This is certainly not true here because cluster policies generally target specific regions. The mean comparison tests in Appendix 2 actually show that the targeted regions had on average significantly higher levels of patenting, R&D and population density before the implementation of the policy. On the contrary, the difference regarding the specialization indicator $EGindex$ is not significant. Highly innovative regions seem to have been targeted in priority but there is no evidence that selection into the program was also decided according to an industrial specialization criterion. In addition, the mean comparison tests for the period following the “treatment” show that the difference in patenting increases by 42% whereas the difference in R&D expenses drops by 31%. This

suggests that the treated group has substantially raised its R&D productivity after the policy start.

Even if the treated regions have not been selected randomly, one can correct this selection bias by controlling for the determinants of the regions' selection that might also affect regions' patenting (Besley and Case, 2000). To control the unobserved regional characteristics and yearly common shocks that may affect both the treatment and the outcome of interest, we first estimate a second equation wherein we replace the dummies $after_t$ and $treated_i$ by a full set of year and region fixed effects. We keep this specification in all subsequent regressions. Then, in a specification not displayed here, we introduce R&D, specialization ($EGindex$), and population density ($denspop$) as controls. Only R&D proves significant. The industrial specialization index $EGindex$ is not far from the 10% significance level whereas population density ($denspop$) is very far from being significant. We decide to keep the two former variables in the regressions and do not include population density. Removing $EGindex$ as well does not change the results. Consequently, regressions (3) to (6) in Table 1 contain the two covariates that are considered as the main determinants of patenting (Jaffe, 1989, Audretsch and Feldman, 1996):

- $R\&Dint_{it-1}$, which is the total in-house R&D per capita of region i at year $t-1$ ⁴, and
- $EGindex_{it}$, which is an Ellison-Glaeser index of industrial specialization (see Appendix).

The policy makers who selected the “Competitiveness clusters” may have chosen the regions with a high level of R&D because they were expected to be more reactive to the treatment. Also, they may have selected some regions because they considered them insufficiently specialized.

In a fourth regression, we vary the sample of regions to check consistency, removing the NUTS3 regions surrounding Paris and Lyon. Starting from the fifth regression, we differentiate the two kinds of cluster policies: the one implemented for “National-level” clusters and the one applied to “World-class” clusters. Finally, we check for reverse causality generated by an anticipatory response to the policy, introducing leads and lags of the two cluster policies. The leads detect any anticipatory response and the lags show the ex post timing of the policy incidence (Autor, 2003).

Table 1 reports the results. The average incidence of the French cluster policy is positive and significant throughout all regressions. However, it is clearly overestimated in the first one since it remains divided by three once the region fixed effects are introduced (columns 2, 3 and 4). The introduction of patenting determinants (from column 3) and the modification of the regions sample (column 4) do not change the coefficient: one supplementary “Competitiveness cluster” label produces on average a rise of 0.11-0.14% in regional patenting per capita. The regression in column 5 reveals that this positive but low incidence comes from the policy applied to “World-class” clusters whereas the effect of the cluster policy applied to “National-level” clusters is positive but not significant. Moreover, the regression in column 6 reveals an anticipatory effect of the cluster policy applied to “National-level” clusters, one year before the treatment. It might have biased upward the coefficient of $treatmentaft_nat$ in the previous regression. No such problem is detected for the

⁴ The choice of lagging R&D expenditures one year is justified by the fact that our dependent variable is constructed with patent applications, not with granted patents. The literature generally considers that the average time lag between the date of the R&D expense and the patent application is 18 months (see, e.g., Gurmu et al. 2010). We tested regressions with various lags on the R&D variable but the latter is not significant when it is lagged more than one year. An average of $R\&Dt-1$ and $R\&Dt-2$ is not significant either.

incidence coefficient of *treatmentaft_wcc*. In addition, the lags of this variable reveal that the incidence of the “World-class cluster” policy is null in the first year but increases significantly afterwards and stabilizes at +0.3% in 2007 and 2008. After three years, this cluster policy produced a cumulated rise in patenting per capita of 0.76% for those regions that obtained one “World-Class Cluster” label.

