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Abstract

This paper examines the effectiveness of the French competitiveness cluster policy on participating SMEs in terms of innovation and economic performance. Using an original dataset, we construct different measures of treatment with crossover designs. The findings indicate substantial additionality effects on R&D and employment and weak or insignificant effects on other types of economic performance. While only adhering to clusters induces much stronger positive impacts on SMEs than only participating in R&D collaborative projects, the policy is most effective when the two treatments are simultaneously used. To achieve its impact on SMEs, the cluster policy should not overlook low-cost instruments such as animation actions and common services.

Keywords: Cluster Policy, Multiple Treatments, SMEs, Policy Evaluation, Conditional Difference-in-Difference

JEL Classification: C14, C21, O32, O38

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1 Introduction

Following diverse theoretical approaches emphasizing the importance of supporting clusters of agglomerated firms to achieve higher capacity to innovate, higher productivity and sustainable development, most countries established a cluster policy during the 1990s and 2000s. In Europe, encouraged by the European Council, such policies consist of diverse programs and instruments implemented by government or local authorities to support the emergence of clusters or upgrades to existing ones. Despite the great diversity of cluster policies across countries (Sopoligová and Pavelková, 2017), the policies generally include two main types of action: animation activities on the one hand, which consist of promoting networking among participants and exchange of services, and, on the other hand, financial support to collaborative R&D projects through subsidies. With the aim of continuously improving the efficiency of cluster policies as evidence-based policies, the importance of evaluation has been widely emphasized (Commission, 2016; Tactics, 2012). As with innovation policies in general, evaluation studies of cluster policies in a diversity of contexts and countries have developed recently (Uyarra and Ramlogan, 2012). However, there is still a relative abundance of studies evaluating the effect of government support on R&D expenditure compared to the number of studies evaluating additionality effects on firms' economic performances. Further, most studies evaluate simple policy instrument using a dichotomic variable (being a member of a cluster or not), and there is still a lack of studies using multiple instruments (or policy mix) approaches.

The main purpose of this paper is to examine and better understand the effectiveness of cluster policy on the innovation and economic performance of SMEs by considering a multiple treatments with crossover designs approach.

To that end, the French competitiveness cluster policy appears to be a particularly relevant case. This industrial policy, implemented since 2004, aims to bring new creativity to the way that France conducts its innovation and regional policy using cluster dynamism. A competitiveness cluster is defined by the 2005 finance law as *"grouping on the same territory, of companies, higher education institutions, and public or private research centers which have to work together to implement innovation projects for economic development"*. As a policy, the competitiveness cluster program consists of multiple overlapping instruments: in addition to the development of low-cost animation actions aimed at developing connectivity between actors affiliated with the cluster organization, the program allows for the direct funding of firms' R&D projects through the Unique Interministerial Fund (FUI), which is the main funding instrument of the competitiveness cluster policy.

In the literature, there are few studies assessing the impact of this French competitiveness cluster policy. These studies include Erdyn-Technopolis and Bearpoint (2012); Fontagné et al. (2013); Brossard et al. (2014); Bellégo and Dortet-Bernadet (2014); Ben Hassine and Mathieu (2017) and Chaudey and Dessertine (2016). Globally, the findings of these studies reject the crowding out hypothesis and suggest weak positive impacts on the input additionality (private R&D and employment in R&D) of SMEs[3], but no substantial effects in terms of output additionality (innovation and market performance) are found. However, none of these studies control more than one instrument at the same time. However, the competitiveness cluster policy is a mix of several public innovation instruments; therefore, it may make sense to consider cluster adhesion and FUI project participation as two different and possibly overlapping treatments for SMEs when evaluating the policy's effects. Indeed, the lack of conclusive results on the effectiveness of the policy may be partly attributable to the lack of adequate data and methodology but also to the simultaneity of several policy instruments. Moreover, the capacity to separately evaluate the impact of two instruments that represent very different budgetary costs is of key interest for policy makers.

This paper participates in this growing literature on evaluation of the competitiveness cluster policy by focusing on its impacts in terms of input and output additionality of SMEs, which are the main targeted participants, but also by comparing the different treatment options. To this end, we use the conditional difference-in-difference method, which consists of combining difference-in-difference with a matching technique for a multiple overlapping treatment approach. Our sample is issued from an original dataset combining different data sources. It is composed of unbalanced panel data over the 2005-2012 period and covering French SMEs. What are the factors that determine the participation of firms in the cluster policy? What are the impacts of adhering to clusters or participating in the FUI project? Do firms perform better when they combine both instruments? These are the questions we attempt to answer in this paper.

The findings suggest the rejection of any crowding-out effect, no matter which treatment

[3]A small or medium-sized firm is a firm with fewer than 250 workers and having a turnover not exceeding €50 million or a total balance sheet not exceeding €43 million.

option is used, and indicate substantial additionality effects on R&D and employment. The effects on other types of economic performance (turnover, value added and export) are generally weak or nonexistent. Moreover, the results show the effectiveness of the multi-instruments dimension of the policy, as the effects of the policy on R&D and employment appear stronger for SMEs that simultaneously benefit from cluster membership and subsidized collaborative R&D projects. It is also shown that only adhering to clusters induces stronger positive impacts on SMEs than only benefiting from R&D collaborative projects. This result confirms that for the cluster policy to achieve its impact on SMEs, it may be a good option to extend beyond a mere R&D subsidies policy and emphasize low-cost instruments such as animation actions.

The paper is organized as follows. Section 2 presents the related literature review. Section 3 presents the French competitiveness cluster policy. Section 4 presents the econometric methodology we use to assess the impact of the policy. Section 5 describes the data in detail and presents summary statistics for the main variables. Section 6 presents the results, and section 7 concludes.

2 Related literature

Cluster policies are considered a good public instrument to support private R&D activities and to improve firms' performance. Although there is an important literature on the impact of clusters on firms' innovative and economic performance, many concern de facto phenomena of firms agglomeration, and few studies assess the causal impact of policies aiming at fostering or reinforcing clusters. Some studies assess the effectiveness of cluster policies (see Criscuolo et al. (2007) in the United Kingdom; Branstetter and Sakakibara (2002), Nishimura and Okamuro (2011a) and Nishimura and Okamuro (2011b) in Japan; Falck et al. (2010) and Engel et al. (2013) in Germany; Dujardin et al. (2015) in Belgium; and Martin et al. (2011), Fontagné et al. (2013), Bellégo and Dortet-Bernadet (2014), Abdesslem et al. (2016), Chaudey and Dessertine (2016) and Ben Hassine and Mathieu (2017) in France). They mostly use difference-in-difference or conditional difference-in-difference empirical methodologies.

As cluster policies include R&D and innovation incentives as well as an economic development perspective, empirical evaluation studies often consider these two aspects of cluster policies' impact. Below, we distinguish between the studies evaluating the effectiveness of cluster policies in terms of R&D and innovation on the one hand and economic performance on the other hand.

2.1 Effects of the cluster policy on R&D spending and the innovation of firms

In the literature, the studies focusing on the impact of cluster policies on input additionality are quite limited. Bellégo and Dortet-Bernadet (2014) and Ben Hassine and Mathieu (2017) analyze the impacts of the French cluster policy on the private R&D spending of SMEs and ETIs using microdata and the conditional difference-in-difference method. Their findings reject the crowding-out hypothesis and conclude that an additional effect exists.

Moreover, Bellégo and Dortet-Bernadet (2014), Chaudey and Dessertine (2016) and, more recently, Ben Hassine and Mathieu (2017) find that the French competitiveness cluster policy has had positive effects on the employment of personnel devoted to R&D, especially in terms of engineering and technical and scientific staff. Although cluster policies have been considered a good instrument for supporting local SMEs' innovation, there exist few empirical assessments of innovation outcomes.

Some studies show the effectiveness of cluster policies using the number of patents or innovation (Branstetter and Sakakibara, 2002; Nishimura and Okamuro, 2011a,b; Falck et al., 2010; Engel et al., 2013; Brossard et al., 2014). Branstetter and Sakakibara (2002) and Nishimura and Okamuro (2011a) analyze the effects of cluster policies in Japan on patenting activity and innovation of firms and find positive impacts on innovation outcomes. In Germany, Falck et al. (2010) and Engel et al. (2013) find that cluster policies stimulate the innovation process and increase innovation outcomes. In France, Brossard et al. (2014) find that the competitiveness cluster policy has had a significant positive impact on regional patenting in a context where input and output additionality on innovation are confounded. However, Martin et al. (2011) find that the local productive systems (LPS) policy has had no effect on the innovation of firms. Similarly, Bellégo and Dortet-Bernadet (2014) find that the competitiveness cluster policy has had no effect on firms' patents, on the sales of innovative products or on the improvement of innovation processes. These results are confirmed by a more recent study by Ben Hassine and Mathieu (2017), which analyzes the same policy and finds that it has had no effect on firms' innovation and especially on filed patents. On the whole, there is consensual evidence that there is no additional effect of the French cluster policies on innovation once its positive impact on R&D expenditure is taken into account (Dieye and Massard, 2019).

2.2 The effects of cluster policies on firms' economic performance

There is limited empirical evidence and ambiguous results concerning the effects of cluster policies on the economic performance of firms. Some studies find positive effects of cluster policies on total employment (Criscuolo et al., 2007; Dujardin et al., 2015; Chaudey and Dessertine, 2016; Abdesslem et al., 2016), turnover (Falck et al., 2010), total factor and labor productivity, exports and total fixed assets (Abdesslem et al., 2016). However, other studies conclude that there is no significant effect of cluster policies on total factor productivity (Criscuolo et al., 2007; Dujardin et al., 2015), labor productivity (Martin et al., 2011; Dujardin et al., 2015), total employment (Martin et al., 2011; Ben Hassine and Mathieu, 2017), turnover and value added (Bellégo and Dortet-Bernadet, 2014; Ben Hassine and Mathieu, 2017), and exports (Dujardin et al., 2015; Ben Hassine and Mathieu, 2017).

In sum, the findings of studies evaluating the effect of the cluster policy on firms' innovative activities and economic performance are still mixed and not clearly conclusive. One set of difficulties is linked to all single instrument policy evaluation, such as addressing nonrandom selection and missing data. However, when it comes to cluster policies, additional difficulties often emanate from the fuzziness of the policy instruments used, which generally combine several treatments option for firms: subsidies, joining the association that manages a common platform, or specific advisory services, among others. Most of the existing studies do not deal with complex schemes and consider only one dichotomic treatment variable: belonging or not belonging to a cluster. In this paper, using an original database on the French case, we contribute to this literature by developing a new impact assessment of a cluster policy on the innovative and economic performance of SMEs using a multiple overlapping instruments approach that allows us to consider two different instruments of the cluster policy and their possible combination. The singular design of the French competitiveness cluster policy makes it an interesting case to develop such an approach.

3 The French competitiveness cluster policy: mixing animation actions and subsidies for collaborative R&D

3.1 Definition and implementation of the policy

Created in 2004, the competitiveness cluster policy aims to build on synergies and collaborative innovation projects to give partner firms the chance to become first in their markets, both in France and abroad. A competitiveness cluster, labeled "Pôle de Compétitivité" by the dedicated interministerial committee, is an association that brings together, based on a targeted theme, companies, research laboratories, training establishments and national and local public authorities.

The core activity of the clusters is to develop collaborative innovation projects while integrating the potential economic benefits as early as possible. According to the DATAR, clusters are supposed to have two main priorities (DATAR, 2004). The first consists of reinforcing the economic benefits of R&D projects and becoming manufacturers of the products of the future by transforming collaborative R&D efforts into innovative products, processes, and services to be released onto the market. The second consists of supporting firms by offering them collective and individual services to access funding, international markets, and industrial properties and also by addressing their needs in terms of skills and individual assistance.

After a positive evaluation of the first phase of the policy (2006-2008), the government proceeded to the launch of the second phase (2009-2012), which is often called "Pôles 2.0". In addition to continuing the support of private R&D, the second phase has set three priorities. First, it aims to strengthen the animation and strategic management of the clusters, notably through the implementation of more rigorous "contracts of performance". Second, it seeks to enable the development of structured projects, particularly platforms of innovation[4]. Third, it aims to increase support for the development of innovation ecosystems and the growth of firms. The third phase (2013-2018) of the policy was launched in 2013 with the specific purpose of substantially increasing the economic outputs from the R&D projects by increasing

[4]Platforms of innovation include infrastructures and mutualized equipment for R&D and innovation intended to offer resources (services, equipment rental, etc.) that allow agents to foster collaborative R&D and can even serve as laboratories or living labs for testing.

support for SMEs and mid-tier firms (ETIs).

After the disappearance of certain clusters that did not achieve their goals and the labeling of new clusters over time, 71 clusters have been recognized by the national authorities during these phases, covering a large part of the French territory (see Figure(7) in the Appendices).

