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Agents of innovation: Clusters in Industry 4.0

Mariza Tsakalerou[a,*], Saltanat Akhmadi[a]

[a]*School of Engineering and Digital Sciences, Nazarbayev University, 53 Kabanbay ave., Nur-Sultan 010000, Kazakhstan*

* Corresponding author. *E-mail address:* mariza.tsakalerou@nu.edu.kz

Abstract

Intelligent manufacturing has spurred an unprecedented growth of inventive activity as evidenced by the exponential growth of patent applications relevant to Industry 4.0. This growth however is driven by relatively few applicants and an apparent regional concentration of inventive activity in the form of industrial clusters. The World Intellectual Property Organization (WIPO) has identified the top innovation clusters in terms of patent applications and recorded their primary characteristics. In this paper WIPO data are mined to develop new insights into industrial clusters and their impact on innovation in Industry 4.0. The major objective is to contribute towards a better understanding of industrial clusters, not just as examples of economic agglomeration but primarily as innovation agents. The findings of this paper provide valuable insights into those cluster characteristics that are conducive to world-class innovation performance and hints at the collaborative dynamics of their structure that need to change for improved efficiency.

Keywords: Digital transformation; intelligent manufacturing; industrial clusters, innovation management.

1. Introduction

The digital transformation of traditional manufacturing and the emergence of smart factories as the central point of Industry 4.0 has led to an explosion of innovation as evidenced by the unprecedented growth of technological patents.

The European Patent Office 2017 report (EPO) revealed that the number of patent applications at the EPO increased exponentially during the 25 years between 1991-2016, with Industry 4.0 patent applications rising by 54% in the last three years of the surveyed period (compared to the 8% growth of patent applications in general) [1].

The increase in patent applications in Industry 4.0 is driven by a limited number of applicants. During the 5-year period from 2011 to 2016, the top-25 applicants accounted for 48% of all applications in Industry 4.0 filed at the EPO. Furthermore, the report makes it evident that inventive activity in Industry 4.0 is regionally concentrated lending credence to the thesis that the clustering of industrial activity is an agent of innovation.

Industrial clusters are examples of economic agglomeration, the tendency that is of firms in a particular field to concentrate geographically to achieve economies of scale and scope. Key in this concept is the hypothesis that when enough resources and competences amass to reach a critical threshold in a geographical location, this confers a sustainable competitive advantage over other places in a given economic activity.

The industrial cluster concept has grasped the imagination of policymakers and proved extremely popular with governments eager to develop regional policies to promote employment and growth. Despite the fact that it has not been conclusively proven that clusters invariably boost business performance and local development [2, 3, 4], the popularity of the cluster concept amongst policymakers remains intact.

Over the years, the concept of clusters has evolved to include diverse types of agglomeration (from local productive systems, to industrial districts and business networks) yet a globally

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accepted definition of clusters remains elusive. Admittedly though, a large part of the popularity of clusters lies in the vagueness and definitional elusiveness of the concept [5]. It is precisely this ambiguity that allows both to apply the cluster concept to different realities and to prevent an accurate policy evaluation [6].

In the era of Industry 4.0, where small and medium-sized firms increasingly have to compete internationally [7], clusters can play an important role in supporting firm competitiveness by increasing productivity, innovation and firm formation and providing spillover effects to their entire geographical region. Indeed, clusters have become a worldwide fad primarily because they have been associated with innovation and the knowledge economy [8]. Most national innovation systems and policies from industrial districts to science parks and university research include clusters as an integral part of their arsenal. The evidence though of a positive association between clusters and innovation capacity is not consistent [9, 10] and questions have been raised on whether clusters help a firm's knowledge creation in Industry 4.0 [11].

The problems present in defining clusters, in assessing their performance and in developing coherent, evidence-driven policies are real. The primary challenge for cluster management is how to leverage innovation to benefit the firms in the cluster as well as the geographic region as a whole. As the clustering effect evolves from mere economic agglomeration into an innovation agent, it is important to focus on ways to leverage this potential for development. The key challenge is of course to be able to identify the themes, the sectors and the actors that will make such leveraging successful.

