Special Section

Clusters

Identifying and Ranking the World's Largest Clusters of Inventive Activity

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The Global Innovation Index (GII) has traditionally focused on the innovation performance of countries. This focus is rooted in the recognition that innovation outcomes are determined by factors—such as national policies, laws and institutions, federal spending, and cultural ties—that operate at the level of countries as a whole. The country perspective will continue to be a central focus of the GII. However, this emphasis masks important differences in innovation performance within countries, because innovation activities tend to be geographically concentrated in specific clusters linked to a single city or a set of neighbouring cities.

Adopting a cluster perspective opens the door to better understanding the determinants of innovation performance that do not operate at the country level—such as physical and economic geography, sub-national policies and institutions, social networks, and local labour market linkages. The GII has long recognized that innovation hubs at the city or regional level tend to be drivers of innovation performance that deserve an in-depth analysis.[1] Unfortunately, gaining empirical insight into the comparative performance of individual innovation clusters is challenging. There is neither a generally accepted definition of what actually constitutes an innovation cluster nor an 'off-the-shelf' list of such clusters (see the section on assessing regional innovation clusters in Chapter 1). In addition, the geographical boundaries of innovation clusters typically do not correspond to the geographical units for which governments or other entities collect statistical data.

Seeking to overcome these challenges, this special section presents an empirical approach to identifying and ranking the world's largest clusters of inventive activity on the basis of patent filings. Patent data offer rich information on the location of innovative activity. Many researchers have already made use of these data to study individual clusters or selected clusters within a particular region.[2] Our approach goes beyond existing work by identifying and ranking innovation clusters on an internationally comparable basis.

We present our empirical approach in several stages. We first describe the patent data that underlie our research and explain how we geocoded these data to enable the identification of clusters in the next section. We then describe the algorithm we employed to map clusters. Once identified, we discuss how we measured the size of the clusters and explore how sensitive the resulting top 100 rankings are to the algorithm's input parameters. We finally present the key characteristics of the top 100 clusters as they emerge from patent data, and end with a few concluding remarks.

Description of patent data

Patents protect inventions that are new, involve an inventive step, and are capable of industrial application. Innovators interested in obtaining exclusive rights for their inventions have to formally apply for protection at authoritative offices. The patent records of these offices thus offer rich—and otherwise rare—information on the nature of inventive activity. Nonetheless, it is important to point out at the outset that patent data provide only an incomplete and imperfect perspective on overall innovative activity. The well-known limitations of patent data include the following:[3]

- Patents (mostly) capture technological inventions and thus miss out on non-technological innovations—such as organizational or logistical advances—that can be an important source of productivity gains in an economy.
- Patents do not capture all technological inventions because inventors can also protect their

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inventions with trade secrets—another option for protecting inventions but not a perfect substitute.

- Some industries use the patent system more intensively than others, depending on the nature of relevant technologies and prevailing business strategies.[4]
- Some patents are more valuable and technologically important than others; indeed, research has pointed to a highly skewed distribution of patent value, with relatively few patents accounting for a high share of the overall value of patents.[5]

These limitations do not mean that patent data cannot usefully inform innovation research. However, they should be kept in mind when interpreting the cluster rankings described in this section.

For our investigation, we rely on patents published between 2011 and 2015 under the Patent Cooperation Treaty (PCT) System, which is operated by the World Intellectual Property Organization (WIPO). The PCT is an international cooperation agreement that patent applicants use when they seek patent protection internationally. The System came into force in 1978; by 2010, it had 142 members that together accounted for more than 98% of national and regional patent filings worldwide.[6] In a nutshell, by filing a patent application under the PCT, applicants can delay deciding whether and in which countries they would like to pursue exclusive rights for their inventions, thereby saving in fees and legal costs. In addition, the patent receives a first evaluation, which similarly helps applicants in their subsequent patent filing decisions.[7]

Our reliance on PCT filing data has two motivations. First, the PCT System applies a single set of procedural rules to applicants from around the world and collects information based on uniform filing standards. This reduces potential biases that would arise if similar information was collected from different national sources applying different rules and standards. Second, PCT applications are likely to capture the most commercially valuable inventions. Patenting is a costly process, and the larger the number of jurisdictions in which a patent is sought, the greater the patenting cost. An applicant will seek international patent protection only if the underlying invention generates a sufficiently high return—one that is higher than for patents that are filed only domestically.[8]

On the downside, not all patent applications for which applicants pursue protection internationally go through the PCT System, and not every PCT application will eventually result in a granted patent.[9] Systemic differences in PCT use across countries, industries, and applicants may thus introduce a measurement bias, which—again—should be kept in mind when interpreting our cluster rankings.

Geocoding PCT inventor addresses

Between 2011 and 2015, approximately 950,000 applications were published under the PCT System. Each of these applications lists the names and addresses of the inventor(s) responsible for the invention described in the application. In total, these amount to 2.7 million addresses.

Previous work using patent data assigned inventors to districts, primarily on the basis of the postal codes included in their addresses.[10] However, this approach biases the identification and measurement of clusters because of the so-called modifiable areal unit problem (MAUP)—the choice of district boundaries exerting a strong influence on the shape and size of clusters.[11] The MAUP bias would be compounded in our case, because we seek to identify clusters on an internationally comparable basis and the geographical units associated with postal codes, for example, differ substantially in both characteristics and size, both within and across countries.

For this reason, we geocoded inventor addresses at a higher level of accuracy—ideally at the rooftop level—using the returns of Google Maps. Although the quality of the returns varied, we were able to obtain highly accurate geo-coordinates for most inventors.[12] Table 1 presents a summary of the geocoding results for the top PCT-filing countries. If Google Maps could not identify a specific geocode associated with an address, it typically returned an approximate area where that address is found. Extrapolating this information we were able to categorize our results into different accuracy scores. For most countries, more than two-thirds of the returned geocodes were within a 100 metre accuracy radius and more than 90% of the returns were within a 25 kilometre radius, which is the accuracy threshold we employed for geocodes to be used for identifying clusters.[13] Since patent applications can list more than one inventor, the share of PCT filings with at least one inventor meeting the accuracy threshold is even higher.

Density-based cluster identification

Researchers have used a variety of methods to identify clusters from raw spatial data, depending on the nature of the data and the hypothesized forces giving rise to clustering. These methods range from pure visual identification to different kinds of technical algorithms.

Table 1: Summary of geocoding results

Country	Addresses (%) Geocode accuracy of ≤100 m	Geocode accuracy of ≤10 km	Geocode accuracy of ≤25 km	Share of PCT filings covered by accurate geocodes (%)
Australia	84.6	96.6	97.3	97.9
Austria	92.5	97.6	98.9	99.1
Belgium	54.8	93.0	95.4	96.3
Canada	78.3	95.6	95.9	96.8
China	25.4	60.8	94.9	94.9
Denmark	92.2	94.1	94.1	95.5
Finland	85.3	92.1	93.0	95.2
France	85.2	93.3	94.2	96.8
Germany	96.8	97.9	97.9	98.7
Hungary	90.1	91.4	91.4	94.5
India	60.6	76.7	77.5	85.2
Israel	64.8	79.2	86.9	80.1
Italy	83.5	85.4	85.4	88.3
Japan	81.7	89.9	89.9	91.3
Malaysia	76.0	79.8	79.8	83.2
Netherlands	96.9	99.4	99.5	99.5
Norway	86.8	94.4	94.9	95.5
Korea, Rep.	34.7	78.6	89.4	89.3
Russian Federation	54.5	90.2	93.6	96.1
Singapore	78.1	79.0	79.0	84.5
Spain	66.1	96.0	98.8	98.8
Sweden	91.2	92.0	92.0	94.8
Switzerland	83.7	97.7	98.2	98.5
United Kingdom	70.7	97.5	97.8	98.2
United States of America	83.0	91.7	97.5	98.1

Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.

