THE DETERMINANTS OF THE SCIENCE-BASED CLUSTER GROWTH: THE CASE OF NANOTECHNOLOGIES

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Abstract

There is growing academic and policy interests in the factors that underpin the formation and the growth of clusters, especially for such 'hyped up' scientific and technological fields as the nanotechnologies. This paper analyses the determinants of scientific cluster growth (measured by the number of publications that emanate there from), distinguishing between structural effects (i.e. initial cluster size, scientific field composition and geographic location) on the one hand and its scientific variety, organizational diversity and degree of openness (in terms of collaboration with outside actors) on the other. Overall, scientific variety enhances clusters growth, but organizational diversity slows it down. However, patterns of growth are different in Asia, Europe and North America. It seems that cluster evolution is highly contingent on national systems of innovation and on the history of collaboration amongst local actors. Policy makers and cluster strategists must design specific policies by zone, and should not simply attempt to replicate best practices from one zone to another. Slow growth may reflect also 'elitist' strategies - those based on quality rather than on numbers.

Keywords: cluster growth, nanotechnology, scientific district, publication

1. *INTRODUCTION*

There is a move towards geographic concentrations of universities and firms involved in research. Both recent university mergers (as at Manchester and Helsinki) and the increasing numbers of large and diversified campuses testify to the importance of large groups of scientists being co-located. Knowledge creation and innovations are often cumulative, and tacit knowledge circulates within scientific clusters through direct and repeated interactions between cluster members. Clusters encourage the flow of knowledge between actors, especially between science based firms and universities and other non-for profit actors (Bathelt *et al.*, 2004; Hakanson, 2005; Storper *et al.*, 2004). Empirical studies find that knowledge moves more slowly across national, regional, organizational boundaries, and that knowledge spillovers tend to be localized (Smith *et al.*, 2005; Tallman *et al.*, 2007). However, Gordon *et al.*'s (Gordon *et al.*, 2005) critical examination of the role of local 'milieu' has suggested that specifically local informal information spillovers are very much less important for successful innovation than has been suggested.

Different contributors (Cooke, 2001; Rothaermel *et al.*, 2008; Saxenian, 1994; Zucker *et al.*, 1998) have examined the effects of clusters on economic development. This paper focuses on what determines the evolution of scientific clusters, an under-explored consideration that is important to a variety of constituencies, including regional development agencies, corporate managers, university administrators and public bodies. Following Lee et al. (Lee *et al.*, 2009), it analyses the endogenous and exogenous factors of the growth of scientific clusters,

Science is cumulative, and publication has long been recognized as the main indicator of scientific production. Our study focuses on clusters in nanotechnologies (nanodistrict), seeking to explain the factors that determine their growth, measured as the growth of publication numbers within a cluster. The number of publications produced within a cluster is usually taken as a good indication of the size of the local scientific community (Autant-Bernard *et al.*, 2006). Which are the characteristics of the clusters which witness high growth during the last decade? Are they focused on one discipline or do they involve highly diverse actors?

Three elements have been identified as being potentially influential in such scientific growth: the variety of the knowledge base (which we approximate by measuring the total number of scientific disciplines within the cluster); the diversity of actors (approximated by the diversity of organizations – Universities, firms, national labs, etc.) and the level of collaboration (measured by the degree of openness to scientific collaboration). We divide the analysis in two parts: first we look at structural variables (such as the initial size of the cluster, its geographic area, and its distribution across scientific fields) and, second, we explore leverage variables, which can be influenced by actors' strategies or by policy makers. Leverage variables focus on one of the fields to create a specific competence or to create a new organization to operate in a new scientific field or which leads to new collaborations. Finally, we interviewed university leaders within clusters to help us to better understand and interpret our results.

The context of the study is the emerging nanotechnology industries, which is a particularly appropriate setting to study cluster evolution as nanosciences and nanotechnologies are often described as being highly geographically clustered (www.nanoeconomics.org). Compared to biotech clusters, where firms have often been set up around large scientific universities (Zucker *et al.*, 1998), nanotechnology clusters are more diversely patterned, and may be located near to large firms already involved in one of nanotechnology' parent disciplines, or to large universities where research in nano-related technologies is undertaken, or to where the type of large technology platforms needed to perform nanotechnology research are available (Robinson *et al.*, 2007).

The next section reviews the different elements which influence the evolution of clusters; section three presents the nanotech industries and their regional cluster dynamics and section four presents our data and methods. Section five reports our results, which are then discussed in section six. The concluding section discusses the public policy and strategic implications of nano-cluster evolution and of its determinants.

2. CLUSTERING AND CLUSTER EVOLUTION

We draw on industrial cluster analysis framework to study the factors that influence the evolution of scientific clusters. Following the tradition initiated by Pouder and St Johns (Pouder *et al.*, 1996), Atherton (Atherton, 2003), Lee et al. (Lee *et al.*, 2009) and Menzel and Fornahl (Menzel *et al.*, 2010), we explore three key factors which explain the formation and growth of the clusters: scientific variety, organizational diversity and openness for collaboration.

Scientific variety

Geographic physical proximity of organizations in the same industry generates benefits for co-located actors as information and knowledge spillovers flow between them. Knowledge flows across organization boundaries, and such streams are strengthened by spatial and cognitive proximity (Boschma, 2005; Jaffe, 1986; Nesta, 2008). Analyzing the effects of geographic agglomeration in scientific clusters, Whittington et al. (Bunker-Whittington *et al.*, 2009) emphasize four mutually-reinforcing mechanisms that stimulate scientific and technological creation within clusters: first, the presence of a strong local scientific workforce makes it easier for firms to recruit researchers and skilled engineers; second, knowledge flows within and between firms, laboratories and other organizations are stimulated by short term inter-organization mobility of personnel; third, a concentration of scientists fosters social exchanges within ‘virtual’ colleges or communities of practices; and finally, the presence of universities and public sector research organizations nearby also provide the cluster with positive spillovers, as geographic proximity allows circulation of tacit knowledge and fosters the replication of knowledge, giving a unique advantage for innovation. Scholars note that proximity with companies in the same industry is important in enhancing cluster effects, via the combination of geographic and cognitive proximities (Boschma, 2005). These effects can be extended to enhance scientific production and innovation in nearby universities and research organizations (and other relevant actors) which support developments in complementary and related scientific and technological competencies, so that it makes sense to speak about ‘a biotech cluster’ or ‘a nanotech cluster’ as scientific specializations emerge.

However, the positive impact of such ‘collocated similitude’ may be counterbalanced by two elements. By analogy with what happens in firms, we can follow Nesta (Nesta, 2008) who has shown that it is the specialization (*depth)* of large firms’ knowledge bases that stimulates innovation in the short run, but its variety (*breath)* that enhances its innovativeness over the longer term. Zhang *et al.* (Zhang *et al.*, 2007) reach similar results when studying R&D collaborative agreements, identifying the breadth of a firm’s knowledge base as a determinant of its alliance dynamics. We define scientific variety as the number of scientific subfields represented in a cluster, and consider the breadth of scientific and technological knowledge in the cluster as the portfolio of competences available in the area i.e. the total number of scientific fields in which cluster members are involved to. As the number of regional level scientific and technological varieties increase, the size of the cluster can be expected to increase. Scientific and technological diversity allows cluster members to avoid being ‘locked-in’ to one discipline or technology too early, and provides actors with a continuous flow of ‘newness’. As technologies and scientific disciplines follow life cycles, the presence of a wide range of disciplines within the cluster may also help to generate continuous renewal. Thus, the literature on industrial spillovers highlights two opposite mechanisms: on the one hand, specialization enhances the innovation capabilities of actors; on the other diversity is required to stimulate cluster growth. As our intuition is that the positive effect of diversity will be dominant, we formulate hypothesis H1:

> *H1: The broader and more varied the scientific knowledge base, the greater the growth of the cluster.*

Organizational diversity

Scientific variety is not the only source of the continuous renewal of streams of scientific and technological discovery within clusters. The strategic actions of different actors who are simultaneously exploring divergent hypotheses or scientific paths also create a regular flow of new knowledge, even if there is some duplication: thus organizational diversity is likely to be a driver of scientific diversity. We define organizational diversity as the number of different entities involved in the clusters, including both the total number of its members and their diversity (universities, small firms, large firms, etc.). From the point of view of the individual entities involved, we hypothesize that diversity allows them to explore different bodies of knowledge, and to conduct and support different kinds of organizational agreements.

