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ON THE CONCENTRATION OF INNOVATION IN TOP CITIES IN THE DIGITAL AGE

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Abstract

This paper investigates how digital technologies have shaped the concentration of inventive activity in cities across 30 OECD countries. It finds that patenting is highly concentrated: from 2010 to 2014, 10% of cities accounted for 64% of patent applications to the European Patent Office, with the top five (Tokyo, Seoul, San Francisco, Higashiosaka and Paris) representing 21.8% of applications. The share of the top cities in total patenting increased modestly from 1995 to 2014. Digital technology patent applications are more concentrated in top cities than applications in other technology fields. In the United States, which has led digital technology deployment, the concentration of patent applications in top cities increased more than in Japan and Europe over the two decades. Econometric results confirm that digital technology relates positively to patenting activities in cities and that it benefits top cities, in particular, thereby strengthening the concentration of innovation in these cities.

Keywords: regional concentration of innovation, geography of innovation, cities, digital technologies, patenting, innovation, local knowledge spillovers, OECD countries

JEL codes: R12, O31, O34

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1. Introduction

Digital technologies are transforming all economies, affecting and shaping territorial, industrial and social inclusiveness. The reduction in cost and improvement in quality of digital technologies have made knowledge more footloose, as it can be easily transferred to all “connected” regions. These technical opportunities for cross-geographic collaboration could boost innovation activities as they benefit from the combination of diverse sources of knowledge. Yet, distance has not become irrelevant contrary to the statements in Cairncross’s “The death of distance” (2001) and Friedman’s “The World is Flat” (2005). A few cities are home to a large number of top global inventors and top innovations. The difficulty of sharing complex tacit knowledge and the advantages of co-location that innovators critically need (finance, qualified human capital, etc.) may explain why innovation is so concentrated in top cities. Those new and old dynamics, however, change cities’ role in digital innovation as digital technologies continue to improve and result in more or less geographic inclusiveness. Yet to date there has been little empirical work investigating the impacts of digital technology on the concentration of inventive activities at global and cross-country level.

The paper investigates empirically the concentration of inventive activity in cities across 30 OECD countries and the role digital technologies have played in affecting the geography of innovation over the two decades from 1995 to 2014. The study investigates how functional urban areas (FUAs) – referred to as cities in this paper – dominate in national and global patent applications at the European Patent Office (EPO). The paper also investigates econometrically what role digital technologies have played for cities’ patenting activities and for the top cities’ patenting in particular. In our database, cities account for all patent applications for which we could geolocate their inventors, except for 1% that were invented outside of cities. The sample includes 1.8 million patent applications at the EPO that were filed by 1.6 million inventors located in 1 022 cities across the 30 OECD countries. The advantage of using FUAs rather than administrative boundaries of cities is that not only cities themselves but also neighbouring areas that are home to commuters working in urban areas are included.

We find that patenting remain highly concentrated in a few leading cities at the global and national levels: 10% of cities globally accounted for 64% of patent applications in 2010-14, and the leading 5 (Tokyo, Seoul, San Francisco, Higashiosaka and Paris) accounted for more than 1 in every 5 (22%) patent applications. At the global and national levels, the share of the top cities in total patenting increased moderately from 1995 to 2014.

As regards the impacts of digital technology on the concentration of inventive activities in cities, digital technology has become cheaper and more effective for the exchange of data and knowledge and for collaboration across geographic distances. Collaboration across geographic distance has increased, as visible in intensified cross-border relations in scientific production. Yet, digital technology patent applications are more concentrated in top cities than patent applications in any other technology. The United States, which has led digital technology development, has experienced a more important increase in the concentration of patenting activities in top cities (an increase of 10.5 percentage points in the top 10% of cities between 1995 and 2014) compared to Japan (with an increase of 5.4 percentage points, although starting from higher levels of concentration) and Europe (where concentration remained stable). Econometric results confirm digital technology relates positively to cities’ patenting activities. Top cities benefit even more from digital technology than cities that rank further behind in terms of patent applications. Thus, our evidence suggests digital technologies strengthen the concentration of innovation in top cities.

The findings are relevant for policy in a number of ways. The way research and innovation work in the digital age affects not only aggregate economic performance but also how inclusive participation in and benefits from the digital economy are. This includes in particular how different geographic areas within countries participate in digital innovation. Until recently, the attention of analysts focused on aggregate economic performance, i.e. average income, productivity, etc. However, divergence in innovation and economic performance across geographic areas within countries has remained at high levels over the past decades, to the extent of becoming a focal point in discussions on economic and social sustainability. Innovation, due to its important role for wealth creation, is an important part of this discussion. Consequently, the other objective for innovation policy is distributional: ensuring that no cities and regions are left out of the innovation ecosystem, as they critically shape engagement and consequently the benefits different members of society receive from digital innovation, notably by participating as workers, entrepreneurs and investors (OECD, 2017). The extent to which these two objectives are coincident or contradictory depends on the relative strength of geographical concentration and dispersion forces.

Our empirical results support the hypothesis that agglomeration forces outweigh dispersion forces, pointing to a trade-off between efficiency and equality in the geography of innovation across cities. Policies to help boost aggregate efficiency of public spending in innovation while reducing concentration include “smart specialisation” policies. These can support regions that are lagging behind, and such efforts can help generate jobs and income by enabling regions and cities to catch up without requiring important innovation-related resources that may benefit cities that are more dynamic. Another important condition for regional participation in the digital age consists in providing for digital connectivity, access to data and linkages with top innovating cities.