Having considered the alternative options,[14] we adopted the density-based algorithm for discovering clusters originally proposed by Ester et al. (1996), also referred to as the 'DBSCAN algorithm'. Two reasons determined this choice. First, this algorithm can account for inventor address points that do not belong to any cluster or 'noise points'. This is important for our dataset, because patenting can occur outside of any innovation cluster—by, say, single 'garage inventors'. Second, we are interested in descriptively measuring the innovation output of different localities, while initially being agnostic about what precisely drives the formation of these clusters. The DBSCAN algorithm allows us to flexibly map clusters across countries with varying physical and economic geographies on the basis of the same density criteria.

We performed the DBSCAN algorithm on the geocoded inventor locations. In doing so, we treated multiple listings of the same address—for example, a single inventor being listed in multiple patent applications—as separate data points.

The DBSCAN algorithm requires two input parameters: the radius of the cluster-identifying circle around any given data point, and the minimum number of data points within that circle required for them to be counted towards a cluster. The choice of these input parameters critically determines the shape and size of identified clusters. We tested various combinations of input parameters with three guiding criteria. First, we focused on identifying the world's largest innovation clusters, which calls for a relatively high-density threshold. Second, we visually inspected the resulting clusters to evaluate the extent to which they correspond to intuitive notions of existing clusters. Third, we made use of co-inventor relationships to evaluate the fit of the identified clusters. In particular, we gave preference to parameters that minimized the share of co-inventors outside the identified cluster but located within 160 kilometres of the cluster midpoint.

On the basis of these criteria, we settled on baseline input parameters of 13 kilometres (radius) and 2,000 (minimum number of data points), corresponding to a density of approximately five listed inventors per square kilometre.[15] With these parameter values, the DBSCAN algorithm identified 162 clusters in 25 countries.

Although most clusters were geographically separated from one another, a few were contiguous.[16] In order to decide whether to merge these contiguous clusters into one, we again made use of co-inventor relationships. In particular, we calculated the share of a cluster's co-inventors belonging to all the other clusters as well as to two noise categories—namely, co-inventors located within and beyond 80 kilometres of the cluster midpoint not belonging to any other cluster. We then merged two clusters if two conditions were met for at least one of the clusters: first, the minimum distance between any two points of the two clusters was less than 5 kilometres; and second, the neighbouring cluster accounted for the largest share of co-inventors among all clusters worldwide plus the two noise categories. This procedure led to the merging of 16 contiguous clusters into eight distinct clusters, so that we ended up with 154 clusters for our ranking.[17]

Measuring cluster size and sensitivity analysis

We measured the size of the identified clusters by the number of PCT applications associated with the data points in a given cluster. In doing so, we adopted a fractional counting approach, whereby counts reflect the share of a patent's inventors present in a particular cluster.[18] For example, a patent that lists three inventors in cluster A and one inventor in cluster B would contribute 0.75 to cluster A and 0.25 to cluster B.[19]

Table 1 in Annex 2 presents the resulting ranking of the top 100 clusters. The top 100 clusters account for 59.0% of all PCT filings in 2011–15, the period under consideration. We named clusters according to the main city or cities covered by the cluster. Tokyo–Yokohama—with a wide margin—emerges as the top-ranking cluster, followed by Shenzhen–Hong Kong (China), San Jose–San Francisco, Seoul, and Osaka–Kobe–Kyoto. These five clusters alone account for 23.9 % of all PCT filings.

Figure 1 in Annex 1 depicts the location of the top-100 clusters on a world map, also showing the 'raw' inventor address data points. Figures 2–4 offer zoomed-in regional perspectives and Figures 5–7 depict the shape of the top-3 clusters.[20]

The distribution of clusters across countries is highly uneven. Seven countries feature four or more clusters in the top 100: the United States of America (USA, has 31), Germany (12), Japan (8), China (7), France (5), Canada (4), and the Republic of Korea (4). An additional 16 countries host between one and three clusters.[21] Among middle-income economies other than China, India features three clusters and Malaysia and the Russian Federation each feature one. The top 100 do not include any cluster from Latin America and the Caribbean, Sub-Saharan Africa, or Northern Africa and Western Asia.

The distribution of clusters within countries is also uneven. Notably, in the case of the USA, fewer than half of the 50 states feature a cluster, while California (CA), New York (NY), and Texas (TX) each feature three or more. Finally, note that several clusters span more than one territory—most notable of these is the cluster located in the tri-border region around Basel.

How sensitive is the ranking presented in Table 1 in Annex 2 to different cluster-identifying input parameters? We tested different combinations of input parameters and compared the results to our baseline results. Two important insights emerged. First, although different input parameters influence the exact shape and size of the clusters, the resulting rankings were for the most part similar, with clusters moving up or down only a few ranks, especially for those in the top 30.[22] Tokyo–Yokohama consistently emerged as the top cluster. Second, two prominent (sets of) clusters were particularly sensitive to the chosen input parameters: New York and Frankfurt–Mannheim either emerged as broad clusters—as shown in Table 1 in Annex 2 —or were divided into smaller clusters associated with the main population centres within those two clusters. These included Trenton, New Jersey (NJ); Newark, NJ; and Armonk, NY, for the former, and Wiesbaden, Mannheim–Heidelberg, and Karlsruhe for the latter. Once divided, the smaller clusters had lower ranks, though Frankfurt and New York typically remained within the top 30.

Cluster characteristics

As already mentioned, patent data provide rich information on the nature of inventive activity and we can exploit these data further to characterize the top 100 clusters. Table 2 in Annex 2 presents the largest patent filing entity, the main field of technology, the share of universities and public research organizations (PROs), the largest co-inventing cluster,[23] and the share of women inventors associated with each cluster.

For most clusters, the largest patent applicant is a company, although for several of them it is a university—most notably the Massachusetts Institute of Technology for the 8th ranked Boston–Cambridge cluster. Interestingly, several companies constitute the top applicant for more than one cluster. Ericsson stands out as the largest applicant in five different clusters. Siemens and Intel each appear as the top applicant in four different clusters.

There are pronounced differences in the share of PCT filings accounted for by a cluster's top applicant. For many clusters, this share stands below 10%, suggesting a high degree of applicant diversity. For others, this share is higher, pointing to a more concentrated distribution of applicants within clusters. Most notably, Philips accounts for 85% of the 18th ranked Eindhoven cluster, suggesting a cluster largely revolving around a single company.

Cluster diversity is also reflected in the share of the main technological field associated with a cluster's patent filings. For example, the 2nd ranked Shenzhen–Hong Kong (China) cluster has a strong focus on digital communications, with around 41% of patent filings falling into this technology field. By contrast, the 1st ranked Tokyo–Yokohama cluster appears significantly more diversified, with its main technology field—electrical machinery, apparatus, and energy—accounting for only 6.3% of its PCT filings. The most prominent technology field among the top 100 clusters is medical technology—accounting for the top field in 17 clusters—followed by digital communication (16), pharmaceuticals (15), and computer technology (12). Overall, 18 different technology fields—out of a total of 35—feature as the top field in at least one cluster.

