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SMEs' Performance in French Competitiveness Clusters

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Abstract:

This article analyzes the evolution of small and medium-sized enterprises (SMEs) embedded in French competitiveness clusters, relative to similar companies outside those clusters, during 2005–2013. The French competitiveness clusters seek to increase SMEs' size and performance, to enhance innovation and employment at a societal level. Therefore, the current study includes the impacts of capital invested and equity on profitability. The findings reveal some interesting results: Sales, employment, R&D, and value added produce relative increases, but financial returns exhibit significant relative decreases that mainly affect the smallest companies, whereas larger ones record strong increases. Findings revealing that the smallest SMEs are unable to reap gains from their cluster membership are a matter of grave concern for both companies and policymakers.

Keywords: cluster, competitiveness, industrial policy, SME, financial performance

Jel Codes : G32, L25, L53, O38

1. Introduction

Created in 2005 as part of a new French industrial policy, competitiveness clusters (i.e., *pôles de compétitivité*) were designed to enhance the nation's international industrial competitiveness. Relying on concepts developed and popularized by Porter (1990), these clusters have sought to improve the economic efficiency of their member firms by increasing the returns to scale through concentrated, spatial localization. In turn, policymakers assume beneficial spillover effects from clusters that increase their attractiveness. However, because of the protean nature of these likely benefits, studies trying to assess the relevance of clusters and cluster policies investigate a range of different subjects: regional development, R&D activity, export and employment rates, and clusters governance, to name a few.

This study takes a different approach to study, over time, the economic and financial performance (i.e., efficiency and profitability, respectively) of small and medium-sized enterprises (SMEs) that join French competitiveness clusters and receive subsidies to collaborate on R&D projects. The SMEs are critical to these clusters, as efficient means for spreading innovation and increasing employment. With a sample of 966 SMEs, including 174 that joined competitiveness clusters in 2006, the results from a difference-in-difference (DID) approach reveal that R&D expenses, sales, and employment increase significantly, in support of predictions of cluster benefits. However, we also show that the smallest SMEs suffer strong decreases in their operating and financial returns, suggesting that benefits are not equally distributed among cluster members.

In the next section, we outline the foundations of the French competitiveness clusters concept and policy, as well as reviewing existing literature related to individual firms in clusters. After we present our methodology and sample, we describe our main results. Finally, we detail these findings and their implications in the conclusion.

2. French competitiveness clusters and related literature

Publicly funded competitiveness clusters seek to make French industry more competitive on an international level by encouraging growth and jobs in key markets, especially those with substantial technological components. The goals are manifold—spanning macro-, sectoral- and micro–levels—because the related policy reflects the intersection of industrial and regional development policies (Duranton et al., 2010). In this sense, French competitiveness clusters express a political willingness to steer economic activity. They are generally organized around leading companies that define the R&D projects and then are joined by other actors, such as SMEs and academic labs. They cannot be viewed simply as a flat network of companies in the same area (Arzeni et al., 2007). The governance and performance of these clusters are monitored by local and national public authorities that provide incentives (e.g., subsidies) to promote collaborative R&D and enhance the likelihood of success.

Most of the support for French competitiveness clusters comes from public funds. The Fonds Unique Interministériel (FUI),[1] launched in 2005, managed M€240 in 2006 to finance companies undertaking collaborative R&D projects in competitiveness clusters. The average amount allocated to a project was M€1.2, shared among different partners (DGCIS[2], 2013). The clusters in turn have two main priorities: (1) reinforce the economic benefits of R&D projects by releasing innovative products and services in markets and (2) support the growth of SMEs and mid-tier companies (*entreprise de taille intermédiaire* [ETIs]) by offering access to financing and international development, forecasts of skill needs, and individual assistance, such as advice and tutoring. Proponents of this policy assert that "For individual firms, being a partner in a competitiveness cluster is to benefit from an improvement in performance through interaction with other partner firms. This improvement comes from a better use of existing capital, labour, knowledge and information."[3] That is, improvements to the partners' performance is an explicit goal of this policy.