The observation of emerging spatial data on innovation has shown that innovative activities tend to be concentrated in clusters linked to a single city or a set of neighboring cities [12]. Adopting such a cluster view of innovation opens the door to a better understanding of the local dynamics of innovation. Innovation hubs at the city- or regional level tend to be drivers of innovation performance deserving in-depth analysis. Unfortunately, gaining empirical insight into the comparative performance of individual innovation clusters is challenging. There is neither a generally accepted definition of what constitutes an innovation cluster, nor correspondence of innovation clusters with geographical units for which statistical data is routinely collected.

Seeking to overcome these challenges, the World Intellectual Property Organization recently released a working paper identifying the world's top-100 innovation clusters based on their patent activity [13]. This is a novel attempt to identify global innovation hotspots through patent filings on a global scale and to compare cluster performance within and across countries in a systematic, data-driven way. Previously, patent data from Spain were used to provide robust evidence of the existence of innovation clustering in industrial districts [14]. The working paper was showcased as a special section in the WIPO Global Innovation Index 2017 report [15].

While patent data offer rich information on the localization of innovation [16], they provide only an incomplete and imperfect perspective as they (mostly) capture technological innovations. Such innovations are characteristic of Industry 4.0 advances but nevertheless there are swathes of the economy where patents are not necessary or useful [17]. With these caveats in mind, the empirical data presented in the WIPO 2017 report [15] are mined to develop new insights into industrial clusters and to identify key characteristics of, and their association with, the success of top manufacturing clusters internationally. The objective of this paper is to contribute towards a better understanding of manufacturing clusters, not just as examples of economic agglomeration but primarily as innovation agents in Industry 4.0, and to provide new insights into what determines the innovation performance of such clusters.

The paper is organized as follows. In Section 2, the cluster identification approach invented by Bergguist, Fink & Raffo in [13] is described and a composite of their results is presented in tabular form. In Section 3, the structural characteristics of the top innovative clusters are highlighted and discussed. Then, in Section 4, the data are mined to assess which characteristics appear to be predictors of cluster success. Finally, in Section 5, the results of the analysis are presented and, in Section 6, the conclusions and some directions for future research are discussed.

2. Cluster identification

Bergguist et. al focused their attention on the approximately 950,000 patent applications published under the Patent Cooperation Treaty (PCT) System between 2011 and 2015 [13]. The PCT system is operated by WIPO and has 142 member countries that together account for more than 98 percent of patent filings worldwide.

Their reliance on PCT filing data was motivated by two reasons. First, PCT enforces the same strict application rules around the world and collects information based on uniform filing standards. It is thus expected that the data collected will be comparable in nature and of high quality. Second, seeking an international PCT patent is a costly and lengthy process that will only be pursued by applicants with a reasonable expectation of sufficiently high return. Thus, PCT data are more likely to capture the most commercially valuable inventions. On the downside, not all international patent applications go through the PCT system, and not every PCT application will eventually result in a granted patent.

Once the PCT data were collected, the issue of how to identify the clusters emerged naturally. There are many techniques available in the field of spatial data mining for grouping similar types of objects in a group (cluster) that are broadly classified in four categories: (i) Hierarchical Methods; (ii) Partitioning Methods; (iii) Grid-Based Methods and (iv) Density-Based Methods [18]. Practice has shown that Density-Based Methods are more effective and efficient for handling raw spatial data.

The Density-Based Spatial Clustering of Application of Noise (DBSCAN) algorithm is currently the tool of choice in spatial clustering with noisy data. The algorithm groups together points with many nearby neighbors on the basis of two pre-defined density parameters: (i) the radius of the cluster-identifying circle around any given data point; and (ii) the minimum number of data points within that circle required for them to be considered a cluster. The attributes of DBSCAN that make it particularly appealing are that it can discover clusters with arbitrary shapes without the need to predict their number in advance; that it is robust to outliers and allows for merging similar clusters; and that it can be tweaked to improve its time and space complexity [18].

Bergguist et. al adopted the DBSCAN algorithm to discover innovation clusters across countries with varying economic geography on the basis of the total PCT filings during the 2011-2015 period. The authors settled on baseline density parameters of 13km (radius) and 2,000 (minimum number of data points), corresponding to a density of approximately 5 listed inventors per square kilometer, a relatively high-density threshold. With these parameter values, they identified 162 clusters in 25 countries. The top-100 international clusters, representing 23 countries and accounting for 60% of all PCT filings during the 2011-2015 period, were subsequently identified.