Interesting variation also exists in the prominence of universities and PROs among the top 100 clusters. For some clusters—in particular, Baltimore, Daejeon, Grenoble, Kuala Lumpur, and Singapore—universities and PROs account for more than one-third of PCT filings. In many others, inventive activity largely occurs in companies, with academic institutions accounting for negligible filing shares. Interestingly, many clusters featuring medical technology or pharmaceuticals as their top field have relatively high university and PRO shares, underlying the importance of science linkages in these two fields.

How do the top 100 clusters connect to one another? One way of answering this question is to look at co-inventors located outside a cluster's borders, specifically in the other 99 clusters. On this basis, Table 2 in Annex 2 identifies a cluster's most important partner cluster—defined as the cluster accounting for the largest share of external co-inventors. At least two interesting insights emerge. First, distance and cluster size—in line with the classic gravity model of economists—can in many cases explain the identity of the top partner cluster. For example, Tokyo–Yokohama is the top partner cluster for all other clusters in Japan and Seoul is the top partner cluster for all other clusters in the Republic of Korea. Second, the San Jose–San Francisco cluster is by far the most collaborative cluster, emerging as the top partner in 24 cases, including 6 clusters located outside of the USA.

The value of the top partner's share of external co-inventors captures the diversity of partner clusters. The low share for San Jose–San Francisco confirms the high degree of partner diversity for this cluster. Conversely, many clusters in Japan and the Republic of Korea show high shares, pointing to a more confined set of partners—possibly influenced by language barriers.

The last column in Table 2 in Annex 2 presents the share of women inventors among all inventors located in a particular cluster. As can be seen, women inventors account for fewer than one-third of all inventors across all clusters. However, there is substantial variation in the extent of women's participation; among the top 10 clusters alone the share ranges from 5.6% for Nagoya to 28.9% for Shenzhen–Hong Kong (China). Overall, the patterns shown largely reflect prior insights on the participation of women inventors: clusters in China and the Republic of Korea tend to be relatively more gender equal, as are clusters for which the main field of technology is either pharmaceuticals or biotechnology. [24]

Concluding remarks

This special section has described an empirical approach towards identifying and measuring the size of the world's largest clusters of inventive activity on the basis of international patent filings. It provides a fresh perspective on the spatial agglomeration of innovative activity, relying on a globally harmonized set of criteria.

Notwithstanding the measurement progress offered by this approach, it is important to view the analysis presented here as a first step in a longer-term effort to better capture innovative activity at the sub-national level. Our approach relies exclusively on patent data, which are an imperfect metric for inventive activity and an even less perfect metric for innovative activity more broadly. In addition, although the identification and ranking of clusters is reasonably robust to different input parameter choices, the rankings should be used with due caution. Aside from Tokyo's top rank, they are best interpreted as orders of magnitude, with clusters moving up and down a few ranks depending on meaningful parameter choices.

For the future, we aim to improve and broaden the analysis presented here in at least three ways. First, we will seek to obtain more empirical insights into the forces giving rise to clustering and use these insights to refine our cluster identification approach. Second, we will analyse clusters at the level of specific technologies and industries. Finally, we will try to include other measures of innovative activity—such as scientific publications and the performance of universities and firms—in the analysis to obtain a more complete picture of the innovation taking place across the world's largest clusters.

Notes

1 See especially the 2013 edition of the GII on the theme of 'Local Dynamics of Innovation'.

2 See, for example, Boix and Galletto, 2007.

3 See IPO (2015) for a practical guide on the value and limitations of patent information for empirical analysis and WIPO (2011) for additional background on the economics of the patent system.

4 See, for example, Hall and Ziedonis, 2001.

5 See, for example, Gambardella et al., 2008.

6 The four largest economies that were not party to the PCT System in 2010 were Saudi Arabia, Argentina, the Bolivarian Republic of Venezuela, and Pakistan. Saudi Arabia joined in 2013. An applicant from a non-member state can still file a PCT application if there is a co-applicant from a member state. However, non-membership generally has a negative effect on the participation of applicants from non-members in the System, which one should keep in mind when interpreting the rankings presented here. The 98% coverage figure is an estimate based on national patent filing statistics available in WIPO's IP Statistics Data Centre (http://ipstats.wipo.int).

7 See WIPO (2016) for a more detailed description of the PCT System.

8 For other empirical investigations relying on PCT data, see Miguelez and Fink (2013) and Lax-Martínez et al. (2016).

9 In 2015, so-called PCT national phase entries accounted for 57% of non-resident patent filings worldwide (WIPO, 2016). However, this figure understates the 'market share' of the PCT, because it does not account for PCT applications that do not see any subsequent national phase entry.

10 See, for example, Maraut et al., 2008.

11 See Oppenshaw (1983) for the seminal discussion of the MAUP.

12 For some jurisdictions, this required fine-tuning the address feeds—mainly by progressively removing information that seemingly confused the API's address matching algorithm, such as the applicant name or outdated postal codes.

13 The choice of this threshold partly reflects the reporting categories of the Google Maps API and the choice of cluster density parameters, as described in the next section.

14 For a recent review of clustering methodologies, see Sharma et al., 2016.

15 Since DBSCAN relies on latitude and longitude coordinates to calculate the distance between two points, the second (inverse) geodetic problem implies somewhat shorter distances the further away those points are from the equator.

16 The presence of contiguous clusters partly reflects the nature of the DBSCAN algorithm, because this method has difficulties accounting for obstacles—such as rivers or train tracks—that cut through a cluster. Imperfect geocodes—say, those with an accuracy radius of only 25 kilometres—may compound this problem because they often lead to the same geocode covering a large number of listed inventors. Our choice of a relatively large radius (13 kilometres) for DBSCAN minimizes but does not completely overcome these problems.

17 In particular, we merged Alzenau with Frankfurt–Mannheim, Karlsruhe with Frankfurt–Mannheim, Bonn with Cologne–Dusseldorf, two separate clusters in Houston clusters into a single entity, Södertälje with Stockholm, Takasaki with Tokyo–Yokohama, and Tsukuba with Tokyo–Yokohama. In addition, we merged Cheongju with Daejeon. Although Daejeon was only the second largest co-inventing cluster for Cheongju after Seoul, this largely reflects the strong presence of the Seoul cluster in the Republic of Korea. Indeed, all other identified clusters in the Republic of Korea feature Seoul as the largest co-inventing cluster (see Table 2 in Annex 2). It is also worth pointing out that the merging of clusters had a negligible influence on the overall ranking of clusters, because at least one of the merging entities was always small in size.

18 As alternative size measures, we also tested the simple count of listed inventors belong to a given cluster, and the (non-fractional) number of patents associated with those inventors. The resulting rankings correlated closely with the ranking relying on the fractional count for the top 35 clusters, though it led to several sizeable rank shifts for the remaining clusters that overall showed smaller differences in size scores. We report only rankings relying on fractional patent counts because this is the conceptually most appropriate size measure.

19 Our fractional counts ignore inventors for which we obtained inaccurate geocodes (> 25 kilometres). For example, if a patent has three inventors and the geocode for one inventor is inaccurate, we assigned 0.5 scores to the two inventors with accurate geocodes. However, given the small share of listed inventors and patents affected (see Table 1), the resulting measurement bias is likely to be small.

20 Note that the visualization of the Shenzhen–Hong Kong (China) cluster is somewhat misleading, as the relatively less accurate geocoding results for China (see Table 1) imply that many Chinese addresses are associated with the same geocode; in fact inventors located in Shenzhen account for a far higher share of cluster points than inventors located in Hong Kong (China).

21 This count of clusters assigns multi-territory clusters to the territory accounting for the largest share of PCT filings. Note that an additional two countries—Norway and Hungary—feature clusters that do not rank among the top 100.

