THE DETERMINANTS OF THE SCIENCE-BASED CLUSTER GROWTH

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

Abstract[1]

There is growing academic and policy interest in the factors that underpin the performance of clusters, especially for such ‘hyped up’ scientific and technological fields as the nanotechnologies. The paper analyses the determinants of scientific cluster growth (measured by the number of publications within the cluster), distinguishing between structural effects (i.e. 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. Structural effects explain about 66% of the variance of cluster growth, emphasizing the history and path dependency of clusters. Scientific variety influences the scientific cluster growth while organizational diversity demonstrates an inverted U shape effect on growth. Policy makers and cluster strategists may foster scientific cluster growth by influencing scientific variety and monitoring organizational diversity as well as its collaboration with actors outside the cluster. However, the main effects remain structural ones. Slow growth may reflect also ‘elitist’ strategies based on quality rather than on numbers.

Keywords: cluster growth, nanotechnology, scientific district, publication

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1. INTRODUCTION

As the internet and modern communication technologies have emerged across the ever-more globalized world, geographic distance has been pronounced dead (Cairncross, 1997). With actors increasingly able to source knowledge globally - especially in science and technology - location is supposed to have diminished in importance. Scientists and engineers are involved in large communities that extend beyond the boundaries of firm, region and cluster, and their high geographic mobility and ability to work at distance apparently support this notion of the diminishing importance of geographic distances (Gittelman, 2008).

But at the same time, geographic concentrations seem to be increasing in scientific and technological activity. Recent university mergers (as in Manchester or Helsinki) as well as moves towards large and diversified campuses testify to the importance of large groups of scientists being co-located. Scientific clusters may be defined in the same way as industrial ones: *'geographically proximate groups in a particular field, linked by commonalities and complementarities* (Porter, 1998). They 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 the local 'milieu' has suggested that specifically local informal information spillovers are of very much more limited importance for successful innovation than has been suggested.

The aim of this paper is to understand what determines the evolution of scientific and technological clusters, an under-explored concern that is important for a variety of constituencies including regional development agencies, corporate managers, university administrators and public bodies. A.L. Saxenian (Saxenian, 1994) examines why more innovations emerged from some clusters than from others. She works from case studies to show that high quality informal exchange, interfirm mobility and networking were the key reasons why the Silicon Valley outperformed the Boston Route 128 clusters. Rothaermel and Ku (Rothaermel *et al.*, 2008) found that financial, intellectual and human capital endowments are the critical ingredients to explain inter-cluster innovation differentials, and we complement their case study-based approaches by studying the determinants of cluster growth from statistical and econometric perspectives.

Our study focuses on clusters in nanotechnologies (nanotech clusters) seeking to explain the factors that determine scientific cluster growth. Science is cumulative, and publication has long been recognized as the main indicator of scientific production. We focus on the size of the agglomeration and therefore take the growth in publication numbers associated with a cluster as indicative of cluster growth, and base our examination on the analysis of the determinants of the growth of scientific publications associated with clusters. The number of publication produced within a cluster is usually taken as a good indication of the number of scientists. Three elements have been identified as being potentially influential for growth: the variety of the knowledge base (which we approximate by the total number of scientific disciplines within the cluster); the different scientific strategies pursued by actors (measured by the diversity of institutions) and the level of collaboration (measured by the degree of openness for scientific collaboration). We divide the analysis in two parts, looking first at structural variables such as the initial size of the cluster, its geographic area, and its distribution across scientific fields. Second, we explore leverage variables, which can be influenced by actors' strategies or by policy makers. Leverage variables concern the focus on one discipline to create a specific competence or the creation of a new organization which takes care of a new scientific field or which leads to new collaborations.

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 cluster are more diversely patterned, and may be located near large firms already involved in one of nanotechnology' parent disciplines, 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 the determinants of cluster evolution.

2. CLUSTERING AND CLUSTER EVOLUTION

The paper focuses on cluster growth, and we draw from industrial cluster analysis framework to study the factors which influence the evolution of scientific clusters. It does not focus on the positive effects of geographic proximity (Feldman *et al.*, 2001; Krugman, 1991; Marshall, 1920; Pouder *et al.*, 1996), nor on the linkages between clusters and value chain integration/de-integration (Sturgeon *et al.*, 2008), nor on the positive effect of the creation and exchange of tacit knowledge (Bell *et al.*, 2007; Boschma, 2005; Pinch *et al.*, 2003). Following the tradition initiated by Pouder and St Johns (Pouder *et al.*, 1996) and Menzel and Fornahl (Menzel *et al.*, 2010), we explore scientific variety, organizational diversity and openness for collaboration as three key elements that stimulate cluster evolution.

Scientific variety

Geographic physical proximity of organizations in the same industry generates benefits for co-located actors as information and knowledge spill over to nearby actors. Knowledge flows across organization boundaries, but such streams are strengthened by spatial and cognitive proximity (Boschma, 2005; Jaffe, 1986; Nesta, 2008). Analyzing the effects of geographic agglomeration, Whittington et al. (Whittington *et al.*, 2009) emphasize four mechanisms that stimulate innovation 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; third, a concentration of scientists fosters social exchanges within ‘virtual’ colleges or communities of practices ; and finally, universities and public sector research organizations also provide the cluster with positive spillovers, as geographic proximity to the discovery process gives a unique advantage for innovation, fostering the replication of knowledge.