For each top cluster, the key technology field was noted based on the WIPO technology concordance table linking International Patent Classification (IPC) symbols with thirty-five fields of technology listed in Table 1. Overall, 18 different technology fields – out of a total of 35 – feature as the top field in at least one cluster and are indicated in bold in Table 1.

Table 2 is a composite table prepared for this paper based on data compiled from [13]. In the table, the clusters are: (i) named according to the main city or cities covered by the cluster; (ii) the countries they singularly (or mostly) belong to are represented by their 2-letter abbreviation according to the International Naming Convention (ISO3166-A2) and (iii) are ranked according to number of total filings during the 2011-2015 period.

Table 2 is augmented with four additional columns. For each ranked cluster, the total number of filings of the top patent filing entity in the cluster is recorded in order to understand better the hierarchical or heterarchical nature of the cluster. Similarly, for each ranked cluster, the total number of patent filings in the most frequently mentioned technology sector is recorded, in order to understand better the monothematic or polythematic nature of the cluster.

Finally, for each ranked cluster the total contribution of all public research organizations (PRO) to the patent filings of the cluster is clearly noted. The term PRO encompasses all universities, colleges, polytechnics, university hospitals, medical centers and all other public research entities [19].

3. Top cluster characteristics

The PCT filing data in Table 2 provide a wealth of information on the nature of and characteristics of the top-100 clusters. Tokyo–Yokohama emerges with a wide margin as the top-ranking cluster, followed by Shenzhen–Hong Kong, San Jose–San Francisco, Seoul, and Osaka–Kobe–Kyoto. These five clusters alone account for 24% of all PCT filings.

Europe (38), North America (35) and Asia (26) have the lion's share of clusters in the top-100, with the only remaining cluster in Oceania (1). The distribution of clusters across countries is highly uneven. Seven countries feature four or more clusters in the top-100: the United States (31), Germany (12), Japan (8), China (7), France (5), Canada (4), and the Republic of Korea (4). The other sixteen countries feature between one and three clusters. Among middle-income economies and other than China, India features three clusters, and Malaysia and the Russia each feature one.

Table 1. IPC concordance table of technology sectors and fields.

INDUSTRY SECTOR	TECHNOLOGY FIELD
Electrical Engineering (EE)	**Electrical machinery, apparatus, energy** Audio-visual technology Telecommunications **Digital communication** Basic communication processes **Computer technology** IT methods for management **Semiconductors**
Instruments (IN)	**Optics** Measurement Analysis of biological materials Control **Medical technology**
Chemistry (CE)	**Organic fine chemistry** **Biotechnology** **Pharmaceuticals** Macromolecular chemistry, polymers **Food chemistry** **Basic materials chemistry** Materials, metallurgy Surface technology, coating Micro-structural and nanotechnology Chemical engineering Environmental technology
Mechanical Engineering (ME)	Handling Machine tools **Engines, pumps, turbines** **Textile and paper machines** **Other special machines** Thermal processes and apparatus **Mechanical elements** **Transport**
Other Fields (OF)	**Furniture, games** Other consumer goods **Civil engineering**

Data source: WIPO The Global Innovation Index 2018 - Energizing the World with Innovation. Accessed at http://www.wipo.int/ipstats/en/.

The distribution of clusters within countries is also uneven. For instance, in the case of the United States only 21 states feature a cluster, with California (4), New York (3), Texas (3), Pennsylvania (2) and Ohio (2) in the forefront.

Naturally, counting the number of top-100 clusters for each country can be deceptive. Table 3 summarizes the total PCT filings for the years 2011-2015 for each country represented in the top-100, along with the total number of filings of its clusters.

As regards the top technology sector in terms of PCT filings for each of the top-100 clusters, the most occurrences correspond to Electrical Engineering (38), followed by Chemistry (28), Instruments (19), Mechanical Engineering (12) and Other Fields (3). In fact, the top-8 clusters feature Electrical Engineering as their prominent technology sector. A closer examination of the original data reveals that taking the top-100 clusters as a whole, the leading fields are medical technology (17), digital communications (16) and pharmaceuticals (15) followed by computer technology (11).