22 For this sensitivity analysis, we ignored extreme parameter values that led to counter-intuitive results—such as mega-clusters spanning several hundred kilometres.

23 The 'largest co-inventing cluster' refers to the cluster that appears most often as the location of a listed co-inventor for patents associated with a primary cluster.

24 See Lax-Martínez et al., 2016.

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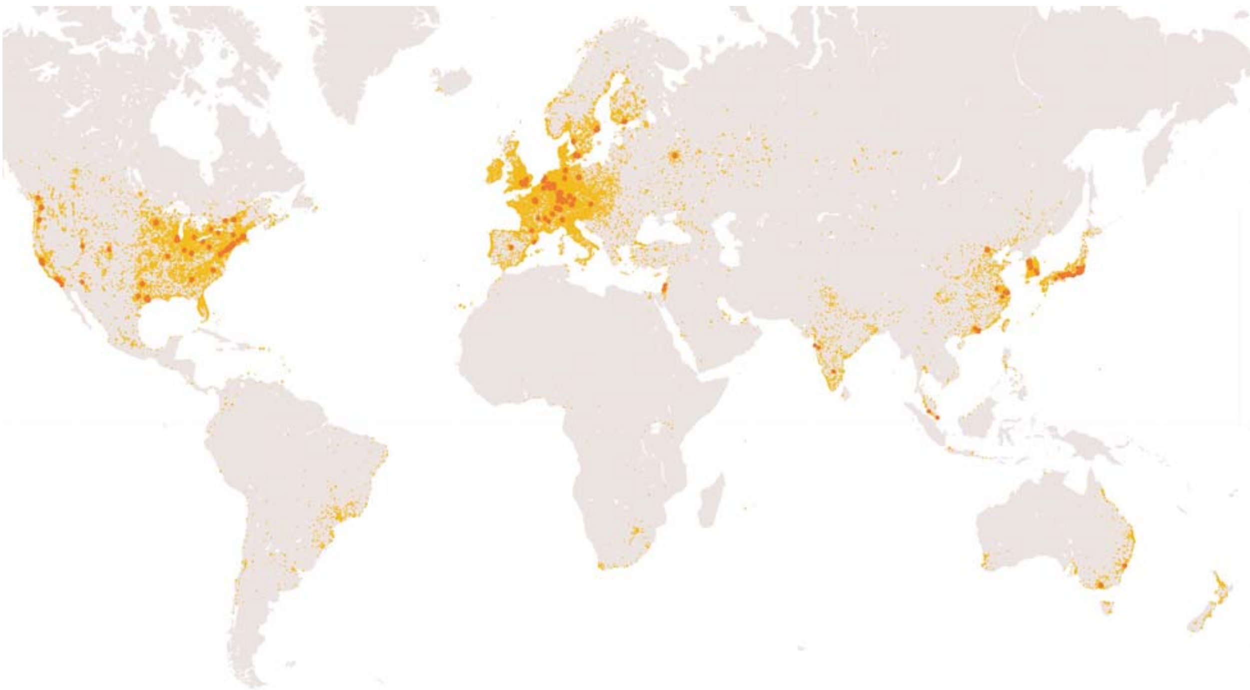
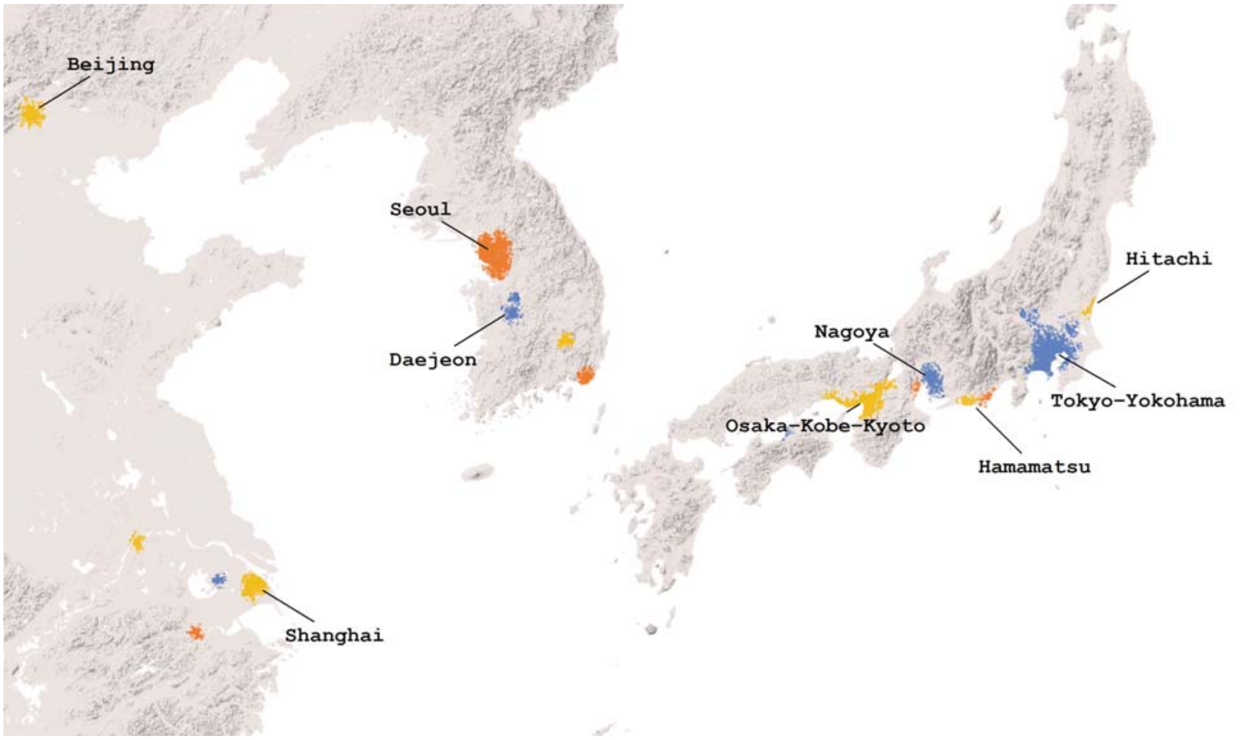
Maps of Clusters

Figure 1: Top 100 clusters worldwide



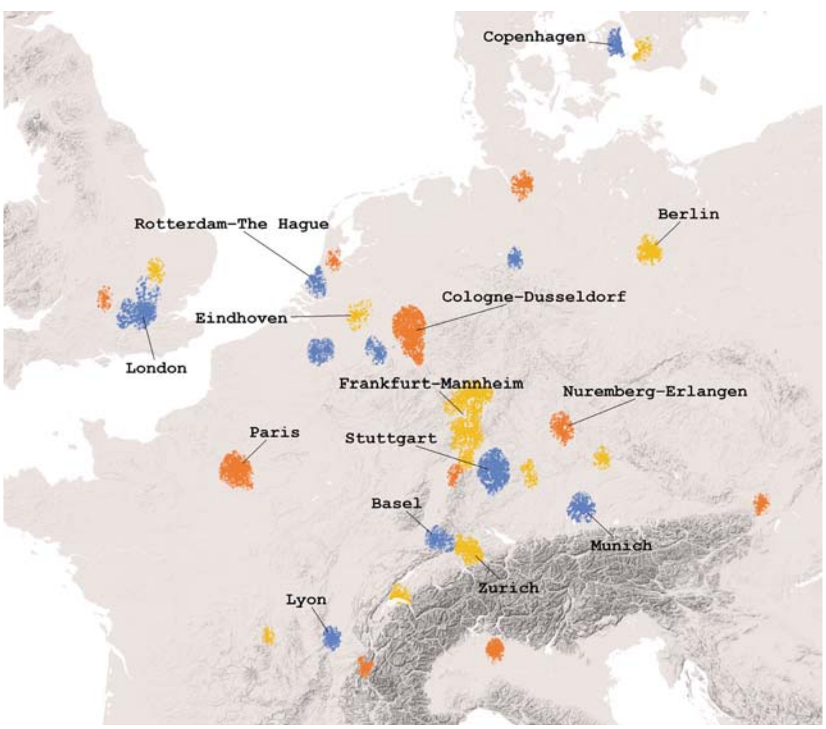
Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.
Map data: Google, INEGI 2017.
Note: Yellow colour represents noise; orange dots represent clusters.