These four mechanisms are self-reinforcing in emphasizing cluster effects based on geographic and cognitive proximities. Scholars note that proximity with companies in the same industry is important in enhancing cluster effects, as geographic and cognitive proximities are combined (Boschma, 2005). Such 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. It thus 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. First, Nesta (Nesta, 2008) 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, highlighting the breadth of a firm's knowledge base as a determinant of its alliance dynamics. Second, when analyzing the economic dynamics of regions, Frenken *et al.* (Frenken *et al.*, 2007) argue that it is spillovers *between* sectors that stimulate employment growth in a specific region, thus emphasizing the positive role of diversity of industries and breadth of knowledge base on cluster evolution. 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. 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 help to generate continuous renewal.

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 the positive effect of diversity dominates, we formulate hypothesis H1:

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

Organizational diversity

Scientific variety is not the only source of the continuous renewal of streams of scientific and technological discoveries 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 appears 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 cluster members and their diversity (universities, small firms, large firms, etc.). As clusters are defined only by their geographic proximity, entry and exit are fluid, and diversity is (potentially) beneficial for all actors involved in the cluster, which will itself benefit from the dynamism of its actors. 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.

To enhance organizational diversity, fluid entry and exit - as well as competition amongst actors - lead to a constant renewal of actors within the cluster, reducing the risk of stagnation (Pouder and St. John, 1996; McFadyen, 2004 #8598}. Ann Markusen (Markusen, 1985) underlines how a diversity of actors brings a large range of potential partners. Clusters attract local firms to move nearby. Science parks have been created to co-locate similar actors. This diversity also leads to the implantation of subsidiaries or research division of multinational firms into the cluster, and has been identified as one of the reasons of the success of the Silicon Valley, while the (comparatively) inward looking orientation of Pittsburgh and Detroit rendered them more vulnerable. Different scientific organizations will have different goals and pursue different strategies, and so will likely define and implement different scientific policies. In particular, the 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 amongst actors. Focusing more on the specific role of firms, Audretsch and Fritsch (Audretsch *et al.*, 2002) underline the key role of start-ups in regional growth, while McEvily and Zaheer (McEvily *et al.*, 1999) show that firms that are connected with diverse actors build more competitive competencies than those with homogeneous resources.

However, cluster growth may also suffer from too much organizational diversity. Different organizations may pursue uncoordinated strategies and lead actors to compete for resources within the cluster. Thus inward orientation and within-cluster competition may lead to levels of local rivalry that are detrimental for all cluster 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. But when diversity becomes too high, competition for resources amongst local organizations is sharpened, and may lead cluster growth to slow down.

H2: The growth of the cluster follows an inverted U shape as the organizational diversity increases.

Cluster Size

Scientific variety, organizational diversity and size go hand with hand as the range of actors and the number of scientific paths within the cluster depends upon its size. Large clusters are "technically" more diverse than small ones. A higher number of different disciplines are explored, increasing scientific variety and a larger number of actors are deploying activities and strategies, increasing organizational diversity. Thus, scientific variety and organizational diversity effects must be separated from those of cluster size. Large clusters may grow quicker than smaller clusters due to increasing returns to scale and to urbanization economies, but, as travel times and costs will increase as clusters grow (especially those in cities/conurbations) there may be a limit to the growth of scientific clusters. but increasing travel times and costs as clusters grow (especially those in cities/conurbations) may then limit the growth of scientific clusters or at least the benefits to be in a cluster. Thus, the effect of scientific variety and organizational diversity must be moderated by the initial size of the cluster.

H3: Organizational diversity and scientific variety effects on the scientific cluster growth are moderated by its initial size

Scientific variety may result from internal diversity of actors or from the richness of the collaboration portfolio. Actors who collaborate beyond the cluster gain advantages from the knowledge network capabilities of other groups or clusters. Sourcing knowledge and competencies beyond the cluster, they hybridize cluster capabilities with those from outside, renewing internal competencies and opening room for new research areas. However, the level of collaboration decreases with the size of the cluster as internal actors are able to source knowledge and resources within the cluster. If variety is beneficial to cluster growth, we can hypothesize that collaboration outside the cluster will also enhance the cluster growth (Bathelt *et al.*, 2004). This growth should be moderated by cluster size as the propensity for collaboration of large clusters is lower than that of small clusters, which are more obliged to source knowledge outside given their more limited number of within-cluster scientific fields.

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. 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 research (hereafter 'nanotechnology') appear to have the potential to revolutionalize many industry sectors, in particular by fostering convergence between previously distinct technology-driven sectors. Only 20 years have elapsed since IBM invented its tunneling and atomic force microscopy instruments, so nanotechnology is still in its early stages. Scientific production in nanotechnologies has been booming as publications multiplied three-fold between 1998 and 2006. It is a fast growing area that combines knowledge from different disciplines - chemistry, physics, biotechnology and microelectronics - sourcing the creation of new knowledge in the hybridization of existing knowledge. The number of publications measures the scientific production of a specific area. The production of nanotechnology is highly concentrated, with only 200 clusters worldwide which count for more than 70% of total publication numbers. (One of the most notable features is that nanotechnology publication growth in Asia outperforms that in Europe and North America.)

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. We are using the number of publications as a proxy of the size of the cluster.