The theoretical background for such cluster policies comes from Marshall (1920), who describes increasing returns due to positive agglomeration externalities that arise from geographic concentration, including infrastructures, cost pulling, concentration of specialized inputs (e.g., labor), and knowledge spillovers. In the second half of the 20th century, the emergence of successful geographical areas (e.g., Silicon Valley, City of London) renewed academic research and gave rise to the concept of clusters (Porter, 1990). The concept was highly attractive to policymakers during a period of deindustrialization, leading to public policies in many countries (Uyarra et Ramlogan, 2012). These public policies aimed to address market failures due to externalities and information asymmetries, with the underlying

[1] Inter-ministerial Single Fund (ISF)
[2] Direction Générale de la Compétitivité, de l'Industrie et des Services (Public Head Office for Competitiveness, Industry and Services)
[3] See http://competitivite.gouv.fr/

assumption that market inefficiencies that disrupt connections among firms are detrimental to innovation, but the public sector has a means to reduce them. This action may be particularly pertinent to innovation efforts. Industrial clusters can increase R&D investments by promoting collaborative R&D that enables firms to internalize knowledge spillovers and reduce uncertainties that arise from collaboration (Rosenthal and Strange, 2004; Nishimura and Okamuro, 2011).

Yet both cluster benefit assumptions and the rationale for public policy have been criticized (Duranton, 2011). For example, concentrated localization might invoke benefits, but it also leads to costs, such as congestion and competition costs in input and output markets, increased labor costs, and higher real estate prices (Pouder and St. John, 1996; Baptista and Swann, 1998). The ultimate effect thus is uncertain, as is its magnitude. Furthermore, controversies continue to surround the real effects of public policies (Duranton, 2011): If the goal is to make an existing cluster work better, the risk of crowding-out activities arises. Political interference also can distort economic choices. Finally, recent empirical evidence casts some doubt on the real benefits of clusters, or at least their scope. Empirical evidence still struggles to affirm the benefits of cluster policies.

Most studies attempting to do so rely on individual firm data and check for the existence or magnitude of several specific externalities that reflect policy objectives, such as employment, R&D, patents, exports, growth, network intensity, or fundraising ability. For example, research on innovation suggests that clusters concentrate knowledge and specialized workers, which intensifies R&D activities. Beaudry and Breschi (2003), examining patenting activity in clusters located in the United Kingdom and Italy, find that benefits arise in clusters but only for already embedded firms. Falck et al. (2010) examine the effects of cluster policies in Bavaria and affirm that firms included in these clusters are more prone to innovation. Similar results from Tsuji and Miyara (2009) and Nishimura and Okamuro (2011) refer to Japanese firms, and Delgado et al. (2010) confirm them among U.S. firms, offering strong evidence of new firm creation and employment increases in U.S. clusters. Spence et al. (2010), studying 300 industries in Canada, find higher income and growth. However, Feser et al. (2008) offer mixed results from a sample of Appalachian firms, revealing new business creation but no employment growth. In Sweden, Wennberg and Linqvist (2010) uncover similar results, such that along with a better survival rate, greater concentration in specialized clusters relates to better survival chances. Rosenthal and Strange (2004) report just small improvements in wages and labor productivity.

But other findings add more nuance or contradict these positive findings. For example, by examining the relationship of cluster size and firm performance—measured by discontinuance, initial public offerings, private equity operations, patents, and strategic alliances—among U.S. biotech firms, Folta et al. (2006) find a negative link that suggests diseconomies of scale as cluster size increases. With their focus on companies in French competitiveness clusters, Fontagné et al. (2013) study export performance and determine that exporting firms in French competitiveness clusters export more than others in the same sector at the same location but also were more dynamic before entering these clusters.

By investigating 345 French firms included in Local Productive Systems (LPS, an earlier version of competitiveness clusters), Martin et al. (2011) tried to establish whether their efficiency, as measured by total factor productivity, was better. Their disappointing results indicated that LPS firms were less productive when they entered the system and did not improve thereafter, such that their productivity even declined slightly (4%), though single-plant firms appeared to make small gains. These authors found no link to employment. Duranton et al. (2010) instead report a significant but modest rise in work productivity for companies embedded in French competitiveness clusters; they highlight the small size of French clusters compared with U.S or U.K. versions.