Clusters are defined by geographic proximity amongst actors. The fluidity of entry and exit - as well as competition amongst actors - lead to a constant renewal of actors within the cluster, reducing the risk of stagnation (McFadyen *et al.*, 2004; Pouder *et al.*, 1996). Ann Markusen (Markusen, 1985) underlines how a diversity of actors brings a large range of potential partners, while Lee et al. (Lee *et al.*, 2009) analyze the constrating effects on endogenous versus endogenous growth. Clusters attract local firms to move nearby, and science parks have been created to co-locate similar actors. This diversity also leads multinational firms to set up subsidiaries or research divisions within the cluster, and has been identified as one of the reasons for the success of the Silicon Valley, while the (comparatively) inward looking orientation of Pittsburgh and Detroit rendered them more vulnerable. Co-location of various categories of actors involved in scientific production - firms, universities, public sector research organizations etc. - may contribute to the growth of the cluster by providing it with complementary capabilities and competencies. Co-location of firms and universities expands the ways in which scientific questions can be formulated and addressed within the same environment, and may stimulate different teams to co-engage in research in a particular field or topic, as well as fuelling technology transfer and knowledge circulation between actors. We can thus suggest that clusters are likely to perform better when they comprise heterogeneous members who provide complementary resources, competencies and information flows:

> *H2: When organizational diversity is higher, the cluster growth rate is higher.*

Cluster Size

Scientific variety, organizational diversity and cluster size go hand in hand, since the range of actors and the number of scientific paths within the cluster will both depend on its size. Large clusters are "technically" more diverse than small ones, and will have a lower "technical" growth rate (as the denominator of the growth rate is larger). Small clusters have the capacity to expand a lot. In larger clusters more different disciplines are explored - increasing scientific variety - and more actors are deploying different activities and strategies, increasing organizational diversity. The increase of ordinary factors - such as travel times and costs - as clusters grow (especially those in cities/conurbations) represent a limit to the growth of scientific clusters, so the effect of scientific variety and organizational diversity must be moderated by the initial size of the cluster.

> *H3: The effects of scientific variety (hypothesis 3a) and organizational diversity (hypothesis 3b) on the growth of a scientific cluster are moderated by its initial size*

Scientific variety may result from internal diversity of a cluster's actors or from the richness of their portfolios of collaborations. Actors who collaborate with others beyond the cluster gain can advantages from the knowledge network capabilities of other groups or clusters. Sourcing knowledge and competencies from beyond the cluster, they can hybridize them with cluster capabilities, renewing internal competencies and opening up new research areas. However, the level of such outside collaboration is expected to decrease with the size of the cluster, as actors within large clusters are able to source diverse knowledge and resources. Just as variety is beneficial to cluster growth, we can hypothesize that collaboration outside the cluster will also enhance cluster growth (Bathelt *et al.*, 2004), but that this growth will be moderated by cluster size, since large clusters' propensity for collaboration is less than that of small clusters, which need to source knowledge from outside given the more limited number scientific fields within their 'home' cluster.

> *H4: The higher the level of collaboration (moderated by the cluster size) the higher the cluster growth rate*

3. DATA AND METHODS

To explore the determinants of the evolution of scientific clusters, we focus on a new emerging field: nanotechnologies. Nanotechnology emerged only 20 years, when IBM invented its tunneling and atomic force microscopy instruments. Defined as the manipulation of molecular sized materials to create new products and processes that derive novel features from their nanoscale properties, nanoscience and nanotechnology (hereafter 'nanotechnology' or nanotech) appear to have the potential to revolutionalize many industry sectors.As a converging technology that inherits from parent technologies i.e. biology, microelectronics, artificial intelligence, physics and chemistry, nanotechnology is a particularly suitable field in which to analyze the determinants of clustering. Nanotech research is highly concentrated, with only 200 clusters worldwide accounting for more than 70% of total publication numbers. Scientific activities are organized around technological platforms which play a key role in such geographic concentration (Robinson *et al.*, 2007).

Our study focuses on clusters in nanotechnologies (nanotech clusters) and is based on the analysis of the determinants of the growth of scientific publications. Publication is the main indicator of scientific production as science is cumulative. The number of publications measures the scientific production of a specific area and it is used as a proxy of the size of the cluster. Scientific publication has been booming in nanotechnologies has been booming as publications multiplied three-fold between 1998 and 2006, redistributing scientific capabilities worldwide.

To identify researches in nanotechnologies, we use a validated search strategy based on keywords (Mogoutov *et al.*, 2007) to extract publications from ISI/web of Science. The general research equation defines the different nanotechnology subfields, which include physics, physical chemistry, applied physics, biochemistry, chemistry, analytical chemistry, material science and macromolecules. From a methodological standpoint, publications yield more consistent geographic information about institutions and their addresses than patent documentation does about inventors and assignees. The collected data is then transformed into a relational database, and a set of matching tools and a unique classification scheme used to help manage the identity of actors and their geo-localization.. The database includes *actors*

- authors, institutes, laboratories; *content* – keywords, classes and concepts extracted using text mining techniques; *locations* – countries, cities and spatial clusters; and *scientometric indicators* based on analysis of citations and inter-citation networks, as well as providing information about the scientific fields, keywords and journal titles. We focus on institutions as our level of analysis i.e. publications are assigned to clusters on the basis of the authors' institution's addresses (same institution name, same address). From an empirical standpoint, we identify the different institutions (firms, research laboratories or university departments, etc.). within clusters by their names and addresses – where they differ, we consider them as different institutions.

As in all scientometric analysis, we define *publication* as the number of articles published in the field of nanotechnology, and *publication participation* as the participation of an institution in a publication (of course, co-authoring means that participation numbers are higher than publication numbers). The following example illustrates the counting method for the different variables. The publication RSTUV, co-authored by author R from institution α in Europe, author S from institution β in Europe, author T from institution β in Europe, author U from institution γ in Asia and author V from institution δ in the US, would yield a count of: 1 publication, 5 authors (R, S, T, U and V), 4 institutional participations (α, β, γ and δ) and 3 geographic area participations (Europe, Asia and the US). For our purposes, the count we are interested in is that of the institutional participations (in this case, 4).

We define nanotech *clusters* as geographic agglomerations that registered a cumulative number of more than 1,000 nanotechnology publications between 1998 and 2006. (The number of publications in 1998 may be very low, but they are included if their cumulative number has reached 1,000 by 2006.) All publications from the surrounding 50 km (or 30 km for Japan, Korea, and Taiwan) are considered as belonging to the cluster. When publications are located between two clusters (i.e, there is an overlap), they are grouped if they are close (i.e. more than 20% of their addresses overlap)or attributed to the nearest cluster when the overlap is under 20%.] To interpret the results and to better understand the different dynamics of the clusters in each region, we conducted eleven semi-direct explorative interviews within universities in clusters in the US, Asia and Europe (MIT, Caltech, Univ of Chicago, Shanghai Jiao-Tong University Hsinchu, National Chiao-Tong Univ., University of Tsukuba, University of Manchester, Karlsruhe Institute of Technology, TU Dresden, EPFL and Unil – Lausanne, Swizterland, University of Aalto et VTT.)