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. The collected data was 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. From a methodological standpoint, publications yield more consistent geographic information about institutions and their addresses than patent documentation does about inventors and assignees. The database includes *actors* - key 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 cluster on the basis of the institution's addresses. From an empirical standpoint, we identify the different institutions within clusters by their names and addresses – where they differ, we consider them as different institutions (firm, research laboratory or university department, etc.).

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 institution level participations (α, β, γ and δ) and 3 geographic area level participations (Europe, Asia and the US). For our purposes, the count we are interested in is that of the institution level participations (in this case, 4).

We define nanotech *clusters* as geographic agglomerations which have 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), if they are close (i.e. more than 20% of their addresses overlap) they are grouped; when the overlap is under 20%, publications are attributed to the nearest cluster.

To interpret the results and to better understand the different dynamics of the clusters in each region, we conducted ten semi-direct explorative interviews within universities in clusters in the US, Asia and Europe.

4. RESEARCH CONTEXT IN NANOTECHNOLOGIES

Nanotechnologies did not emerge from nowhere, but have grown from their parent fields of chemistry, physics, microelectronics and life sciences. Empirical evidence has shown that research in nanotechnologies has been geographically concentrated since the outset, 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 and Size	SIZE (cumulative no. of pub participations)				Out of Cluster*	Total	Average
	Large 10000 -40000	Medium 5000 -1000	Small 2000 -5000	Emergent 1000 -2000			
EU** # of clusters	1	9	40	31	***	81	
# of pub part	16,385	66,607	131,339	45,906	102,979	363,216	3,213
% of pub part	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%	

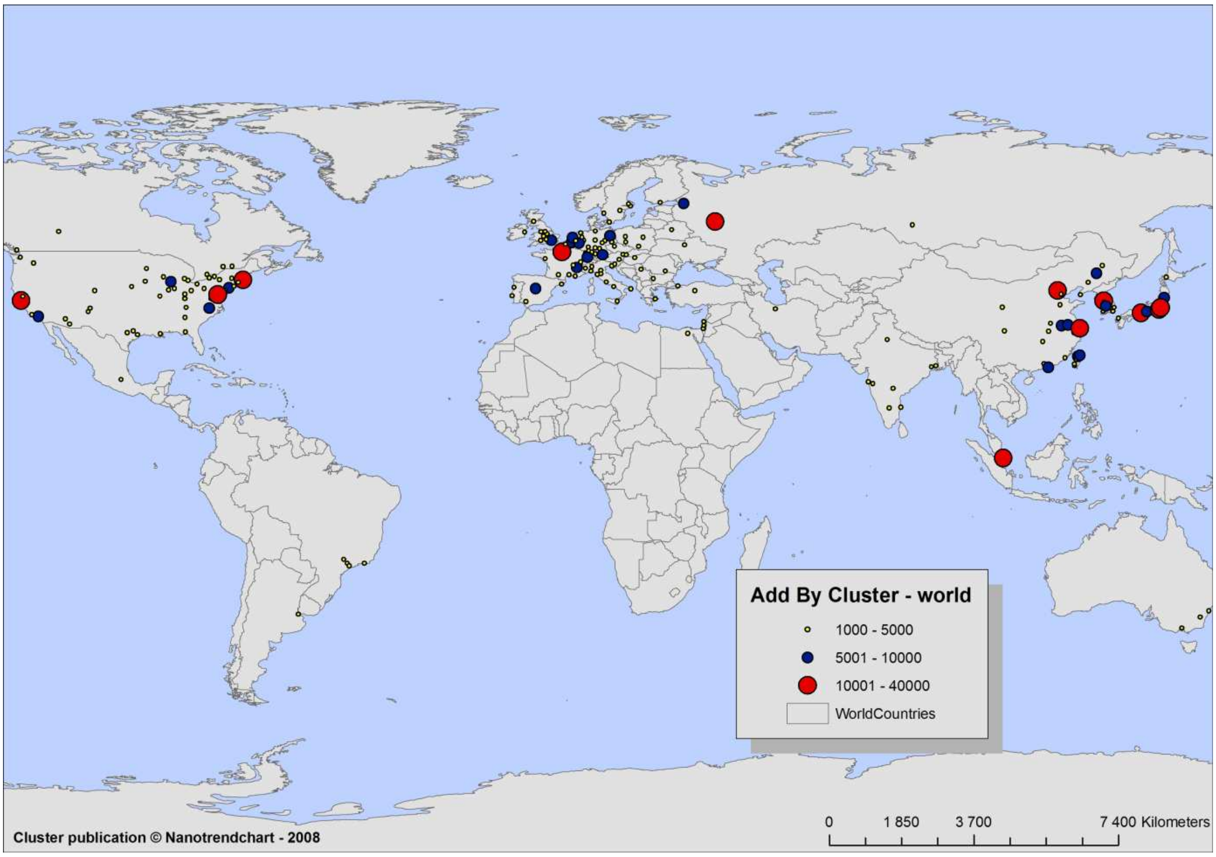
* This column represents publication participations not from cluster

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

*** 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 (the mean size of Asian clusters is larger than anywhere else) showing that scientific production is much more clustered in this region than anywhere else (and especially in South Korea and Japan).. Europe hosts more than 35% of the emergent and small clusters, and scientific production (as represented by publication) appears more distributed in Europe 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 24%.

