Economics Bulletin

Volume 34, Issue 1

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.

Citation: Olivier Brossard and Inès Moussa, (2014) "The French cluster policy put to the test with differences-in-differences estimates", *Economics Bulletin*, Vol. 34 No. 1 pp. 520-529.
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Submitted: September 26, 2013. **Published:** March 31, 2014.

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). If these studies proved very useful to assess the different types of agglomeration externalities supporting industrial and innovative clusters, they do not tell us whether deliberate cluster policies are able to stimulate innovation production in clusters. The aim of this paper is to provide such a policy assessment for the case of a large-scale cluster policy implemented recently in France.

The empirical 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 1999[1]. 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 implement reliable before-after comparisons of 'treated' and 'non-treated' territories, except if one can control for the determinants of the selection into the cluster policy treatment. The French government launched in 2004 a policy named "Politique des Pôles de compétitivité" that lasted long enough to fulfill the requirements for a difference-in-differences evaluation. Indeed, all the 94 metropolitan NUTS 3 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 not random, but we could control for the characteristics that influenced it. 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 contribution of this paper is to provide the first difference-in-differences evaluation of the recent French "Competitivity clusters" initiative. Section 2 describes this policy. Section 3 presents the method and the econometric results. Section 4 concludes.

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[1] Note that Martin et al. (2011) assess the impact of the 1999 French cluster initiative on productivity, not on innovation. This policy was abandoned and replaced by the more ambitious one that is evaluated in the present paper.

2. The French cluster policy since 2004

The French "Competitivity 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" targeted by the program. Because our observation period ends in 2008, we use the clusters 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-localization[2]. 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. If they collaborated in an approved R&D project, firms belonging to a "Pôle" and located in predefined R&D zones[3] could be totally exempted of income tax during their first three years of positive net income and obtain a 50% tax discount during the following two years. This tax exemption was suppressed in 2009. 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 is not a cluster policy in the sense of encouraging territorial specialization[4]. 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 strives to attract young innovative firms in specific R&D zones wherein they will be able to obtain exemptions of taxes and social security charges.

3. Methodology and results

To assess the regional impact of a nationwide cluster policy, the first methodological challenge is to properly localize the treatment and to correctly measure its intensity. It is therefore necessary to determine which territorial units really benefit from the policy and what dose of treatment they receive. In the French case, a "Pôle de compétitivité" is generally granted to a single administrative "Région". These geographical areas correspond to the NUTS 2 level in the European classification of territorial units[5]. A few clusters, however, are

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[2] 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.

[3] R&D zones are, for each cluster, a restrictive list of municipalities established by a decree of the Ministry of Economics and Finance.

[4] The mean comparison tests displayed in Appendix 2 show that the treated regions do not have a significantly different level of industrial specialization compared to the non-treated ones.

[5] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU for the purpose of harmonization of EU regional statistics. When feasible, the NUTS classification is based on the administrative divisions applied in the Member States. NUTS 2 regions

attached to several NUTS 2 regions. For instance, the cluster “Aerospace Valley” is officially a partnership between “Région Aquitaine” and “Région Midi-Pyrénées”. Be that as it may, the geographical targeting of the policy is always narrower than the NUTS 2 level. Indeed, the information on the localization of cluster members that is provided by the Industry Directorate General reveals that 80 to 100% of the establishments and employees of a cluster are located in two or three “départements” (NUTS 3 regions[6]). The remaining members of the cluster are scattered on the whole French territory. This means that only a few (NUTS 3) “départements” of an officially targeted (NUTS 2) “région” actually receive the treatment. We therefore consider that the territories benefiting from the program are only those that contain a significant number of cluster members, that is to say the three main “départements” of each cluster. We thus localize the treatment in accordance with the distribution of the cluster’s workforce between these three main NUTS 3 regions. If a NUTS 3 region hosts one third of the cluster’s total labor force, we consider that it receives a treatment dose of 0.33. There is a second source of variation of treatment intensities across “départements”: a NUTS 2 region can have won several competitivity clusters. For instance, “Région Midi-Pyrénées” actually received three competitivity clusters whose members are located in various “départements” of the “Région”. We therefore construct our policy dose variable as a weighted count of the total number of “Competitivity clusters” obtained by treated “départements”. More precisely, we localize each cluster in the three NUTS 3 regions wherein its workforce is mainly located. We then sum up the total number of clusters present in each NUTS 3 region, weighting each cluster by the share of its total workforce employed in the considered NUTS 3 region. Eventually, among our 94 NUTS 3 regions, 72 are endowed with at least a piece of cluster but only 28 receive a “World-class cluster” label and the corresponding program. French NUTS 3 regions obtained an average of 0.48 clusters, with a maximum of 3.27 in the “Rhône” “département”.