Table 2. Cluster ranking based on total 2011-2015 PCT filings.

#	Cluster Localization	Country	Total Filings	Top Entity Filings[a]	Top Sector[b]	Top Sector Filings[c]	Total PRO Filings[d]
1	Tokyo–Yokohama	JP	94,079	6,021	EE	5,927	2,728
2	Shenzhen–Hong Kong	CN	41,218	13,355	EE	16,982	495
3	San Jose–San Francisco, CA	US	34,324	2,231	EE	6,281	1,167
4	Seoul	KR	34,187	5,675	EE	3,555	3,692
5	Osaka–Kobe–Kyoto	JP	23,512	2,445	EE	1,951	988
6	San Diego, CA	US	16,908	9,485	EE	3,990	524
7	Beijing	CN	15,185	2,141	EE	3,432	2,885
8	Boston–Cambridge, MA	US	13,819	843	CH	1,714	2,294
9	Nagoya	JP	13,515	5,730	ME	1,757	257
10	Paris	FR	13,461	1,036	ME	1,090	1,292
11	New York, NY	US	12,215	513	CH	1,331	1,515
12	Frankfurt–Mannheim	DE	11,813	2,327	CH	851	508
13	Houston, TX	US	9,825	1,267	OF	2,466	511
14	Stuttgart	DE	9,528	4,545	ME	1,077	219
15	Seattle, WA	US	8,396	3,518	EE	2,905	353
16	Cologne–Dusseldorf	DE	7,957	613	CH	565	191
17	Chicago, IL	US	7,789	904	EE	576	428
18	Eindhoven	NL	7,222	6,131	IN	1,293	65
19	Shanghai	CN	6,639	285	EE	631	757
20	Munich	DE	6,578	770	ME	526	289
21	London	GB	6,548	399	EE	471	498
22	Tel Aviv	IL	5,659	232	EE	724	504
23	Daejeon	KR	5,507	1,090	EE	589	1,867
24	Stockholm	SE	5,211	2,298	EE	1,397	26
25	Los Angeles, CA	US	5,027	422	IN	478	1,066
26	Minneapolis, MN	US	4,422	624	IN	1,446	177
27	Portland, OR	US	4,146	2,036	EE	829	104
28	Nuremberg–Erlangen	DE	4,049	1,680	EE	466	336
29	Irvine, CA	US	3,965	317	IN	860	119
30	Berlin	DE	3,632	461	EE	309	458
31	Zurich	CH	3,615	228	IN	231	289
32	Philadelphia, PA	US	3,172	279	CH	504	606
33	Plano, TX	US	3,147	538	OF	481	145
34	Helsinki–Espoo	FI	3,045	639	EE	597	82
35	Singapore	SG	2,996	458	IN	147	1,064
36	Basel	CH	2,804	297	CH	367	84
37	Raleigh–Durham, NC	US	2,775	308	CH	258	547
38	Hitachi	JP	2,648	858	EE	527	13
39	Copenhagen	DK	2,613	272	CH	290	311
40	Hamamatsu	JP	2,496	626	ME	287	82
41	Washington, DC	US	2,491	289	CH	366	389
42	Cincinnati, OH	US	2,481	826	IN	638	102
43	Bengaluru	IN	2,479	228	EE	439	82
44	Sydney	AU	2,380	107	IN	209	257
45	Rotterdam–The Hague	NL	2,235	273	ME	125	501
46	Atlanta, GA	US	2,162	154	IN	238	203
47	Montreal, QC	CA	2,124	232	EE	253	204
48	Toronto, ON	CA	2,094	63	EE	155	209
49	Austin, TX	US	2,089	230	EE	409	263
50	Lyon	FR	2,063	196	CH	165	186

[a]**Top Entity Filings**: number of patent filings of the most innovative firm in the cluster (as measured by its patent applications)
[b]**Top Sector**: industry sector that the largest number of cluster patents filed belong to (cf. Table 1)
[c]**Top Sector Filings**: number of patent filings in the industry sector with the largest number of cluster patents filed
[d]**Total PRO Filings**: number of patent filings in the cluster contributed by public research organizations (PRO)