Map 1: Publications in nanotechnologies worldwide



Map 1 reveals the geographical clustering patterns of the world’s 200 nanotechnology clusters, based on the number of publications, with red points representing the large clusters. Scientific publications remain highly concentrated in Europe, within a large number of medium and small clusters close to each other; bipolar in the US (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 are first performed worldwide and then by geographic areas. Dependent and independent variables are presented in the following sections.

Dependent variable

The notion of cluster performance is not straightforward and the concept has been operationalized in many ways. Audretsch (Audretsch, 1995) considered the number 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 a scientific cluster productivity is mirrored in its publications, which we approximate by the annual growth of the number of publication participations associated with the cluster between 1998 and 2006.

The models estimate the influence of variety of scientific field and of actors, and the effects of clusters' scientific openness on their growth. 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.

Table 2: Average cluster growth rates by area

Area	Large 10000-40000	Medium 5000-10000	Small 2000-5000	Emergent 1000-2000	out-cluster	Average
EU	7.6%	9.4%	9.6%	11.0%	11.7%	10.2%
US/Canada	10.5%	11.8%	11.2%	12.0%	11.4%	11.2%
Asia	15.6%	17.0%	24.2%	24.1%	17.4%	18.0%
Other	5.5%	5.1%	13.2%	13.5%	12.3%	11.3%
Average	13.2%	12.4%	12.9%	13.4%	12.9%	12.9%

Table 2 exhibits the average cluster growth rate by geographic zones. It reveals three main features:

The average annual growth of nanotechnology publications is very high, around 13% (as compared to the 3% annual growth of the ISI database as whole);

Numbers of publications associated with large clusters are growing quickly, but those of emergent and small clusters in the same areas are growing even more quickly;

Asian clusters are growing significantly more rapidly than those in other regions.

Structural variables

Three different groups of structural variables are defined:

- The first group contains the initial size of the cluster, measured by the logarithm of the number of publications in 1998 (*L1998)* as well as the square and cube of that size (*$L^2$1998* and *$L^3$1998) to test the linearity of the growth*;
- The second group is world geographic areas i.e. *Asia; EU* (i.e. EU25 & candidates & associated countries), *USA/Canada* and *Rest* of the world;
- The third group 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 publication categories given for each journal by JCR/ISI (223 categories). 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 published in nanotechnology 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 publications co-authored (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 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 average cluster growth rate.

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

Table 3: Description of the population

	L1998	L2006	SCVAR	ORGDIV	OUTCOLLAB	ENG	EVOL
Mean	5.17	6.19	0.07	0.39	5.23	1.04	1.01
Std	0.80	0.73	0.02	0.26	2.78	0.29	0.53
Min	3.53	4.85	0.03	0.05	1.00	0.44	0.14
P10	4.35	5.31	0.04	0.11	2.57	0.69	0.48
Q25	4.55	5.63	0.05	0.18	3.25	0.85	0.67
Med	5.12	6.07	0.06	0.31	4.52	1.01	0.85
Q75	5.71	6.57	0.08	0.56	6.64	1.20	1.25
P90	6.23	7.17	0.09	0.83	8.79	1.41	1.79
Max	7.98	8.64	0.17	0.99	19.34	2.15	2.84

Table 4: Bivariate correlations

Pearson correlation coeff, N = 200 Prob > |r| under H0: Rho=0											
	EVOL	L1998	SCVAR	ORGDIV	OUTCOLLAB	001 PHYS	002 ENG	003 ELECT	004 LIFE	005 AGRI	006 MED
EVOL	1.00000	-0.44818 <.0001	0.23587 0.0008	-0.05023 0.4800	-0.31780 <.0001	0.13394 0.0586	0.52927 <.0001	-0.31138 <.0001	-0.30160 <.0001	-0.17756 0.0119	-0.23267 0.0009
L1998	-0.44818 <.0001	1.00000	-0.12692 0.0733	-0.34567 <.0001	-0.01084 0.8790	-0.09268 0.1918	-0.33628 <.0001	0.38771 <.0001	0.12678 0.0736	-0.11947 0.0920	0.16017 0.0235
SCVAR	0.23587 0.0008	-0.12692 0.0733	1.00000	0.02534 0.7217	-0.05065 0.4763	0.52720 <.0001	0.45500 <.0001	0.29848 <.0001	-0.76688 <.0001	-0.52256 <.0001	-0.66730 <.0001
ORGDIV	-0.05023 0.4800	-0.34567 <.0001	0.02534 0.7217	1.00000	-0.05790 0.4155	-0.14374 0.0423	-0.14246 0.0442	0.06927 0.3297	0.17037 0.0159	0.21461 0.0023	-0.01769 0.8036
OUTCOLLAB	-0.31780 <.0001	-0.01084 0.8790	-0.05065 0.4763	-0.05790 0.4155	1.00000	0.04266 0.5486	-0.10053 0.1566	0.04729 0.5061	0.01705 0.8106	0.08335 0.2406	-0.02281 0.7486
001 PHYS	0.13394 0.0586	-0.09268 0.1918	0.52720 <.0001	-0.14374 0.0423	0.04266 0.5486	1.00000	0.10266 0.1480	0.05635 0.4280	-0.74068 <.0001	-0.46245 <.0001	-0.70514 <.0001
002 ENG	0.52927 <.0001	-0.33628 <.0001	0.45500 <.0001	-0.14246 0.0442	-0.10053 0.1566	0.10266 0.1480	1.00000	-0.32330 <.0001	-0.59007 <.0001	-0.32071 <.0001	-0.44499 <.0001
003 ELECT	-0.31138 <.0001	0.38771 <.0001	0.29848 <.0001	0.06927 0.3297	0.04729 0.5061	0.05635 0.4280	-0.32330 <.0001	1.00000	-0.25466 0.0003	-0.23411 0.0008	-0.23866 0.0007
004 LIFE	-0.30160 <.0001	0.12678 0.0736	-0.76688 <.0001	0.17037 0.0159	0.01705 0.8106	-0.74068 <.0001	-0.59007 <.0001	-0.25466 0.0003	1.00000	0.55288 <.0001	0.83589 <.0001
005 AGRI	-0.17756 0.0119	-0.11947 0.0920	-0.52256 <.0001	0.21461 0.0023	0.08335 0.2406	-0.46245 <.0001	-0.32071 <.0001	-0.23411 0.0008	0.55288 <.0001	1.00000	0.30901 <.0001
006 MED	-0.23267 0.0009	0.16017 0.0235	-0.66730 <.0001	-0.01769 0.8036	-0.02281 0.7486	-0.70514 <.0001	-0.44499 <.0001	-0.23866 0.0007	0.83589 <.0001	0.30901 <.0001	1.00000