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

$$log\ (pat\_int_{it}) = \alpha + \beta treatment\ after_{it} + \gamma after_t + \delta treated_i + \varepsilon_{it} \qquad (1)$$

where:

- pat_int_{it} is the total number of patents *per capita* filed by region i at year t,
- $treatmentafter_{it}$ is a crossed variable equal to the weighted number of “competitivity 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 “competitivity cluster”,
- ε_{it} is the usual idiosyncratic error term.

The results of this baseline specification are displayed in Table I, column 1. Appendix 1 describes the variables and the data sources. The estimates are implemented over the 94 French metropolitan NUTS 3 regions 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., 2004). We therefore use Huber-White standard-errors clustered at the region level throughout.

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comprise between 800000 and 3 million inhabitants; NUTS 3 regions contain between 150000 and 800000 people. In France, NUTS 3 regions are called “Départements” and NUTS 2 regions are called “Régions”. The latter include between two and eight “Départements”.

[6] We use “NUTS 3 region” and “département” as synonyms in the sequel.

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

$$E(pat\_int_{treated}^{after} - pat\_int_{treated}^{before}) - E(pat\_int_{non\ treated}^{after} - pat\_int_{non\ treated}^{before}) \quad (2)$$

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 policy makers who selected the "Competitivity 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. 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.

Even if the treated regions have not been selected randomly, one can correct the selection bias by controlling for the determinants of selection into the treatment that might also affect regions' patenting (Besley and Case, 2000). To do so, the choice of control variables must be guided by what theory considers as the main determinants of patenting/innovation. The three main determinants that are suggested by the innovation production theory are R&D expenses, the degree of industrial specialization/diversity and the level or urbanization (see e.g. Jaffe, 1989, Audretsch and Feldman, 1996 and 1999). The mean comparison tests displayed in Appendix 2 assess whether these factors differentiate the treated and non-treated regions. They show in particular that selected regions have much higher levels of R&D expense than the non-treated ones. We thus decide to introduce as control variables in regressions (3) to (6) the two following covariates[7]:

- $R\&Dint_{it-1}$, which is the total in-house R&D per capita of region i at year t-1[8], and
- $EGindex_{it}$, an Ellison-Glaeser index of industrial specialization (defined in the Appendix).

Moreover, to better control the unobserved regional characteristics and yearly common shocks that may affect both the treatment and the outcome of interest, we replace the dummies $after_t$ and $treated_i$ by a full set of year and region fixed effects in regressions (2) to (6).

[7] In a specification not displayed here, we introduced R&D, specialization (*EGindex*), and population density (*denspop*) as controls. Only R&D proves significant. The industrial specialization index *EGindex* was not far from the 10% significance level whereas population density (*denspop*) was very far from being significant. We consequently decided to keep the two former variables in the regressions and did not include population density. Removing *EGindex* as well does not change the results.

[8] 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.

In regression (4), we vary the sample of regions to check consistency, removing the NUTS 3 regions surrounding Paris and Lyon. Starting from regression (5), 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 in regression (6) 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 impact 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 (starting from column 3) and the modification of the regions sample (column 4) do not change the coefficient: one supplementary "Competitivity 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 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.