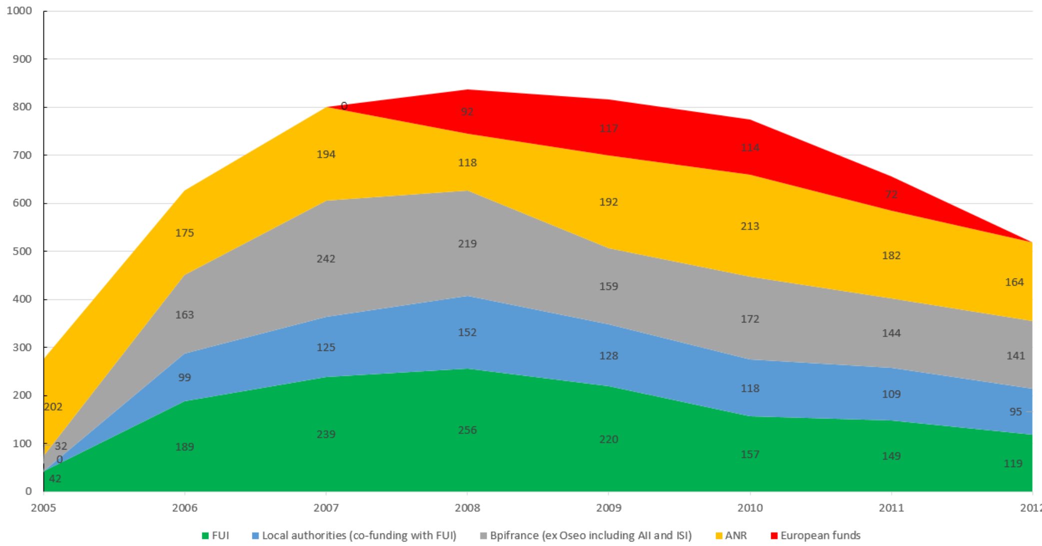
3.2 Funding and budgets of the French cluster policy

For a firm, the first way to benefit from the French cluster policy is to become a member of a competitiveness cluster. This way, it can benefit from animation activities: networking events, communication and promotion especially at the international level, technological platforms and other services (technological monitoring, financial or legal advisory services, etc.). Although it represents a very small share of the total budget dedicated to the competitiveness cluster policy (less than 10 percent), the animation budget has been considered essential for SMEs that lack internal competencies to develop such activities.

On the other hand, firms may also benefit from the FUI subsidies. FUI is the main instrument of funding for the competitiveness cluster policy. It regroups government resources that come from numerous diverse ministries and interministry agencies involving, among others, economy, industry, equipment, agriculture, defense or health. The main objective of the FUI is to finance collaborative R&D projects involving enterprises, laboratories and public research centers, and it is oriented toward the development of products or services that are susceptible to being launched on the market in the short or medium term.

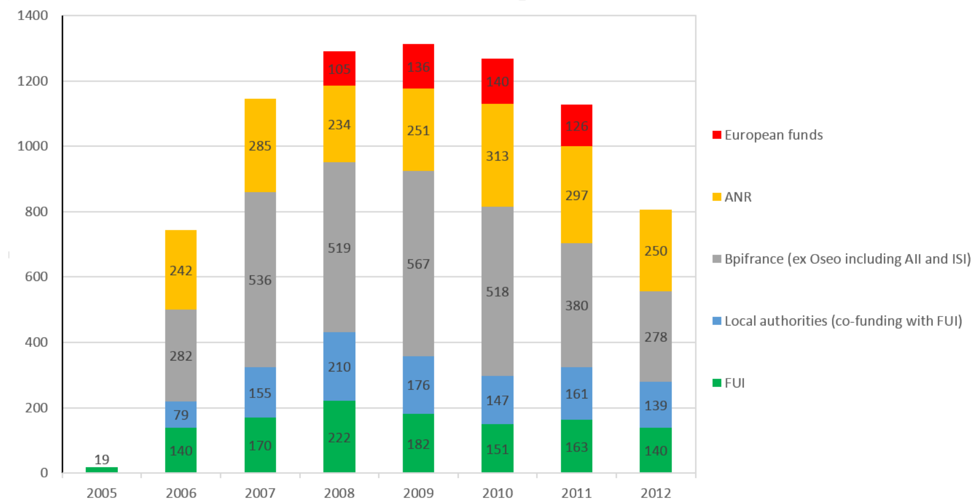
Between 2006 and 2012, the FUI enabled the funding of 1187 projects (Figure 2) for a total amount of more than €1.37 billion (Figure 1).

Figure 1: Funding (€M) allocated to the competitiveness cluster policy (2005 to 2012)



Source: Data from the annual dashboards of the DGCIS, author's representation

Figure 2: Number of collaborative R&D projects by source of funding (2005 to 2012)



Source: Data from the annual dashboards of the DGCIS, author's representation

4 Methodology

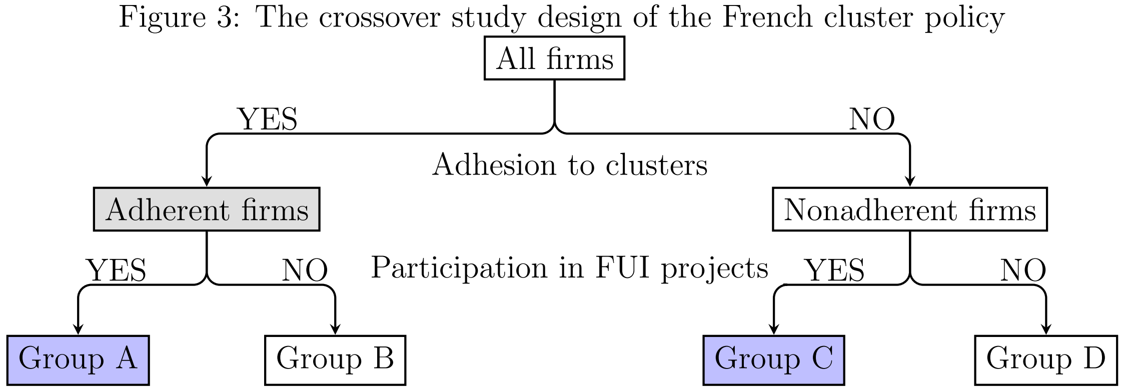
4.1 Quasi-experimental design

To evaluate the impacts of the competitiveness cluster policy, it is necessary to thoroughly understand the structure of participation and the characteristics of participating firms. In this study, our strategy for identifying participating firms is different from those of Bellégo and

Dortet-Bernadet (2014) and Ben Hassine and Mathieu (2017). In these studies, the authors consider firms that are members of a cluster association as participants and all other firms as controls. Here, we go further and consider two levels of treatment. We present in the figure (3) the strategy of the identification of firms' participation in the policy. On the one hand, we have a group of firms that are members of at least one cluster association, and among this group, some firms have participated in FUI projects, and others have not. On the other hand, we have a group of firms that are not members of a cluster, and among this group, some firms have participated in FUI projects, and others have not. Therefore, when evaluating the effect of the policy on firms' performance, by considering firms that are members of clusters as participants and all other firms as nonparticipants, one may underestimate the effects of the policy. Correspondingly, one may underestimate the effect on nonmember firms that participate in FUI R&D projects by considering them controls. Hence, by comparing adherents and nonadherents, one may underestimate the overall effect of the policy.

To deal with this problem and assess the impact of the competitiveness cluster policy, we distinguish two levels of treatment and compare these two different treatment options. The first level of treatment is participation in a cluster association (membership), which allows firms to benefit from animation actions, and the second is participation in FUI projects, which allows firms to benefit from subsidies for collaborative R&D. We aim to investigate the impact of each treatment separately and also to understand whether the combination of the two treatments is better than having just one of the two. To this end, we created four groups (see Figure 3) to identify an appropriate control group that has good overlap with the treated groups.

Figure 3: The crossover study design of the French cluster policy



- Group A belongs to clusters and participates in projects (both treatments).

- Group B belongs to clusters and does not participate in projects (treatment 1 only).

- Group C participates in projects and does not belong to clusters (treatment 2 only).

- Group D does not belong to clusters, does not participate in projects and constitutes the pure comparison group.

As explained above, Table 1 shows the crossover design and allows us to identify each treatment group and the appropriate control group. We can, therefore, estimate the impact of being a member of a cluster by comparing the outcome of Group B with the outcome of Group D, which is the pure comparison group. We can also estimate the impact of participation in an FUI project by comparing the outcome of Group C with the outcome of Group D. In addition, this design makes it possible to compare the incremental impact of participating in a project when a firm has already adhered to a cluster (corresponding to the difference in outcomes between Group A and Group D).

Table 1: Treatment and comparison groups for the policy evaluation

		Treatment 1 (Cluster)	
		Treatment	Comparison
Treatment 2 (FUI project)	Treatment	Group A	Group C
	Comparison	Group B	Group D

4.2 Econometric strategy

The main challenge of the impact evaluation of the competitiveness cluster policy is to determine what would have happened to the participating firms if the policy had not existed. Therefore, we must determine the potential outcome of a participant in the absence of the policy. Let us consider Y_i^T and Y_i^C as two potential outcomes of firm i; the causal effect of the treatment on the outcome would be defined as the difference between the two potential outcomes: $(\Delta = Y_i^T - Y_i^C)$. Ideally, we wish to compare how the same firm would have fared with and without participation in the policy, but we cannot do so because at a given point in time, a firm cannot be both a participant and a nonparticipant in the policy. The challenge of the evaluation study is to construct a counterfactual framework that would represent a participant's outcome (not observed) in the absence of the policy. The counterfactual framework was developed by Roy (1951) and Rubin (1974) and has since been adopted by many statisticians and econometricians, including (Rosenbaum and Rubin, 1983; Heckman et al., 1997; Angrist, 1998; Imbens and Wooldridge, 2009).

For observational studies, the assignment of treatments is typically not random; especially for the competitiveness cluster policy, the selection process is not randomized because it is based on calls for projects. According to Fontagné et al. (2013), there are two selection problems: the first is related to the selection of the financed projects among others by public authorities, and the second is the self-selection of firms that decide to be a member of a cluster or to participate in a project. To deal with this bias and the potential bias that may arise due to the apparent difference in outcomes between the treated and untreated groups and the characteristics that influence firms' participation in the policy, we use the propensity score matching (PSM) method to assess the impact of the policy. PSM attempts to reduce the bias due to confounding variables (Dehejia and Wahba, 1999) by mimicking randomization and creating a treated sample of firms that is comparable in all observed characteristics to an untreated sample of firms. The matching estimators have recently been applied and discussed by (Heckman et al., 1998; Angrist, 1998; Dehejia and Wahba, 1999, 2002; Lechner, 2002 and Garrido et al., 2014).

PSM constructs a statistical comparison group that is based on a model of the probability of participating in the policy, using observed characteristics that are unaffected by the program. Rosenbaum and Rubin (1983) show that in PSM, each participant is matched to a nonparticipant on the basis of a single propensity score, reflecting the probability of participating conditional on their different observed characteristics. For a theoretical formulation, we assume a binary treatment D conditional on a set of observed characteristics X and the potential outcomes Y. Here, $D = 1$ if the firm participates in the policy, and $D = 0$ if it does not. The propensity score, defined as the conditional probability P of participation given the set of characteristics, is as follows:

$$P(X) = Pr(D = 1|X) \tag{1}$$

Here, we assign an estimated propensity score to every sampled firm[5]. We estimate

[5]It is worth noting that the validity of PSM depends on two conditions. The first condition, the *conditional independence assumption (CIA), or unconfoundedness* $((Y^T, Y^C) \perp D|X)$, implies that a set of observable

the propensity score by using a logistic regression. To avoid matching on the predicted probabilities, which compress the propensity scores near zero and one, Rubin and Thomas (1992) and, more recently, Sekhon (2011) and Diamond and Sekhon (2013) have recommended matching on the linear propensity score instead of the propensity score itself. The linear propensity score is computed as follows:

$$log(P_i(X)) = log\left(\frac{P_i(X)}{1 - P_i(X)}\right) \tag{2}$$

where $P_i(X)$ is the estimated propensity score.

We define the common support and check the balancing test to be sure that the distributions of the two groups are similar. Formally, we check whether $P(X|D=1) = P(X|D=0)$. Then, we match participants to nonparticipants using a matching algorithm. We match each participant firm to the comparison firm with the closest propensity score using the *nearest-neighbor (NN)* algorithm, which is one of the most frequently used matching techniques. As in the NN matching technique, the difference in propensity scores for a participant and its closest comparison neighbor may be very high; thus, we tend to reduce the bias by combining it with a *caliper*[6] (Cochrane and Rubin, 1973; Rosenbaum and Rubin, 1985), which imposes a threshold for the maximum tolerated difference between matched firms. To limit the increase in bias and to increase the quality of matching and enforce common support, we perform one-to-one matching with replacement.

As explained by Khandker et al. (2010), if conditional independence holds, and if there is a sizable overlap in $P(X)$ across participants and nonparticipants, the PSM estimator for the effect of the treatment on the treated (ATT) can be specified as the mean difference in Y over the common support, weighting the comparison units by the propensity score distribution of participants. Then, the outcomes of participating and nonparticipating firms with similar propensity scores are compared to obtain the policy effect. The ATT estimator based on the

characteristics X exists that is not affected by the treatment and potential outcomes Y and that is independent of the treatment assignment D. The second condition is the sizable *common support assumption (CSA)* ($0 < P(D=1|X) < 1$), which implies that the observations of the participating firms have nearby comparison observations in the propensity score distribution (Heckman et al., 1999).

[6]A caliper of 0.25 standard deviations of each treated observation was used, as recommended in the literature (Cochrane and Rubin, 1973; Rosenbaum and Rubin, 1985 and, more recently, Stuart, 2010; Caliendo and Kopeinig, 2008). Rosenbaum and Rubin, 1985 explained that a caliper of 0.25 can reduce 90% of bias.