Table 4 shows the relation between the different variables, and in particular the relation between the different variables and *EVOL*, the dependent variable which represents cluster growth. Cluster growth varies positively with scientific variety (*SCVAR)*, and with specialization in engineering and physics (*ENG* and *PHYS)*, but negatively with the initial cluster size and with other specializations, especially life sciences (*LIFE, AGRI* and *MED*). The organizational diversity (*ORGDIV*) is linked with the initial size of the cluster but is not directly correlated with cluster growth (*EVOL*), nor with scientific variety. The level of collaboration outside the cluster (*OUTCOLLAB*) is negatively correlated with the cluster growth, but with none of the other variables.

5. RESULTS

To test the determinants of cluster growth rate between 1998 and 2006, we perform OLS regression. Table 5 presents 10 models of cluster growth. Models 1 to 3b present the structural variables which are introduced step by step: initial size of the cluster which (taken together with its square and cube) explain about 40% of variance in cluster growth; then geographic areas, which explain about 65% of the variance; and then scientific discipline. Altogether, these structural variables explain about 68% of variance in cluster growth rates. Models 4 and 4b then introduce the leverage variables *SCVAR, ORGDIV* and *OUTCOLLAB*. Finally, models 5, 6, 7 and 8 test the moderated effect of cluster size on cluster growth.

Table 5: OLS regressions predicting the growth of the clusters

(200 observations)		Model 1		Model 2		Model 3		Model 3b		Model 4		Model 4b		Model 5		Model 6		Model 7	
	Variable		Pr >|t|				Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|		Pr >
	Intercept	26.65	<.0001	21.06	<.0001	19.56	<.0001	20.11	<.0001	20.16	<.0001	21.42	<.0001	20.26	<.0001	19.28	<.0001	20.32	<.00
SIZE	L1998	-12.79	<.0001	-9.96	<.0001	-9.36	<.0001	-8.92	<.0001	-9.34	<.0001	-9.33	<.0001	-9.48	<.0001	-8.96	<.0001	-9.39	<.00
	$L^2$1998	2.09	<.0001	1.68	<.0001	1.58	<.0001	1.51	<.0001	1.58	<.0001	1.58	<.0001	1.62	<.0001	1.53	<.0001	1.59	<.00
	$L^3$1998	-0.11	<.0001	-0.09	<.0001	-0.09	<.0001	-0.08	<.0001	-0.09	<.0001	-0.09	<.0001	-0.09	<.0001	-0.09	<.0001	-0.09	<.00
AREA	Area-Other			-0.61	<.0001	-0.58	<.0001	-0.60	<.0001	-0.61	<.0001	-0.60	<.0001	-0.60	<.0001	-0.60	<.0001	-0.61	<.00
	Area-EU25 etc			-0.69	<.0001	-0.63	<.0001	-0.68	<.0001	-0.58	<.0001	-0.59	<.0001	-0.58	<.0001	-0.59	<.0001	-0.58	<.00
	Area-US/Canada			-0.63	<.0001	-0.53	<.0001	-0.63	<.0001	-0.50	<.0001	-0.54	<.0001	-0.50	<.0001	-0.51	<.0001	-0.50	<.00
	Area –Asia			0	ref	0	Ref	0	ref	0	Ref	0	Ref	0	ref	0	ref	0	Ref
SPECIALIZATIO N	PHYS							-0.70	0.02			-0.74	0.01						
	ENG					0.24	0.01			0.25	0.01			0.25	0.01	0.25	0.01	0.25	0.0
	ELECT							-0.35	0.00			-0.20	0.05						
	LIFE							-0.07	0.47			-0.05	0.55						
	AGRI							-0.04	0.35			-0.03	0.46						
	MED							-0.01	0.83			-0.05	0.30						
Open DIV	SCVAR									-2.72	0.02	-1.70	0.30	-2.74	0.02	1.62	0.82	-2.70	0.0
	ORGDIV									-0.38	0.0002	-0.39	0.0002	-0.38	0.0002	-0.38	0.0002	-0.51	0.4
	ORGDIV2																		
	OUTCOLLAB									-0.09	0.001	-0.09	0.001	-0.05	0.50	-0.09	0.0004	-0.09	0.00
	OUTCOLLAB2									0.004	0.01	0.004	0.01	0.004	0.03	0.004	0.01	0.004	0.0
INTER	OUTCOLLAB* L1998													-0.01	0.49				
	SCVAR* L1998															-0.86	0.53		
	ORGDIV* L1998																	0.03	0.8
	Mean of response	1.01		1.01		1.01		1.01		1.01		1.01		1.01		1.01		1.01	