4. Conclusion

We realize difference-in-differences estimates of the impact of two cluster policies implemented in France since 2005. We show that only one produced a significant positive impact on regional patenting: the policy targeting so-called “World-Class” clusters. Whether the augmentation of patenting observed in the three years following the start of this policy is valuable remains however an open question. To answer, one would need to expand the observation period and use information on the comparative costs of this policy. Nevertheless, if the yearly +0,3% impact had maintained until today, this would mean a +2% increase in regional patenting since the beginning of this policy.

Table 1: Difference-in-differences estimates of the impact of the French “Competitivity clusters” policy.
 Dependent variable: patenting per capita in French NUTS3 regions.

	(1)	(2)	(3)	(4)	(5)	(6)
$R\&Dint_{it-1}$			0.091** (0.043)	0.130*** (0.049)	0.091** (0.043)	0.092*** (0.044)
$EGindex_{it}$			0.352 (0.241)	0.391* (0.214)	0.354 (0.242)	0.350 (0.243)
$treatmentafter_{it}$	0.312*** (0.111)	0.110** (0.0473)	0.112** (0.047)	0.137** (0.057)		
$treatmentaft_nat_{it}$					0.077 (0.052)	
$treatmentaft_wcc_{it}$					0.235** (0.101)	
$after_t$	-0.057 (0.074)					
$treated_t$	0.447*** (0.139)					
$treatmentnat_tp2_{it}$						-0.028 (0.027)
$treatmentnat_tp1_{it}$						0.047* (0.028)
$treatmentnat_t0_{it}$						0.043 (0.042)
$treatmentnat_tm1_{it}$						0.038 (0.048)
$treatmentnat_tm2_{it}$						0.080 (0.076)
$treatmentnat_tm3_{it}$						0.156 (0.095)
$treatmentwcc_tp2_{it}$						-0.004 (0.060)
$treatmentwcc_tp1_{it}$						-0.015 (0.057)
$treatmentwcc_t0_{it}$						0.076 (0.089)
$treatmentwcc_tm1_{it}$						0.165* (0.095)
$treatmentwcc_tm2_{it}$						0.300** (0.148)
$treatmentwcc_tm3_{it}$						0.303* (0.159)
<i>Constant</i>	-9.195**** (0.112)	-7.850**** (0.083)	-7.873**** (0.08)	-8.586**** (0.147)	-7.873**** (0.08)	-7.912**** (0.095)
<i>N</i>	1128	1128	1128	936	1128	1128

OLS estimates. Cluster-robust standard-errors in parentheses.

Full set of year and region dummies included in all regressions except the first one.

$treatmentnat_tp2_{it}$ = (weighted number of “National-Level Competitivity Clusters” granted to region i) \times (dummy = 1 two years before 2005). $treatmentnat_tm1_{it}$ = (weighted number of “National-Level Competitivity Clusters” granted to region i) \times (dummy = 1 one year after 2005). Same logic for all leads and lags. When “wcc” replaces “nat”, the crossed dummy is constructed with the weighted number of “World-Class Competitivity Clusters”. *, **, *** and **** indicate significance at 10%, 5%, 1% and 0,1% level. Other variables are defined in Appendix 1.

Appendix1: Variables definitions, descriptive statistics and sources

Variable	Definition		Mean	Std. Dev.	Min	Max	Observations
<i>pat_int_{it}</i>	Ratio of the number of patent applications of region <i>i</i> at year <i>t</i> over the population of region <i>i</i> at year <i>t</i>	Overall	0.0002	0.0002	0	0.0013	N=1128
		Between		0.0001	0.00004	0.0008	n =94
		Within		0.0001	-0.00001	0.0008	T=12
<i>R&Dint_{it-1}</i>	In-house R&D per capita; region <i>i</i> , year <i>t-1</i>	Overall	0.7724	1.4736	0	15.947	N=1128
		Between		1.0657	0.01416	6.9139	n =94
		Within		1.0232	-4.1445	9.8054	T=12
<i>EGindex_{it}</i>	Ellison-Glaeser index of technological and industrial diversity of region <i>i</i> at year <i>t</i>	Overall	0.0215	0.1219	-1.4248	0.9928	N=1128
		Between		0.0698	-0.2314	0.3072	n =94
		Within		0.1002	-1.172	1.1352	T=12
<i>treatmentafter</i>	(weighted number of “Competitiveness clusters” granted to region <i>i</i>) × (dummy = 1 when year ≥2005)	Overall	0.1616	0.4720	0	3.27	N=1128
		Between		0.2387	0	1.085	n =94
		Within		0.4079	-0.9233	2.3466	T=12
<i>treatmentaft_nat</i>	(weighted number of “National competitiveness clusters” granted to region <i>i</i>) × (dummy = 1 when year ≥2005)	Overall	0.1267	0.3832	0	2.62	N=1128
		Between		0.196	0	0.8683	n =94
		Within		0.33	-0.7417	1.9067	T=12
<i>treatmentaft_wcc</i>	(weighted number of “World-class competitiveness clusters” granted to region <i>i</i>) × (dummy = 1 when year ≥2005)	Overall	0.035	0.1514	0	1.52	N=1128
		Between		0.0821	0	0.4267	n =94
		Within		0.1275	-0.3917	1.1283	T=12