The project benefited from work conducted by the OECD Working Party on Innovation and Technology Policy (TIP) on “digital and open innovation” (OECD, 2019a), and in particular the characterisation of innovation dynamics in the digital age (Guellec and Paunov, 2019; Paunov and Planes-Satorra, 2019). The work also builds on the OECD’s Going Digital work as well as the work conducted on innovation and its policies as well as work on regional innovation dynamics. It also benefited from valuable insights from the Bertelsmann Foundation’s “Inclusive Productivity” project and the activities it is engaged in.

The remainder of the paper is structured as follows. Section 2 discusses the conceptual framework and literature review while section 3 presents the data used in this analysis and discusses the role of top cities in patenting. Section 4 discusses the evidence on digital technology and the concentration of patenting in cities. Section 5 discusses dynamics of innovation and digital technology in cities in Germany. Section 6 presents results from an econometric analysis. Section 7 discusses the policy implications.

2. Framework and literature review

The advantages of geographic concentration for innovation

"Clusters" or "ecosystems" – sets of companies and research laboratories close to each other – are a core feature of the geography of innovation. These clusters have different compositions and structures, related to their area of specialty and their history (e.g. aeronautics in Toulouse, finance in London and Frankfurt, automotive in Stuttgart). Many of them have an "anchor" company, public laboratory or large university that drove the creation of the cluster, such as Stanford University for Silicon Valley or CEA for Grenoble (where large companies such as STMicroelectronics also have a driving role). Some clusters are much more innovative than others (e.g. Silicon Valley, Cambridge region). The role of large cities is also particularly noteworthy, with the largest cities accounting for the majority of patenting (OECD, 2015a). These examples represent a phenomenon that is well established in the literature on the geography of innovation, namely, that innovation activities are concentrated geographically (OECD, 2015b) and more so than is the case of production activities (see Carlino and Kerr, 2015, for an overview of this literature). Strong geographic concentration holds for both industry and research innovation activities (see Audretsch and Feldman (1996) on business innovation, Buzard et al. (2017) on R&D laboratories, Chen et al. (2010) on venture capital), and has given rise to debates regarding territorial (and subsequently social) inequalities and the raising gap between global cities and the rest (e.g. Odendahl et al., 2019).

Empirical studies have documented the advantages of concentration for innovation. There is a "premium for qualification" (the level of wages, all other things being equal, and especially the skill level, is higher in larger cities and, as shown in Autor, 2019, much larger for skilled workers) and higher research productivity (measured by the number of patents or highly cited articles per researcher) in areas in which much research is conducted. Innovation activities are also more efficient when they are conducted in greater spatial proximity with each other, so-called "agglomeration benefits". A recent study finds that inventors' patent filings and their quality as measured by citations rises significantly when inventors move to larger technology clusters (Moretti, 2019). The benefits of agglomeration are even stronger when the proximity is very high, and decrease very sharply with distance. A study for the United States estimates that, depending on the industry, the benefits are high in a circle of a mile (1 mile), 10 times weaker at 5 miles, and zero at more than 10 miles (Rosenthal and Strange, 2003).

Why this concentration of innovation activities? What factors explain the specialisation of cities or regions? There are two main explanations for the benefits of agglomeration. A first explanation refers to common infrastructures used by innovators, for example large scientific equipment (e.g. particle accelerators) and hospitals (for clinical research), but also "soft" infrastructures such as venture capitalist firms, financial, legal and business advice, etc. (e.g. Ellison et al, 2010; Porter, 1990; Feldman, 1994; Helsley and Strange, 2002). An essential "soft" infrastructure provided in agglomerations for innovators is the dense pool of skilled labour. Thick labour markets improve the quality of matching: large labour pools make it easier for specialised workers and firms to be selective and engage in productive matches (Berliant, Reed and Wang, 2006; Strange, Hejazi and Tang, 2006;

Hunt, 2007; Krugman, 1991; Moretti, 2004; Florida, 2003). These infrastructures are necessary for innovation, they are costly to set up and hard to divide. They will therefore attract innovators to the places where they are and reinforce the position of leading places.

Related to this is the proximity of research institutions, as these provide knowledge and skilled labour, notably researchers (e.g. Furman and MacGarvie, 2007; Saxenian, 1994, Feldman and Florida, 1994). Large universities tend to nurture innovation ecosystems. The availability of a large pool of skilled workers they supply gives depth to the corresponding labour market, which might attract further businesses.

A second explanation for the concentration of innovation activities refers to the geographic confines of knowledge externalities (Marshall, 1890; Jaffe, Trajtenberg and Henderson, 1993; Audretsch and Feldman, 2004; Thompson, 2006; Murata et al., 2014). Innovators are generally more effective when they can interact with other innovators. Interactions are of many different types, formal (conferences, institutionalised collaborations) or informal (socialization, random encounters). While geographic proximity is not necessary for those interactions, it facilitates interactions at massive scale (as a large number of innovators are co-located in agglomerations), high frequency of exchange (as no specific travels are needed to exchange) and the possibility of random encounters of relevance to innovators (as at-distance encounters often require planning). Geographic proximity also facilitates social proximity by nurturing trust, notably as the same social networks are shared and members are eager to maintain their reputation. Higher social proximity in turn increases the density of interactions and jointly with trust facilitates collaboration in innovation (Pittaway et al., 2004; Storper and Venables, 2004; Agrawal, Kapur and McHale, 2008).