PSM can be written as follows:

$$\Delta^{ATT} = E_{P(X)|D=1}\{E[Y^T|D=1, P(X)] - E[Y^C|D=0, P(X)]\} \tag{3}$$

As PSM takes into account only firms' observed characteristics, bias may arise because the firms' unobserved characteristics may influence their decision to participate in the policy, and the effect may be a mix of the policy effect and the unobserved characteristics. To deal with this endogeneity bias due to selection based on unobserved characteristics, we combine PSM with the difference-in-difference (DiD) method, also known as conditional difference-in-difference (CDiD) (Heckman et al., 1997; Abadie and Imbens, 2006; Blundell and Costa Dias, 2009). The advantage of CDiD is that after controlling for selection based on observable characteristics, it removes firms' individual systematic effects and also eliminates the time effects, thus consistently estimating the treatment effect. The main limit of this method is that it does not take into account the eventual relevant unobserved time-varying factors. CDiD can be implemented in a three-step procedure. First, it estimates the propensity score; second, it matches treated firms with control firms; and third, it exploits the longitudinal nature of the data by estimating a DiD estimator for each treated firm with its matched counterfactual(s).

With panel data over two time periods $t = \{1, 2\}$, the local linear DiD estimator for the mean difference in outcomes Y_{it} across participants i and nonparticipants j in the common support is given by

$$\Delta^{ATT}_{CDiD} = \frac{1}{N_T}\left[\sum_{i \in T}(Y^T_{i2} - Y^T_{i1}) - \sum_{i \in C}\omega(i,j)(Y^C_{j2} - Y^C_{j1})\right] \tag{4}$$

where Y^T_{it} and Y^C_{jt} are, respectively, the outcomes for participant i and nonparticipant j in time period $t = \{1, 2\}$. $\omega(i, j)$ is the weight (using a PSM approach) given to the j^{th} control firm matched to treatment firm i. The empirical model is as follows:

$$y_{i,t} = \alpha_i + \lambda t + \beta D_{i,t} + controlfactors + \epsilon_{i,t} \tag{5}$$

where α_i is the fixed effect that captures the time-invariant unobserved heterogeneity that was part of the selection bias. t is a set of dummies for every single year, which are more precise than just *pre−* and *post−* time period because we have many years of data and multiple treatments. $D_{i,t}$ is the indicator of treatment of firm i in year t, and β is the parameter of interest and corresponds to the ATT of a mixed method (DiD combined with PSM).

To implement the matching and compute the ATT, we use the *matching* package (Sekhon, 2011) explained theoretically in the work of Diamond and Sekhon (2013).

To evaluate the impact of the policy, we first test the hypothesis of input additionality (R&D spending and employment related to R&D). Then, we test the hypothesis of output additionality (outcome variables related to firms' innovation and economic performance). All these variables are explained in more detail in the next section.

5 Data and variables

5.1 Data sources

We combine data from several sources and build a rich firm-level panel dataset for French SMEs covering the 2005-2012 period, which is relevant to observe the impacts of the policy before and after the launch of the competitiveness cluster policy. In this work, we use several datasets from different sources, such as the DGE[7] and FUI datasets for the participation of firms, respectively, in clusters and FUI projects, the R&D survey (Ministry of Research) for variables related to patents and R&D, the FICUS-FARE database for the economic and accounting variables, the LIFI database for the groups and nationality of firms and, finally, the Declarations of Social Data (DADS) database for employment-related variables.

The DGE survey and the FUI dataset provide information on participation in clusters (starting in 2005) and FUI projects (which started in 2007) until 2012. The DGE tracks the evolution of the cluster policy and updates the list of the adherent firms annually. The FUI has data on all projects in the framework of the clusters, and we can identify all firms that participate in the projects. By combining these two datasets, we are able to identify all adherent firms and nonadherent firms that participate in projects. Therefore, this allows us to construct the different dummy treatment variables previously presented: only adhering to a cluster, only participating in R&D projects or combining the two treatments.

The R&D survey conducted by the MESR is the main source of data about firms' R&D activities and innovation. This survey covers companies operating in French territory and performing work related to R&D.

[7]Direction Générale des Entreprises, ex-DGCIS (Direction Générale de la Compétitivité, de l'Industrie et des Services)

Measuring the effects of the policy on firms' R&D-related variables using the econometric method presented in the next section implies knowing the evolution of participant firms' characteristics and comparing them with those of firms in the nonparticipant control group. The R&D survey is a nonexhaustive census for SMEs; therefore, it is impossible to obtain these firms' characteristics over the years. However, the surveyed SMEs return systematically in the survey at least every five years. Because of this constraint, we do not choose a scope for the study as in the studies of Bellégo and Dortet-Bernadet (2014) and Ben Hassine and Mathieu (2017), in which only firms that have been surveyed for at least two consecutive years and spent less than €16 million in R&D are considered. With the objective of not losing many firms, we retain in our data, in addition to the SMEs that belong to clusters or participate in FUI projects, all the SMEs that appear at least twice in the dataset, whatever the amount of their R&D expenditure. To avoid including bias in the estimates, we do not follow Bellégo and Dortet-Bernadet (2014), who used a weighting approach, but we follow Ben Hassine and Mathieu (2017) by applying linear interpolation and extrapolation[8] to retain SMEs and their characteristics related to R&D.

To complete the information on firm characteristics, we mainly use the FICUS-FARE dataset, which is an annual firm-level dataset that covers almost all French firms. It provides economic and accounting indicators (related to the balance sheet), such as turnover, value added, and export. This dataset also provides variables on investment and exploitation subsidies that firms have received, firm age, and the economic sectors in which firms operate. To identify foreign companies, the scope of the groups and the position of a firm in its group, we use data on financial links (LIFI) provided by the French National Institute for Statistics (INSEE)[9].

Finally, the DADS dataset, available at the establishment level, provides information related to employment and geographical location. This dataset allows us to better localize the activities of firms and to know the number of employees (and the structure of employment

[8]Linear interpolation allows us to estimate the missing values between two given points. The strategy for linear interpolation is to use the arithmetic mean to fill a gap or missing value between two data points. Linear extrapolation allows us to use the arithmetic mean to estimate values outside the interval between two points by using a subset of the data instead of the entire dataset to estimate the missing values.

[9]These are all French private sector companies with an equity portfolio exceeding €1.2 million, with a turnover above €60 million, or with more than 500 employees, regardless of the sector.

by type of qualification and activity sector)[10]. We have aggregated the number of total employees and the employment of executives, managers and intellectual professionals at the firm level.

5.2 Outcome and control variables

To evaluate the impact of the policy, we first test the hypothesis of input additionality on several outcome variables. We use as outcome variables internal and external R&D spending (respectively $dird$ and $derd$), firms' total R&D budget ($budgetot$), subsidies ($financ\_pub$) and firms' self-financed projects ($financ\_pro$). We also use variables related to employment in R&D, such as employment of researchers ($researchemp$) and employment of executives, managers and intellectual professionals ($cs3$). Indeed, there are different ways to enhance the innovation input within firms. Comparing these different R&D input variables may help us better understand how cluster incentives act. For example, when comparing internal and external R&D expenditure, we may obtain some information about the collaborative and open behavior of firms **?**.

To test the hypothesis of output additionality, we use outcome variables related to firms' innovation and economic performance. For innovation, we use the total number of patents ($patent$) the firm has filed as an innovation proxy. To measure the effects of the policy in terms of performance related to employment, we use variables such as total average employees (eff_moy_et). For economic performance related to the market, we use indicators such as turnover ($turnover$) and value added ($valueadded$). Finally, exports ($export$) are also considered as the main indicator of innovation-based firm competitiveness Freel et al. (2019).

To explain the participation process and account for the selection problem, we use the empirical evidence and the information available in our dataset to choose variables to calculate the propensity to participate in the policy. Previous studies identified certain firm characteristics that can influence the decision to participate in cluster policies, such as size, age, being a member of a group, experience in public subsidies, export, economic sector and geographical location.

In the literature, the size of a firm is considered an important characteristic that influences

[10]The DADS dataset contains only employer establishments; thus, not all employing establishments are included in the files. In addition, the data of special regimes provided by the DGFIP (Direction Générale des Finances Publiques) and of the Ministry of Defense are not included in the DADS dataset.

participation in a cluster policy. We include the logarithm of the number of employees (*emp*). Older firms are expected to spend more on R&D, to have a greater accumulation of absorptive capacity and therefore to be more likely to participate in clusters. We calculate firm age as the number of years (*age*) that the firm has been operating in the market. Firms belonging to a group may be more likely to participate in clusters because they presumably have better access to information about governmental actions due to their network linkages. We include a dummy variable (*appgroup*) that takes the value of one if the firm is a member of a group and zero otherwise.

Firms that have already received public subsidies may better know the administrative procedures and be more likely to participate in public policies. We include a dummy variable (*dum_sub*) that takes the value of one if the firm has already benefited from a public subsidy and zero otherwise. Firms that export are more exposed to international competition and are more likely to participate in the policy because the reduction in R&D costs is very important to them and enables them to continue to be competitive in the market. We include a dummy (*dum_export*) that takes the value of one if the firm exports and zero otherwise.

For the economic sector, firms that operate in high-technology manufacturing or in the highly knowledge-intensive sector may be more likely to participate in the cluster policy. Some previous studies suggest that public policies for firms mainly benefit companies in highly dynamic sectors. To control for the economic sector in which the firm operates, we include a dummy (*dum_sec_man*) that takes the value of one if the firm operates in the sector of manufacture of electrical, computer and electronic equipment and machinery. We also include another dummy variable (*dum_sec_hkis*) that takes the value of one if the firm operates in the sector of highly knowledge-intensive services.

Geographical location is a very important characteristic for a firm's decision to participate in the policy because of the proximity of potential partners, knowledge flows, and agglomeration economies. The geographical location (*loc*) of the firms in our study consists of eight dummy variables that correspond to the eight French metropolitan NUTS1 regions.

Table 2 shows all the variables classified into three groups. The first group of variables concerns input outcome variables (R&D spending and employment related to R&D). The second group of variables is related to output outcome variables (patents, total employment, and economic performance). The third group of variables is related to the determinants of firms' participation in the policy; they are used as controls to calculate the propensity score to control the selection bias.

After merging all these datasets, we obtain an unbalanced panel dataset at the firm level that covers the 2005-2012 period. After filtering out the French SMEs on which we have information for no more than one year, we obtain a dataset containing 41,449 observations.

Table 2: Description of variables

Variable	**Source**	**Description**
		Input outcome variables
derd	R&D	External R&D spending of the firm (subcontract with partners) (in k €)
dird	R&D	Internal R&D spending of the firm (for its own or for its partners) (in k €)
budgetot	R&D	Total Research and development budget (DIRD+DERD) of the firm (in k €)
financ_pro	R&D	R&D funding made by the firm itself (self-financed) (in k €)
financ_pub	R&D	Public funding for the firm's R&D (in k €)
cs3	DADS	Number of employees in executives, managers and high intellectual professions (CS3)
researchemp	R&D	Number of researcher employees (full-time equivalent)
		Output outcome variables
totbrev	R&D	Total number of patents filed by the firm
eff_moy_et	DADS	Firm's average employees in full-time equivalent
turnover	FICUS-FARE	Total turnover of the firm in euros (in k €)
valueadded	FICUS-FARE	The firm's value added before taxes (in k €)
export	FICUS-FARE	Total export turnover of the firm (in k €)
		Other control variables used to compute the propensity scores
p_adh_ent	DGE	1 if the firm has adhered to at least one cluster for a given year, 0 otherwise
f_part_ent	FUI	1 if the firm has participated in at least one FUI project for a given year, 0 otherwise
log(emp)	DADS	Firm size measured by the logarithm of its total number of employees (full-time equivalent)
age	FICUS-FARE	The firm's age defined as the number of years the firm has been established
appgroup	LIFI	1 if the firm is membership of a group, 0 otherwise
dum_subven	FICUS-FARE	1 if the firm has received public subsidies, 0 otherwise
dum_sec_man	FICUS-FARE	1 if the firm operates in the high-technology manufacturing sector, 0 otherwise
dum_sec_hkis	FICUS-FARE	1 if the firm operates in high-knowledge intensive services, 0 otherwise
loc	DADS	Eight dummy variables corresponding to the eight French metropolitan NUTS1 regions

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi.

In the pooled sample, 33,317 firms did not participate in the policy, 1,734 received both treatments (Group A), 5,963 adhered only to clusters (Group B), and 358 participated only in FUI projects (Group C). To avoid using treated firms in any year as a control, we created a pure control group (Group D) that is similar for the three groups and is composed of 27,354 observations before matching. Table 3 presents the descriptive statistics for each group of treated and nontreated firms for the entire period[11].

[11]Tables 13 to 16 in the Appendices give, for each year, the pre- and posttreatment characteristics of the

These statistics show significant differences between participating firms and nonparticipating firms on most of the R&D, innovation and economic variables. All three treatment groups show higher average outcome variables than the controls. The firms in Group B have, on average, lower indicators on all types of outcomes. Group C is composed of older firms that have higher indicators in terms of all types of economic performance. Our strategy, consisting of defining specific models and controls for the two types of treatment and their combination, is justified.