Figure 2: Regional clusters: Asia



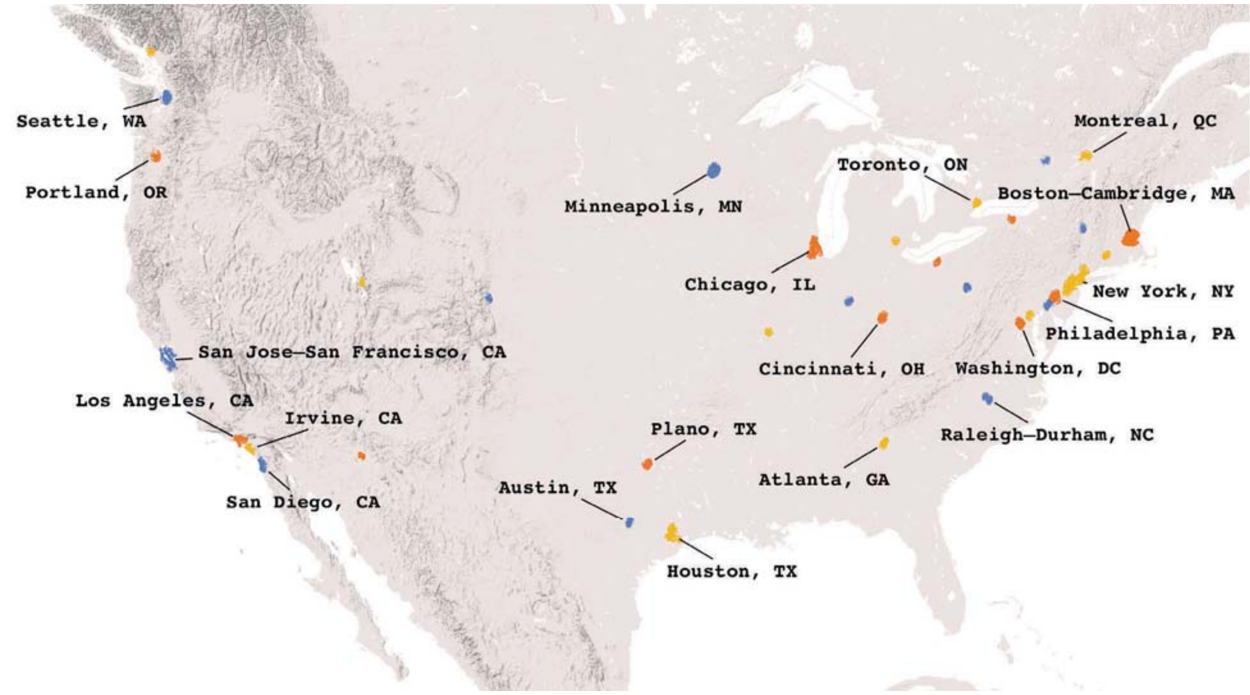
Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.
Map data: Google, SK telcom, ZENRIN 2017.
Note: Colours have been assigned based on the colour of the nearest neighbours (in order to make clear the distinction between any two clusters).

Figure 3: Regional clusters: Europe



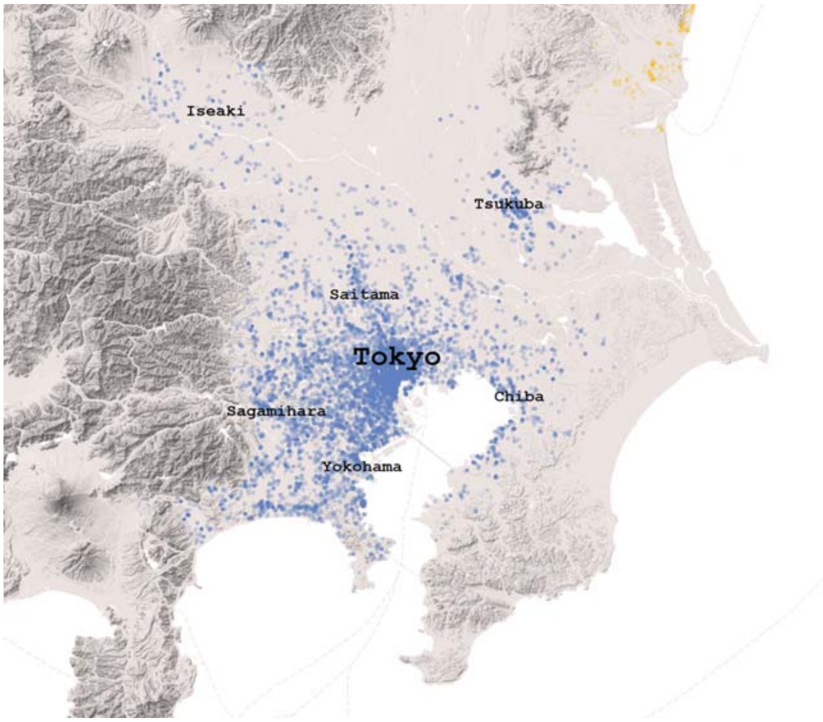
Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.
Map data: Google, Inst. Geogr. Nacional, GeoBasis-DE/BKG 2017.
Note: Colours have been assigned based on the colour of the nearest neighbours (in order to make clear the distinction between any two clusters).

Figure 4: Regional clusters: Northern America



Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.
Map data: Google, INEGI 2017.
Note: Colours have been assigned based on the colour of the nearest neighbours (in order to make clear the distinction between any two clusters).

Figure 5: Top-ranked cluster: Tokyo–Yokohama

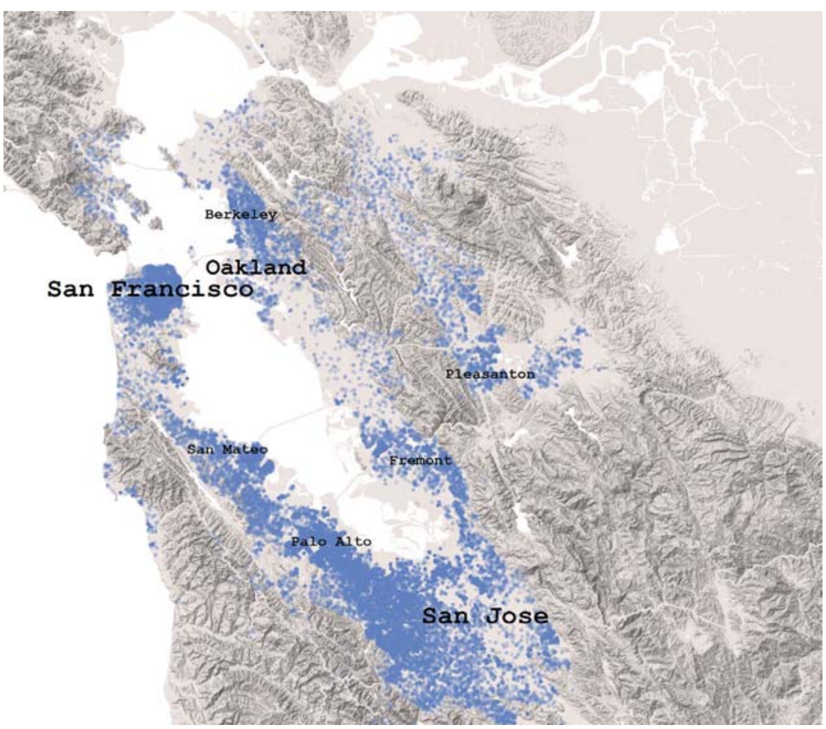


Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.
Map data: Google, ZENRIN 2017.