4. RESEARCH CONTEXT IN NANOTECHNOLOGIES

Nanotechnologies grow from existing knowledge bases, evolving from their parent fields of chemistry, physics, microelectronics and life sciences. Empirical evidence has shown that research in nanotechnologies has been geographically concentrated from the start, and has developed in a small number of clusters spread across the world. Table 1 presents the number of clusters of different sizes in each region (first line), the total number of participations in publications associated with the cluster involved ('publication participations') (line 2) and percentages of the total (line 3) for each geographic area between 1998-2006.

Table 1: Number and size of clusters by area, numbers and percentages of publication participants (1998-2006).

AREA		SIZE (cumulative no. of pub participations)				Out of Cluster**	Total	Average
		Large (>10k€)	Medium (5-10k€)	Small (2-5k€)	Emergent (1-2k€)			
EU*	# of clusters	1	9	40	31	***	81	
	# of publication participations	16,385	66,607	131,339	45,906	102,979	363,216	3,213
	% of publication participations	4.51%	18.34%	36.16%	12.64%	28.35%	100%	
US/ Canada		3	4	24	21		52	
		41,118	27,811	75,367	28,532	77,142	249,970	3,324
		16.45%	11.13%	30.15%	11.41%	30.86%	100%	
Asia		7	9	21	12		49	
		141,089	65,701	61,384	18,140	66,335	352,649	5,843
		40.01%	18.63%	17.41%	5.14%	18.81%	100%	
Other		1	1	7	9		18	
		10,368	5,287	18,805	12,698	42,137	89,295	2,620
		11.61%	5.92%	21.06%	14.22%	47.19%	100%	
Total		12	23	92	73		200	
		208,960	165,406	286,895	105,276	288,593	1,055,130	3,833
		19.80%	15.68%	27.19%	9.98%	27.35%	100%	

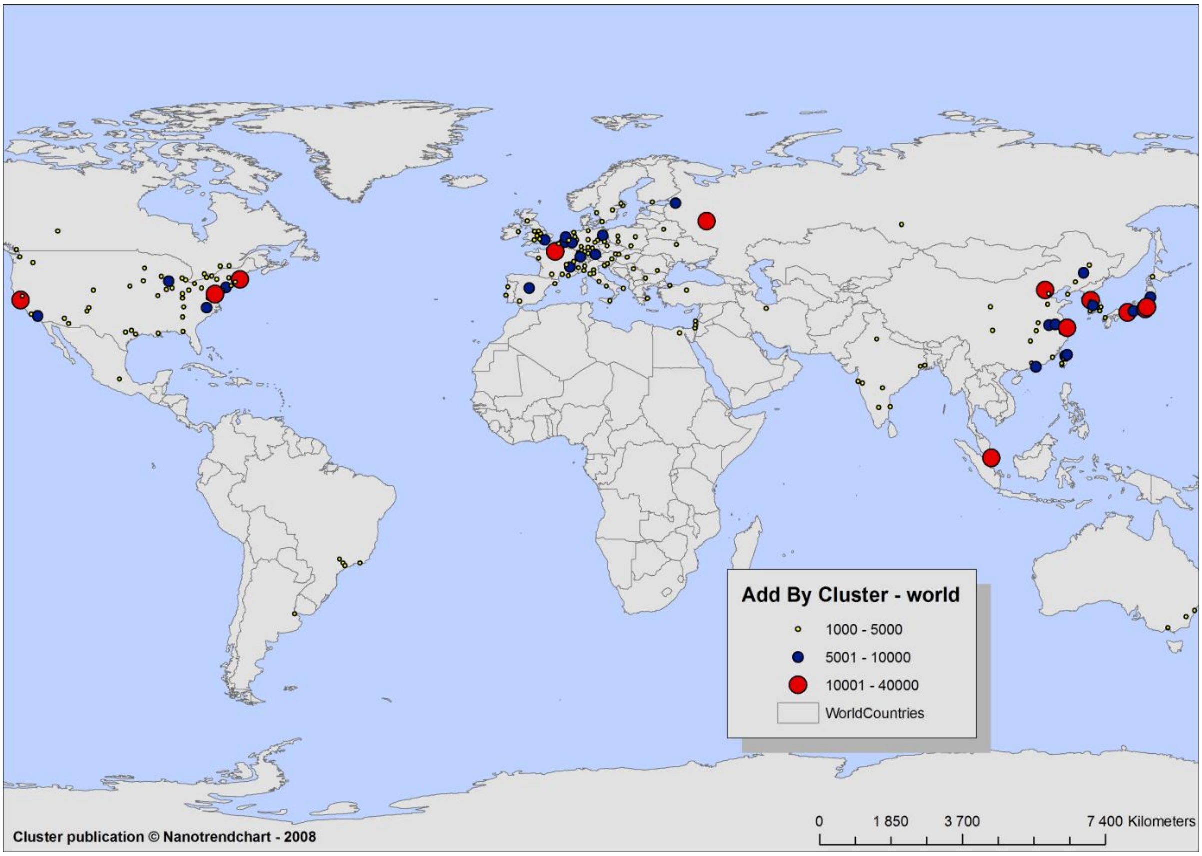
* *EU area is EU25 counties, plus Candidate & Associated Countries*

** *This column represents publication participations not from cluster*

*** *There is no number of clusters as publications are out of clusters.*

Asia has the smallest cluster count but the highest number of large clusters (thus the largest mean cluster size) showing that scientific production is much more clustered in this region than elsewhere (and especially in South Korea and Japan). Europe hosts more than 35% of the emergent and small clusters, and scientific production (as represented by publications) appears more distributed there and in the US, which host (respectively) 71 and 45 of the 165 small and emergent clusters, and where about 30% of production is ‘out of cluster’. In terms of publication participants, Asia’s large and medium clusters taken together account for more than 58% of publication participation numbers, compared to only 23% in Europe and 27% in the US/Canada. Asia and Europe each produce about 34% of the total number of publication participations, while US/Canada contributes only about 24%.

Map 1: Publications in nanotechnologies worldwide



Map 1 reveals the geographical patterns of the world's 200 nanotechnology clusters, based on their number of publications, with red points representing the largest clusters. Scientific publications remain highly concentrated in Europe (where there are a large number of medium and small clusters close to each other); bipolar in the US (mostly on the East and West coasts); and in Asia concentrated in Japan and South Korea, more dispersed in China, and with two large 'outlier' clusters in Moscow and Singapore. (For the specific case of the US, our distribution of clusters is similar to that reported by Shapira et al (Shapira *et al.*, 2008).) To study the determinants of scientific cluster growth, we perform OLS regressions on the annual growth rate of the number of publication participations from 1996 to 2008. Analyses were first performed worldwide and then by geographic areas: the dependent and independent variables are presented in the following sections.

Dependent variable

This paper focuses on cluster growth, a different notion from cluster performance, which not so straightforward, and which has been operationalized in many ways. Audretsch (Audretsch, 1995) considered numbers of innovations, while Audretsch and Feldman (Audretsch *et al.*, 1996) focused on rates of technology transfer and Piore and Sabel (Piore *et al.*, 1984) on employment growth. We prefer to analyze cluster growth without any explicit reference to performance, which allows us to avoid difficult theoretical debates about linkages between the two. Empirically, the evolution of scientific cluster productivity is mirrored in its publications, and approached by the mean annual growths of the numbers of publication participations associated with each cluster between 1998 and 2006.

The models estimate the influence of variety of scientific field and of actors on clusters' growth, and the effects of their scientific openness. Our strategy to analyze the determinants of the cluster growth has been to split out two categories of variables: *structural variables* which describe the cluster and *leverage variables* which cluster actors can 'play' strategically. Figure 1 displays the average growth by cluster size, revealing generally similar means whatever the size – although faster growth for small and emergent clusters – and higher diversity in large clusters and in outliers. Looked at in geographic terms, Figure 2 shows that Asian clusters display higher growth. Figure 3 sum ups these two dimensions size and areas, and confirms that Asian clusters grow faster whatever their size.