Importantly, those advantages of geographic proximity facilitate the transfer of tacit knowledge, i.e. the aspects of an invention that are difficult to write down and require (face-to-face) explanations, limiting the seamless diffusion of knowledge. Competing firms also have incentives to avoid seamless diffusion of knowledge, as holding knowledge secret allows them to charge a price for it. This explains why knowledge used for new inventions also displays a strong “home bias” in that new inventions are applied much more intensively where they were invented than in geographically more distant locations that could benefit similarly (e.g. Jaffe et al. 1993; Jaffe and Trajtenberg, 1996, 1999; Sonn and Storper, 2008; Arzaghi and Henderson, 2008; Rosenthal and Strange, 2008; Drivas and Economidou, 2015; Kerr and Kominers, 2015; Buzard et al., 2017). It also explains why much collaboration is local: the propensity to co-patent with co-inventors from the same region (average 50%) is much higher than with co-inventors from other regions in the same country (average 29%) and from foreign regions (average 21%) (data for 2010-12 for TL3 regions) (OECD, 2016a).

The benefits of agglomeration are however not without limits, in particular because it generates specific costs. There are generic costs related to congestion (access to transport, housing, etc.). Common research infrastructures cannot all be located in one place. The externalities of knowledge are also dependent on networks of people and are therefore not infinitely extensible. Moreover, innovation benefits from collaborations across geographic distances and actors, as sourcing inputs from diverse actors and across different geographic locations can lead to more and higher-impact innovations, the more so as innovation can be conceptualised as recombination of existing knowledge (see e.g. Arthur, 2007).

What impact could digital technologies have on the geography of innovation?

The defining characteristic of digital innovation is the central role played by digital data in innovation processes. Data have a specific property called "non-rivalry", which means that the same data can be used at the same time by any number of users, and that they circulate at very low marginal cost. Hence, digital data are potentially a universally available input, possibly accessible to any number of users wherever they are located. In a world of pure data, location does not matter anymore. Innovators could locate anywhere and have access to the same pool of data. This differs from the past manufacturing era where R&D labs would co-locate with factories because much of the knowledge and know-how in particular was located in the factories. When knowledge is digital such a constraint does not apply anymore. In other words, in particular the knowledge spillover benefits to agglomeration may change with advances in digital technology.

However, data is not the only input to innovation: skills is the second important input for digital innovation as they are complementary to data in the innovation process. A drop in the price of either input triggers an increase in the demand for the other one. Hence the increase in demand for skills (and their market price) following the progress of digitalisation. As described above, skilled labour is subject to locational forces and externalities. Then, contrary to data, skills tend to favour concentration. Digitalisation could even further strengthen the trend towards geographical concentration as physical barriers to the concentration of knowledge activities (e.g. a strong connection with manufacturing facilities) disappear. Hence, easier access to knowledge for all, while the ability to using it is still unequal, could mean higher inequalities in performance.

A wider set of inputs benefiting agglomeration in cities in the digital age relates to the advantage of "smart cities". These follow an urban development model based on the utilisation of skilled individuals, technology adoption and diffusion for the creation of new products and services often enabled by digital technologies (Angelidou, 2014, 2015). Benefiting from the traditional advantages of agglomerations, these cities are emerging as living laboratories and large-scale experimental test beds for many digital service innovations, such as new transportation models among other services (OECD, 2015a; OECD, 2015c). Data-driven mobile applications made possible by instantaneous large-scale data availability, known under the label of "sharing economy", have benefited from dynamic urban environments. Cities have been at the heart of innovative start-up accelerator programmes that exploit data-driven innovations for health, e-commerce and communication as well as improved public service delivery (such as garbage treatment or city lighting). Such dynamics may strengthen a positive relation between growth of regions with urban agglomerations compared to those without (Ahrend and Schumann, 2014).

Two other developments may enhance the impacts of digital technologies on reducing the geographic concentration of innovation as they facilitate collaborations. First, the increase in the international mobility of highly skilled individuals establishes new connections that can then be exploited at a distance by digital collaboration. With globalisation, international knowledge circulation has increased over the past decade, specifically among students and researchers. Since the mid-1970s, there has been more than a fivefold increase in foreign students (from around 0.8 million in 1975 to more than 4 million in 2010) (OECD, 2016b). Second, global trade integration has led to wider fragmentation of production, facilitating cross-border specialisations and opportunities to collaborate across geographic distances beyond production. The foreign value added content of gross exports of the USA increased significantly between 2005 and 2012 (from USD 128 billion to USD 247 billion, with a decline in 2008-09 in the context of the economic crisis). A similar upward trend is observed in many OECD countries (WTO/OECD, 2019).