An important question remains opened for subsequent research on this French cluster policy: only the policy targeting the so-called "world-class" clusters seems to produce a significant improvement of regional patenting; why is the policy designed for "national-level clusters" unsuccessful? One could make the hypothesis that it is because they do not obtain the critical amount of financial support that is necessary to generate significant innovation benefits. The policy implication would then be that too dispersed cluster policies may not be effective. However, this needs much further exploration to be confirmed since it is necessary to assess rigorously whether this is really this scale difference in the amount of the financial support that produces the difference in innovation productivity.

Table I. 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**	0.130***	0.091**	0.092***
			(0.043)	(0.049)	(0.043)	(0.044)
$EGindex_{it}$			0.352	0.391*	0.354	0.350
			(0.241)	(0.214)	(0.242)	(0.243)
$treatmentafter_{it}$	0.312***	0.110**	0.112**	0.137**		
	(0.111)	(0.0473)	(0.047)	(0.057)		
$treatmentaft\_nat_{it}$					0.077	
					(0.052)	
$treatmentaft\_wcc_{it}$					0.235**	
					(0.101)	
$after_t$	-0.057					
	(0.074)					
$treated_i$	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)
Constant	-9.195****	-7.850****	-7.873****	-8.586****	-7.873****	-7.912****
	(0.112)	(0.083)	(0.08)	(0.147)	(0.08)	(0.095)
N	1128	1128	1128	936	1128	1128

OLS estimates. Cluster-robust standard-errors in parentheses. *, **, *** and **** indicate significance at 10%, 5%, 1% and 0,1% level.

Full set of year and region dummies included in all regressions except the first one. In regression (4), the NUTS 3 regions surrounding Paris and Lyon are excluded from the sample.

Definition of crossed variables: $treatmentnat\_tp2_{it}$ = (weighted number of "National-Level Competitivity Clusters" granted to region *i*) × (dummy = 1 two years before 2005). $treatmentnat\_tm1_{it}$ = (weighted number of "National-Level Competitivity Clusters" granted to region *i*) × (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".

Other variables are defined in Appendix 1.

Appendix1: Variables definitions, descriptive statistics and sources

Variable	*Definition*		*Mean*	*Std. Dev.*	Min	Max	*Observations*
pat_int$_{it}$	Ratio of the number of patent applications of region *i* at year *t* over the population of region *i* at year *t*	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
R&Dint$_{it-1}$	In-house R&D per capita; region *i*, year *t-1*	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
EGindex$_{it}$	Ellison-Glaeser index of technological and industrial diversity of region *i* at year *t*	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
treatmentafter$_{it}$	(weighted number of "Competitivity clusters" granted to region *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
treatmentaft_nat$_{it}$	(weighted number of "National competitivity clusters" granted to region *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
treatmentaft_wcc$_{it}$	(weighted number of "World-class competitivity clusters" granted to region *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 fillings 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 "Competitivity 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)			
pat_int$_{it}$	Non treated	176	0.00012	0.00000	−0.000080	−11.1563****
	Treated	576	0.00020	0.00000		
R&Dint$_{it-1}$	Non treated	176	0.43152	0.05457	−0.509588	−5.4446****
	Treated	576	0.94111	0.07604		
EGindex$_{it}$	Non treated	176	0.01651	0.01690	−0.000582	−0.0336
	Treated	576	0.01709	0.00376		
denspop$_{it}$	Non treated	176	323.6994	93.41804	-277.2025	-1.9398*
	Treated	576	600.9019	108.1431		
			AFTER (2005-2008)			
pat_int$_{it}$	Non treated	88	0.00015	0.00002	−0.000113	−5.4755****
	Treated	288	0.00026	0.00001		
R&Dint$_{it-1}$	Non treated	88	0.40556	0.09850	−0.349759	−3.0059**
	Treated	288	0.75532	0.06195		
EGindex$_{it}$	Non treated	88	0.04621	0.01566	0.0205301	1.2696
	Treated	288	0.02568	0.00403		
denspop$_{it}$	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 test 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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