	Root MSE	0.41		0.32		0.31		0.31		0.28		0.28		0.28		0.28		0.28	
	R-Square	0.39		0.65		0.66		0.68		0.72		0.73		0.73		0.73		0.72	
	Adj R-Sq	0.38		0.64		0.65		0.66		0.71		0.70		0.71		0.71		0.71	

Structural effects

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

The **initial size** of the cluster is measured by the logarithm of the number of publications in the first year of our study (1998): L1998 (We also define $L^2$1998 and $L^3$1998 as the square and cube of the size.) Model 1 presents the structural variable *size*. The effect of initial size on growth is non-linear: introducing of the square and cube of size in model 1 doubles the R^2 (from 20 to 39%). At first, the initial *Size* has a negative effect on cluster growth: but amongst the small clusters, the largest grew more than the smallest ones. The only large clusters which are fast growing are the Asian ones. **Geographic areas**. Model 2 includes the geographic areas, which explains 42% of the variance in cluster growth. All together, the two structural variables (initial size and geographic areas) taken together explain about 65% of the R-square. Asian clusters grew significantly more rapidly than European and American clusters. 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. In the rest of the world, the Moscow cluster is larger than any other outside the triad. Ceteris paribus, the average growth rate of American clusters is 37% *(1 – exp(-0.45))* slower than the Asian one. Standard deviation in Asia is higher, revealing higher variations in cluster growth there than elsewhere.. Graz, Lisbon, Naples, Aveiro and Istanbul (in Europe) and also Teheran (outside the triad), have higher than mean growth rates, although not outstanding compared to Asian cluster growth.

In terms of **scientific specializations,** *ENG* is the reference category in the different models (see appendix 1 for detailed information). Model 3 shows a positive impact for this specialization, except in the US. An increase of 1 in the *ENG* specialization index is associated with a 28% increase in publication numbers *(exp(0.25) -1)* in 2006 compared to the mean. Models 3 and 4 reveal that clusters specialized in *PHYS* and *ELECT* grew significantly slower than those specialized in *ENG*, while *LIFE, AGRI* and *MED* specializations had no significant effects on growth. 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 *PHYS* (Physical, Chemical and Earth science), *ENG* (Engineering, Computing and Technology) and *ELEC* (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

Models 4 and 4b analyze the role of the diversity on cluster growth. The introduction of variety/diversity variables (the Hinferdhal indexes of organizational diversity, scientific variety and index of outside collaborations) increases the explanation power (R^2) of the different models (*i.e.* model 4 vs. 3, model 4b vs. 3b). In addition to the specific impact of the *ENG* specialization, *scientific variety* impacts positively on cluster growth rates, meaning that the empirical evidence supports hypothesis 1 (*'The broader and more varied the scientific knowledge base, the higher the growth of the cluster.')*. Decreases of 0.1 point in the Herfindhal index (*SCVAR*) (higher variety of scientific fields within the cluster) were associated with increases of around in 9.7%, the number of publications in 2006 *(1-exp(-3.36))/10.* Thus within nanotechnologies which already cover a wide range of disciplines and subfields, scientific variety plays an important role for a sustainable growth.

Organizational diversity also impacts cluster growth positively. Diversity implies that different actors promote their own strategies to develop devices and innovate in nanotechnologies, but while this fragmentation of scientific actors creates frontiers between them, it seems not to affect cluster growth: rather it seems that diversity of actors counter-balances boundary effects. Organizational diversity and scientific variety go hand with hand, suggesting that organizational frontiers within clusters do not slow down information circulation: however, organizational diversity and scientific variety are not directly correlated. Model 8 supports hypothesis 2 (The growth of the cluster follows an inverted U shape as the organizational diversity increases). Measured by the Hinferdhal index, organizational diversity first increases (negative sign of the Hinferdhal) and thus decreases (positive sign of the ORGDIV^2). Organizational diversity stimulates cluster growth until too much diversity is reached, creating organizational boundaries and limiting knowledge circulation.

Regarding hypothesis H3 (Organizational diversity and scientific variety effects on the scientific cluster growth are moderated by its initial size), the moderating effect of size on diversity is tested in models 5, 6, 7 and 8. The only significant interaction term is ORGDIV*L1998 which has a positive effect on growth, which means that the increase of organizational diversity leads influences the cluster growth until a maximum and then slows it down when we control for the cluster initial size.

Finally, the *degree of outside collaboration* has a negative impact on growth. This may be a result of geographical patterns of collaboration, as Asian clusters (which grow faster) show a lower proportion of co-authorship outside their clusters. Thus hypothesis H4 *'The higher the level of collaboration (moderated by its size) the higher the cluster growth rate'* is not supported.