Evidence on digital technologies and the geographic concentration of innovation

The little empirical evidence reported in the literature on the impact of digital technology on the geographic concentration of innovation does not bring clear-cut conclusions regarding the impact of digital technology. First, one set of studies focus on the most well-known hub associated with the digital economy: Silicon Valley and the San Francisco Bay Area more generally. To the extent that this region and sector is a frontrunner regarding the adoption of leading-edge digital technology, some indirect lessons on how digitalisation affects the geography of innovation may be learned from those studies. Overall, studies on the Silicon Valley area paint a picture of a cluster that relies on geographic proximity to exploit joint infrastructures, including skills and access to venture capital, as well as knowledge spillovers, notably from Stanford University (Saxenian, 1994; Chen et al., 2010; Kerr and Kominers, 2015; Guzman, 2018). With the progressive application of digital technologies to different industries, concentration increased further as industries previously innovating elsewhere (incl. automotive) started locating R&D laboratories and engaged patenting activities in the Silicon Valley area (Paunov and Planes-Satorra, 2019; Forman, Goldfarb and Greenstein, 2016). This trend is the more so notable in view of rising costs of agglomeration, including real estate.

As regards start-ups in the digital sector, Florida and King (2018) show that venture-capital-backed start-up activity has moved over the past years from suburbs to denser urban centres. Start-ups in fields such as media, entertainment and information technology were more clustered in urban city centres, while biotech and medical start-ups cluster near universities and laboratories with related scientific and technological capabilities. We are not aware of other studies that compare the geographic concentration of the digital sector to other economic sectors.

Second, a few studies investigated how digital technologies affected the geographic concentration of innovation. This limited evidence is largely inconclusive also in view of differences in core studies' dimensions (the technology measure, the sample characteristics, country and time period analysed). The following studies found digital technologies reduced concentration: Analysing US counties' patenting from 1990-2005, Forman, Goldfarb and Greenstein (2015) find evidence to suggest that the adoption of the Internet mitigated the widened concentration of patenting across US counties. They show that among the group of counties that were early adopters of the Internet, there was little change in the concentration of patenting contrary to the overall trend. Forman and Zeebroeck (2012, 2019) find that the adoption of early-generation Internet technology increased the collaboration of research teams located in distant geographic units of multi-national firms in the 1992-98 period. However, only collaborations of research teams sharing the same technology base increased rather than collaborations across specialisations. Differently from these findings, Gray et al. (2015), using data from pharmaceutical plants in the USA over a 13-year period (1994-2007), show that Internet adoption did not reduce the benefits from co-location between manufacturing facilities and R&D activities.

Studies that explore the early effects of digital technologies on research collaborations also had mixed results. Some find that the introduction of early network technologies (such as BITNET) increased scientific collaboration, especially across universities (Agrawal and Goldfarb, 2008; Ding et al., 2009). In contrast, Jones, Wuchty and Uzzi (2008) find, based on information of 662 US universities and 4.2 million research papers from 1975 and 2005, that there has been a constant rise in the frequency of collaboration among researchers of different universities over time, but do not find the increase to relate systematically to the introduction of the Internet.

Finally, relevant indirect evidence also comes from research on the evolution of the effect of distance on knowledge spillovers and the benefits from digital platforms for innovation. First, a number of studies have found a diminishing effect of distance for knowledge spillovers (e.g. Aldieri, 2013; Thompson, 2006). A study by Crescenzi et al. (2016) shows that while in the 1990s, a 1 kilometre increase in distance between potential collaborators resulted in 5% less collaborations, in the 2000s the same distance reduced collaboration by 2%. While this trend may be attributed to the greater ease of exchanging knowledge across distances, whether digital technologies were drivers of those dynamics is not established in this work. Second, Jeppesen and Lakhani (2010) document how greater diversity of solvers of innovation challenges – which may include solvers from different geographic locations – improves the quality of solutions submitted to the online platform InnoCentive. The crowdsourcing platform posts innovation challenges and invites anyone to submit their solutions. This points to a strong rationale for taking up platforms, while wider implications on the geography of innovation are difficult to draw from this assessment. Theoretical work by Afuah and Tucci (2012) on the advantages of crowdsourcing for problem sourcing corroborates this hypothesis, particularly as the costs associated with digital technologies are low and the quality high. Van Alstyne and Brynjolfsson (1996, 2005) provide a related framework that points to the advantages of better digital connectivity for collaborations, but also point out that collaborations may be less diverse than those undertaken in geographic clusters.

Implications for the empirical analysis

In conclusion, the following implication arises for the empirical analysis of the impacts of digital technologies on the concentration of innovation activities in cities: There are two opposite forces at work. On the one hand, knowledge spreads more freely irrespective of geographic distance. On the other hand, the "skills" factor enhanced by advantages from cities' infrastructures favours further concentration in cities. The impact on the geography of innovation will depend on how important knowledge diffusion and skills/infrastructure dynamics required in the digital age are relative to each other.

3. Data

Description of the database

Our analysis is based on a database that covers 1 820 622 patent applications, drawn from 2 225 220 patent applications to the European Patent Office (EPO) that were deposited by 1 567 592 inventors located in 1 022 cities across the 30 OECD countries included in our study over the period 1995-2014 (Table 1). We draw these data from the PATSTAT database (2018, autumn version). In our analysis, we also use data on countries' uptake of digital infrastructure from International Telecommunication Union (ITU, 2019) and general country information from the World Bank's World Development Indicators.