Figure 6: Second-ranked cluster: Shenzhen–Hong Kong (China)

Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017.
Map data: Google 2017.

Figure 7: Third-ranked cluster: San Jose–San Francisco



Source: WIPO IP Statistics Database, February 2017; Google Maps API, April 2017
Map data: Google 2017.

Table 1: Cluster ranking

Rank	Cluster name	Territory(ies)	Number of PCT filings
1	Tokyo–Yokohama	Japan	94,079
2	Shenzhen–Hong Kong (China)	China/Hong Kong (China)	41,218
3	San Jose–San Francisco, CA	United States of America	34,324
4	Seoul	Korea, Rep.	34,187
5	Osaka–Kobe–Kyoto	Japan	23,512
6	San Diego, CA	United States of America	16,908
7	Beijing	China	15,185
8	Boston–Cambridge, MA	United States of America	13,819
9	Nagoya	Japan	13,515
10	Paris	France	13,461
11	New York, NY	United States of America	12,215
12	Frankfurt–Mannheim	Germany	11,813
13	Houston, TX	United States of America	9,825
14	Stuttgart	Germany	9,528
15	Seattle, WA	United States of America	8,396
16	Cologne–Dusseldorf	Germany	7,957
17	Chicago, IL	United States of America	7,789
18	Eindhoven	Netherlands/Belgium	7,222
19	Shanghai	China	6,639
20	Munich	Germany	6,578
21	London	United Kingdom	6,548
22	Tel Aviv	Israel	5,659
23	Daejeon	Korea, Rep.	5,507
24	Stockholm	Sweden	5,211
25	Los Angeles, CA	United States of America	5,027
26	Minneapolis, MN	United States of America	4,422
27	Portland, OR	United States of America	4,146
28	Nuremberg–Erlangen	Germany	4,049
29	Irvine, CA	United States of America	3,965
30	Berlin	Germany	3,632
31	Zurich	Switzerland/Germany	3,615
32	Philadelphia, PA	United States of America	3,172
33	Plano, TX	United States of America	3,147
34	Helsinki–Espoo	Finland	3,045
35	Singapore	Singapore	2,996
36	Basel	Switzerland/France/Germany	2,804
37	Raleigh–Durham, NC	United States of America	2,775
38	Hitachi	Japan	2,648
39	Copenhagen	Denmark	2,613
40	Hamamatsu	Japan	2,496
41	Washington, DC	United States of America	2,491
42	Cincinnati, OH	United States of America	2,481
43	Bengaluru	India	2,479
44	Sydney	Australia	2,380
45	Rotterdam–The Hague	Netherlands	2,235
46	Atlanta, GA	United States of America	2,162
47	Montreal, QC	Canada	2,124
48	Toronto, ON	Canada	2,094
49	Austin, TX	United States of America	2,089
50	Lyon	France	2,063

(Continued)

Table 1: Cluster ranking *(continued)*

Rank	Cluster name	Territory(ies)	Number of PCT filings
51	Wilmington, DL	United States of America	2,046
52	Barcelona	Spain	2,003
53	Regensburg	Germany	2,001
54	Brussels–Leuven	Belgium	1,994
55	Cambridge	United Kingdom	1,984
56	Grenoble	France	1,969
57	Moscow	Russian Federation	1,915
58	Milan	Italy	1,909
59	Hamburg	Germany	1,870
60	Melbourne	Australia	1,799
61	Madrid	Spain	1,796
62	Malmö	Sweden	1,737
63	Guangzhou	China	1,670
64	Indianapolis, IN	United States of America	1,596
65	Lausanne	Switzerland/France	1,580
66	Ottawa, ON	Canada	1,560
67	Hartford, CT	United States of America	1,540
68	Busan	Korea, Rep.	1,470
69	Gothenburg	Sweden	1,461
70	Rochester, NY	United States of America	1,414
71	Vienna	Austria	1,403
72	Phoenix, AZ	United States of America	1,378
73	Vancouver, BC	Canada	1,362
74	Heidenheim–Aalen	Germany	1,352
75	Cleveland, OH	United States of America	1,346
76	Boulder, CO	United States of America	1,319
77	Yokkaichi	Japan	1,318
78	Haifa	Israel	1,298
79	Salt Lake City, UT	United States of America	1,293
80	Ann Arbor, MI	United States of America	1,289
81	Pittsburgh, PA	United States of America	1,283
82	Aachen	Germany/Netherlands/Belgium	1,279
83	Shizuoka	Japan	1,241
84	Buhl	Germany	1,223
85	Hangzhou	China	1,213
86	Albany, NY	United States of America	1,184
87	St. Louis, MO	United States of America	1,138
88	Oxford	United Kingdom	1,134
89	Baltimore, MD	United States	1,089
90	Daegu	Korea, Rep.	1,085
91	Amsterdam	Netherlands	1,063
92	Kuala Lumpur	Malaysia	1,049
93	Clermont-Ferrand	France	1,041
94	Nanjing	China	1,030
95	Mumbai	India	1,012
96	Pune	India	1,006
97	Shikokuchuo	Japan	995
98	Toulouse	France	991
99	Hannover	Germany	979
100	Suzhou	China	956

Notes: The number of PCT filings refers to the 2011–15 period. It represents the inventor fractional count of patents associated with a cluster, as explained in the text.