Table 3: Average of firms characteristics across the different samples

	Global sample		Group A	Group B	Group C	Group D
	Treatment	Control	Treatment	Treatment	Treatment	Control
	Input outcome variables					
derd	159.7	126.7	176.6	154.8	220.1	128.3
dird	826.4	496.9	1193.4	719.7	1271.8	447.6
budgetot	981.8	622.1	1370.1	869.0	1449.9	575.9
financ_pub	107.8	35.4	196.4	82.0	197.0	26.2
financ_pro	741.9	487.8	996.7	667.8	1044.4	453.0
researchemp	5.8	3.4	8.8	4.9	9.0	3.0
cs3	15.7	11.6	21.9	13.9	20.7	11.3
	Output outcome variables					
totbrev	1.5	0.9	2.1	1.3	1.3	0.8
eff_moy_et	47.7	45.2	50.0	47.1	54.4	44.6
turnover	10094.9	11062.9	11206.8	9771.6	12095.0	11275.7
export	4054.6	4044.1	5306.1	3690.7	5628.2	4105.3
valueadded	2971.9	3267.1	3235.3	2895.3	3824.5	3318.5
	Other control variables					
emp	49.0	41.1	57.8	46.5	55.5	40.5
age	22.7	26.0	21.4	23.1	23.6	26.6
dum_export	0.7	0.7	0.8	0.7	0.7	0.7
dum_subven	0.8	0.5	0.9	0.7	0.8	0.5
Observations	7697	33752	1734	5963	358	27354

Note: Patents are in unit, R&D and salary variables are in thousand €, employment-related variables are in unit, and market-related variables are in thousand €.
Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi

6 Results

In this section, we first explain the drivers of firms' participation in the policy and then present our strategy of constructing an adequate counterfactual framework for participant firms.

firms. Finally, we present the estimated effects of the policy on participant firms' performance, discuss our results by group and compare them.

6.1 Estimated propensities to participate in the policy

We use the PSM approach to compute the probability of a firm's participation in the policy based on its observable characteristics. As explained previously, we create three treatment groups to identify an appropriate control group with good overlap.

Following Ben Hassine and Mathieu (2017), we estimate the logistic model for each year to first take into account the entry and exit of firms from the policy, assuming that the determinant of participation in the policy may evolve over time. Therefore, in our study, the participation of a firm in the policy means that the firm participated for the first time or had participated before and remained a participant. All firms that were treated at least one time were excluded from the control group. Indeed, when a firm departs from (exits) the policy, it may continue to benefit from the network and cooperative linkages that it established while it was participating in the policy, both from information acquired through its participation in previous years and from its high exposure to spillovers. Therefore, we estimate the effect for each year, taking into account the new entry/exit issue. As explained in the previous section, to calculate propensity scores, we control some firm characteristics, such as size, age, being a member of a group, experience in public subsidies, economic sector, export and geographical location. All the control variables used are measured for the year 2005, which is the pretreatment reference year.

The results for Group A (firms benefiting from both treatments) presented in Table 4 show that the firm size measured by the logarithm of total employees (*emp*) plays an important role and is positive and significant, as expected. Larger firms in terms of employment are more likely to be members of clusters and to participate in projects at the same time, with a declining effect after the first phase of the policy (coefficient 0,5 for 2007 and 2008 to 0,3 for 2011 and 2012). Once accounting for the size effects, younger firms are more likely to participate in the policy (firm age coefficient negative and significant). The dummy variable (*pubsub*) is positive and very significant, meaning that if a firm has already benefited from public subsidies, it better knows the administrative procedures to benefit from another subsidy and therefore has an increased probability of participating in the public policy. In terms of economic sector, the results suggest that, in contrast to firms operating in high-technology manufacturing sectors, firms operating in the highly knowledge-intensive skills sector (kis) are more likely to participate in the cluster policy. Finally, firms with an export status are more likely to participate in the policy. Although their probability of participation in the policy seems to be nonsignificant between 2008 and 2010, its significance reappears in 2011 and 2012.

Comparing the results for Group B and Group C, i.e., firms choosing to only be members of clusters (Table 5) compared to firms only participating in subsidized R&D projects (Table 6), the main conclusions are the following. The size of firms is an important driver of firms' participation for both treatments at the very beginning of the policy implementation. However, this variable's level and significance tend to reduce over the year for group B while, on the contrary, remaining highly significant for Group C. Firms only participating in FUI projects are also older than those only adhering to clusters (the age coefficient is most of the time insignificant for Group C). Another difference between the two groups concerns the export variable. It is insignificant over the whole period for Group C and, on the contrary, positive and significant over the whole period for Group B, meaning that the animation and common services proposed by clusters attract more young exporting firms that the R&D subsidies program does. On the other hand, no statistically significant differences exist between the two treatments in terms of experience in public subsidies and the economic sector. Having previously received public subsidies and operating in the highly knowledge-intensive skills sector positively impact the probability both of adhering to clusters and of participating in FUI projects.

These results are globally consistent with those of previous studies evaluating the effects of public cluster policies. However, when distinguishing the three different possible treatments, they put stress on some main sources of heterogeneity of the effects across the three groups. In particular, it is worth noting that firms choosing to only adhere to a cluster without participating in an FUI project are smaller, younger and more oriented toward exportation.

Table 4: Group A participation by year (2007-2012)

	Participation in competitiveness clusters and in FUI projects					
	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
log(emp05)	0.5***	0.5***	0.4***	0.4***	0.3***	0.3***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
age05	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(0.01)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
appgroup05	0.5**	0.2	0.1	0.2	0.02	−0.1
	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
dum_subven05	1.3***	1.3***	1.3***	1.2***	1.1***	1.1***
	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
dum_sec_man_electro05	−1.0	−1.4	−1.0	−0.6	0.4	0.3
	(1.0)	(1.0)	(0.7)	(0.6)	(0.4)	(0.4)
dum_sec_hkis05	1.1***	0.8***	0.8***	0.8***	0.9***	0.8***
	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
dum_export05	0.4*	0.1	0.1	0.1	0.3*	0.3**
	(0.2)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
Constant	−18.7	−17.1	−16.9	−16.8	−16.9	−16.7
	(406.2)	(271.8)	(270.1)	(248.8)	(247.3)	(247.5)
Location dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	8,143	7,410	7,729	7,687	7,598	7,463

Note: The columns give the estimates corresponding to the marginal effect of the considered variable on the firm's probability to participate in the policy. All the control variables used between 2007 and 2012 are measured for the year 2005 which is the pre-treatment reference year. The location dummies consist of eight dummy variables corresponding to the eight French metropolitan NUTS1 regions. Standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 5: Group B participation by year (2006-2012)

	Participation in competitiveness clusters						
	(2006)	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
log(emp05)	0.3***	0.2***	0.2***	0.1***	0.1***	0.1**	0.1*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
age05	−0.01***	−0.01***	−0.01***	−0.004**	−0.003*	−0.004***	−0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
appgroup05	0.2*	0.1	0.1	0.1	0.1	0.1*	0.2***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
dum_subven05	1.2***	1.0***	1.0***	0.9***	0.9***	0.9***	0.9***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
dum_sec_man_electro05	−0.2	0.1	−0.3	0.1	0.3	0.1	0.1
	(0.3)	(0.2)	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)
dum_sec_hkis05	0.7***	0.5***	0.6***	0.7***	0.7***	0.6***	0.7***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
dum_export05	0.4***	0.2**	0.2**	0.3***	0.2***	0.2***	0.2**
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Constant	−4.1***	−3.5***	−4.0***	−3.8***	−4.0***	−3.9***	−3.9***
	(0.8)	(0.8)	(1.1)	(1.1)	(1.1)	(1.1)	(1.1)
Location dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	
Observations	8,859	8,938	8,011	8,303	8,278	8,275	8,070

Note: The columns give the estimates corresponding to the marginal effect of the considered variable on the firm's probability to participate in the policy. All the control variables used between 2007 and 2012 are measured for the year 2005 which is the pre-treatment reference year. The location dummies consist of eight dummy variables corresponding to the eight French metropolitan NUTS1 regions. Standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

Table 6: Group C participation by year (2007-2012)

	Participation in FUI projects					
	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
log(emp05)	0.5*	0.3*	0.4***	0.4***	0.4***	0.5***
	(0.3)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
age05	−0.001	−0.01	−0.01*	−0.01	−0.01**	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
appgroup05	−1.3**	0.2	0.1	−0.2	0.4	0.2
	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
dum_subven05	1.6**	1.0***	0.9***	0.8***	1.1***	0.9***
	(0.7)	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)
dum_sec_man_electro05	−16.0	0.5	−0.2	1.0	−0.5	−0.5
	(3, 128.5)	(1.0)	(1.0)	(0.6)	(1.0)	(1.0)
dum_sec_hkis05	0.1	1.0***	1.0***	0.9***	0.6**	0.6**
	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
dum_export05	−0.1	0.3	0.4	0.3	0.1	−0.1
	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
Constant	−24.8	−23.8	−18.0	−18.0	−17.7	−17.8
	(13, 669.4)	(8, 994.0)	(445.8)	(410.5)	(413.1)	(415.6)
Location dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	8,025	7,231	7,497	7,437	7,324	7,190

Note: The columns give the estimates corresponding to the marginal effect of the considered variable on the firm's probability to participate in the policy. All the control variables used between 2007 and 2012 are measured for the year 2005 which is the pre-treatment reference year. The location dummies consist of eight dummy variables corresponding to the eight French metropolitan NUTS1 regions. Standard errors are in parentheses below the estimates. The significance levels: ***1%; **5%; *10%.

6.2 Balancing firms' characteristics before/after matching

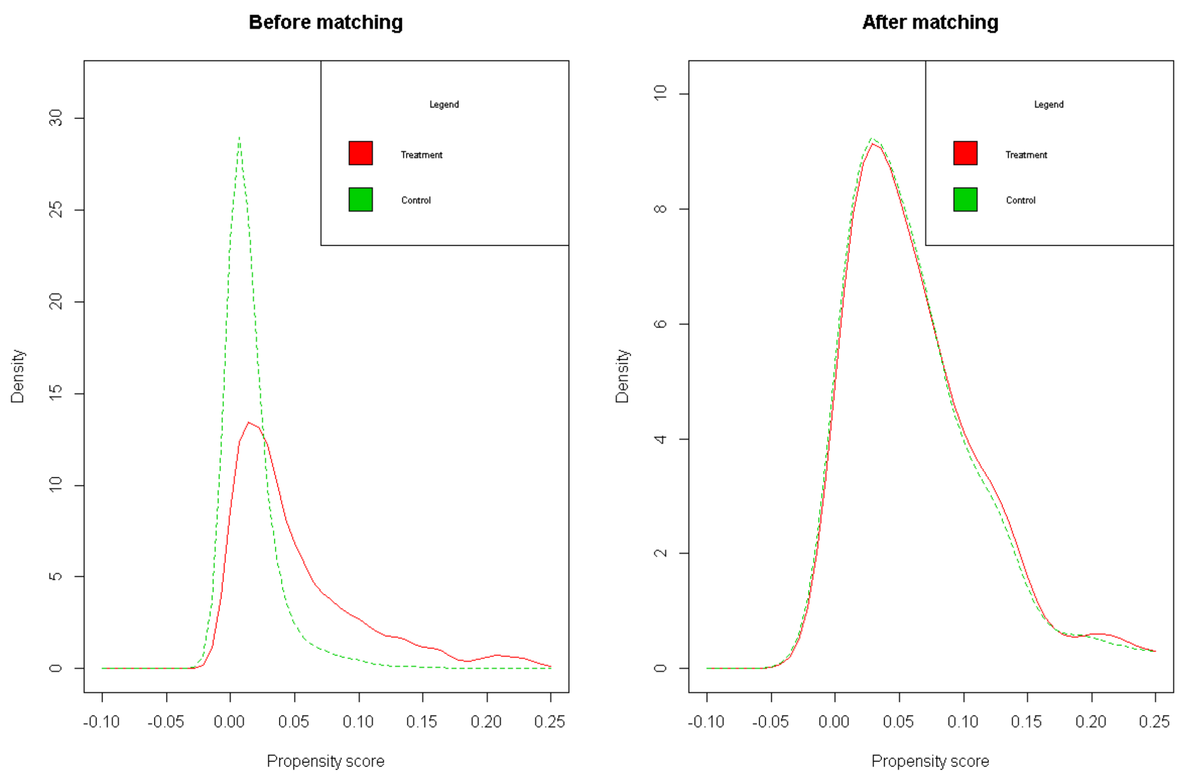
To compare the firms' characteristics before and after matching, we consider 2005 as the reference year (pretreatment year) and create treatment and control groups for each year. We create several subgroups within each of the three different samples, Group A, Group B, and Group C. The control groups across these subsamples are similar and vary between 8,060 and 7,108 observations before matching.

The prematching differences between the treated and control groups for these characteristics are in general relatively high and may bias our estimates. Thus, using the propensity score, we apply the matching procedure described in section 3 for each group.

Tables 17, 18 and 19 in the Appendices present the before-and-after-matching differences in the characteristics of firms. As shown in these tables, the distances between the treatment and control groups are very high before matching. After applying the matching between the treated and control firms, we obtain good improvement in the balance of characteristics between the two groups for each year, and the distances between the treated and control firms are exactly the same. Despite all the restrictions applied, there are very few firms that have no similar controls and are dropped from the datasets (see the last lines of the three tables).

Figures 4, 5 and 6 show, respectively, the distribution of the propensity score before and after matching for Group A, Group B and Group C[12].