We conduct our study at the level of cities by using the functional urban area (FUA) definition developed by the OECD and the European Commission. The definition allows capturing 1 088 urban areas – of which 1 022 had patent applications – in a comparable way across the 30 countries that are part of our analysis (Table 1). The advantage of this definition is that it avoids using administrative boundaries that often do not capture the "actual" size of cities in a coherent way. Administrative boundaries do not delineate cities well where neighbouring regions are integrated parts of cities' ecosystems, including labour markets and industry agglomerations: business parks and housing for cities' employees may locate outside of cities' administrative boundaries yet be part of the same urban area.

A FUA is defined as a densely inhabited city and its surrounding area (commuting zone) whose labour market is highly integrated with the city. In all countries except for Israel, FUA are identified in four steps: first, using gridded population data, an *urban centre* is delineated, defined as a set of contiguous, high-density grid cells of 1 square kilometre (with at least 1 500 residents per square kilometre) with a population of more than 50 000 people[1]; second, a *city* is defined, which includes one or more local units that have at least 50% of their residents inside a urban centre; third, the *commuting zone* is identified, defined as a set of contiguous local units that have at least 15% of their employed residents working in the city; finally, a *functional urban area* is defined as the combination of the city with its commuting zone. Four types of cities are identified on this basis: small urban areas (50 000 – 100 000 people), medium-sized urban areas (100 000 – 250 000 people), metropolitan areas (250 000 - 1.5 million) and large metropolitan areas (more than 1.5 million) (OECD, 2019b). The same definitions are applied across countries, using population density and travel-to-work flow information, and consequently they are appropriate for our cross-country analysis. Dijkstra, Poelman and Veneri (2019) and Moreno Monroy, Schiavina and Veneri (forthcoming) provide more information respectively on the EU-OECD FUA definition used for all countries in our sample except Israel and the global FUA definition used for Israel. To avoid any bias introduced by the different methodology, we exclude Israel from the econometric analysis.

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[1] A lower threshold of 1 000 people for km2 is applied to Canada and the United States, where several metropolitan areas develop in a less compact manner.

Table 1. Sample description

Country Name	Number of geolocated patent applications, 1995-2014	Number of cities (FUA) with patent applications (FUA)	Share of inventor patent observations in the sample in total inventor patent applications	Share of patent application observations in the sample in total patent applications	Share of inventor patent applications in cities (FUA) in total country patent applications	Share of city (FUA) population in total national population
Australia	14 834	18	84%	83%	100%	76%
Austria	19 965	6	73%	71%	80%	54%
Chile	446	20	95%	95%	100%	53%
Denmark	15 094	4	74%	69%	93%	56%
Estonia	341	3	93%	93%	99%	53%
Finland	18 174	7	70%	69%	100%	53%
France	118 526	84	76%	74%	98%	62%
Germany	308 006	96	73%	71%	100%	74%
Greece	1 504	14	98%	97%	89%	46%
Hungary	2 123	19	78%	74%	100%	51%
Iceland	542	1	100%	100%	98%	75%
Ireland	4 221	5	80%	79%	100%	29%
Israel	8 187	6	100%	100%	100%	n.a.
Italy	61 715	82	76%	74%	100%	51%
Japan	380 698	61	95%	96%	100%	75%
South Korea	63 993	21	90%	90%	100%	80%
Latvia	240	2	100%	100%	100%	46%
Lithuania	230	6	100%	100%	90%	36%
Luxembourg	1 405	1	86%	85%	100%	100%
Mexico	1 052	57	90%	89%	100%	37%
Netherlands	51 968	35	83%	80%	100%	73%
Norway	7 034	6	84%	82%	78%	47%
Poland	2 596	54	69%	67%	100%	36%
Portugal	1 070	11	71%	68%	100%	50%
Slovak Republic	645	8	99%	99%	63%	28%
Spain	18 503	74	84%	82%	100%	60%
Sweden	34 627	12	72%	71%	83%	54%
Switzerland	38 174	10	70%	67%	80%	48%
United Kingdom	82 924	91	77%	76%	100%	77%
United States	561 784	208	88%	87%	100%	73%
Sample average	**60 687**	**34**	**84%**	**82%**	**95%**	**57%***
Total	**1 820 622**	**1 022**				

Notes: The share of FUA population is calculated as the total population living in FUAs (based on the average population over 2000-2014 as population data prior to 2000 is not available) over the total country population. The number of geolocated patent applications reported in the first column is a fractional count of patent applications with each patent application counting as 1/number of inventors per patent. The difference between the third and fourth column is that the former counts what patent-inventor application observations where geolocated while the second gives the share of patent applications that were geolocated (using the fractional count of patent applications as reported in the first column). *The sample average in the final column excludes Israel due to missing FUA population data.