Figure 1 Average cluster growth distribution by Cluster size

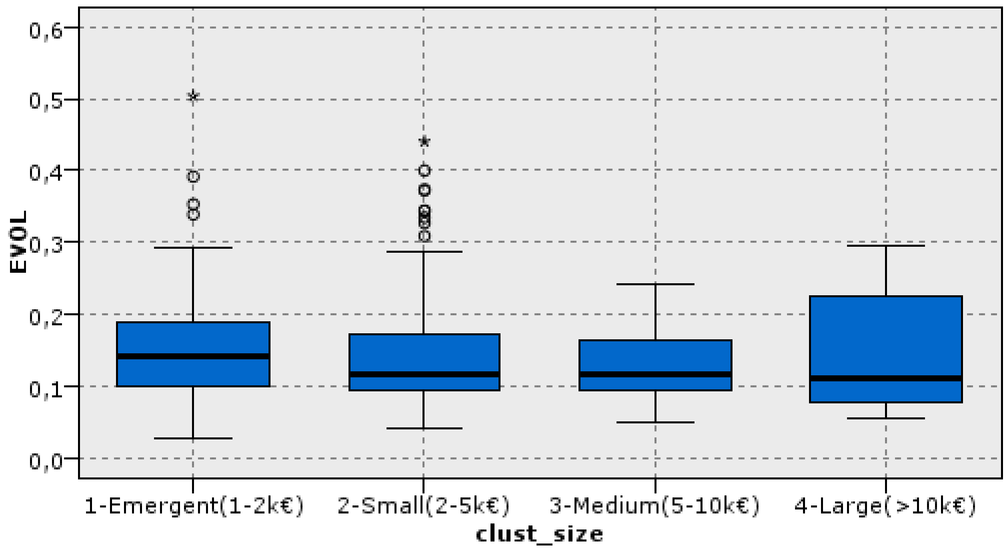


Figure 2 Average cluster growth distribution by Cluster Area

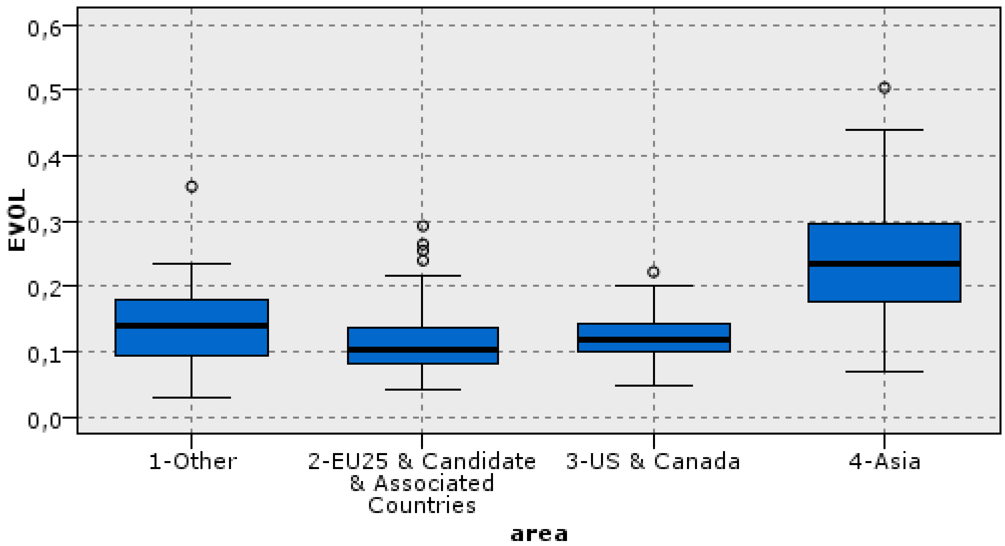
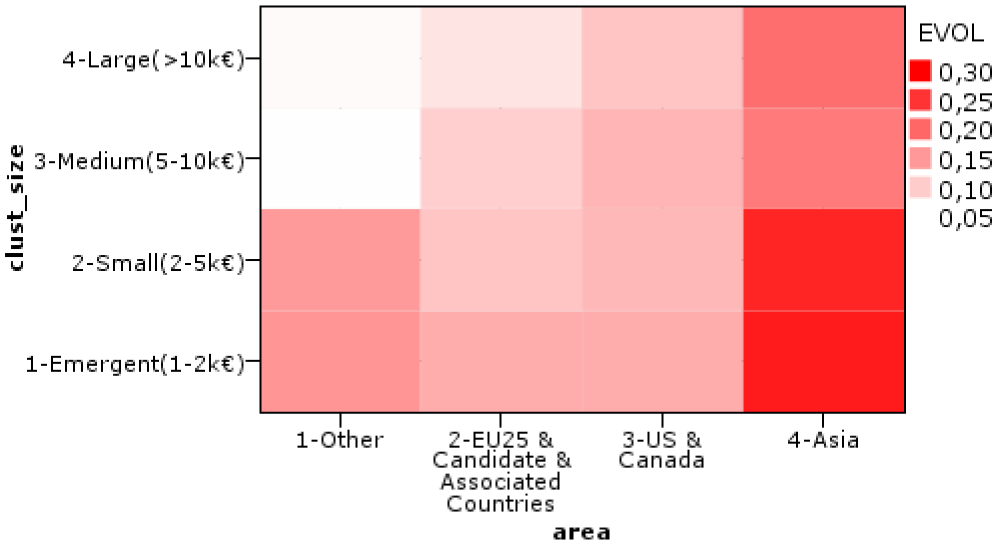


Figure 3 Heat map: Average cluster growth distribution by Cluster Area & size



All together the three Figures reveal three main features. The average annual growth of nanotechnology publications is very high, around 15% (as compared to the 3% annual growth of the ISI database as whole); numbers of publications associated with large clusters are growing quickly, and emergent and small clusters have more outliers as seen in Fig 1. Asian clusters are growing significantly more rapidly than those in other regions.

Structural variables

Three different types of structural variables are defined:

- The first type contains the initial size of the cluster, measured by the logarithm of the number of publications in 1998 (*L1998);*
- The second type is world geographic areas i.e. *Asia; EU* (i.e. EU25 & candidates & associated countries), *USA/Canada* and *Rest* of the world;
- The third type is scientific specializations. It indicates the main specialization of the cluster as well as the portfolio of specialization. It describes the specialization into six categories 001 to 006 - respectively Physics (*PHYS*), Engineering, Computing &

Technology (*ENG*), Electricity and Electronics (*ELEC*), Life Sciences and Biology (*LIFE*), Agriculture (*AGRI*) and Medical Sciences (*MED*) – which represent the highest aggregation levels in the Thomson ISI database (see appendix 1 for detailed information). (*ENG* is used as the reference category in our various models.)

Leverage variables

We construct three indexes for the scientific variety (*SCVAR*) and organizational (*ORGDIV*) diversity of clusters, and for collaboration with actors outside the cluster *(OUTCOLLAB).* So:

- $SCVAR_j$ is the Herfindhal index for the detailed JCR/ISI publication categories (of which there are 223). Thus:

  $SCVAR_j = \sum_i (C_{ij}/C_{.j})^2$ where *i* is the scientific category, *j* is the cluster and *C* represents the number of publications in each category. It is a leverage variable as the recruitment of a small group of highly specialized researchers may create a new scientific subfield within the cluster;

- $ORGDIV_j$ is the Herfindhal index for actors who have published in nanotechnology as identified from their addresses. Thus $ORGDIV_j = \sum_a (C_{aj}/C_{.j})^2$ where *a* is the specific actor (university department, firm, research organization or not-for-profit organization), *j* the cluster and *C* the total number of publication;
- OUTCOLLAB is the index of collaboration i.e. the number of publications with at least one address from outside the cluster, divided by the number of co-authored publications (i.e. with at least two addresses). OUTCOLLAB has two faces: it reveals the degree to which cluster actors are able to mobilize contributors from other clusters or beyond clusters, and also represents the ‘leakage’ or dissemination of knowledge from the cluster to the outside world;
- L1998 is the logarithm of the number of publications in 1998;

- L2006 is the logarithm of the number of publications in 2006; and
- EVOL is the mean of Cluster's Annual Growth .