6. DISCUSSION

Nanotechnology grew rapidly between 1998 and 2006, as did publication numbers, which almost trebled. Our analysis of the determinants of the cluster growth reveals that structural variables are keys to determine their evolution, underlining the role of path dependency in the cluster evolution. Different patterns, different organizations of the clusters and different scientific specialization will lead to a differential growth In our population, clusters specialized in engineering (and to a smaller extent in physics), Asian clusters and clusters that demonstrate scientific diversity have grown faster than others.. Policy makers play a critical role to influence the leverage variables i.e. scientific variety, organizational diversity and collaborations outside of the cluster. Three contributions of the paper are discussed: the very role of diversity and variety in scientific cluster growth; public policy measures to foster growth and the potential of generalization, as the determinants of the cluster growth seem to be different in Asia, Europe and in the USA.

Scientific variety and organizational diversity to foster scientific growth

The analysis of the determinants of the growth of nanotechnology clusters does not fully support existing approaches which underline organizational diversity as a key resource for cluster development. According to Frenken (Frenken *et al.*, 2007), gains from diversity at the cluster level (Jacobs externalities) provide central support for cluster growth and generate strong path dependencies in the spatial specialization of clusters. The role of organizational diversity on cluster growth follows an inverted U shape which is by the initial size of the cluster. The form of the curve explains why organizational diversity and scientific variety are not correlated. Organization diversity fosters scientific variety during the emergence phase, allowing the exploration of 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 slows down growth. Scholars working on knowledge have pointed out that organizations erect barriers to knowledge flows, so that it circulates more easily within than between organization (Bell *et al.*, 2007; Lavie *et al.*, 2008; Zeller, 2002), and it seems that proximity does not fully counter balance the negative effects of such boundaries. Organizational diversity also enhances local competition for resources amongst organizations. As a cluster is formed by local organizations in interconnected fields, its proximity enhances competition between local actors, and - as there is no ex ante mechanism to align actors' strategies - this slows down the growth of the cluster. Organizational diversity plays its major role on cluster growth during the emerging phase. Scientific diversity has a constant and positive effect on cluster growth, by enhancing the creation of scientific opportunities and thus development of the cluster.

Different patterns of growth by continent.

Cluster evolution in Asia outperforms that in America and Europe. Continent-level econometric analyses reveal specific patterns, as shown in appendix 2. Despite their difference in terms of scientific profile, Europe (which displays balanced scientific specialization - see table 6) and Asia (which is specialized in Physics and Engineering) have similar determinants of cluster growth. The negative impact of organizational diversity and the lack of significance of scientific variety reveal the fragmented landscape of institutions involved in nanotechnology research, with initial size and levels of collaboration with authors outside the cluster also having negative impacts on the evolution of scientific clusters. The picture is rather different for the US/Canada zone, where it shows a significant positive impact of scientific specialization in life sciences and a positive impact of scientific variety, but where neither institutional diversity nor collaboration play significant roles. When interviewing those in charge of strategy in different clusters worldwide, policies seem different in Europe and Asia on the one hand, and in 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 growth in numerical terms more generally. In the US/Canada, leading institutions within clusters are focusing on quality rather than on numbers. When interviewed, University vice presidents in charge of research in US clusters stated that the number of publications was not regarded as an important indicator, and that they only analyzed citation numbers, endowments and fund raising. The interviewees reported a strategy to influence the evolution of the scientific field, the formation of the research agenda and the definition of the new research questions. It seems to be an evolution of the so-called "publish or perish" to "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. It seems aligned with top university policies, based on highly selective competition to recruit students, for faculties to achieve publication in top journals and to raise funds.

Path dependency and public policies

Cluster evolution is mostly influenced by structural elements such as initial size, continental location and specialization, and this paper highlights strong path dependency effects. History plays a key role in creating patterns of specialization and of organization between actors, and also of modes of collaborations and degree of openness outside the cluster. Saxenian's story about the Silicon Valley, or stories 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.

The scope for public policy remains limited on 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" which coordinate clusters. For the first point, in Asian and European clusters, policy makers and university strategists tend to merge different universities, as in Helsinki or Manchester, but aiming to reduce organizational barriers to knowledge flows and to foster knowledge hybridization within the same large institution is a long process. The second type of cluster policy is to support the formation of specialized teams or institutes to stimulate scientific variety by increasing of organizational diversity. This counterbalances policies that focus on concentrating on a fast growing scientific field, but may have uncertain effects, as the reduction of scientific variety slows down growth in the long run. The creation or reinforcement of allied disciplines 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, so that policies aimed at regrouping different institutions and erasing boundaries may enhance cluster growth. Third, local policy makers may support the set up of "umbrella organization" which orchestrates the networking amongst organizations within the cluster and coordinate ex ante the scientific strategy of the cluster. Finally, public policies that stimulate collaboration between clusters must be conducted carefully, as they may reduce their potential for growth. Collaborations must be targeted to high growth clusters.

7. CONCLUSION

Proximity is not dead, contrary to Cairncross's (1997) pronouncement. Empirical results provide researchers, policy makers and firms with a balanced picture: the growth of scientific cluster is strongly path dependent and determined by the structural characteristics of the cluster. The initial size of the cluster, its location (continent) as well as the main scientific fields in which it specializes (life science in the US, Engineering and electronics in Asia) explain 2/3 of the variations in scientific cluster growth. Leverage variables – which explain 1/3 of the variation - constitute the main triggers of growth for policy makers. Scientific variety is a key element to influence 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[2]. Surprisingly, having fostering growth during the emerging phase, organizational diversity plays a negative thereafter, and does not appear as an engine of

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[2] The influence of policy makers or strategists who are fostering the creation of scientific teams to increase the cluster scientific variety is higher for small clusters than for large ones.

scientific variety.