Source: Authors' calculations on PATSTAT database (2018, autumn version)

We rely for our analysis on the information on the geolocation of inventors –i.e. street, postcode, city and country– recorded by EPO patent applications. We use the address of patent inventors on patent documents to capture where knowledge production took place. Information on patent owners, by contrast, may indicate the location of headquarters, which may not relate to where the invention described in a patent application was made. Using the address information of patent owners may consequently bias results, suggesting more patenting takes place in capital cities that are often home to headquarters. In order to identify the city where the inventor is located (if any), a combination of postcode matching, word matching and geolocation matching is used. We match inventors to their corresponding city using postcode information for countries where postcode information is consistently reported. Where postcode information is weak, a word-search algorithm is used to match municipalities to their corresponding city. We generate and use the geolocation information to locate inventors for the remaining observations.[2] This methodology allowed allocating 84% of the total number of patent-inventor pairs, with at a minimum of 70% matched observations by country. At patent application level, the geolocation matching corresponds to 82% of total patent applications (Table 1).[3]

Interestingly, we find that inventors located in large metropolitan cities with more than 1.5 million inhabitants accounted for more than 62% of patent applications. Metropolitan cities of more than 250 000 inhabitants but fewer than 1.5 million accounted for another 31%. Only 1% of patent applications were located outside of cities. Inventor concentration is much higher than the share of the population in cities. While cities are home to more than 50% of the population in 20 of the 30 countries analysed, only in 8 of these countries population living in cities is higher than 75%.[4]

The data allows identifying technology classes for patent applications – including digital technologies – at the most disaggregated level. We use two classifications. First, we classify patents into 5 broad technology domains by means of the Schmoch (2008) correspondence: communication & tech, consumer goods, biotechnology, medical technology and machine tools. Second, we also use the technology classes to identify Information and Communication Technology (ICT) patents at a more disaggregated level following the J-Tag taxonomy proposed by Inaba and Squicciarini (2017). In the context of our analysis, we do not find substantial differences in results whether we use the former or latter approach to identify digital technologies. We use the more disaggregated J-Tag definition of ICT for the empirical analysis and we aggregate technology classes at 4-digits, 3-digits and 2-digits, which yields respectively 638, 124 and 28 technology classes. At the most disaggregated level the sample includes 68 528 technology classes at 9-digits.

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[2] The exact approach applied differs by country as the quality of inventor address information varies. While use postcode and/or geolocation information for inventors from the France, Iceland, Norway, Sweden and Slovak Republic and United States, we apply mainly a word algorithm for all other countries. A detailed account of the matching of inventor address information to FUA is available from the authors upon request.

[3] Further matching is being undertaken to complete the matching of each country and expand the sample to include all OECD countries.

[4] The statistics use population data of cities (FUA) for 2015 and apply to all countries in the sample except for Israel as population information for FUA is not available.

Empirical facts about the concentration of innovation in cities

This section presents empirical facts on the distribution of innovation – as measured by patent applications filed by inventors – across cities.

Fact 1: The concentration of patenting in a few leading cities is high at global and national level.

At global level, the concentration of patenting is significant, with 10% of the 1 022 functional urban areas across 30 OECD countries accounting for close to 2 in 3 (64%) of patent applications, and more than 1 in 2 (54%) and about 1 in 3 (31%) of all patents filed in the top 5% and 1% cities (average for 2010-2014). This number is the more so important as these cities represent only 31.4%[5] (top 10%, 103 FUA), 24.6% (top 5%, 52 FUA) and 12.7% (top 1%, 11 FUA) of the total population in the 30 countries under analysis. This evidence points to important inequalities in innovation capacities within countries, in that a large number of cities only contribute marginally to overall national patenting efforts. Such levels of concentration point to the importance of clusters with strong innovation capacities as illustrated by the famous examples of Silicon Valley and Boston's Route 128.

The level of concentration in top cities differs, however, across countries (Table 2). Japan and the United States are more concentrated than the global average, with more than 2 in 3 patents filed in the top 10% cities, while Germany and the United Kingdom are significantly less concentrated as is the average of the European countries of our sample.

Table 2. Average share of patent applications of the top 10%, 5% and 1% cities for 2010-14

	Top 10%	Top 5%	Top 1%
Japan	87.9	84.0	51.3
United States	67.0	53.4	25.2
Total*	63.8	54.1	31.1
France	60.6	53.9	34.2
Europe	48.7	37.7	17.1
United Kingdom	42.9	30.8	12.9
Germany	37.7	24.7	7.1

Note: The Europe sample includes the following 23 countries: Austria, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom. Total* refers to all 30 countries in our database.

Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Interestingly, concentration is also high among the top 10 global cities, which jointly represent 1% of all cities across the 30 countries we investigate. The leading five cities globally (Tokyo, Seoul, San Francisco, Higashiosaka and Paris) account for 21.8% of total global patent applications to the EPO over the 2010-14 period, but only 8.3% of the population in the 30 countries in 2014.

Similar granular concentration dynamics apply at country level. One or two cities generally account for a large share of overall patenting with a gap to the next city in the ranking; it is the case of San Francisco in the USA, London in the UK, Paris in France, Munich and Stuttgart in Germany, Tokyo in Japan, and Milan in Italy. The gap is substantive in France, with more than 35 percentage points of difference between Paris and Grenoble, and Japan,