All these studies control for a vast number of variables, such as industry, cluster size, and the geographical or sectoral level of aggregation. Yet little attention has focused on SMEs' financial performance, even though these firms account for most of the business and employment in continental Europe. Therefore, we seek to contribute to cluster literature in three main ways. First, we focus on SMEs' performance, because they are explicit targets of French policymakers; specifically, we note the performance of SMEs that receive subsidies to join collaborative projects. Using these companies' financial accounts, we test whether their performance improves after they join a cluster. Our performance measures include R&D, value added, and employment, together with financial returns. These returns are notably absent from previous studies but are highly relevant from a policy perspective, in that they drive firms' strategies and represent a necessary condition for firm sustainability.

Second, we evaluate the relative performances of partner firms using a difference-in-difference (DID) approach and data over the course of nine years, from 2005, when the first French competitiveness clusters launched and some companies were recorded as eligible for public financing, to 2013, or two years after these companies were supposed to have launched new products that incorporated the results of their subsidized, collaborative R&D. We compare these companies against control companies that did not join competitiveness clusters.

Third, we provide a nuanced, contrasted picture. In terms of sales, value added, and employment, the performance of firms in competitiveness clusters increases strongly compared with the control companies, in support of a cluster efficiency hypothesis and cluster policies. However, the returns on assets and equity for the target companies decrease relative to the control firms. The great dispersion of our variables across samples prompted us to split the companies into segments, on the basis of their size, and thus reveal that small and big SMEs in competitiveness clusters record strongly diverging developments, such that rates of return increase for big SMEs while decreasing for small SMEs.

3. Methodology and samples

To assess the impact of French competitiveness clusters on individual SMEs, we applied a DID analysis to the period 2005–2013, comparing a sample of firms that joined competitiveness clusters and a control sample of firms outside them. We used the Diane Bureau Van Dijk database, which offers extensive financial statements related to French companies over a 10-year period.

3.1. Target firm sample

Our target sample consists of companies selected by the FUI during the first "call for projects" in 2005 and funded in 2006 to undertake collaborative R&D projects in competitiveness clusters. These projects were required to lead to marketable innovations by 2011 at the latest. Thus, with the 2005–2013 study period, we can measure the effect of the clusters on their performance. We identified 215 companies included in 73 collaborative R&D projects backed by the FUI in 2006 for which financial statements were available for the whole period. Of these 215 companies, we kept only SMEs[4] and also excluded subsidiaries, which have limited business autonomy. We thus ended with a sample of 174 target companies embedded in competitiveness clusters since 2006, when they started conducting collaborative projects.

3.2. Control sample

[4] We use the European Union's definition of SME: companies that employ fewer than 250 persons and whose annual turnover does not exceed 50 million Euros or whose total annual balance sheet does not exceed EUR 43 million.

The control sample is composed of companies that are similar to those in the target sample but that remained outside of any competitiveness clusters. Each matching company in the control sample met the following criteria in 2005: It belonged to the same four-digit sector, and its size, measured by number of employees in 2005, was within 25% of the matched target firm, as were its total assets and annual sales. If more than five control companies matched a target, we computed the Euclidian distance between each target company and the control options, then kept the five neighbors nearest the target. At the end of this process, we had gathered a sample of 792 control companies, or an average of 4.55 controls per target.

By construction, the two samples are similar. Table 1 presents the descriptive statistics for both samples for 2005, before the target companies entered any clusters, and highlights the similarities between these companies.

Table 1. Employment, sales, and total assets of target and control companies prior to clustering

Variable	Median	Mean	SD	Q1	Q3	IQR	Number of Companies
Sample 1: Targets							
Employment	19	43.6	54.46	8	49	41	174
Sales (k€)	2145.33	5144.06	7671.77	484.24	6333.93	5849.69	174
Total assets (k€)	1993.92	5782.28	12113.29	774.9	5054.36	4279.46	174
Sample 2: Controls							
Employment	20	34.87	40.53	12	36	24	792
Sales (k€)	2633.15	5139.74	6709.77	1045.67	5934.61	4888.94	792
Total assets (k€)	1792.07	4868.28	17718.27	825.70	4292.90	3467.2	792

The medians and means are close for all the variables, but the standard deviation values indicate a greater dispersion of employment and sales for target companies, whereas the standard deviation of total assets is more important for the control companies.