Table 3 presents the description of the population (cluster sizes are expressed in logs) and Table 4 shows their bivariate correlations.

Table 3: Description of the population

Variable	Label	Min	Mean	Max	Std Dev	25th Pctl	50th Pctl	75th Pctl
pub1998	Pub(1998)	34.00	254.59	2928.00	308.06	95.00	167.00	301.00
pub2006	Pub(2006)	128.00	671.24	5656.00	746.39	279.50	433.00	713.00
sum_98_06	Total Pub (1998-2006)	1018.00	3832.69	35363.00	4297.51	1586.50	2456.50	4130.00
VarPub1999_1998	Pub Annual Growth - 1999/1998-	-0.25	0.16	0.82	0.22	0.01	0.13	0.27
VarPub2000_1999	Pub Annual Growth - 2000/1999-	-0.27	0.09	0.90	0.17	-0.02	0.08	0.17
VarPub2001_2000	Pub Annual Growth - 2001/2000-	-0.28	0.16	2.85	0.27	0.02	0.13	0.24
VarPub2002_2001	Pub Annual Growth - 2002/2001-	-0.24	0.18	0.77	0.17	0.05	0.18	0.30
VarPub2003_2002	Pub Annual Growth - 2003/2002-	-0.34	0.12	0.88	0.20	-0.02	0.10	0.22
VarPub2004_2003	Pub Annual Growth - 2004/2003-	-0.25	0.18	0.83	0.18	0.07	0.16	0.27
VarPub2005_2004	Pub Annual Growth - 2005/2004-	-0.22	0.19	0.76	0.17	0.07	0.19	0.29
VarPub2006_2005	Pub Annual Growth - 2006/2005-	-0.26	0.13	0.89	0.16	0.03	0.10	0.21
EVOL	Evolution(Mean of Annual Growths)	0.03	0.15	0.50	0.08	0.10	0.13	0.18
Percfirm	firms share in Cluster	0.00	3.64	27.02	4.80	0.56	1.85	4.59
txouv1x	Cluster Openness Rate	1.00	5.23	19.34	2.78	3.25	4.52	6.64
_001PHYS	Spec. index in Physics	0.67	1.00	1.42	0.12	0.92	1.00	1.08
_002ENG	Spec. index in Engineering/Computing Technology	0.44	1.04	2.15	0.29	0.85	1.01	1.20
_003ELEC	Spec. index in Electricity/Electronics	0.30	0.91	1.83	0.27	0.73	0.89	1.07
_004LIFE	Spec. index in LifeSciences/Biology	0.08	1.03	3.54	0.64	0.49	0.94	1.43
_005AGRI	Spec. index in Agriculture	0.08	1.15	4.53	0.75	0.65	1.00	1.47
_006MED	Spec. index in Medical Sciences	0.00	0.99	6.22	1.01	0.25	0.61	1.63
hhi9	Herfindahl Index(ISI 9)	0.25	0.35	0.55	0.05	0.31	0.34	0.38
Hhidet	Herfindahl Index(ISI)	0.03	0.07	0.17	0.02	0.05	0.06	0.08
Hhiact	Herfindahl Index(Actors)	0.05	0.39	0.99	0.26	0.18	0.31	0.56

Table 4: Bivariate correlations

Spearman Correlation Coefficients, N = 200 Prob > |r| under H0: Rho=0	EVOL	DumASIA	lgpub1998	percfirm	txouv1x	_001PHYS	_002ENG	_003ELEC	_004LIFE	_005AGRI	_006MED	hhi9	hhidet	hhiact
EVOL	1.00000	0.54720	-0.51452	-0.43973	-0.41251	0.09940	0.43662	-0.32087	-0.27733	-0.14092	-0.27480	0.24854	0.20326	0.02189
Evolution(Mean of Annual Growths)		<.0001	<.0001	<.0001	<.0001	0.1614	<.0001	<.0001	<.0001	0.0466	<.0001	0.0004	0.0039	0.7583
DumASIA	0.54720	1.00000	-0.11931	-0.27753	-0.32510	0.30758	0.46787	0.03292	-0.55063	-0.44552	-0.47441	0.45961	0.46243	-0.02205
ASIA Dummy	<.0001		0.0924	<.0001	<.0001	<.0001	<.0001	0.6435	<.0001	<.0001	<.0001	<.0001	<.0001	0.7566
lgpub1998	-0.51452	-0.11931	1.00000	0.50197	0.05116	-0.08812	-0.30688	0.41099	0.14396	-0.05441	0.18062	-0.18511	-0.11889	-0.33624
log Pub(1998)	<.0001	0.0924		<.0001	0.4719	0.2147	<.0001	<.0001	0.0420	0.4441	0.0105	0.0087	0.0936	<.0001
Percfirm	-0.43973	-0.27753	0.50197	1.00000	0.19903	-0.38523	-0.36641	0.22293	0.48513	0.18480	0.50015	-0.49891	-0.37825	-0.13842
firms share in Cluster	<.0001	<.0001	<.0001		0.0047	<.0001	<.0001	0.0015	<.0001	0.0088	<.0001	<.0001	<.0001	0.0506
txouv1x	-0.41251	-0.32510	0.05116	0.19903	1.00000	0.03417	-0.08128	0.08392	0.06732	0.07303	0.10043	-0.03717	-0.07687	-0.14040
Cluster Openness Rate	<.0001	<.0001	0.4719	0.0047		0.6310	0.2526	0.2374	0.3435	0.3041	0.1571	0.6013	0.2793	0.0474
_001PHYS	0.09940	0.30758	-0.08812	-0.38523	0.03417	1.00000	0.18124	0.04444	-0.71285	-0.55883	-0.69980	0.92907	0.66460	-0.14227
Spec. index in Physics	0.1614	<.0001	0.2147	<.0001	0.6310		0.0102	0.5321	<.0001	<.0001	<.0001	<.0001	<.0001	0.0445
_002ENG	0.43662	0.46787	-0.30688	-0.36641	-0.08128	0.18124	1.00000	-0.31707	-0.59993	-0.38119	-0.44805	0.41130	0.42318	-0.14559
Spec. index in Eng./Comp.Tech.	<.0001	<.0001	<.0001	<.0001	0.2526	0.0102		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0397
_003ELEC	-0.32087	0.03292	0.41099	0.22293	0.08392	0.04444	-0.31707	1.00000	-0.18977	-0.20338	-0.12307	-0.01612	0.26955	-0.00162
Spec. index in ElectricityElectronics	<.0001	0.6435	<.0001	0.0015	0.2374	0.5321	<.0001		0.0071	0.0039	0.0825	0.8207	0.0001	0.9819
_004LIFE	-0.27733	-0.55063	0.14396	0.48513	0.06732	-0.71285	-0.59993	-0.18977	1.00000	0.69077	0.80335	-0.87058	-0.85795	0.14750
Spec. index in LifeSciencesBiology	<.0001	<.0001	0.0420	<.0001	0.3435	<.0001	<.0001	0.0071		<.0001	<.0001	<.0001	<.0001	0.0371
_005AGRI	-0.14092	-0.44552	-0.05441	0.18480	0.07303	-0.55883	-0.38119	-0.20338	0.69077	1.00000	0.51834	-0.67439	-0.66192	0.15649
Spec. index in Agriculture	0.0466	<.0001	0.4441	0.0088	0.3041	<.0001	<.0001	0.0039	<.0001		<.0001	<.0001	<.0001	0.0269
_006MED	-0.27480	-0.47441	0.18062	0.50015	0.10043	-0.69980	-0.44805	-0.12307	0.80335	0.51834	1.00000	-0.82280	-0.78319	-0.08246
Spec. index in Medical Sciences	<.0001	<.0001	0.0105	<.0001	0.1571	<.0001	<.0001	0.0825	<.0001	<.0001		<.0001	<.0001	0.2457
hhi9	0.24854	0.45961	-0.18511	-0.49891	-0.03717	0.92907	0.41130	-0.01612	-0.87058	-0.67439	-0.82280	1.00000	0.79341	-0.13231
Herfindahl Index(ISI 9)	0.0004	<.0001	0.0087	<.0001	0.6013	<.0001	<.0001	0.8207	<.0001	<.0001	<.0001		<.0001	0.0618
Hhidet	0.20326	0.46243	-0.11889	-0.37825	-0.07687	0.66460	0.42318	0.26955	-0.85795	-0.66192	-0.78319	0.79341	1.00000	-0.04036
Herfindahl Index(ISI)	0.0039	<.0001	0.0936	<.0001	0.2793	<.0001	<.0001	0.0001	<.0001	<.0001	<.0001	<.0001		0.5704
Hhiact	0.02189	-0.02205	-0.33624	-0.13842	-0.14040	-0.14227	-0.14559	-0.00162	0.14750	0.15649	-0.08246	-0.13231	-0.04036	1.00000
Herfindahl Index(Actors)	0.7583	0.7566	<.0001	0.0506	0.0474	0.0445	0.0397	0.9819	0.0371	0.0269	0.2457	0.0618	0.5704	