Figure 4: Propensity score density before and after matching for Group A (year 2007)



[12] Figure 4 shows the distribution in Group A in 2007, Figure 5 shows the distribution in Group B in 2006, and Figure 6 shows the distribution in Group C in 2008. Checking the other years, we found little difference in the results.

Figure 5: Propensity score density before and after matching for Group B (year 2006)

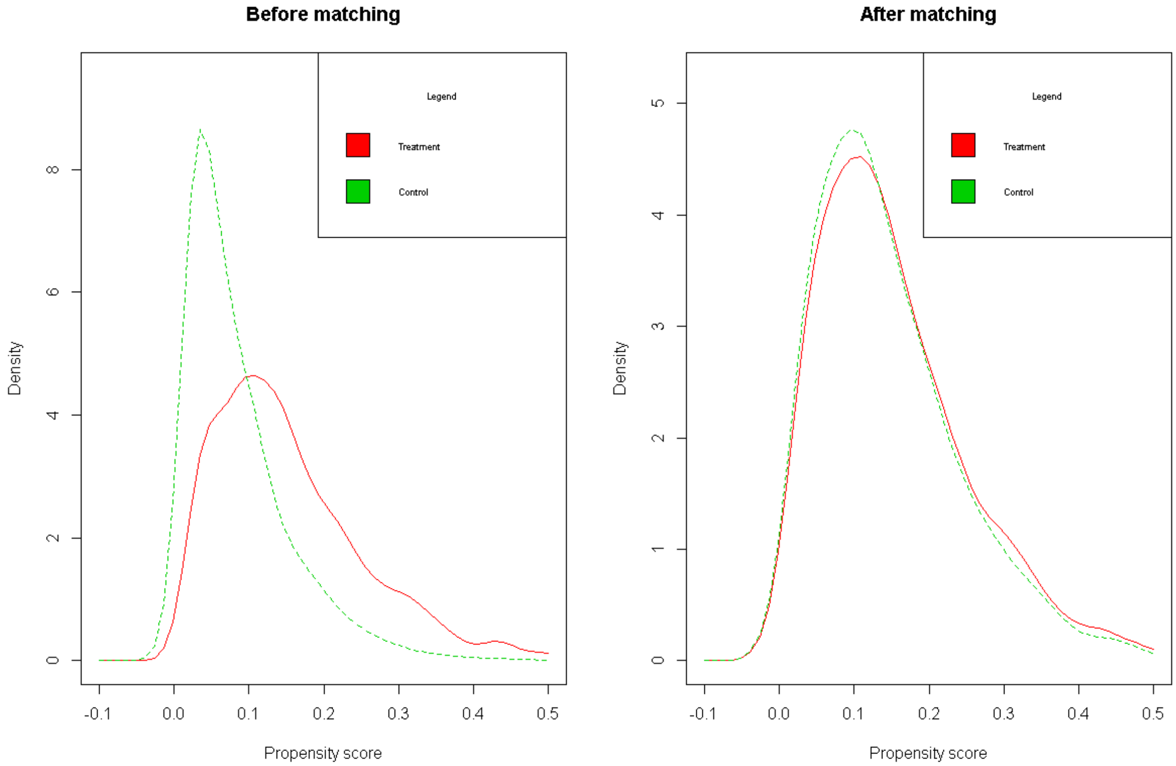
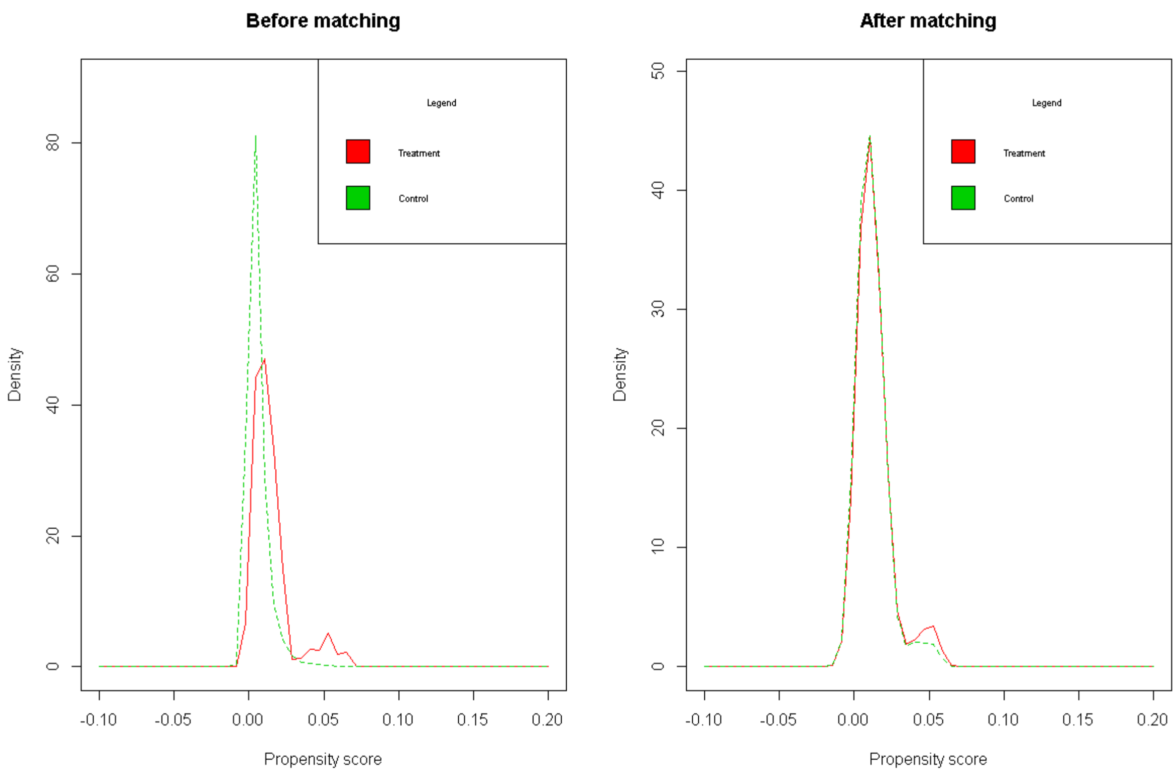


Figure 6: Propensity score density before and after matching for Group C (year 2008)



The figures show that our matching on the conditional probability of participation in the policy given a set of covariates produces samples with similar distributions of linear propensity scores between participant and control SMEs in the three different groups. We therefore consider that our quasi-experimental design to mimic a randomized experiment enables us to obtain data similar to those of a true control experiment and therefore to respect the CIA and common support assumptions. This finding indicates the adequacy of the common support and the validity of the propensity score, which enables a more precise policy impact evaluation.

6.3 Average treatment effects of the policy on firms' outcomes

We have shown in the previous section that the matching procedure results in a proper balance between the treatment and counterfactual groups; therefore, the method allows for the computation of the ATT. The estimates of the matching estimators and standard errors estimated using the Abadie and Imbens (2006) method are provided by the *Matching* packages (Sekhon, 2011).

The estimations are based on three different treatment options and are classified into two types of outcome variables: input outcome variables (R&D spending and employment related to R&D) and output outcome variables (patents and economic performance).

6.3.1 Effects on innovation input additionality

The results concerning input additionality are summarized in Table 7 for Group A, Table 8 for Group B and Table 9 for Group C. For all groups, the results suggest the rejection of the crowding-out hypothesis. However, one can conclude in favor of input additionality effects only for Group A and Group B, with a growing impact during the second phase of the policy (after 2009) for the latter group. In contrast, SMEs that only participate in an FUI project and do not adhere to a cluster show no impact of the policy in terms of total R&D spending. It is also worth noting that Group B, which gathers SMEs only adhering to clusters, is the only group that displays a positive impact on private funding of R&D all over the period, even though of a smaller magnitude than Group A (plus €263,870 to 386,860, depending on the year for Group A, compared to plus €114,370 to 195,070, depending on the year for Group B). Although it may be an expected effect of the policy to encourage external

R&D expenditure, as a marker of open practice for innovation, no clear impact of the cluster policy on external R&D expenditure is found, regardless of the group.

When focusing on employment related to R&D, similar results appears for Group C. Only participating in an FUI project does not have any significant impact in terms of employment of researchers and skilled workers. On the contrary, the impact is highly significant in terms of researcher and skilled worker employment for SMEs that cumulate the two treatments (plus 1.5 to 2.5 researchers and plus 2.3 to 4.1 CS3 employees, depending on the year). The effects on researcher employment is also positive with a lesser magnitude for SMEs that are only members of clusters without participating in FUI projects. The effect is less obvious for CS3 employees, as it appears positive and significant only for 2007 and 2008 in this group.

Table 7: Innovation input additionality effects for Group A

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
			External R&D Expenditure			
Estimate	66.68	74.98***	65.20***	-20.20	104.62	-821.22**
	(77.78)	(44.14)	(29.55)	(36.40)	(74.71)	(430.80)
			Internal R&D Expenditure			
Estimate	-228.58	167.18	286.89***	305.87***	284.65***	326.79***
	(356.94)	(110.25)	(110.09)	(99.09)	(93.68)	(95.49)
			Total Budget in R&D			
Estimate	-249.36	376.07***	209.41**	379.52***	424.96***	-477.48
	(660.39)	(120.13)	(101.11)	(136.02)	(127.90)	(428.30)
			Private funding			
Estimate	-287.01	358.29***	204.21	263.87**	386.86***	-527.16
	(657.54)	(119.83)	(140.14)	(116.48)	(141.38)	(424.90)
			Public funding			
Estimate	20.95	68.31**	89.67***	78.60***	72.47***	142.43***
	(18.96)	(30.25)	(29.52)	(24.62)	(20.06)	(40.19)
			Researchers			
Estimate	0.62	1.75***	1.49***	1.88***	1.85***	2.52***
	(0.41)	(0.56)	(0.45)	(0.46)	(0.46)	(0.51)
			CS3 employment			
Estimate	2.33***	3.35***	2.69***	4.10***	2.80***	1.67
	(1.07)	(1.12)	(1.17)	(1.28)	(1.30)	(1.32)
Nb. Obs	270	440	610	650	700	710

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

Table 8: Innovation input additionality effects for Group B

	(2006)	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
				External R&D Expenditure			
Estimate	2.41	14.81	-111.12	-199.32	32.64	58.02**	43.05
	(11.46)	(41.47)	(204.68)	(192.87)	(31.66)	(28.92)	(37.51)
				Internal R&D Expenditure			
Estimate	29.77	7.72	75.25*	65.59	120.64**	145.61***	143.62**
	(26.92)	(86.33)	(44.58)	(52.89)	(53.43)	(51.56)	(65.22)
				Total Budget in R&D			
Estimate	11.38	48.54	154.48*	90.67	151.03**	160.42***	155.88**
	(26.91)	(98.26)	(81.30)	(154.12)	(73.31)	(58.20)	(77.96)
				Private funding			
Estimate	18.70	114.37*	150.04*	126.43*	149.26**	188.07***	195.07***
	(33.22)	(65.17)	(78.62)	(69.02)	(71.12)	(67.35)	(71.09)
				Public funding			
Estimate	6.31	6.00	5.86	26.69**	39.60**	29.77*	37.93**
	(4.56)	(5.90)	(9.02)	(11.00)	(17.32)	(17.25)	(16.30)
				Researchers			
Estimate	0.15	0.61***	0.89***	0.79***	0.48**	0.60***	0.59***
	(0.10)	(0.13)	(0.17)	(0.16)	(0.21)	(0.19)	(0.21)
				CS3 employment			
Estimate	0.26	1.25***	0.85**	0.01	0.59	0.02	1.08
	(0.27)	(0.30)	(0.36)	(0.55)	(0.55)	(0.67)	(0.69)
Nb. Obs	1594	1858	1642	1758	1832	2054	1924

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

Table 9: Innovation input additionality effects for Group C

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
			External R&D Expenditure			
Estimate	63.35**	183.08	-67.55	-1678.50	6.81	28.31
	(28.90)	(129.40)	(48.82)	(1756.90)	(52.30)	(41.70)
			Internal R&D Expenditure			
Estimate	348.47***	81.32	-143.83	232.05	548.44*	215.73*
	(140.20)	(96.82)	(169.38)	(204.37)	(319.15)	(126.41)
			Total Budget in R&D			
Estimate	278.59*	262.94	-153.72	388.84	190.02	79.94
	(155.99)	(228.11)	(176.15)	(326.63)	(133.91)	(167.73)
			Private funding			
Estimate	329.59**	29.61	177.09	376.56	-165.99	253.38**
	(147.47)	(90.98)	(226.33)	(243.83)	(156.15)	(126.43)
			Public funding			
Estimate	-3.47	51.64	-0.99	98.10***	186.65**	70.04
	(16.41)	(49.55)	(46.50)	(39.32)	(86.39)	(66.42)
			Researchers			
Estimate	1.31	0.08	-1.04	1.05	0.34	1.39*
	(1.01)	(0.46)	(1.30)	(1.11)	(0.68)	(0.84)
			CS3 employment			
Estimate	-3.18*	0.37	1.45	-0.71	5.04**	1.34
	(1.95)	(1.49)	(3.45)	(2.69)	(2.45)	(3.43)
Nb. Obs	34	82	146	150	152	164

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

In sum, the comparison of the different treatment options reveals that the policy associated with both treatments (Group A) outperforms both cluster adhesion and FUI project participation considered separately. More interestingly, being a member of a cluster seems to be more effective than participating in FUI projects with regard to input additionality. As is also revealed by Afcha Chávez and Garcia-Quevedo (2016), only benefiting from R&D subsidies does not generally have a contemporaneous impact on innovation input for participating SMEs. Beyond the temporal gap there are also conditions concerning the characteristics of firms. What our results point to is that for SMEs in French clusters, nonfinancial support is more effective in fostering their R&D expenditure than pure financial support to collaborative R&D projects. In line with Cano-Kollmann et al. (2016), this suggests that, for policy makers facing salient budgetary constraints, relying on animation action may be the more efficient strategy. Indeed, the high level of absorptive capabilities necessary to benefit from collaborative R&D projects creates a selection bias in such an instrument that reinforces a possible deadweight effect.