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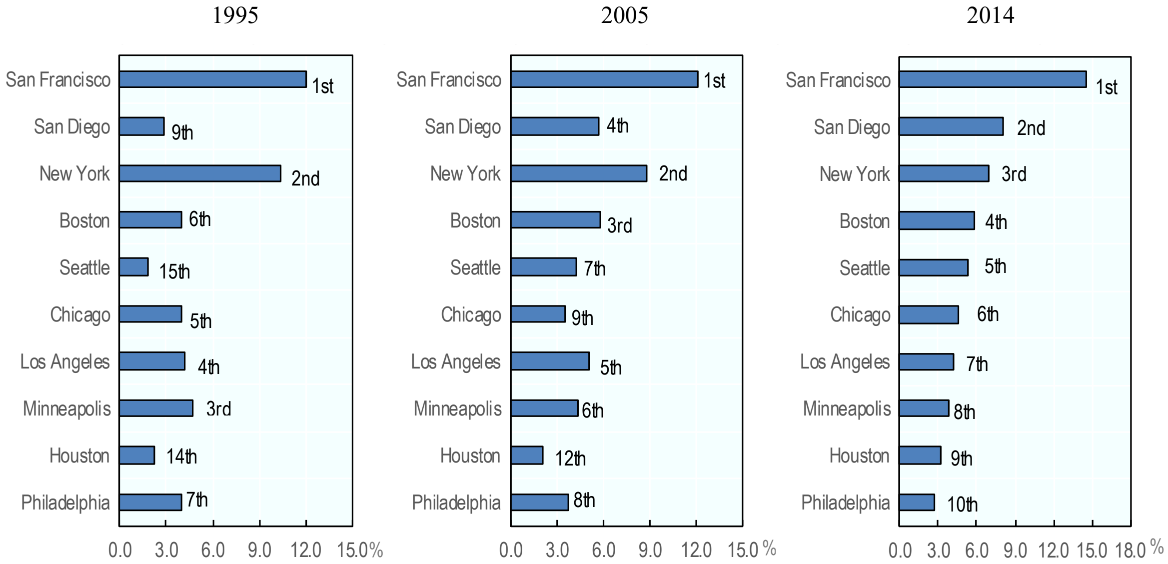
[5] As our data do not include population data for Israel's FUA contained in the top 10%, we use 2018 data from Israel's Census Bureau from this website:

with a more than 33 percentage points of difference between Tokyo and Higashiosaka. The pattern does not apply to Germany where innovation is more dispersed, with no single city having a share of more than 4.2% in total patent applications and only 5 cities accounting for 2% of total patents or more.

In the United States, San Francisco is the top city in the country in terms of patenting (Figure 1). In 2014, the city accounted for 14.6% of patent applications and 2.1% of the US population.

Figure 1. Ranking and share of top 10 cities in patent applications, United States, 1995, 2005 and 2014

Share of US patent applications



Note: The cities (FUA) selected correspond to the top 10 in patent applications in 2014.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Paris (which accounts for 18% of the country population) is the top city in France in terms of patent applications (46.7% of the total in 2014) and well ahead of the second (Grenoble, 11.4%) (Figure 2).

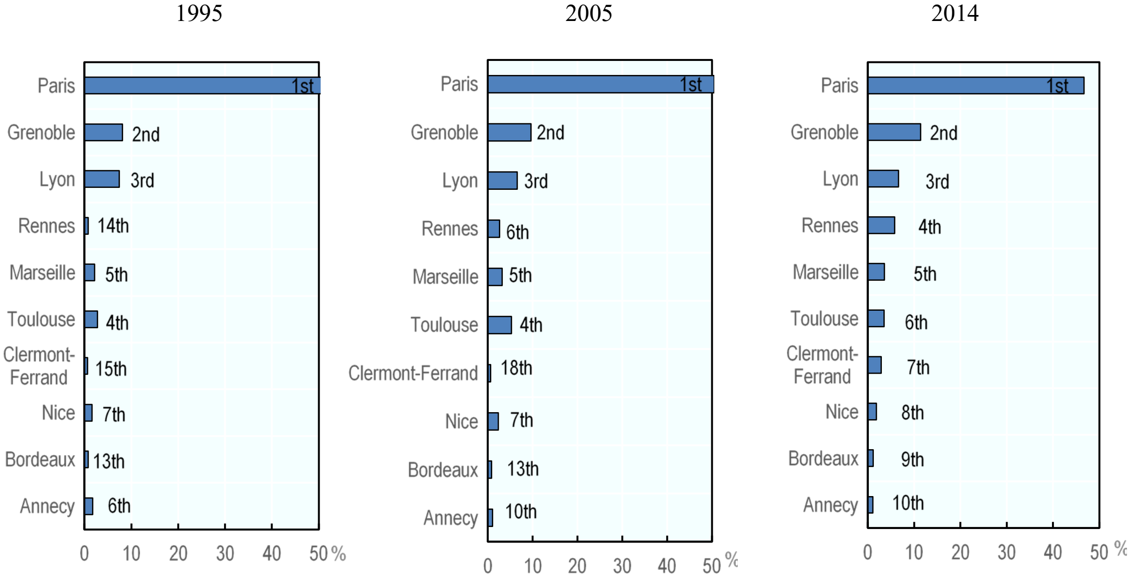
In Japan, patent applications are highly concentrated in Tokyo (53.6% of patent applications in 2014), followed at a distance by Higashiosaka (20%) (Figure 3). Such concentration reflects the high geographic concentration of population and economic activity in Tokyo, which accounts for 28% of the total population.

In the United Kingdom, London (which accounts for 18% of the country population) is the top city in terms of patenting, accounting for 18% of total patent applications in 2014, followed by Cambridge (7.3%) and Rushmoor (5.9%) (Figure 4).