Table 4 shows the relations between the different variables. The openness rate has a negative direct effect. Cluster growth varies positively with scientific variety (*SCVAR)* but negatively with initial cluster size; and positively with specialization in engineering (*ENG)*, but negatively with other specializations, especially life sciences (*LIFE*, *AGRI* and *MED*). While the diversity of actors (*HHIACT*) is linked with the initial size of the cluster, it is not directly correlated with cluster growth (*EVOL*), nor with scientific variety. The level of collaboration outside the cluster (*TXOUV1X*) is negatively correlated with the cluster growth, but with none of the other variables.

5. RESULTS

Our estimation strategy was based on using OLS regressions to estimate the annual growth of the number of publication. We first run the regression on all the variables and then adopt a strategy to maximize the adjusted R-square. Four models have been ran, one with all the variables, two which maximize the Adjusted R-square and the last one with interaction terms based on correlated variables (Table 4). Table 5 presents the best model (based on the Adj R-square criteria) to test the four hypotheses First of all, Asian clusters are growing significantly faster whatever the model. Second, size plays a moderating role as well as the diversity of technologies.

Table 5: OLS regressions explaining the mean of cluster's annual growths

Parameter Estimate		Model 1		Model 2		Model 3		Model 4	
Variable	Label	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|	Parameter Estimate	Pr > |t|
Intercept	Intercept	2.39547	0.2246	0.42202	<.0001	0.48962	<.0001	2.868874966	0.1163
DumASIA	ASIA Dummy	0.10684	<.0001	0.09532	<.0001	0.11572	<.0001	0.099984455	<.0001
DumEU	EU25 & Candidate & Associated Countries Dummy	0.00615	0.6604	-	-	-	-	-	-
DumUSCanada	US & Canada Dummy	0.02365	0.1882	-	-	-		-	-
lgpub1998	log Pub(1998)meg	-0.04712	<.0001	-0.04611	<.0001	-0.04613	<.0001	-0.004781555	0.8041
percfirm	firms share in Cluster	-0.00084178	0.3201			-0.00107	0.1918	-0.012292303	0.0630
txouv1x	Cluster Openness Rate	-0.00392	0.0065	-0.00520	<.0001	-	-	-0.008672100	0.4426
_001PHYS	Spec. index in Physics	-1.09780	0.2733	-	-	-0.06701	0.0404	-1.443591153	0.1161
_002ENG	Spec. index in EngineeringComputingTechnology	-0.37084	0.3503	0.02152	0.1553	-	-	-0.499273150	0.1715
_003ELEC	Spec. index in ElectricityElectronics	-0.32471	0.2765	-0.03841	0.0108	-0.04368	0.0043	-0.409172537	0.1383
_004LIFE	Spec. index in LifeSciencesBiology	-0.20077	0.3268	-	-	-	-	-0.259259655	0.1717
_005AGRI	Spec. index in Agriculture	-0.03497	0.3403	-	-	-	-	-0.048006595	0.1548
_006MED	Spec. index in Medical Sciences	-0.03746	0.3116	-	-	-	-	-0.050547755	0.1326
hhi9	Herfindahl Index(ISI 9)	0.23892	0.4796	-	-	-	-	0.295296734	0.3756
hhidet	Herfindahl Index(ISI)	-0.10659	0.7531	-	-	-	-	2.188924710	0.0744
hhiact	Herfindahl Index(Actors)	-0.06396	0.0004	-0.04222	0.0050	-0.04652	0.0024	-0.015515086	0.8772
percfirm*hhidet	Interactions							0.084621380	0.0595
txouv1x*hhidet								0.100752310	0.2184
lgpub1998*hhidet								-0.618776031	0.0090
lgpub1998*hhiact								-0.007295850	0.7197
lgpub1998*txouv1x								-0.000412622	0.8162
lgpub1998*percfirm								0.001033637	0.2745
Model quality									
R_Square			0.6833		0.6691		0.6479		0.703389
Adj R_Square			0.6575		0.6588		0.6370		

Structural effects

Three different groups of structural variables are defined: size, geographic areas, and scientific specialization.

The **initial size** of the cluster (L1998), measured by the logarithm of the number of publications in 1998 has the expected negative impact on the cluster growth. The larger the cluster in 1998, the lower will be the growth rate. This effect disappears when the the size is used as a moderator. **Geographic areas**. Asian clusters are growing at higher rate than other. The initial distribution of cluster size is similar worldwide, but, even though cluster sizes are rather similar on average in Asia (differences are not significant), size distributions are more asymmetric than in Europe and in the US, with more large and medium clusters.

The **percentage of firms** within the clusters has a negative impact on its growth. As firms are rather involved on innovation and patent, it seems normal that the higher the percentage of firms within the clusters, the lower the growth rate of the number of publications. This effect disappears when the percentage of firms is moderated by technological diversity, leading to a positive effect. When firms are associated with the introduction of technological diversity, the presence of firms has a significant and positive effect on cluster growth.

In terms of **scientific specializations,** clusters which demonstrate specialization in physics and Electricity/Electronics grow significantly less rapidly than others. When scientific specialization is moderated by the size, the effects disappear. Table 6 reveals the different patterns of scientific specialization by areas. Comparing each area to the world 100 index (see table 6), Asia appears to specialize in physics (Physical, Chemical and Earth science), engineering (Engineering, Computing and Technology) and Electricity/Electronics, which together account for about 85% of Asian nanotechnology publications, but is under specialized in Life sciences in general, where clusters have grown more slowly. While Asian clusters specialize in fast-growing scientific fields, European clusters are more balanced and those in US/Canada are more specialized in life sciences where, again, growth rates are generally lower.