6.3.2 Effects on output additionality

The results on output additionality are summarized in Table 10 for Group A, Table 11 for Group B and Table 12 for Group C. These tables show that the competitiveness cluster policy had positive effects on innovation measured by the number of filed patents in 2008 (0.9 patent) and 2009 (1.4 patents) for SMEs that at the same time adhere to clusters and participate in FUI projects. On the contrary, there is a tendency toward negative effects on patent filing for SMEs that are only members of clusters and not engaged in R&D FUI projects. Significant positive effects are found on the turnover, value added and export of adherent SMEs (Group B) only in 2011. To this, we can add positive impacts on value added in 2009 and 2011 for SMEs that only participate in FUI projects (Group C). Such weak and inconsistent results, however, only confirm the findings of previous works that found no impact of cluster policies in terms of innovation or economic performance, especially in the French case.

Very different, however, are our findings concerning total employment. Indeed, the positive effect of the competitiveness cluster policy on SMEs' total employment appears highly significant between 2007 and 2012 (plus 3 to 6.7 employees depending on the year) for Group A. It is also positive between 2007 and 2012 for Group B, with a smaller magnitude than for Group A during the first phase of a policy, before a clear positive inflexion during the second phase of the policy (plus 1.2 in 2007 toward more than 5 employees in 2011 and 2012). As for Group C, we observe a positive effect of participation in FUI projects on the average number of employees in 2009 (6.6 employees); however, no significant effect is observed for the other years, and the sign of the coefficient is sometimes negative.

Similar to what we observed for R&D input indicators, the comparison of the different treatment options reveals that, for total employment, the policy associating both treatments (Group A) outperforms both cluster adhesion and FUI project participation when used separately. In addition, being a member of clusters seems to be more effective than participating in FUI projects with regard to the employment indicator.

Table 10: Effects of participation on output additionality in Group A

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
			Total Patents			
Estimate	-0.39	0.93***	1.36***	0.90	0.37	0.04
	(0.41)	(0.42)	(0.62)	(0.57)	(0.51)	(0.33)
			Average number of employees (full-time equivalent)			
Estimate	2.98*	6.06***	6.19***	6.56***	6.27***	5.91***
	(1.79)	(1.62)	(1.63)	(2.05)	(2.18)	(1.79)
			Turnover			
Estimate	-4542.00	-2682.60	-1947.30	-644.42	88.64	2075.40
	(3006.30)	(2355.20)	(1867.70)	(1847.50)	(1517.90)	(1378.00)
			Added Value			
Estimate	-133.57	-389.44	-665.45	-442.94	-134.54	-71.56
	(243.96)	(618.89)	(498.38)	(466.80)	(526.94)	(365.85)
			Export			
Estimate	62.93	-546.26	-508.47	-161.77	521.26	268.50
	(558.38)	(695.78)	(761.50)	(724.98)	(703.27)	(519.24)
Nb. Obs	270	440	610	650	700	710

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

Table 11: Effects of participation on output additionality in Group B

	(2006)	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
				Total Patents			
Estimate	-0.58**	0.00	0.01	0.13	-0.25	-0.50**	-0.48
	(0.25)	(0.23)	(0.31)	(0.23)	(0.30)	(0.25)	(0.32)
				Average number of employees (full-time equivalent)			
Estimate	1.23**	1.39	2.50***	1.14	3.20***	5.80***	5.34***
	(0.52)	(0.92)	(0.85)	(1.04)	(1.12)	(1.40)	(1.22)
				Turnover			
Estimate	-603.77	-1368.40*	-662.55	1525.70	90.32	1238.30*	66.10
	(577.33)	(730.69)	(584.95)	(1715.00)	(453.97)	(669.33)	(694.39)
				Added Value			
Estimate	-140.12	57.65	-121.08	-88.51	36.08	302.41*	349.42
	(169.58)	(177.06)	(243.01)	(246.89)	(233.48)	(179.73)	(252.97)
				Export			
Estimate	-222.87	41.67	-2.72	-412.86	96.44	896.83***	395.60
	(304.58)	(854.73)	(248.44)	(381.66)	(286.39)	(288.93)	(374.68)
Nb. Obs	1594	1858	1642	1758	1832	2054	1924

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

Table 12: Effects of participation on output additionality in Group C

	(2007)	(2008)	(2009)	(2010)	(2011)	(2012)
			Total Patents			
Estimate	1.15	-0.53	-0.80	-0.87	-2.50	-2.35
	(1.24)	(1.13)	(1.06)	(0.92)	(1.81)	(1.65)
			Average number of employees (full-time equivalent)			
Estimate	-1.38	2.86	6.63*	-4.64	-0.92	1.43
	(2.01)	(3.44)	(3.57)	(4.32)	(4.30)	(5.33)
			Turnover			
Estimate	659.35	-1379.80	1301.00	1548.90	1551.20	845.17
	(2807.00)	(1741.30)	(1224.40)	(1435.20)	(1920.00)	(1207.10)
			Added Value			
Estimate	-160.06	662.61	2167.40**	1132.30	1457.10*	148.18
	(413.65)	(947.68)	(1019.40)	(1031.80)	(799.27)	(820.03)
			Export			
Estimate	570.24	402.71	971.75	736.00	529.03	-615.79
	(1513.90)	(1616.80)	(830.72)	(1125.00)	(694.10)	(1437.00)
Nb. Obs	34	82	146	150	152	164

Note: The ATT estimates are the mean difference between treatment group and corresponding control groups. One-to-one matching with replacement was implemented to decrease bias. Bootstrap with 1000 replications was used to estimate standard errors for the propensity score matching. The columns give the estimates and robust standard errors are below the estimates. Significance levels: ***1%; **5%; *10%.

7 Conclusion

This paper measures the effectiveness of the French competitiveness cluster policy on participating SMEs' innovation and economic performance. We combine data from several sources to build a rich firm-level panel dataset covering the 2005-2012 period and use an original strategy to identify participating firms and determine the structure of participation. We consider two levels of treatment: cluster membership, allowing firms to benefit from networking animation and common services and platforms; and FUI project participation, allowing firms to benefit from subsidies to invest in collaborative R&D projects. As these are overlapping treatments, we distinguish three groups of treatment: firms receiving both treatments, firms receiving only the first treatment and firms receiving only the second treatment. We use the CDiD estimator, which is a combination of PSM with the DiD method, to account for selection bias due to observable and unobserved characteristics when creating a counterfactual framework. We determine an adequate sampling, precisely estimate differences in outcomes between the treatment and control groups and conduct several independent matchings for each type of treatment in each time period. This is justified by the heterogeneity of the selection criteria corresponding to the different treatments.

Although the importance and selection process of the competitiveness cluster policy intervention is often gauged by the amount of allocated FUI subsidies Sopoligová and Pavelková (2017). Cluster policy in Europe and Asia: A comparison using selected cluster policy characteristics. Journal of International Studies, 10(3), 35-50. for example), this measure is not a good gauge in terms of the number and characteristics of treated SMEs. Few SMEs only participate in FUI projects (358 observations). The number of SMEs that are only members of clusters without participating in FUI projects is three times higher than the number of SMEs associated with both treatments (5963 compared to 1734 observations). These are globally smaller, younger and more oriented towards exportation than firms participating in subsidized R&D projects.

Taking into account this heterogeneity in the selection process, our impact evaluation results are threefold. First, we show that full participation in the multi-instrument competitiveness cluster policy has strong positive effects on participating SMEs' innovation input (private R&D spending and R&D employment). This results are in line with previous studies evaluating the effects of the competitiveness cluster policy on SMEs' performance. Joint participation in clusters and projects brings a strong multiplier effect to privately financed R&D, but there is also a positive impact on SMEs that only adhere to clusters. Moreover, no crowding-out effect is observed, regardless of the treatment option.

Second, with regard to output performance, this study brings new evidence regarding the impact of the competitiveness cluster policy on total employment. The effects are strongly positive for total employment for SMEs that receive both treatments and to a lesser extent for SMEs that only belong to clusters. But the effects on employment are very weak or nonexistent for SMEs that only participate in FUI projects. The policy effects on other types of output performance (patents, turnover, value added, and export) are generally weak or nonexistent. These findings regarding the absence of impacts on output performance more related to the market are in line with the results of previous studies.

Finally, when we compare the effects of the policy through the three treatment options, the results suggest that the effects are heterogeneous. A comparison of the two policy instruments reveals that the effects are stronger for SMEs that receive both treatments, slightly weaker for those that are only a member of a cluster and very weak or nonexistent for those that participate only in FUI projects. These findings highlight the importance of strengthening the animation and strategic management of the clusters and also of providing services for firms in clusters. The development of structuring projects, such as innovation platforms intended to offer services or resources, and the development of innovation ecosystems seem to have a greater impact on SMEs' performance than financing of R&D projects only. The combination of these structuring projects and the increase in SMEs' absorptive capacity may explain the large effect of cluster adhesion on employment.

Despite the robustness checks and the contribution this work brings to the literature on the evaluation of cluster policies, it is nonetheless only one step in a still longer process to improve our understanding of cluster policies' impact. The absence of a significant effect on output performance is not easy to interpret. It may be due to data limitations and the small number of observations in some cases (notable concerning the group of enterprises that only participate in FUI projects), but it may also be due to the fact that the policy is unsuccessful or was highly successful and generated large positive spillovers for nonparticipant firms. One avenue for future research would be to complement this econometric evaluation with studies measuring the indirect effects of this policy through spillovers and externalities. It would also be relevant in the French case to better control for the influence of other instruments of the national or local policy mix in favor of R&D and innovation, such as the Research Tax Credit, which has been one of the most generous in the world since 2008.

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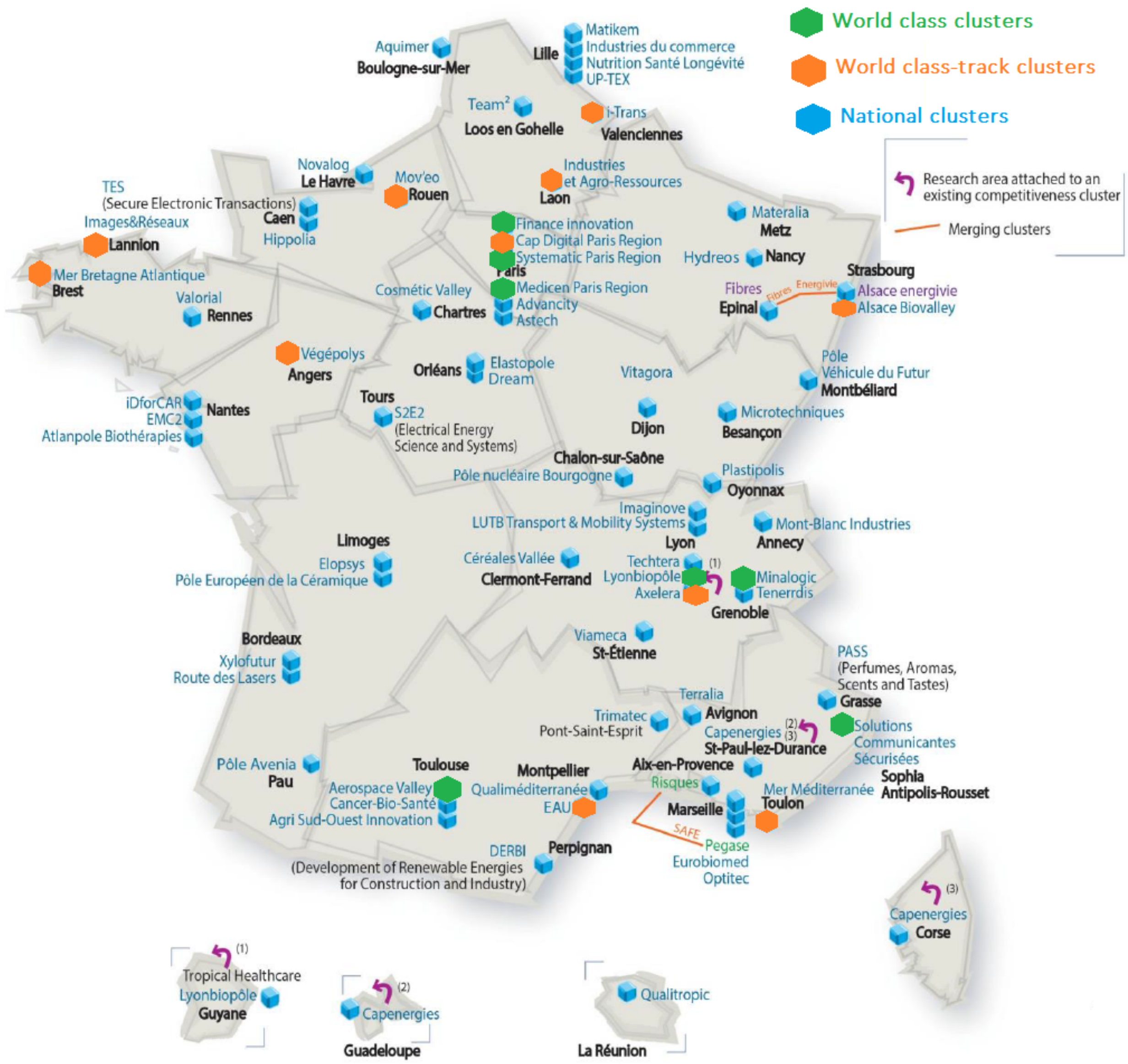
9 Appendices