#	Cluster Localization	Country	Total Filings	Top Entity Filings[a]	Top Sector[b]	Top Sector Filings[c]	Total PRO Filings[d]
51	Wilmington, DL	US	2,046	964	CH	168	80
52	Barcelona	ES	2,003	174	CH	188	347
53	Regensburg	DE	2,001	734	EE	516	24
54	Brussels–Leuven	BE	1,994	94	CH	122	245
55	Cambridge	GB	1,984	133	EE	161	206
56	Grenoble	FR	1,969	872	EE	213	969
57	Moscow	RU	1,915	36	CH	117	36
58	Milan	IT	1,909	162	CH	101	82
59	Hamburg	DE	1,870	206	CH	264	58
60	Melbourne	AU	1,799	92	CH	104	293
61	Madrid	ES	1,796	239	EE	199	462
62	Malmö	SE	1,737	339	EE	219	14
63	Guangzhou	CN	1,670	114	EE	114	322
64	Indianapolis, IN	US	1,596	361	CH	137	109
65	Lausanne	CH	1,580	436	CH	119	196
66	Ottawa, ON	CA	1,560	259	EE	471	67
67	Hartford, CT	US	1,540	1012	ME	610	22
68	Busan	KR	1,470	82	IN	76	326
69	Gothenborg	SE	1,461	324	EE	137	4
70	Rochester, NY	US	1,414	540	ME	140	143
71	Vienna	AT	1,403	60	CH	109	146
72	Phoenix, AZ	US	1,378	212	EE	163	23
73	Vancouver, BC	CA	1,362	93	CH	75	159
74	Heidenheim–Aalen	DE	1,352	296	IN	215	3
75	Cleveland, OH	US	1,346	131	IN	149	268
76	Boulder, CO	US	1,319	77	IN	153	92
77	Yokkaichi	JP	1,318	515	EE	426	9
78	Haifa	IL	1,298	140	IN	241	113
79	Salt Lake City, UT	US	1,293	193	IN	250	207
80	Ann Arbor, MI	US	1,289	352	CH	92	380
81	Pittsburgh, PA	US	1,283	164	IN	115	273
82	Aachen	DE	1,279	170	EE	115	134
83	Shizuoka	JP	1,241	597	IN	139	4
84	Buhl	DE	1,223	594	ME	538	6
85	Hangzhou	CN	1,213	321	EE	205	146
86	Albany, NY	US	1,184	651	EE	117	77
87	St. Louis, MO	US	1,138	131	CH	118	155
88	Oxford	GB	1,134	313	CH	94	355
89	Baltimore, MD	US	1,089	493	CH	163	565
90	Daegu	KR	1,085	131	IN	84	283
91	Amsterdam	NL	1,063	309	CH	91	98
92	Kuala Lumpur	MY	1,049	525	EE	120	713
93	Clermont-Ferrand	FR	1,041	771	ME	274	31
94	Nanjing	CN	1,030	104	EE	90	318
95	Mumbai	IN	1,012	68	CH	156	60
96	Pune	IN	1,006	233	CH	158	246
97	Shikokuchuo	JP	995	896	IN	520	6
98	Toulouse	FR	991	100	ME	99	177
99	Hannover	DE	979	140	ME	150	70
100	Suzhou	CN	956	74	OT	76	57

[a]**Top Entity Filings**: number of patent filings of the most innovative firm in the cluster (as measured by its patent applications)
[b]**Top Sector**: industry sector to which the largest number of cluster patents filed belongs to (cf. Table 1)
[c]**Top Sector Filings**: number of patent filings in the industry sector with the largest number of cluster patents filed
[d]**Total PRO Filings**: number of patent filings in the cluster contributed by public research organizations (PRO)

4. Cluster analytics

The PCT filing data presented in the previous sections provide rich information on the nature, scope and level of inventive activity of the top clusters worldwide and are amenable to further analysis in order to identify the factors that appear to be intrinsic in their success in Industry 4.0. For the objectives of this paper three issues figure prominently.