Table 6: index of specialization

	Clusters in					
Index of Scientific Specialization	Asia	EU	US/ Canada	Other	Index World	Total (% of publications)
Physical, Chemical & Earth Sciences (PHYS)	105.2	100.7	88.1	111.0	100	50.75%
Engineering, Computing & Technology (ENG)	115.6	96.3	80.1	103.0	100	20.10%
Electronics & Telecom. Collection (ELEC)	108.4	93.0	99.1	91.4	100	15.07%
Life Sciences (LIFE)	51.9	109.4	171.6	60.0	100	10.31%
Agriculture, Biology & Environ'l Sciences (AGRI)	59.0	114.6	1.421	105.6	100	1.78%
Clinical Medicine (MED)	34.8	113.5	1.933	56.2	100	1.78%
% of publication per area	33.42%	34.42%	23.69%	8.46%		100%

Leverage variables

The introduction of variety/diversity variables (the Hinferdhal indexes of organizational diversity, scientific variety and index of outside collaborations) and their interaction effects increase the explanation power (R^2) of the different models (*i.e.* model 4 vs. 3 or 1). S*cientific variety* impacts positively on cluster growth rates, only when it is moderated by initial cluster size. Thus hypothesis 1 *('The broader and more varied the scientific knowledge base, the higher the growth of the cluster.')* is not validated, but hypothesis 3a is supported. *Organizational diversity* has a negative impact on cluster growth, which suggests that organizational frontiers within clusters slow down information circulation. Highly diverse clusters do not benefit as much from knowledge externalities as do less diverse clusters, so hypothesis H2 is not supported. Organizational diversity and scientific variety do not go hand with hand. When controlling for the cluster size, the effect of diversity/variety becomes non significant. Scientific variety is more important than organizational diversity in enhancing cluster growth. Hypothesis H3b is not supported. When clusters grow, diversity must grow slower than the cluster to lead to endogenous growth.

Finally, the *degree of outside collaboration* appears to have a negative impact on growth, so hypothesis H4 *'The higher the level of collaboration (moderated by its size) the higher the cluster growth rate'* is not supported.

This may be a result of geographical patterns of collaboration, as the faster-growing Asian clusters show a lower proportion of out-cluster co-authors, evidence that their actors are less include to enter into collaboration than those of clusters in other areas. Asian clusters are also larger in average than American and European ones, and their scientific specializations are different than those of other clusters: more specialized in physics and engineering the faster-growing specializations) and less specialized in Medicine and Life sciences, which are growing more slowly.

Table 7 proposes the best OLS (R^2 adjusted procedure) for each geographic area to evaluate the extent to which the determinants of the cluster growth are contingent on geography.

Table 7 : OLS models Analysis by areas (best model by area)

	EU25 Candidate				US & Canada				Asia			
Parameter	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|	Estimate	Pr > |t|
Intercept	0.38610	<.0001	0.441080483	0.0039	-0.14757	0.0079	-.1296990859	0.1201	0.62494	<.0001	0.5575031312	0.1329
lgpub1998	-0.04173	<.0001	-0.020539809	0.4399					-0.06893	<.0001	-.0403300451	0.5243
percfirm			-0.005889582	0.7382			-.0024381715	0.7906			-.0081042711	0.7225
txouv1x	-0.00446	0.0049	-0.057632317	0.0035	0.00310	0.0318	0.0119864480	0.3312	-0.01645	0.0020	-.0358077686	0.4411
_001PHYS												
_002ENG					0.07870	0.0039	0.0745515997	0.0161	0.06066	0.1081	0.0758038962	0.1883
_003ELEC	-0.03424	0.1097	-0.021949048	0.2755								
_004LIFE					0.10170	<.0001	0.0974223285	<.0001				
_005AGRI												
_006MED					-0.02189	0.0002	-.0191150267	0.0114				
hhi9												
hhidet	0.42858	0.1350	2.130931988	0.3248	1.13949	0.0026	-.4879525959	0.8332			-.3187562982	0.9429
hhiact	-0.06227	0.0035	-0.007322705	0.9628			0.1170439079	0.4932	-0.13582	0.0044	0.0961322296	0.7410
hhidet*percfirm			0.040465956	0.6912			0.0522537613	0.3777			0.1374968986	0.4097
txouv1x*hhidet			0.387544924	0.0023			-.0322843607	0.7983			0.1523650887	0.7056
lgpub1998*hhidet			-0.874398922	0.0430			0.3207633577	0.5135			-.2009518160	0.7962
lgpub1998*hhiact			-0.014938272	0.6389			-.0244234257	0.4614			-.0453262734	0.4382
lgpub1998*txouv1x			0.005660247	0.0493			-.0015796325	0.5520			0.0018704254	0.7838
lgpub1998*percfirm			0.000636560	0.8011			-.0002473162	0.8484			-.0006214467	0.7753
R-Square		0.4977		0.639252		0.5397		0.581615		0.6129		0.640062
Adj R-Sq		0.4643		-		0.4896		-		0.5777		-
Dependent Mean				0.11486				0.12406				0.24074
Number of Observations				81				52				49

For clusters in Asia, models without interactions show those specialized in engineering show faster growth than others, but initial size, the degree of out-cluster collaboration and the diversity of actors have negative effects on cluster growth. However, when the interactions are introduced, none of the variables appear to be significant.

For North American clusters, the degree of collaboration outside the cluster, the diversity of scientific fields within the cluster and the relative specialization in engineering and life sciences enhance cluster growth, but when models integrate interactions, only the variables representing scientific specialization are significant.

For Europe, the degree of openness to outside collaboration has a positive impact when it is moderated by the scientific diversity, revealing that clusters may find complementary technologies in other clusters through collaborations. This may be one of the effects of the public policies towards the European Research Area to stimulate collaborations within Europe. The initial size of the cluster plays a negative role on growth, unless it is combined with more scientific diversity as it is suggested by the positive interaction between size and degree of collaboration.

Altogether, therefore, the determinants of the clusters growth seem to be embedded in local and political contexts. There are no unique dynamics which enhance cluster growth, as cluster evolutions seem path dependant and influenced by local, national and supranational environments. If we consider the diversity of political, regional, economic and social environment in Asia (India, Japan, China and Korea), it is not surprising that we cannot identify any variables as being significant determinants of cluster growth, while in more homogenous environments (US, Canada and Europe), degree of openness of the clusters, historic specialization of clusters and scientific diversity clearly appear to influence such growth.

6. DISCUSSION

Nanotechnology research activity grew rapidly between 1998 and 2006, as did publication numbers, which almost trebled. Our analysis of the determinants of cluster growth reveals that geography is important in understanding cluster growth, as the determinants change from one continent to another, even in highly globalised scientific and technological fields where large groups play key roles (Mangematin *et al.*, 2010). Path dependencies and regional (Freel, 2002; Klein, 2003), and national systems innovation (Mowery, 1992; Patel *et al.*, 1995; Stubbart *et al.*, 1995) shape both local environment and patterns of collaboration. The usual relationships between scientific variety, organizational diversity, agglomeration and cluster growth have to be viewed through a geographic prism.

Two contributions of the paper are discussed: (1) the roles of diversity and variety in scientific cluster growth and (2) the specificities of the determinants of cluster growth in Asia, Europe and the USA.

Scientific variety and organizational diversity to foster cluster growth

Our analysis of the determinants of the growth of nanotechnology clusters does not fully support existing approaches which underline scientific variety and organizational diversity as key resources for cluster development. According to Frenken (Frenken *et al.*, 2007), gains in a cluster's diversity provide central support for its growth and generate strong path dependencies in the spatial specialization of clusters. Organizational diversity fosters scientific variety during the emergence phase, fostering the exploration of the different hypothesis promoted by scientists in different organizations. When the field reaches a certain level of maturity - when more instrumentation is required as well as larger teams - organizational fragmentation may slow growth down. Scholars working on knowledge have pointed out that organizations erect barriers against knowledge flows, so that it circulates more easily within than between organization (Bell *et al.*, 2007; Lavie *et al.*, 2008; Zeller, 2002): geographic proximity may not fully counter the negative effects of such organizational boundaries.