Figure 7: Map of the Competitiveness clusters by type



Source: DGE/CGET, 2016: Modified and adapted by the author

Table 13: Firms' pre-post participation characteristics by year in Group A

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	97.6	84.3	211.9	134.4	88.1	83.2	162.9	125.8	80.7	86.8	126.6	116.7
dird	1014.9	428.8	1224.5	438.8	867.3	402.8	1134.5	405.4	843.1	413.2	1077.2	410.9
budgetot	1112.5	513.2	1436.5	573.2	955.4	485.9	1297.4	531.2	916.1	500.0	1203.8	527.6
financ_pub	142.9	23.4	166.9	23.8	118.0	22.1	185.0	26.4	117.9	22.8	213.1	19.6
financ_pro	772.9	425.2	1057.4	434.4	663.2	400.8	975.8	385.7	661.0	409.7	863.4	400.0
eff_rd	12.3	5.1	13.6	5.2	11.4	4.8	13.6	4.9	10.8	5.0	12.2	5.0
researchemp	8.5	2.9	9.2	3.0	6.9	2.7	8.5	2.8	6.6	2.9	8.1	2.9
cs3	19.3	9.8	20.8	10.0	16.4	9.1	20.2	9.8	15.3	9.3	21.2	11.7
	Output outcome variables											
totbrev	2.4	0.7	2.0	0.9	1.2	0.7	2.0	0.7	1.2	0.7	2.5	0.9
eff_moy_et	54.3	46.0	60.0	48.1	46.2	39.6	54.4	42.5	42.2	39.4	51.1	41.8
turnover	12550.8	10778.2	14566.8	12018.6	12451.4	9435.0	11286.5	10818.6	10487.1	9359.1	9470.7	10035.2
valueadded	3423.8	3233.4	3753.6	3611.7	3471.9	2928.1	3195.4	3314.1	3190.7	2873.7	2826.6	3162.4
export	6154.1	3722.3	7212.9	4379.6	4956.7	3238.7	5306.2	3604.2	4448.9	3220.2	4505.4	3503.9
	Other control variables											
emp	56.5	34.5	61.3	36.2	49.2	31.5	60.4	34.4	45.4	31.8	58.3	45.0
age	23.7	29.4	23.7	29.4	24.4	29.4	24.4	29.4	23.2	29.3	23.2	29.3
dum_export	0.8	0.7	0.8	0.7	0.7	0.7	0.9	0.8	0.7	0.7	0.8	0.7
dum_subven	0.8	0.5	0.8	0.5	0.8	0.5	0.9	0.5	0.8	0.5	0.9	0.5
Observations	135	8008	135	8008	220	7190	220	7190	305	7424	305	7424

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	113.0	82.8	145.5	144.1	108.1	81.4	164.7	79.2	96.5	82.0	145.0	118.3
dird	902.3	407.9	1211.2	418.3	811.3	389.5	1179.6	405.5	767.9	390.0	1164.5	410.1
budgetot	1015.3	490.8	1356.6	562.3	919.4	471.0	1344.3	484.4	864.4	472.0	1309.5	528.3
financ_pub	117.4	23.3	202.0	20.1	101.4	24.2	176.2	24.7	104.2	23.7	197.8	18.4
financ_pro	706.8	402.7	1029.6	453.9	649.2	379.4	1063.4	382.0	606.1	381.6	968.7	422.1
eff_rd	10.9	4.9	13.1	5.0	10.0	4.8	12.7	4.9	9.7	4.8	12.5	4.8
researchemp	6.8	2.8	8.7	2.9	6.3	2.7	8.5	2.8	6.0	2.7	8.5	2.7
cs3	15.4	9.3	23.7	12.7	14.2	9.0	22.0	13.1	13.6	9.0	21.5	13.3
	Output outcome variables											
totbrev	1.5	0.7	2.3	0.8	1.5	0.7	1.5	0.6	1.7	0.7	1.6	0.6
eff_moy_et	41.2	39.5	50.8	41.9	37.6	38.1	47.8	41.5	37.6	38.0	48.8	41.6
turnover	9952.3	9371.3	10290.3	10566.3	8781.6	9107.2	11461.3	10876.5	7394.7	9149.4	10538.5	11088.6
valueadded	3049.8	2862.6	3037.1	3331.4	2816.0	2767.7	3557.7	3347.9	2563.2	2794.4	3246.8	3403.8
export	4237.5	3250.5	5061.6	3954.9	3639.0	3114.6	5102.2	3950.7	2710.2	3141.7	4033.3	4207.4
	Other control variables											
emp	45.3	31.8	59.7	46.0	41.4	30.9	57.4	46.7	39.5	30.8	58.5	47.1
age	23.3	29.1	23.3	29.1	24.4	29.2	24.4	29.2	24.4	29.4	24.4	29.4
dum_export	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.7
dum_subven	0.7	0.5	0.9	0.5	0.7	0.5	0.9	0.5	0.7	0.5	0.9	0.5
Observations	325	7362	325	7362	350	7248	350	7248	355	7108	355	7108

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.
Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 14: Firms' pre-post participation characteristics by year in Group B (1/2)

	Period 2005-2006				Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables															
derd	93.3	86.2	102.9	92.9	109.6	84.3	160.7	134.4	105.1	83.2	199.8	125.8	96.5	86.8	145.0	116.7
dird	768.6	436.2	780.1	441.0	714.7	428.8	766.8	438.8	638.1	402.8	712.6	405.4	767.9	413.2	1164.5	410.9
budgetot	858.9	522.4	883.0	534.0	824.4	513.2	923.7	573.2	743.2	485.9	912.4	531.2	864.4	500.0	1309.5	527.6
financ_pub	84.3	24.4	92.4	24.4	75.8	23.4	79.6	23.8	67.8	22.1	77.4	26.4	104.2	22.8	197.8	19.6
financ_pro	630.1	429.4	654.7	420.5	608.9	425.2	685.9	434.4	556.3	400.8	697.8	385.7	606.1	409.7	968.7	400.0
eff_rd	8.9	5.2	9.1	5.3	8.4	5.1	9.0	5.2	7.3	4.8	8.1	4.9	9.7	5.0	12.5	5.0
researchemp	5.3	3.0	5.5	3.0	4.8	2.9	5.4	3.0	4.3	2.7	5.0	2.8	6.0	2.9	8.5	2.9
cs3	14.5	9.9	14.4	9.5	12.8	9.8	13.8	10.0	11.8	9.1	13.2	9.8	13.6	9.3	21.5	11.7
	Output outcome variables															
totbrev	1.6	0.7	1.5	0.7	1.6	0.7	1.6	0.9	1.5	0.7	1.8	0.7	1.7	0.7	1.6	0.9
eff_moy_et	56.1	45.9	57.9	47.1	51.7	46.0	55.3	48.1	44.4	39.6	49.4	42.5	37.6	39.4	48.8	41.8
turnover	12180.6	10741.6	12976.7	11502.6	10886.8	10778.2	11684.7	12018.6	8500.5	9435.0	9940.2	10818.6	7394.7	9359.1	10538.5	10035.2
valueadded	3601.6	3219.0	3811.4	3410.3	3273.4	3233.4	3530.3	3611.7	2676.9	2928.1	2940.8	3314.1	2563.2	2873.7	3246.8	3162.4
export	4556.6	3714.0	5017.5	4130.7	3767.1	3722.3	4300.8	4379.6	2935.1	3238.7	3345.0	3604.2	2710.2	3220.2	4033.3	3503.9
	Other control variables															
emp	46.8	34.7	48.0	35.1	41.9	34.5	46.6	36.2	38.1	31.5	43.5	34.4	39.5	31.8	58.5	45.0
age	27.0	29.3	27.0	29.3	26.7	29.4	26.7	29.4	26.3	29.4	26.3	29.4	24.4	29.3	24.4	29.3
dum_export	0.8	0.7	0.8	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.8	0.7	0.7	0.8	0.7
dum_subven	0.8	0.5	0.8	0.5	0.7	0.5	0.8	0.5	0.7	0.5	0.8	0.5	0.7	0.5	0.9	0.5
Observations	799	8060	799	8060		8008	930	8008	821		821	7190	355	7424	355	7424

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 15: Firms' pre-post participation characteristics by year in Group B (2/2)

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	96.9	82.8	144.7	144.1	91.6	81.4	160.3	79.2	91.6	82.0	160.3	118.3
dird	605.9	407.9	676.5	418.3	648.5	389.5	784.9	405.5	648.5	390.0	784.9	410.1
budgetot	702.7	490.8	821.2	562.3	737.8	471.0	931.9	484.4	737.8	472.0	931.9	528.3
financ_pub	66.9	23.3	93.4	20.1	71.6	24.2	106.1	24.7	71.6	23.7	106.1	18.4
financ_pro	545.8	402.7	640.3	453.9	574.0	379.4	726.7	382.0	574.0	381.6	726.7	422.1
eff_rd	7.0	4.9	7.7	5.0	7.2	4.8	8.2	4.9	7.2	4.8	8.2	4.8
researchemp	4.3	2.8	4.9	2.9	4.4	2.7	5.1	2.8	4.4	2.7	5.1	2.7
cs3	11.1	9.3	14.8	12.7	11.2	9.0	15.6	13.1	11.2	9.0	15.6	13.3
	Output outcome variables											
totbrev	1.2	0.7	1.3	0.8	1.2	0.7	0.9	0.6	1.2	0.7	0.9	0.6
eff_moy_et	39.8	39.5	44.8	41.9	38.6	38.1	45.1	41.5	38.6	38.0	45.1	41.6
turnover	7519.1	9371.3	8743.2	10566.3	7793.6	9107.2	9854.6	10876.5	7793.6	9149.4	9854.6	11088.6
valueadded	2419.3	2862.6	2824.5	3331.4	2393.8	2767.7	2973.1	3347.9	2393.8	2794.4	2973.1	3403.8
export	2632.4	3250.5	3331.5	3954.9	2815.4	3114.6	4068.4	3950.7	2815.4	3141.7	4068.4	4207.4
	Other control variables											
emp	35.1	31.8	50.8	46.0	34.8	30.9	51.8	46.7	34.8	30.8	51.8	47.1
age	26.7	29.1	26.7	29.1	26.3	29.2	26.3	29.2	26.3	29.4	26.3	29.4
dum_export	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.8	0.7
dum_subven	0.7	0.5	0.8	0.5	0.7	0.5	0.7	0.5	0.7	0.5	0.7	0.5
Observations	916	7362	916	7362	1027	7248	1027	7248	1027	7108	1027	7108

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 16: Firms' pre-post participation characteristics by year in Group C

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	44.1	84.3	94.4	134.4	99.6	83.2	136.5	125.8	91.6	86.8	160.3	116.7
dird	728.0	428.8	1007.3	438.8	924.6	402.8	1002.0	405.4	648.5	413.2	784.9	410.9
budgetot	772.1	513.2	1101.7	573.2	1024.3	485.9	1138.5	531.2	737.8	500.0	931.9	527.6
financ_pub	78.2	23.4	71.5	23.8	128.7	22.1	184.8	26.4	71.6	22.8	106.1	19.6
financ_pro	666.9	425.2	1028.1	434.4	744.9	400.8	751.7	385.7	574.0	409.7	726.7	400.0
eff_rd	9.7	5.1	11.1	5.2	11.0	4.8	10.4	4.9	7.2	5.0	8.2	5.0
researchemp	5.7	2.9	7.7	3.0	8.0	2.7	8.0	2.8	4.4	2.9	5.1	2.9
cs3	15.7	9.8	14.1	10.0	12.1	9.1	12.9	9.8	11.2	9.3	15.6	11.7
	Output outcome variables											
totbrev	0.8	0.7	2.0	0.9	1.5	0.7	1.1	0.7	1.2	0.7	0.9	0.9
eff_moy_et	42.8	46.0	43.4	48.1	32.9	39.6	35.3	42.5	38.6	39.4	45.1	41.8
turnover	6248.0	10778.2	5671.1	12018.6	15577.6	9435.0	17134.9	10818.6	7793.6	9359.1	9854.6	10035.2
valueadded	1895.9	3233.4	1946.3	3611.7	2557.6	2928.1	3713.0	3314.1	2393.8	2873.7	2973.1	3162.4
export	2940.5	3722.3	2751.2	4379.6	9231.1	3238.7	10631.0	3604.2	2815.4	3220.2	4068.4	3503.9
	Other control variables											
emp	48.8	34.5	50.2	36.2	36.0	31.5	39.3	34.4	34.8	31.8	51.8	45.0
age	28.7	29.4	28.7	29.4	25.3	29.4	25.3	29.4	26.3	29.3	26.3	29.3
dum_export	0.7	0.7	0.9	0.7	0.8	0.7	0.9	0.8	0.7	0.7	0.8	0.7
dum_subven	0.8	0.5	0.8	0.5	0.7	0.5	0.8	0.5	0.7	0.5	0.7	0.5
Observations	17	8008	17	8008	41	7190	41	7190	1027	7424	1027	7424