The variation of the determinants scientific cluster growth between the continents is surprising, and calls for more attention from policy makers. Policy measures implemented in the one geography should not be replicated in another without careful analysis of the specific situation. Structural dimensions play a central role in creating a favorable context for scientific expansion, and public policies may change such environmental characteristics in the medium run, but are 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 the 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

Table 7: Detailed content of scientific specialization

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

APPENDIX 2: DETERMINANTS OF CLUSTER GROWTH BY AREA

Table 8: OLS regressions predicting cluster growth in EU

		Model 1		Model 3		Model 3b		Model 4		Model 4b	
	Variable		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|
	Intercept	28.55	<.0001	27.46	<.0001	26.85	0.0001	31.57	<.0001	35.58	<.0001
SIZE	l1998	-14.195	0.0001	-13.65	0.0003	-13.17	0.0008	-15.69	<.0001	-17.54	<.0001
	l21998	2.39	0.0004	2.30	0.0010	2.21	0.0020	2.70	<.0001	3.02	<.0001
	l31998	-0.13	0.0012	-0.13	0.0024	-0.12	0.0045	-0.15	<.0001	-0.17	<.0001
TECHNOL	PHYS					-0.02	0.97			-0.20	0.57
	ENG			0.24	0.5045			0.04	0.68		
	ELECT					-0.20	0.15			0.03	0.82
	LIFE					0.03	0.47			0.04	0.69
	AGRI					-0.05	0.78			-0.07	0.14
	MED					-0.01	0.36			-0.09	0.08
DIV	SCVAR							-1.05	0.53	-3.97	0.23
	ORGDIV							-0.48	<.0001	-0.51	<.0001
Open	OUTCOL LAB							-0.10	0.015	-0.10	0.02
	OUTCOL LAB2							0.005	0.05	0.005	0.06
	Mean of Response	0.79		0.79		0.79		0.79		0.79	
	Root MSE	0.23		0.23		0.24		0.20		0.20	
	R-Square	0.48		0.48		0.50		0.65		0.68	
	Adj R-Sq	0.46		0.46		0.44		0.61		0.62	

Table 9: OLS regressions predicting cluster growth in US/Canada

		Model 1		Model 3		Model 3b		Model 4		Model 4b	
	Variable		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|
	Intercept	19.36	0.09	20.24	0.08	16.5	0.14	21.42	0.09	6.46	0.58
SIZE	l1998	-9.82	0.12	-10.34	0.11	-7.99	0.18	-10.77	0.11	-2.75	0.65
	l21998	1.71	0.13	1.81	0.12	1.51	0.18	1.89	0.13	0.53	0.63
	l31998	-0.10	0.15	-0.10	0.13	-0.08	0.19	-0.11	0.14	-0.03	0.62
TECHNOL	PHYS					-0.94	0.16			-1.61	0.03
	ENG			0.09	0.64			0.07	0.74		
	ELECT					-0.25	0.11			-0.43	0.03
	LIFE					0.27	0.04			0.36	0.01
	AGRI					-0.02	0.68			-0.02	0.74
	MED					-0.17	0.002			-0.19	0.001
DIV	SCVAR							-4.52	0.03	7.65	0.025
	ORGDIV							0.23	0.22	0.05	0.77
Open	OUTCOLLAB							-0.02	0.65	0.03	0.46
	OUTCOLLAB2							0.001	0.64	-0.005	0.80
	Mean of Response	0.84		0.84		0.84		0.84		0.84	
	Root MSE	0.25		0.25		0.21		0.25		0.20	
	R-Square	0.11		0.11		0.44		0.22		0.53	
	Adj R-Sq	0.05		0.04		0.34		0.07		0.39	

Table 10: OLS regressions predicting cluster growth in Asia

		Model 1		Model 3		Model 3b		Model 4		Model 4b	
	Variable		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|		Pr >|t|
	Intercept	13.94	0.03	12.18	0.06	13.09	0.05	15.22	0.01	16.77	0.006
SIZE	l1998	-6.06	0.09	-5.44	0.13	-5.23	0.15	-6.64	0.04	-6.56	0.05
	l21998	0.99	0.13	0.89	0.17	0.87	0.19	1.12	0.05	1.10	0.07
	l31998	-0.06	0.15	-0.05	0.19	-0.05	0.21	-0.06	0.06	-0.06	0.08
TECHNOL	PHYS					-0.21	0.78			-0.57	0.50
	ENG			0.35	0.19			0.42	0.16		
	ELECT					-0.50	0.17			-0.34	0.32
	LIFE					-1.06	0.02			-0.87	0.05
	AGRI					-0.03	0.90			-0.02	0.93
	MED					0.57	0.13			0.43	0.24
DIV	SCVAR							-2.22	0.53	-2.43	0.55
	ORGDIV							-0.88	0.004	-0.88	0.005
Open	OUTCOLLAB							-0.10	0.34	-0.09	0.43
	OUTCOLLAB2							0.0003	0.97	0.0007	0.94
	Mean of Response	1.61		1.61		1.61		1.61		1.61	
	Root MSE	0.45		0.44		0.43		0.38		0.39	
	R-Square	0.44		0.46		0.53		0.63		0.66	
	Adj R-Sq	0.40		0.41		0.43		0.56		0.55	