First, whether the presence of a domineering cluster entity affects the total patent filings of the cluster. Second, whether the degree of technological diversity in a cluster has any influence on the total patent filings of the cluster. And third, whether the presence of public research organizations in a cluster is conducive to greater innovation output.

To address these issues, the data in Table 2 – along with the data in [13] - were analyzed. In order to account for the variation in the output of large and small clusters, the data were normalized over the total cluster output, and the following three metrics were defined:

- DOM = Top Entity Filings / Total Cluster Filings (%)
- SPE = Top Sector Filings / Total Cluster Filings (%)
- PRO = Total PRO Filings / Total Cluster Filings (%)

representing respectively the degree of DOMinance of the top firm in the cluster; the level of SPEcialization in the cluster; and the relative contribution of PRO in the cluster. The data were analysed with XLSTAT [20] and the following three tables detail the descriptive statistics of these three variables; the correlation matrix with the p-values (Pearson); and the multicollinearity statistics.

Table 3. Descriptive statistics of the normalized variables.

Statistics	DOM	SPE	PRO
Minimum	0.019	0.049	0.002
Maximum	0.901	0.523	0.680
Mean	0.211	0.142	0.112
Standard Deviation	0.186	0.091	0.186

Table 4. Correlation matrix of the normalized variables.

Variables	DOM	SPE	PRO
DOM	**1** [P=0.000]	0.552 [P<0.001]	-0.077 [P=0.445]
SPE	0.552 [P<0.001]	**1** [P=0.000]	-0.319 [P=0.001]
PRO	-0.077 [P=0.445]	-0.319 [P=0.001]	**1** [P=0.000]

Table 5. Multicollinearity statistics of the normalized variables.

Variables	DOM	SPE	PRO
R^2	0.316	0.382	0.116
Tolerance	0.684	0.618	0.884
VIF	**1.461**	**1.617**	**1.131**

From Table 4, it can be observed that there is some degree of positive correlation between the variables DOM and SPE and some degree of negative correlation between the variables SPE and PRO. The first observation is almost intuitive in the sense that the presence of a dominant firm in a cluster is expected to increase the specialization within the cluster. The second observation, that in a specialized cluster the contribution of public research entities is somewhat diminished, is less so.

The question whether the degree of correlation between these variables is high enough to cause problems when fitting and interpreting a regression model is addressed in Table 5. Indeed, the multicollinearity metric, known as the variance inflation factor (VIF), which measures the correlation and strength of correlation between the explanatory variables has a value close to 1 for all three variables. This implies multicollinearity is not a problem, in the sense that the moderate correlation detected between these three variables is at a level that is not high enough to warrant additional attention.

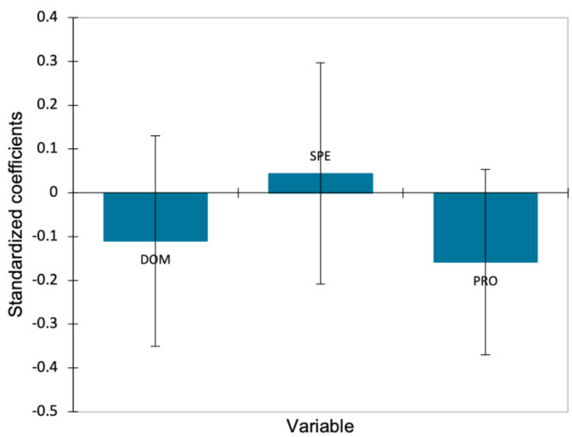
A linear regression model is then constructed to predict the total number of patent filings of a cluster with the regressor variables DOM, SPE and PRO:

$$T = \beta_0 + \beta_1 (DOM) + \beta_2 (SPE) + \beta_3 (PRO) \quad (1)$$

where the regression coefficients β_0, β_1, β_2 and β_3 are computed in Table 6.