3.3. Model and variables

Over our nine-year study period, the target sample companies joined competitiveness clusters and benefited from funding by the FUI; the control sample companies remained outside clusters and received no funding from FUI. We distinguish two subperiods in our study: (1) prior to FUI funding and embeddedness in competitiveness clusters, in 2005, and (2) after the target SMEs joined the competiveness clusters and received FUI funding, in 2006–2013. With a DID method, we estimated the average change in the value of the dependent variable between the two subperiods for the target companies. The double difference thus calculated eliminates the potential for selection bias in determining the target sample. It also removes the trend component, which is likely to distort the interpretation of the results. Formally, for our statistical test, we performed the following regression:

$$y_{jt} = \alpha_j + \delta_t + POST_{jt} + POST_{jt}ISF_j + \varepsilon_{jt}$$

where *j* is a company index, *t* is a year index, and y_{jt} is the performance variable. If company j is a target company, $POST_{jt}$ equals 1 after j receives FUI funding. If j is a control company, $POST_{jt}$ e instead equals 1 after the corresponding target firm receives FUI funding. Furthermore, ISF_j equals 1 for target companies and 0 for control companies. Following Boucly et al. (2011), we use company and time fixed effects in the regression, and as suggested by Bertrand et al. (2004), we cluster error terms at the company × POST level to overcome the potential serial correlation of the outcome variable, which would lead to overestimation of the t-statistics and significance levels.

Because competitiveness clusters aim to promote R&D, growth, and employment and improve operational and financial performance for embedded firms, and SMEs in particular, we used the following dependent variables to assess the impact of clustering:

Promoting R&D. We used R&D to measure companies' innovation effort, because R&D expenses should increase more among target than control companies. We included two variables: R&D (k€), or R&D expenses as reported in the balance sheet assets, which reflects absolute R&D effort, and the R&D ratio, R&D/(intangible assets + tangible assets), which indicates the magnitude of R&D effort by comparing the intangible part of fixed assets relative to total fixed assets.

Favoring growth. As indicators of growth, we used total sales and value added, because innovations and the release of new products should differentiate companies in and outside clusters. Sales are total fiscal year sales revenues; value added is the total value added for the fiscal year.

Favoring employment. Cluster policies are supposed to increase employment, through growth, so we measured employment as the average number of employees in a year and the payroll ratio as payroll/sales revenue. Better paying jobs, designed to attract specialized, qualified labor, should increase this ratio.

Financial performance. For financial performance, we used three criteria: ROE, or return to equity holders (net income/equity); ROA (EBITDA/total assets), which equals operational returns divided between lenders and shareholders; and the absolute book value of equity (absolute value of shareholders' wealth). These variables are important for ensuring firms' future, in that they are central determinants of financing ability.

Subsidies. Operating and investment subsidies could explain why some companies cluster while others do not, in that some companies may possess unique abilities to capture public funding, even before they join a cluster. The SME members of a cluster should show higher increases in these variables over time, compared with control companies.

4. Results

The descriptive statistics for 2005 are in Table 2. We tested for significant differences between companies in the two samples prior to clustering, using a Wilcoxon Mann-Whitney rank-sum test. The results of these nonparametric tests are in Table 3. Finally, Table 4 contains the results of the DID regression with company and time fixed effects. As indicated previously, the errors are clustered at the company × POST level.