Table 2: Cluster characteristics

		Largest applicant		Main field of technology			Largest co-inventing top-100 cluster*		
Rank	Cluster name	Applicant name	Share of PCT filings (%)	Field name	Share of PCT filings (%)	Share of universities & PROs (%)	Partner name	Share of co-inventors (%)	Share of women inventors (%)†
1	Tokyo–Yokohama	Mitsubishi Electric	6.4	Electrical machinery, apparatus, energy	6.3	2.9	Osaka–Kobe–Kyoto	22.8	8.5
2	Shenzhen–Hong Kong (China)	ZTE Corporation	32.4	Digital communication	41.2	1.2	Beijing	11.7	28.9
3	San Jose–San Francisco, CA	Google	6.5	Computer technology	18.3	3.4	Portland, OR	5.3	15.0
4	Seoul	LG Electronics	16.6	Digital communication	10.4	10.8	Daejeon	34.6	27.5
5	Osaka–Kobe–Kyoto	Murata Manufacturing	10.4	Electrical machinery, apparatus, energy	8.3	4.2	Tokyo–Yokohama	51.3	8.6
6	San Diego, CA	Qualcomm	56.1	Digital communication	23.6	3.1	San Jose–San Francisco, CA	14.8	16.9
7	Beijing	BOE Technology Group	14.1	Digital communication	22.6	19.0	San Jose–San Francisco, CA	12.2	31.3
8	Boston–Cambridge, MA	Massachusetts Institute of Technology	6.1	Pharmaceuticals	12.4	16.6	San Jose–San Francisco, CA	6.7	17.4
9	Nagoya	Toyota	42.4	Transport	13.0	1.9	Tokyo–Yokohama	41.2	5.6
10	Paris	L'Oréal	7.7	Transport	8.1	9.6	Lyon	4.5	18.9
11	New York, NY	IBM	4.2	Pharmaceuticals	10.9	12.4	San Jose–San Francisco, CA	5.8	20.0
12	Frankfurt–Mannheim	BASF	19.7	Organic fine chemistry	7.2	4.3	Stuttgart	7.8	13.4
13	Houston, TX	Halliburton	12.9	Civil engineering	25.1	5.2	New York, NY	4.0	11.6
14	Stuttgart	Robert Bosch	47.7	Engines, pumps, turbines	11.3	2.3	Frankfurt–Mannheim	12.6	4.8
15	Seattle, WA	Microsoft	41.9	Computer technology	34.6	4.2	San Jose–San Francisco, CA	16.8	13.2
16	Cologne–Dusseldorf	Henkel	7.7	Basic materials chemistry	7.1	2.4	Frankfurt–Mannheim	10.5	13.7
17	Chicago, IL	Illinois Tool Works	11.6	Digital communication	7.4	5.5	San Jose–San Francisco, CA	4.8	13.1
18	Eindhoven	Philips	84.9	Medical technology	17.9	0.9	Rotterdam–The Hague	7.2	12.0
19	Shanghai	Alcatel Lucent	4.3	Digital communication	9.5	11.4	New York, NY	6.3	30.2
20	Munich	Siemens	11.7	Transport	8.0	4.4	Nuremberg–Erlangen	4.4	9.3
21	London	Unilever	6.1	Digital communication	7.2	7.6	Cambridge	7.9	14.7
22	Tel Aviv	Intel	4.1	Computer technology	12.8	8.9	Haifa	22.3	13.5
23	Daejeon	LG Chem	19.8	Electrical machinery, apparatus, energy	10.7	33.9	Seoul	68.6	27.3
24	Stockholm	Ericsson	44.1	Digital communication	26.8	0.5	San Jose–San Francisco, CA	6.2	10.3
25	Los Angeles, CA	University of California	8.4	Medical technology	9.5	21.2	San Jose–San Francisco, CA	12.1	15.0

Continued)

Table 2: Cluster characteristics *(continued)*

		Largest applicant		Main field of technology			Largest co-inventing top-100 cluster*		
Rank	Cluster name	Applicant name	Share of PCT filings (%)	Field name	Share of PCT filings (%)	Share of universities & PROs (%)	Partner name	Share of co-inventors (%)	Share of women inventors (%)†
26	Minneapolis, MN	Medtronic	14.1	Medical technology	32.7	4.0	San Jose–San Francisco, CA	4.4	12.1
27	Portland, OR	Intel	49.1	Computer technology	20.0	2.5	San Jose–San Francisco, CA	24.8	14.0
28	Nuremberg–Erlangen	Siemens	41.5	Electrical machinery, apparatus, energy	11.5	8.3	Munich	8.1	4.7
29	Irvine, CA	Allergan	8.0	Medical technology	21.7	3.0	Los Angeles, CA	13.9	12.7
30	Berlin	Siemens	12.7	Electrical machinery, apparatus, energy	8.5	12.6	Cologne–Dusseldorf	11.8	11.6
31	Zurich	ABB Technology	6.3	Medical technology	6.4	8.0	Basel	10.2	10.4
32	Philadelphia, PA	University of Pennsylvania	8.8	Pharmaceuticals	15.9	19.1	New York, NY	16.5	19.6
33	Plano, TX	Halliburton	17.1	Civil engineering	15.3	4.6	San Jose–San Francisco, CA	8.3	11.9
34	Helsinki–Espoo	Nokia	21.0	Digital communication	19.6	2.7	Beijing	6.4	14.0
35	Singapore	A*STAR	15.3	Medical technology	4.9	35.5	San Jose–San Francisco, CA	6.8	23.0
36	Basel	Hoffman-La Roche	10.6	Organic fine chemistry	13.1	3.0	Zurich	16.2	16.0
37	Raleigh–Durham, NC	Cree	11.1	Pharmaceuticals	9.3	19.7	Frankfurt–Mannheim	6.9	15.7
38	Hitachi	Hitachi	32.4	Electrical machinery, apparatus, energy	19.9	0.5	Tokyo–Yokohama	86.3	7.1
39	Copenhagen	Novozymes	10.4	Biotechnology	11.1	11.9	Malmö	7.2	17.2
40	Hamamatsu	NTN Corporation	25.1	Transport	11.5	3.3	Tokyo–Yokohama	43.1	6.6
41	Washington, DC	US Department of HHS	11.6	Pharmaceuticals	14.7	15.6	San Jose–San Francisco, CA	7.5	19.4
42	Cincinnati, OH	Procter & Gamble	33.3	Medical technology	25.7	4.1	Frankfurt–Mannheim	4.7	14.6
43	Bengaluru	Hewlett-Packard	9.2	Computer technology	17.7	3.3	San Jose–San Francisco, CA	11.6	14.8
44	Sydney	University of Sydney	4.5	Medical technology	8.8	10.8	Melbourne	10.0	12.5
45	Rotterdam–The Hague	TNO	12.2	Other special machines	5.6	22.4	Amsterdam	8.4	11.2
46	Atlanta, GA	Georgia Tech Research	7.1	Medical technology	11.0	9.4	San Jose–San Francisco, CA	4.6	19.0
47	Montreal, QC	Ericsson	10.9	Digital communication	11.9	9.6	New York, NY	6.9	15.4
48	Toronto, ON	University Health Network	3.0	Computer technology	7.4	10.0	San Jose–San Francisco, CA	4.5	12.6
49	Austin, TX	University of Texas System	11.0	Computer technology	19.6	12.6	San Jose–San Francisco, CA	15.3	9.2
50	Lyon	IFP Energies Nouvelles	9.5	Organic fine chemistry	8.0	9.0	Paris	13.8	21.1
51	Wilmington, DL	Du Pont	47.1	Basic materials chemistry	8.2	3.9	Philadelphia, PA	21.1	15.5
52	Barcelona	Hewlett-Packard	8.7	Pharmaceuticals	9.4	17.3	Madrid	7.6	24.0

Continued)