The comparative econometric results displayed in Tables 5 and 7 reveal a complex pattern. First of all, scientific diversity plays a key role when moderated by initial cluster size. For a given initial size, scientific diversity enhances cluster growth, a result that is in line with previous observations, especially those of Frenken (2007) on clusters and those on firms (Nesta, 2008). Analyzed by geographic area, the impact of scientific diversity is negative in Europe and does not play a significant role in Asia. Organizational diversity has a negative impact in Asia, suggesting that diversity slows down growth. Such results are surprising, scientific variety and organizational diversity usually enhancing growth: Results are in accordance with existing literature only for North America, the area most often studied. The role of scientific variety and organizational diversity seems contingent on national systems of innovation. History and path dependence based on previous patterns of collaborations amongst actors highly influence the growth of science based clusters. Different (unobserved) factors - such as the megapolisation in Asia or European public policy to build the European Area of Research - may interact to counter-balance the positive impact of diversity reported in US studies. Or regional science may be localized, with different determinants and different engines of growth in the different parts of the world.

Outperforming Asia?

Cluster growth in Asia outperforms that in America and Europe, so patterns of growth are apparently contingent on geography. But it also seems that objectives differ according to both geography and relative position on the scientific map. The US/Canada zone has been leading scientific production as a whole. They have been ahead until 2006 for Nanotechnologies and they are now challenged by Europe first and then by Asia..

To better understand these evolutions and actors' strategies, we interviewed those in charge of strategy in different clusters. They reveal that policies differ in Europe and Asia on the one hand and the USA in the other. European and Asian policies have been oriented towards growth, encouraging the merging of institutions and expansion in student numbers, and in numerical size more generally in terms of firms and start-ups, while in the US/Canada, leading universities and clusters institutions within clusters are focusing on quality rather than on numbers. When interviewed, University vice presidents and animators of US clusters denied that publication numbers were important indicators, and that they concentrated only on citation numbers, endowments and fund raising. The strategy they reported was of influencing the evolution of the scientific field, forming the research agenda and defining new research questions, in what could be seen as an evolution of the urge to "publish or perish" towards "be cited or perish". The strategy of leading institutions in the US/Canadian clusters seems to change with the emergence of nanotechnologies. While China, with outstanding growth rates, leads in terms of the publication number growth, it seems that US clusters are changing the rules of the game, emphasizing citations and the influence of visibility rather than domination by numbers, which aligns with emerging top university policies for faculties to achieve publication in top journals and to raise funds as part of a highly selective competition to recruit students.

Path dependency and public policies

Geography strongly influences the cluster evolution, and this paper highlights strong path dependency and important contingent effects. History plays a key role in creating patterns of specialization and of organization and modes of collaborations between actors, and also of degrees of openness to the world beyond the cluster. Saxenian's story about the Silicon Valley, or reports about Minatec (Delemarle *et al.*, 2008) reveal the munificence of the local environment, the tightness of relationships between local actors and the quality of their entrepreneurial spirit as the keys to cluster development.

Public policies differ in Asia, Europe and North America. The scope for public policy remains limited in the short run, since structural elements are the most influential and modifying them is a long process. Within clusters, three different policies have been tried: university mergers to create large institutions; the emergence of small teams to foster scientific diversity; and coordination within "umbrella organizations". For the first point, policy makers and university strategists tend to merge different universities in Asian and European clusters (as at Helsinki and Manchester), but reducing organizational barriers to knowledge flows and fostering knowledge hybridization within the same large institution can be a long process. The second type of policy is to support the formation of specialized teams or institutes to stimulate scientific variety by increasing organizational diversity. While this counterbalances policies that concentrate on a fast growing scientific field, it may have uncertain effects, as reducing scientific variety slows down growth in the long run. The reinforcement of under developed disciplines within the cluster combines a major specialization theme with a level of scientific diversity. The fragmentation of scientific fields into competing organizations may also decrease cluster growth by creating unnecessary boundaries and interfering with knowledge circulation, which can be countered by policies aimed at regrouping different institutions and erasing boundaries, thus enhancing cluster growth. On the third point, local policy makers may support the setting up of "umbrella organization" which orchestrate the networking between cluster organizations and coordinate its scientific strategy ex ante. But public policies that stimulate collaboration between clusters must be conducted carefully, as they may reduce their potential for growth.:

7. CONCLUSION

Despite Cairncross's (1997) pronouncement, proximity is not dead. Empirical results provide researchers, policy makers and firms with a balanced picture: the growth of a scientific cluster is strongly path dependent and will be determined by its structural characteristics. Initial cluster size, location (continent) and the main scientific fields in which it specializes (life sciences in the US, engineering and electronics in Asia) explain 2/3 of the variations in scientific cluster growth. Leverage variables – which explain the other 1/3 - constitute the main triggers of cluster growth. Scientific variety is a key element that influences cluster growth. Policy makers and firm strategists may influence scientific variety by forming new teams and by investing new fields, but their actions will be most effective in small clusters, where the creation of a new team may affect the cluster's scientific variety. Surprisingly, although it fosters growth during the emerging phase, organizational diversity plays a negative role in cluster growth thereafter, and does not appear as an engine of scientific variety.

The variation of the determinants of scientific cluster growth between geographic regions is surprising, and calls for more attention from policy makers. Policy measures implemented in one geography should not be replicated in another without the specific situation being carefully analyzed. Structural dimensions play a central role in creating a favorable context for scientific expansion, but while public policies may change such environmental characteristics in the medium run, they not really likely to do so in the short term.

Finally, our analysis calls for a better understanding of the formation of scientific influence. Do numbers play a key role in the influence of the cluster over the definition of research avenues and the formation of new paradigms? Or do research avenues and exploration of new paradigms result from relationships between highly influential researchers? In that case, the composition of the scientific boards of leading journals, and of the scientific committees of the main conferences, associations with the highest distinctions (like Nobel Prizes) and the number of citations received will be better indicators of a cluster’s scientific influence than sheer publication numbers.

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Appendix 1: Detailed presentation of scientific fields

001 PHYS Physical, Chemical & Earth Sciences (PCES)
Includes over 1,050 journals and books selected for their relevance to research in the physical sciences, chemistry and earth sciences, and classified into disciplines such as: Applied Physics/Condensed Matter/Materials Science Mathematics Inorganic & Nuclear Chemistry
002 ENG Engineering, Computing & Technology (ECT)
Includes over 1,100 journals and books selected for their relevance to research in engineering, computer science, and advanced technology, and classified into disciplines such as: Aerospace Engineering Computer Science & Engineering Optics & Acoustics
003 ELECT Electronics & Telecommunications Collection (EC)
Includes nearly 210 journals and trade publications selected for their relevance to research and development in the electronics industry, and classified into disciplines such as: Electronics & Electrical Engineering Optics & Laser Research & Technology Semiconductors & Solid State Materials Technology Telecommunications Technology
004 LIFE Life Sciences (LS)
Includes over 1,370 journals and books selected for their relevance to research in the life sciences, classified into disciplines such as: Animal & Plant Sciences Cell & Developmental Biology Physiology
005 AGRI Agriculture, Biology & Environmental Sciences (ABES)
Includes over 1,040 journals and books selected for their relevance to research in agriculture, biology, and environmental sciences, and classified into disciplines such as: Aquatic Sciences Biotechnology & Applied Microbiology Entomology/Pest Control
006 MED Clinical Medicine (CM)
Includes over 1,120 journals and books selected for their relevance to research in clinical medicine, classified into disciplines such as: Anesthesia & Intensive Care Cardiovascular & Respiratory Systems Surgery