Table 2. Descriptive statistics, 2005

Variable	Median	Mean	SD	Q1	Q3	IQR
Sample 1: Targets						
R&D (k€)	185.58	309.85	694.82	41.98	574.91	532.93
R&D ratio	0.065	0.1049	0.2383	0.024	0.3549	0.03309
Sales (k€)	2145.33	5144.06	7671.77	484.24	6333.93	5849.69
Value-added (k€)	1069.72	3263.4	5288.99	144.01	4130.12	3986.11
Employment	19	43.6	54.46	8	49	41
Payroll ratio	0.4370	0.5523	1.6572	0.2397	0.6799	0.4402
ROE	0.0465	-0.3852	2.46	-0.1699	0.2284	0.3983
ROA	0.065	0.01467	0.2723	-0.0638	0.1475	0.2113
Equity (k€)	607.447	2527.937	7652.21	188.85	1986.995	1798.145
Investment subsidies (k€)	0	0	109.02	0	3.412	3.412
Operating subsidies (k€)	8.779	49.54	137.736	0	45.145	45.145
Sample 2: Controls						
R&D (k€)	30.47	84.28	211.77	5.87	116.53	110.66
R&D ratio	0.01	0.028	0.128	0	0.058	0.058
Sales (k€)	2633.15	5139.74	6709.77	1045.67	5934.61	4888.94
Value-added (k€)	1309.469	3361.95	5435.01	513.70	3725.49	3211.79
Employment	20	34.87	40.53	12	36	24
Payroll ratio	0.3854	0.4914	1.1541	0.2296	0.5591	0.3295
ROE	0.1873	0.1689	1.676	0.032	0.4001	0.3681
ROA	0.1086	0.0972	0.2081	0.033	0.1877	0.1547
Equity (k€)	639.11	2356.493	13243.82	222.504	1579.552	1357.048
Investment subsidies (k€)	0	567.58	10785.22	0	0	0
Operating subsidies (k€)	0	18.82	68.28	0	8.35	8.35

Table 2 highlights the magnitude and dispersion of each variable across the two samples. Regardless of which sample we consider, the variables indicate great dispersion in their means (standard deviation is superior to the mean) or medians (IQR values). More than one-quarter of the target companies indicate negative ROE or ROA, suggesting their poorer relative performance.

We next tested the significance of these differences with a Wilcoxon Mann-Whitney test (Table 3). Prior to their entry into competitiveness clusters, target companies' R&D was significantly superior to that of control companies, according to both measures we used. For public funding, target companies indicated a greater ability to raise funds to support their operations or investments. However, they underperformed the control companies on value creation indicators, and their ROE and ROA were significantly lower than those of the control companies.

Table 3. Differences between subsamples: Wilcoxon Mann-Whitney tests

Variable	Z	Prob > $\|Z\|$
R&D	4.527	0.000
R&D ratio	4.662	0.000
Sales	-2.101	0.0356
Value-added	-2.170	0.03
Employment	-0.332	0.796
Payroll ratio	1.863	0.0624
ROE	-4.720	0.000
ROA	-3.437	0.0006
Equity	0.226	0.8214
Investment subsidies	2.149	0.0316
Operating subsidies	4.831	0.000

Table 4. Difference-in-difference regression results

	R&D	%R&D	Sales	V-A	Employment	%Payroll	ROE	ROA	Equity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
POST × FUI	.429***	.167***	.406***	.388***	.2788***	-.021	-.172***	-.158***	.299***
	(.000)	(.001)	(.000)	(.000)	(.000)	(.125)	(.000)	(.000)	(.000)
POST	.03	.02	.05	.05	-.02	0	-.02	-.01	0
	(.625)	(.125)	(.213)	(.332)	(1)	(1)	(.099)	(.16)	(1)
Co. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7310	7302	7578	7414	5010	7542	7290	7158	7258
Adj. R^2	.934	.945	.8994	.9058	.9282	.865	.5722	.5647	.897

*** Means statistically significant at the 1% level.

Table 4 also contains the ordinary least square (OLS) estimates of the impact of clustering on the target's behavior. The variables expressed in absolute values (R&D, sales, value added, employment, equity) were log-transformed to support the OLS estimation. The results indicated that clustering had strong, significant impacts on target companies' behaviors. For example, their R&D expenses increased, relative to the control companies, by a significant 42.9%; as a percentage of total assets, R&D expenses rose by 16.7%. The impact of clustering on the R&D efforts of target companies thus are economically substantial. Sales and value added follow similar trends and increase by 40.6% and 38.8%, respectively. That is, clustering effectively favors the growth of SMEs. It also has a positive impact on employment, such that the number of employees grows by 27.88%, though the increase in the payroll ratio is insignificant, due to sales growth. In contrast, the financial performance variables indicate that membership in a competitiveness cluster leads to a strong decrease in the indicators. Compared with their control firms, target companies' ROE decreased by a significant –17.2% and their ROA by –15.8%.