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	Input outcome variables											
derd	112.3	82.8	246.9	144.1	109.1	81.4	142.1	79.2	109.1	82.0	142.1	118.3
dird	861.3	407.9	1095.4	418.3	835.2	389.5	1196.5	405.5	835.2	390.0	1196.5	410.1
budgetot	942.2	490.8	1342.3	562.3	944.3	471.0	1140.8	484.4	944.3	472.0	1140.8	528.3
financ_pub	67.5	23.3	162.8	20.1	93.1	24.2	264.8	24.7	93.1	23.7	264.8	18.4
financ_pro	748.9	402.7	1014.0	453.9	693.3	379.4	731.5	382.0	693.3	381.6	731.5	422.1
eff_rd	10.9	4.9	12.3	5.0	11.1	4.8	10.2	4.9	11.1	4.8	10.2	4.8
researchemp	7.1	2.8	7.8	2.9	7.1	2.7	6.8	2.8	7.1	2.7	6.8	2.7
cs3	13.0	9.3	18.0	12.7	13.9	9.0	20.4	13.1	13.9	9.0	20.4	13.3
	Output outcome variables											
totbrev	2.5	0.7	1.6	0.8	3.3	0.7	0.9	0.6	3.3	0.7	0.9	0.6
eff_moy_et	48.1	39.5	49.8	41.9	56.1	38.1	60.2	41.5	56.1	38.0	60.2	41.6
turnover	14766.5	9371.3	16816.2	10566.3	8889.8	9107.2	10676.4	10876.5	8889.8	9149.4	10676.4	11088.6
valueadded	3047.8	2862.6	4700.6	3331.4	2884.4	2767.7	3950.6	3347.9	2884.4	2794.4	3950.6	3403.8
export	7578.5	3250.5	8730.2	3954.9	3813.9	3114.6	5002.6	3950.7	3813.9	3141.7	5002.6	4207.4
	Other control variables											
emp	41.3	31.8	51.6	46.0	45.4	30.9	58.9	46.7	45.4	30.8	58.9	47.1
age	26.4	29.1	26.4	29.1	24.3	29.2	24.3	29.2	24.3	29.4	24.3	29.4
dum_export	0.8	0.7	0.7	0.7	0.8	0.7	0.8	0.7	0.8	0.7	0.8	0.7
dum_subven	0.7	0.5	0.8	0.5	0.7	0.5	0.9	0.5	0.7	0.5	0.9	0.5
Observations	75	7362	75	7362	76	7248	76	7248	76	7108	76	7108

Note: Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 17: Firms' before-after matching characteristics by year in treatment and control groups (Group A)

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.0548	0.0159	0.0516	0.0512	0.0694	0.0285	0.0641	0.0626	0.0866	0.0375	0.0807	0.0803
log(emp)	3.5609	2.9463	3.5338	3.4960	3.3826	2.8872	3.3536	3.2704	3.2697	2.8719	3.2444	3.2203
age	23.7185	29.4038	23.7970	24.2782	24.4182	29.3794	24.6372	25.7023	23.1770	29.2945	23.4732	25.0705
appgroup	0.7333	0.5714	0.7293	0.6842	0.6545	0.5569	0.6465	0.6000	0.6262	0.5539	0.6174	0.6577
dum_subven	0.7704	0.4925	0.7669	0.6992	0.7545	0.4871	0.7488	0.7302	0.7574	0.4849	0.7517	0.7517
dum_sec_man_electro	0.0074	0.0227	0.0075	0.0075	0.0045	0.0223	0.0047	0.0140	0.0066	0.0216	0.0067	0.0067
dum_sec_hkis	0.5481	0.3749	0.5414	0.5414	0.5182	0.3755	0.5070	0.5209	0.5508	0.3839	0.5403	0.5168
dum_export	0.7852	0.6941	0.7820	0.7970	0.7273	0.6960	0.7209	0.6605	0.7082	0.6905	0.7013	0.7383
Sample sizes:	Control	Treated			Control	Treated			Control	Treated		
All	8008	135			7190	220			7424	305		
Matched	128	133			207	215			284	298		
Unmatched	7880	2			6983	5			7140	7		

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.0887	0.0402	0.0830	0.0822	0.0875	0.0441	0.0875	0.0866	0.0865	0.0456	0.0865	0.0859
log(emp)	3.2508	2.8701	3.2240	3.2591	3.1831	2.8451	3.1831	3.0962	3.1409	2.8452	3.1409	3.1819
age	23.2862	29.0554	23.5472	22.1950	24.3943	29.1738	24.3943	25.3371	24.3775	29.3545	24.3775	25.2451
appgroup	0.6246	0.5531	0.6164	0.5723	0.5829	0.5455	0.5829	0.5086	0.5577	0.5467	0.5577	0.5549
dum_subven	0.7231	0.4822	0.7170	0.7075	0.7057	0.4823	0.7057	0.6943	0.7155	0.4842	0.7155	0.6873
dum_sec_man_electro	0.0092	0.0217	0.0094	0.0126	0.0229	0.0221	0.0229	0.0286	0.0225	0.0219	0.0225	0.0169
dum_sec_hkis	0.5569	0.3858	0.5472	0.5943	0.5686	0.3902	0.5686	0.5686	0.5380	0.3900	0.5380	0.5662
dum_export	0.7046	0.6898	0.6981	0.6887	0.7257	0.6852	0.7257	0.7086	0.7324	0.6871	0.7324	0.7099
Sample sizes:	Control	Treated			Control	Treated			Control	Treated		
All	7362	325			7248	350			7108	355		
Matched	307	318			329	350			334	355		
Unmatched	7055	7			6919	0			6774	0		

Note: All the variables in this table, plus a set of dummy variables indicating the activity sectors and the geographical location of firms, have been used in the estimation of the propensity score. Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 18: Firms' before-after matching characteristics by year in treatment and control groups (Group B)

	Period 2005-2006				Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Before matching		After matching		Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.1533	0.0839	0.1518	0.1500	0.1577	0.0978	0.1569	0.1560	0.1509	0.0970	0.1496	0.1487	0.1485	0.1008	0.1481	0.1468
log(emp)	3.3352	2.9464	3.3286	3.3147	3.2000	2.9463	3.1966	3.1855	3.1005	2.8872	3.0945	3.0965	3.0197	2.8719	3.0172	2.9961
age	27.0225	29.2630	27.0842	26.8693	26.7355	29.4038	26.7705	27.8966	26.2911	29.3794	26.3521	26.4792	26.8214	29.2945	26.8383	27.1788
appgroup	0.6671	0.5697	0.6658	0.6533	0.6258	0.5714	0.6250	0.6196	0.6041	0.5569	0.6027	0.5782	0.5791	0.5539	0.5786	0.5672
dum_subven	0.7672	0.4948	0.7663	0.7538	0.7226	0.4925	0.7220	0.7123	0.7125	0.4871	0.7115	0.7054	0.6860	0.4849	0.6856	0.6936
dum_sec_man_electro	0.0175	0.0218	0.0176	0.0201	0.0237	0.0227	0.0237	0.0205	0.0158	0.0223	0.0159	0.0183	0.0205	0.0216	0.0205	0.0205
dum_sec_hkis	0.4431	0.3787	0.4410	0.4472	0.4366	0.3749	0.4353	0.4440	0.4568	0.3755	0.4548	0.4645	0.4835	0.3839	0.4829	0.4692
dum_export	0.7760	0.6918	0.7751	0.7889	0.7452	0.6941	0.7446	0.7651	0.7369	0.6960	0.7359	0.7494	0.7292	0.6905	0.7289	0.7255
Sample sizes:	Control	Treated			Control	Treated			Control	Treated			Control	Treated		
All	8060	799			8008	930			7190	821			7424	879		
Matched	735	796			839	928			747	818			801	878		
Unmatched	7325	3			7169	2			6443	3			6623	1		

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.1503	0.1057	0.1499	0.1490	0.1670	0.1180	0.1663	0.1654	0.1609	0.1136	0.1602	0.1597
log(emp)	3.0051	2.8701	3.0026	3.0290	2.9710	2.8451	2.9665	2.9629	2.9718	2.8452	2.9670	3.0110
age	26.6648	29.0554	26.6809	26.2645	26.2814	29.1738	26.3093	26.6263	26.4491	29.3545	26.4792	25.2542
appgroup	0.5753	0.5531	0.5749	0.6087	0.5764	0.5455	0.5756	0.5746	0.5946	0.5467	0.5938	0.6188
dum_subven	0.6714	0.4822	0.6710	0.6634	0.6845	0.4823	0.6839	0.6702	0.6788	0.4842	0.6781	0.6667
dum_sec_man_electro	0.0240	0.0217	0.0240	0.0219	0.0204	0.0221	0.0205	0.0195	0.0218	0.0219	0.0219	0.0323
dum_sec_hkis	0.4978	0.3858	0.4973	0.4973	0.4956	0.3902	0.4946	0.5063	0.4969	0.3900	0.4958	0.4781
dum_export	0.7194	0.6898	0.7191	0.7475	0.7128	0.6852	0.7122	0.7024	0.7110	0.6871	0.7104	0.7115
Sample sizes:	Control	Treated			Control	Treated			Control	Treated		
All	7362	916			7248	1027			7108	962		
Matched	831	915			917	1025			860	960		
Unmatched	6531	1			6331	2			6248	2		

Note: All the variables in this table, plus a set of dummy variables indicating the activity sectors and the geographical location of firms, have been used in the estimation of the propensity score. Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

Table 19: Firms' before-after matching characteristics by year in treatment and control groups (Group C)

	Period 2005-2007				Period 2005-2008				Period 2005-2009			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
distance	0.0082	0.0021	0.0082	0.0081	0.0145	0.0056	0.0133	0.0134	0.0271	0.0096	0.0235	0.0232
log(emp)	3.1476	2.9463	3.1476	3.1651	3.2178	2.8872	3.2015	3.1757	3.2669	2.8719	3.2322	3.2841
age	28.7059	29.4038	28.7059	35.2941	25.3171	29.3794	25.4750	30.5750	23.7534	29.2945	23.9296	21.6479
appgroup	0.3529	0.5714	0.3529	0.4706	0.6098	0.5569	0.6000	0.7250	0.6164	0.5539	0.6056	0.5775
dum_subven	0.8235	0.4925	0.8235	0.8235	0.6829	0.4871	0.6750	0.6250	0.6986	0.4849	0.6901	0.6338
dum_sec_man_electro	0.0000	0.0227	0.0000	0.0000	0.0244	0.0223	0.0250	0.0250	0.0137	0.0216	0.0141	0.0141
dum_sec_hkis	0.4118	0.3749	0.4118	0.4706	0.5610	0.3755	0.5500	0.5000	0.5616	0.3839	0.5493	0.5493
dum_export	0.7059	0.6941	0.7059	0.7059	0.7561	0.6960	0.7500	0.8000	0.7671	0.6905	0.7606	0.7465
Sample sizes:	Control	Treated			Control	Treated			Control	Treated		
All	8008	17			7190	41			7424	73		
Matched	17	17			40	40			71	71		
Unmatched	7991	0			7150	1			7353	2		

	Period 2005-2010				Period 2005-2011				Period 2005-2012			
	Before matching		After matching		Before matching		After matching		Before matching		After matching	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
log(emp)	0.0249	0.0099	0.0220	0.0220	0.0280	0.0102	0.0258	0.0254	0.0263	0.0112	0.0245	0.0245
age	3.2730	2.8701	3.2394	3.1496	3.3511	2.8451	3.3274	3.4496	3.3794	2.8452	3.3578	3.4532
appgroup	26.4000	29.0554	26.6438	28.6712	24.3289	29.1738	24.4400	27.3600	26.0244	29.3545	26.1481	25.4568
dum_subven	0.5733	0.5531	0.5616	0.4795	0.6974	0.5455	0.6933	0.7200	0.6585	0.5467	0.6543	0.7284
dum_sec_man_electro	0.6667	0.4822	0.6575	0.6575	0.7237	0.4823	0.7200	0.6400	0.6951	0.4842	0.6914	0.6914
dum_sec_hkis	0.0400	0.0217	0.0411	0.0411	0.0132	0.0221	0.0133	0.0000	0.0122	0.0219	0.0123	0.0123
dum_export	0.5467	0.3858	0.5342	0.5753	0.4737	0.3902	0.4667	0.4800	0.5000	0.3900	0.4938	0.4444
Sample sizes:	0.7600	0.6898	0.7534	0.7123	0.7500	0.6852	0.7467	0.6800	0.7073	0.6871	0.7037	0.7160
All	Control	Treated			Control	Treated			Control	Treated		
Matched	7362	75			7248	76			7108	82		
Unmatched	70	73			74	75			80	81		
	7292	2			7174	1			7028	1		

Note: All the variables in this table, plus a set of dummy variables indicating the activity sectors and the geographical location of firms, have been used in the estimation of the propensity score. Patents are in unit, R&D variables are in thousand, employment-related variables are in unit, and market-related variables are in thousand.

Sources: R&D survey, DGE, FUI, MENESR, INSEE, Ficus-Fare, DADS, Lifi, and the author's calculations.

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