Table 6. Model parameters (Cluster Total):

β	Value	Std. Error	t	Pr > |t|	L-bound (95%)	U-bound (95%)
β_0	7,950	2,728	2.914	**0.004**	2,535	13,365
β_1	-6,712	7,385	-0.909	0.366	-21,370	7,947
β_2	5,467	15,824	0.346	0.730	-25,943	36,878
β_3	-15,368	10,340	-1.486	0.140	-35,894	5,157



A predictive model is thus:

$$T = 7{,}950 - 6{,}712*DOM + 5{,}467*SPE - 15{,}368*PRO \quad (2)$$

with SPE having a positive effect and DOM and PRO having a negative effect on the total cluster filings.

It thus appears that the presence of a dominant firm in an industrial cluster does not help the inventive activity of the cluster as measured by the total number of patent filings. Similarly, the greater the contribution of PRO to the inventive activity of a cluster the less the total productivity of the cluster is. Finally, increased specialization in an industrial cluster has a positive influence on the total number of patent filings.

While these results reveal distinct tendencies with respect to those characteristics of industrial clusters that do matter for innovation, there is an additional question whether such tendencies are moderated by geography. To address this question, the analysis was repeated separately for the 38 clusters located in Europe; the 35 clusters located in North America; and the 22 top clusters located in Asia.

In the interest of brevity, Table 7 details only the variance inflation factors for each subset.

Table 7. VIFs of the normalized variables for each subset.

Dataset	DOM	SPE	PRO
TOTAL (N=100)	**1.461**	**1.617**	**1.131**
Europe (N=38)	1.525	1.706	1.148
N. America (N=35)	1.175	1.344	1.158
Asia (N=22)	2.170	2.487	1.236

The VIFs in Table 7 have values mostly close to 1, and definitely within the range from 1 to 5, which demonstrates that multicollinearity remains not a problem even for the geographical subsets of the clusters.

Proceeding with the regression, the resultant model parameters are summarized in Table 8 for each geographical region.

Table 8. Model parameters (Cluster Total):

β	Europe	N. America	Asia	Variable
β_0	5,780	5,326	21,000	Intercept
β_1	4,450	-6,185	-31,058	**DOM**
β_2	-18,204	12,210	17,385	**SPE**
β_3	-11,134	-11,459	-32,227	**PRO**

It is interesting that while the models for N. America and Asia follow the general trend identified for all 100 industrial clusters, the model for Europe exhibits a distinct reversal. For the 38 European clusters, the presence of a dominant firm in an industrial cluster *does* help the inventive activity of the cluster as measured by the total number of patent filings. On the other hand, increased specialization in an industrial cluster has a negative influence on the total number of patent filings.

5. Discussion

To place the results of the cluster analytics into perspective, it should be noted that member relations within a broadly defined cluster can be defined within the range of two extreme topologies: (i) hierarchical, where a major company dominates the cluster; and (ii) heterarchical, where the members are more or less equivalent [21]. Hierarchical structures are more typical of industrial clusters where one or two major companies are connected to their supply chain partners. Heterarchical structures on the other hand are more typical of service clusters where a lot of similar companies cooperate and compete with each other [22, 23]. The analysis of the top manufacturing clusters in this paper indicates that a higher degree of hierarchy appears to be a distinct advantage in terms of innovation. The presence of a dominant firm in an industrial cluster maybe a hampering factor for innovation as measured by the total number of patent filings.

The results also indicate that while this statement is true for the whole set of the industrial clusters, and for the subsets of Asia and N. America, it is patently *not* true for the European clusters. In fact, the presence of a dominant firm for these clusters appears to be a positive factor for innovation as measured by the total number of patent filings.

Clusters are assumed to confer competitive advantage due to the spatial and relational proximity of their members. It has been theorized that a distinct advantage of clusters has to do with the flow of information in business networks and the production, dissemination and absorption of knowledge [24, 25]. The analysis of the top industrial clusters in this paper indicates that cluster diversity tends to be an impediment and specialization an advantage in terms of innovation performance. Greater specialization in a technology sector is related to an increased number of patent filings for top-100 industrial clusters, as well as for the subsets of Asia and N. America. The opposite is true for the European clusters. It is apparent that these differentiations of the European clusters from the norm deserve further research.

It is difficult to explain the anomaly of the European clusters, other than by observing that 35 out of the 38 clusters in the subset Europe are in the industrial north (12 in Germany; 5 in France, 3 each in the Netherlands, Sweden, UK, and Switzerland; and 1 each in Austria, Belgium, Denmark, and Finland). Only three top clusters are in the South (2 in Spain and 1 in Italy).