In Table 1 the IQR values associated with employment, sales, and total assets illustrate the great size disparity across the target companies. For total assets for example, Q3 is 6.5 times higher than Q1. Therefore, to deepen our analysis and consider the potential influence of size on clustering effects, we split the sample into total asset quartiles. The first subsample contained target companies in the lowest quartile and their control companies; the two interquartile ranges constituted the second subsample; and the third subsample included target companies of the upper quartile and their control companies. The results for the companies in the interquartile range were similar to those in Table 4; we focus instead on the results for the lower and upper quartiles (Table 5). Using logistic regressions, we also control for a possible catching-up effect of lower and upper quartile target companies, after clustering, compared with the control companies (Table 6).

Tableau 5. Difference-in-difference regressions results for the lower and upper quartile subsamples

	Lower Quartile									Upper Quartile								
	R&D (1)	**%R&D (2)**	**Sales (3)**	**V-A (4)**	**Empl. (5)**	**%Payroll (6)**	**ROE (7)**	**ROA (8)**	**Equity (9)**	**R&D (10)**	**%R&D (11)**	**Sales (12)**	**V-A (13)**	**Empl. (14)**	**%Payroll (15)**	**ROE (16)**	**ROA (17)**	**Equity (18)**
POST x FUI	.1473**	-.11	.643***	.421***	.5083***	0.066*	-.304**	-.226**	.525***	.1563***	.1673***	.3351***	.2907***	-0.12	-.203***	.3731***	.1050**	.1546***
	(0.08)	(0.182)	(0.000)	(0.00)	(0.000)	(0.009)	(0.013)	(0.036)	(0.000)	(0.001)	(.006)	(0.000)	(0.000)	(0.761)	(0.000)	(0.000)	(0.031)	(0.001)
POST	.01	.15	-.33	.03	.03	.1181	-.19	.002	.147	.073	.056	.1781	.055	0.02	0.05	.1491	-.051	.0196
	(0.77)	(1)	(1)	(0.16)	(1)	(1)	(0.885)	(1)	(1)	(0.775)	(1)	(1)	(1)	(1)	(1)	(.662)	(1)	(1)
Co. FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1827	1825	1894	1853	1252	1885	1822	1789	1814	1827	1825	1894	1853	1252	1885	1822	1789	1814
Adj. R^2	.9218	.9014	.8591	.8237	.8567	.8947	.5916	.5445	.7723	.9963	.9963	.8439	.8492	.9069	.8666	.6596	.7743	.9119

*** Means statistically significant at the 1% level. ** Means statistically significant at the 5% level. * Means statistically significant at the 10% level.

Tableau 6. Differences between target and control companies in lower and upper quartiles before clustering: Logistic regression results

	Lower Quartile	Interquartile range	Upper Quartile
%R&D	13.53***	8.013***	.374
%Payroll	.438	.903	.3374
ROE	.394**	.922	1.147**
ROA	.084**	.247***	2.534**
Investment subsidies	1.01	.998	.899
Operating subsidies	1.04	1.02**	1.3**
Chi^2	32.76***	27.71***	32.71***
Adjusted R^2	0.1963	0.0654	14.23

***Z < .01. **Z < .05. *Z < .1.

In Table 5, the differences between the results recorded for the lower and upper quartiles are striking; Table 6 also highlights the absence of catching-up effects by target companies after their clustering.

The R&D effort of the lower quartile SMEs is significant. Relative to their control companies, the smallest SMEs that are also embedded in competitiveness clusters increase their R&D effort by 14.73%. Moreover, as Table 6 shows, these companies invest more in R&D than their control counterparts before the clustering. Their sales increase relative to their control companies by 64.3%. Thus, collaboration with other companies appears very beneficial for small SMEs. However, the value added of these companies does not increase at similar proportions; rather, we find a gap of more than 20% between turnover and value-added growth. That is, clustering allows the smallest SMEs to sell more but at decreasing margins, even though their products include more R&D. This phenomenon is specific to lower quartile SMEs; we found no significant difference in the growth of sales versus value added for the other companies in the target sample. The important jump in the number of employees (+50.83%), which coincides with sales growth, leads to an important deterioration of operational and financial performance indicators: ROE decreases by 30.4% and ROA by 22.6%. Compared with companies in other quartiles, these smallest SMEs record the most important erosion of their value creation indicators after clustering.