Table 2: Cluster characteristics *(continued)*

		Largest applicant		Main field of technology			Largest co-inventing top-100 cluster*		
Rank	Cluster name	Applicant name	Share of PCT filings (%)	Field name	Share of PCT filings (%)	Share of universities & PROs (%)	Partner name	Share of co-inventors (%)	Share of women inventors (%)†
53	Regensburg	Osram Opto Semiconductors	36.7	Semiconductors	25.8	1.2	Munich	9.8	6.7
54	Brussels–Leuven	Solvay	4.7	Pharmaceuticals	6.1	12.3	Frankfurt–Mannheim	3.8	17.6
55	Cambridge	Cambridge University	6.7	Computer technology	8.1	10.4	London	17.6	14.9
56	Grenoble	CEA	44.3	Semiconductors	10.8	49.2	Paris	11.6	16.0
57	Moscow	Siemens	1.9	Pharmaceuticals	6.1	1.9	San Jose–San Francisco, CA	1.8	13.8
58	Milan	Pirelli	8.5	Pharmaceuticals	5.3	4.3	London	1.5	15.6
59	Hamburg	Henkel	11.0	Organic fine chemistry	14.1	3.1	Cologne–Dusseldorf	5.8	20.1
60	Melbourne	Monash University	5.1	Pharmaceuticals	5.8	16.3	Sydney	9.0	15.2
61	Madrid	Telefonica	13.3	Digital communication	11.1	25.7	Barcelona	9.0	26.9
62	Malmö	Ericsson	19.5	Digital communication	12.6	0.8	Stockholm	18.1	9.5
63	Guangzhou	South China Univ. of Technology	6.8	Computer technology	6.8	19.3	Shenzhen–Hong Kong (China)	10.4	29.2
64	Indianapolis, IN	Dow Agrosciences	22.6	Basic materials chemistry	8.6	6.8	New York, NY	3.4	16.0
65	Lausanne	Nestec	27.6	Food chemistry	7.5	12.4	Zurich	2.9	17.4
66	Ottawa, ON	Huawei Technologies	16.6	Digital communication	30.2	4.3	Plano, TX	13.6	17.4
67	Hartford, CT	United Technologies	65.7	Engines, pumps, turbines	39.6	1.4	Boston–Cambridge, MA	4.9	9.7
68	Busan	Pusan National University	5.6	Medical technology	5.2	22.2	Seoul	48.6	24.7
69	Gothenburg	Ericsson	22.2	Digital communication	9.4	0.3	Stockholm	12.8	11.4
70	Rochester, NY	Eastman Kodak	38.2	Textile and paper machines	9.9	10.1	San Jose–San Francisco, CA	3.9	15.4
71	Vienna	Technische Universität Wien	4.3	Pharmaceuticals	7.8	10.4	Munich	2.9	12.7
72	Phoenix, AZ	Intel	15.4	Semiconductors	11.8	1.7	Portland, OR	9.0	13.0
73	Vancouver, BC	University of British Columbia	6.8	Pharmaceuticals	5.5	11.7	San Jose–San Francisco, CA	8.9	12.9
74	Heidenheim–Aalen	Carl Zeiss	21.9	Optics	15.9	0.2	Stuttgart	9.9	5.7
75	Cleveland, OH	Cleveland Clinic Foundation	9.7	Medical technology	11.1	19.9	New York, NY	2.5	11.2
76	Boulder, CO	University of Colorado	5.8	Medical technology	11.6	7.0	San Jose–San Francisco, CA	8.6	14.4
77	Yokkaichi	Autonetworks Technologies	39.1	Electrical machinery, apparatus, energy	32.3	0.7	Tokyo–Yokohama	33.8	2.9
78	Haifa	Intel	10.8	Medical technology	18.6	8.7	Tel Aviv	46.9	12.9
79	Salt Lake City, UT	University of Utah	14.9	Medical technology	19.3	16.0	San Jose–San Francisco, CA	7.3	10.8
80	Ann Arbor, MI	University of Michigan	27.3	Pharmaceuticals	7.1	29.5	San Jose–San Francisco, CA	4.2	14.1
81	Pittsburgh, PA	University of Pittsburgh	12.8	Medical technology	9.0	21.3	Boston–Cambridge	4.0	14.0

Continued)

Table 2: Cluster characteristics *(continued)*

		Largest applicant		Main field of technology			Largest co-inventing top-100 cluster*		
Rank	Cluster name	Applicant name	Share of PCT filings (%)	Field name	Share of PCT filings (%)	Share of universities & PROs (%)	Partner name	Share of co-inventors (%)	Share of women inventors (%)†
82	Aachen	Ericsson	13.3	Digital communication	9.0	10.5	Cologne–Dusseldorf	16.7	8.9
83	Shizuoka	Fujifilm	48.1	Optics	11.2	0.3	Tokyo–Yokohama	41.2	8.5
84	Buhl	Schaeffler Technologies	48.6	Mechanical elements	44.0	0.5	Frankfurt–Mannheim	28.0	3.6
85	Hangzhou	Alibaba Group	26.5	Computer technology	16.9	12.0	Shanghai	12.2	27.1
86	Albany, NY	General Electric	55.0	Semiconductors	9.9	6.5	New York, NY	9.6	13.0
87	St. Louis, MO	Monsanto Technologies	11.5	Biotechnology	10.4	13.6	Seattle, WA	6.6	17.4
88	Oxford	Oxford University Limited	27.6	Pharmaceuticals	8.3	31.3	London	15.8	18.1
99	Baltimore, MD	Johns Hopkins University	45.3	Pharmaceuticals	15.0	51.9	Washington, DC	13.0	20.7
90	Daegu	Kyungpook National University	12.1	Medical technology	7.7	26.1	Seoul	51.1	26.3
91	Amsterdam	Shell	29.1	Basic materials chemistry	8.6	9.2	Rotterdam–The Hauge	13.6	13.8
92	Kuala Lumpur	Mimos Berhad	50.0	Computer technology	11.4	68.0	Houston, TX	8.0	25.5
93	Clermont-Ferrand	Michelin	74.1	Transport	26.3	3.0	Paris	13.0	17.0
94	Nanjing	Southeast University	10.1	Digital communication	8.7	30.9	Beijing	10.1	31.5
95	Mumbai	Piramal Enterprises	6.7	Organic fine chemistry	15.4	5.9	Bengaluru	11.1	16.8
96	Pune	CSIR	23.2	Organic fine chemistry	15.7	24.5	San Jose–San Francisco, CA	9.8	12.4
97	Shikokuchuo	Unicharm Corporation	90.0	Medical technology	52.3	0.6	Tokyo–Yokohama	34.5	15.5
98	Toulouse	Continental	10.1	Transport	10.0	17.9	Paris	13.8	19.2
99	Hannover	Continental	14.3	Transport	15.3	7.1	Cologne–Dusseldorf	4.1	8.1
100	Suzhou	Ecovacs Robotics	7.7	Furniture, games	7.9	6.0	Shanghai	9.5	25.4

Notes: PCT filing shares refer to the 2011–15 period and are based on fractional counts, as explained in the text. The identification of technology fields relies on the WIPO technology concordance table linking International Patent Classification (IPC) symbols with 35 fields of technology (available at http://www.wipo.int/ipstats/en/). The identification of universities and public research organizations (PROs) relies on keyword-based searches of PCT applicant names, which encompasses all types of educational and public research entities, including universities, colleges, polytechnics, and university hospitals; it also takes account of the different languages used by PCT applicant names. Patent records may show different names for the same applicant. WIPO carries out a name cleaning and harmonization process based on keyword searching and manual verification. This process takes historical changes into account, but not company structure; in other words, subsidiaries or applicants sharing a common parent company are not consolidated. In the table presented here, the colloquial name of the applicant is used where appropriate and may differ from the actual name listed in the application, or from WIPO's cleaned and harmonized name.

*The largest co-inventing top-100 cluster refers to the cluster hosting the highest share of co-inventors. The share of co-inventors is relative to the total number of co-inventors located outside the cluster in question.

†The identification of women inventors relies on the name dictionary described in Lax-Martínez et al. (2016). With this dictionary, we can attribute gender for more than 90% of listed inventors for each cluster except for Beijing, Bengaluru, Guangzhou, Hangzhou, Kuala Lumpur, Seoul, Shanghai, and Suzhou, for which we attribute gender for 84–90% of listed inventors. The share of women inventors is calculated on the basis of listed inventors, so inventors listed in multiple applications are counted multiple times. The calculation ignores inventors whose gender could not be attributed.