The prevailing German industrial production model in Northern Europe is based upon large industrial concerns which facilitate the economic success of other firms and industries in their region, especially in manufacturing [26]. Indeed, Germany has many regional networks, each with a different focus, but all sharing a common format. In these clusters, large companies are working with SMEs, startups, and local universities and research institutes to develop innovative and globally competitive products [27]. Similar networking concepts do exist in Japan, Korea and to a lesser extent China, but they do not seem to dominate the clustering landscape [28].

Another possible explanation is the distribution of the key cluster sectors in each continent. Figure 1 depicts the prevailing sectors of the top clusters for each geographical area. (To maintain the integrity of the geographical agglomeration, Russia, Israel and Australia are omitted. The three clusters that belong to Other Fields are omitted as well for reasons of scale.) From Figure 1, it is apparent that there is a relatively balanced pre-eminence of the CH, EE and IN sectors in America with the ME sector clearly lagging. The leading sectors in Europe are CH and EE (and to a lesser extent ME). In Asia though the emphasis is almost exclusively on the EE sector.

These variations do reflect the distribution of labor in a globalized world but also provide important clues to the presence of opportunities for further development.

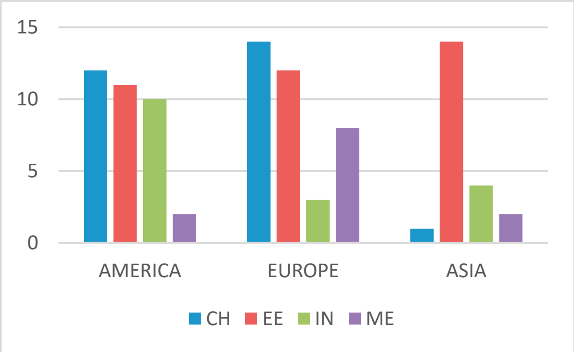


Fig. 1. Sectoral distribution of top clusters across three continents

Finally, it is consistent across the whole set of clusters, *and* of the subsets of Asia, Europe and N. America, that the greater the contribution of public research organizations to the inventive activity of a cluster the lower the total patent productivity of the cluster is. This systematic result appears to be related to the observation that public research organizations are in general more interested in open innovation and publications than in patenting inventions and protecting IP rights.

6. Conclusions

Industry 4.0 is having a profound impact on manufacturing. Digitalization, networking, and the shift towards an innovation-driven economy pose challenges which are difficult to overcome for any single enterprise [29]. In this context, Industrial clusters are evolving from their traditional role of cooperative platforms into innovation hubs for Industry 4.0 [30]. The quest for a new paradigm for the role of clusters in Industry 4.0 is an active topic of research and questions having been raised on whether the spatial proximity advantages of clusters can be imitated by remote digital technologies [11, 31].

The digital transformation of manufacturing has led to an explosion of innovation as evidenced by the unprecedented growth of technological patents. The use of patents as a metric of innovation is a coarse but generally accepted metric [32, 33]. The objective of this paper was to contribute to the development of the new paradigm of clusters by studying the characteristics of the top-100 industrial clusters in the world according to their patent filings. A limitation of this approach is of course the fact that patents do not capture the full spectrum of innovation activities and cannot account for open innovation initiatives.

It has been demonstrated that less hierarchical clusters and clusters with a high degree of specialization tend to be more innovative and that the involvement of universities and public research institutions is an impediment for patent productivity – but not necessarily for innovation. The differentiation of the characteristics of the top European clusters is of course an interesting anomaly that deserves further study.

In Industry 4.0, manufacturing companies need to integrate themselves into industrial networks, and to transform their business structures in order to expand their portfolio of competencies within global value chains. Industrial clusters appear to be still useful (if not even more so) in Industry 4.0, but the collaborative dynamics of their structures will need to adapt.

CRediT author statement

Mariza Tsakalerou: Conceptualization, Methodology, Investigation, Writing– Original Draft, Supervision. Saltanat Akhmadi: Software, Formal Analysis, Writing– Review & Editing, Visualization.

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