The patent count was provided by the French Institute of Intellectual Property (INPI). It recounts all patent applications of French origin published by any possible patent office. Patents are distributed across regions according to the address of the inventor. Only first filings are considered. All sectors are covered.

The R&D figures are from the French R&D survey implemented yearly by the Ministry of Research. The specialization indicator is an Ellison-Glaeser index following the formula:

$$EGindex_{it} = -\frac{G_{it} - H_{it}}{1 - H_{it}} \text{ with: } H_{it} = \sum_e \left(\frac{RD_{et}}{RD_{it}} \right)^2 \text{ and } G_{it} = \frac{\sum_k (S_{ikt} - S_{kt})^2}{1 - \sum_k S_{kt}^2}$$

where S_{ikt} is the share of sector *k* R&D in region *i* R&D employment at year *t*, S_{kt} is the share of sector *k* R&D in national R&D employment at year *t*, RD_{et} is establishment *e* R&D employment at year *t* and RD_{it} is region *i* R&D employment at year *t*. Regions with a high *EGindex* display a high diversity of their R&D activities

The population figures used to scale patents and R&D are from the French institute of statistics (INSEE).

The information on “Competitiveness Clusters” was provided by the Industry Directorate-General (DGCIS).

Appendix 2: Mean comparison tests between treated and non-treated NUTS3 regions

Variables	Group	N. of observations	Mean	Std. error	Difference of mean	Difference≠0
BEFORE (1997-2004)						
<i>pat_int_{it}</i>	Non treated	176	0.00011	0.00000	-0.0000795	-11.1563****
	Treated	576	0.00020	0.00000		
<i>R&Dint_{it-1}</i>	Non treated	176	0.43152	0.05457	-0.5095879	-5.4446****
	Treated	576	0.94111	0.07604		
<i>EGindex_{it}</i>	Non treated	176	0.01651	0.01690	-0.0005818	-0.0336
	Treated	576	0.01709	0.00376		
<i>denspop</i>	Non treated	176	323.6994	93.41804	-277.2025	-1.9398*
	Treated	576	600.9019	108.1431		
AFTER (2005-2008)						
<i>pat_int_{it}</i>	Non treated	88	0.00015	0.00002	-0.000113	-5.4755****
	Treated	288	0.00026	0.00001		
<i>R&Dint_{it-1}</i>	Non treated	88	0.40556	0.09850	-0.349759	-3.0059**
	Treated	288	0.75532	0.06195		
<i>EGindex_{it}</i>	Non treated	88	0.04621	0.01566	0.0205301	1.2696
	Treated	288	0.02568	0.00403		
<i>denspop</i>	Non treated	88	341.0263	140.1997	-282.3656	-1.3377
	Treated	288	623.3919	157.789		

This table reports two subgroup t-tests for the difference in mean value of variables that we suspect to affect both the selection into the treatment (cluster policy) and the outcome of interest (Regions' patents per capita). The first test compares the means of the variables in the treated and non-treated group before the policy is implemented (1997-2004); the second tests does the same after the start of the cluster policy (2005-2008). Column "Difference≠0" reports absolute value of the t-statistics for testing the two-sided hypothesis that the difference in mean value is nonzero. *, ** and **** indicate significance at the 10%, 1% and 0.1% levels.

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