In contrast, the largest SMEs are the only ones that record favorable performance indicators: ROE increases by a significant 37.32% and ROA by 10.50%. These striking results indicate that the performance indicators for the upper quartile target companies outpace those of their control companies before clustering (Table 6). Equity rises by 10%, smaller than for the entire sample. It appears that these companies absorb the significant growth in sales (33.51%) and value added (29.07%) without hiring new employees, so their payroll ratio falls drastically (-

20.3%). Moreover their R&D effort after clustering is moderate (+15.63%), and lower than that of the companies in the interquartile range.

Overall, the quartile regressions highlight an important size effect of clustering efforts and benefits. On the one hand, hiring and R&D efforts seem effectively backed by SMEs in the lower or interquartile size ranges. On the other hand, value creation seems captured mainly by the upper quartile of SMEs.

5. Discussion

This study has sought to assess the effects of membership in French competitiveness clusters on SMEs that join collaborative projects and receive subsidies from the FUI. Few studies have investigated these effects for individual firm performance, even though such measures are central to firms' long-term survival. Unlike other studies, we focus on the returns on capital invested in these companies—in particular, returns on operating assets (ROA) and on equity (ROE). Sales, R&D expenses, and value added may be more relevant from a public policy perspective, but financial returns are more pertinent to lenders and shareholders. In the medium and long run, these returns and their developments are essential conditions for sustained private financing of companies. For these inputs, our results are mixed.

Considering SMEs as a whole, our findings suggest that competitiveness clusters meet their main policy goals. Turnover, R&D, and employment grow at higher rates for these companies than for similar companies that remain outside the clusters. The clustered firms also were more R&D prone than control companies, before joining the collaborative projects. These results resonate with Fontagné et al.'s (2013) findings that companies in competitiveness clusters export better than others when they join a competitiveness cluster, but they also were more efficient on this task before joining the clusters. Similar results come from a DGCIS (2013) study of R&D, licenses, employment, and turnover. For profitability, we show that ROE and ROA were inferior in these companies before clustering, then decline thereafter, compared with the control firms.

Perhaps our most interesting finding though is that the profitability benefits of belonging to clusters get allocated unequally among participating SMEs. Small SMEs see their financial profitability, measured by ROA and ROE, decrease dramatically compared with similar control firms. They appear unable to benefit from their growth, especially in their R&D expenses and sales growth, unlike bigger SMEs in clusters. For financing partners, lenders, and shareholders of these small SMEs, this result is disheartening. It is also a matter of some concern from a policy perspective, because unprofitable companies ultimately cannot remain in the market, which might weaken existing clusters.

Several explanations might illuminate these results. First, small firms might face more diseconomies of scale than their bigger counterparts. Theoretically, cluster members might attain gains, resulting from economies of scale (lowered transaction costs, infrastructure, high quality inputs), but also losses, due to congestion effects (e.g., competition for land and skilled workers). Small and less robust companies might face threshold effects that influence their profitability and also find it difficult to compete efficiently with other, bigger members of their cluster for inputs. With their relative inability to take advantage of their cluster benefits, they leave the spoils of their collaborative projects for their partners in the projects.

Second, small companies might suffer profitability decreases because of the nature of their links with the bigger companies in these clusters. French competitiveness clusters are not spontaneous creations or gatherings; they have resulted from political willingness to bring together companies of various sizes, including very big ones, along with public research and administrative entities. As highlighted by Arzeni et al. (2007), at the center of these clusters, a leading company usually defines the collaborative R&D projects and recruits partners. Cluster governance and performance is monitored by both local and national public authorities, and subsidies offer incentives for SMEs to join them. These processes all persist if bigger companies reap the financial results of R&D, whereas small ones cannot. This explanation is consistent with the increased use of research subcontracting by big companies to small firms in industries such as pharmaceuticals and data processing. This new division of labor transfers the financial risk of research activity from big groups to small companies.

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