Munich and Stuttgart are the top cities in terms of patenting in Germany, with around 4% of patent applications each (and around 3.4% of the total population each) in 2014 (Figure 5). Berlin (2.3%) and Frankfurt (2.1%) are 3rd and 4th in the ranking. Overall, the geographic distribution of patenting activity is less concentrated in Germany than in other countries, reflecting the more even distribution of population and economic activity.

Figure 2. Ranking and share of top 10 cities in patent applications, France, 1995, 2005 and 2014

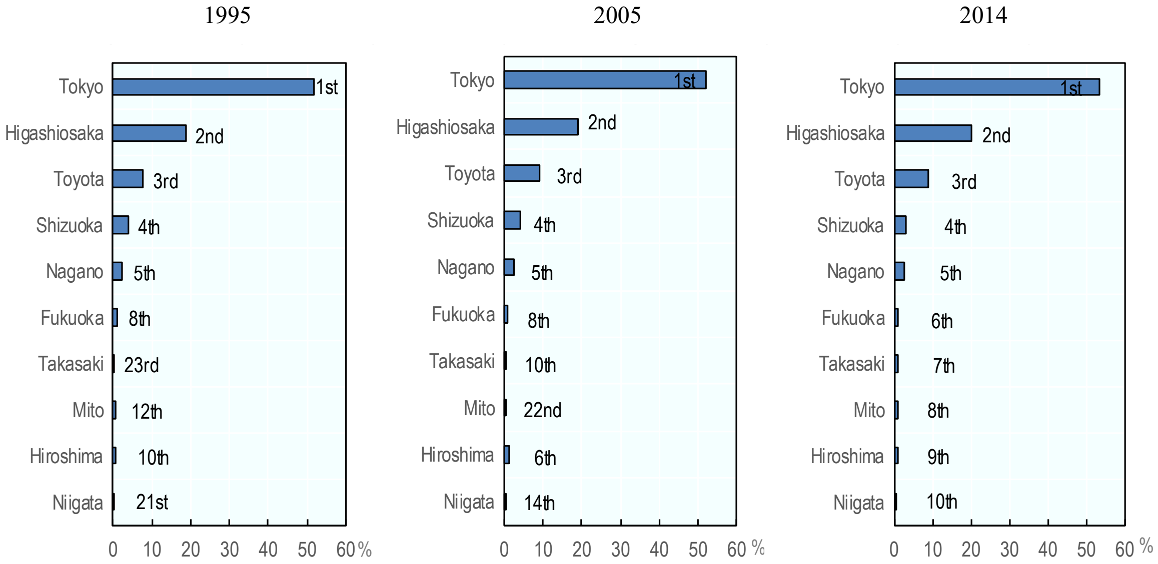
Share of France's patent applications



Note: Cities (FUA) selected correspond to the top 10 in patent applications in 2014.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Figure 3. Ranking and share of top 10 cities in patent applications, Japan, 1995, 2005 and 2014

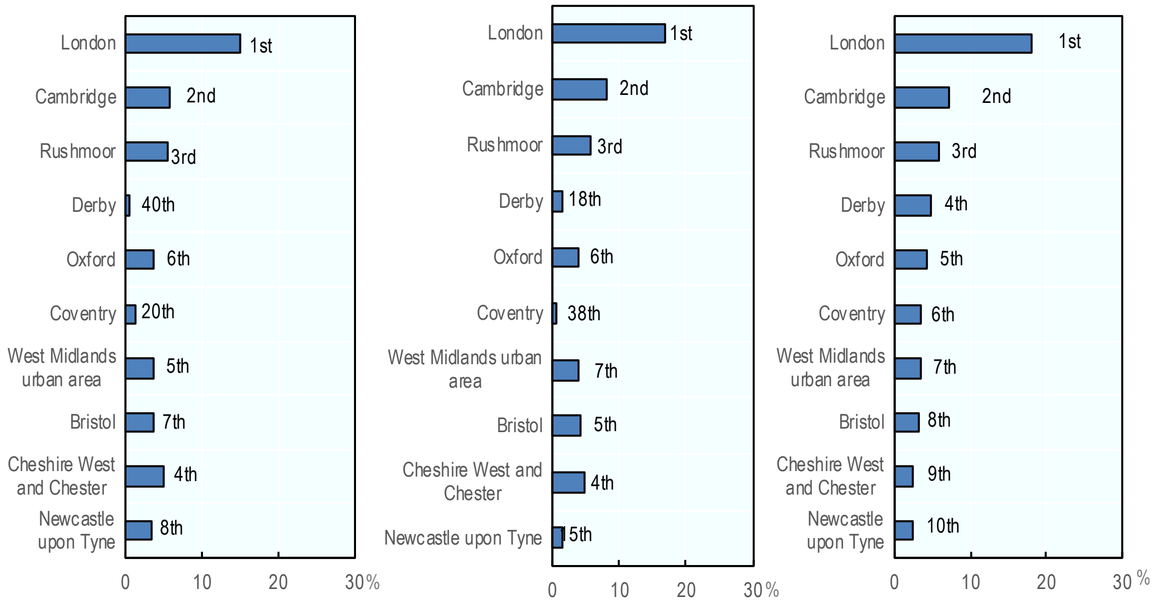
Share of Japan's patent applications



Note: FUA selected correspond to the top 10 in patent applications in 2014.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Figure 4. Ranking and share of top 10 cities in patent applications, United Kingdom, 1995, 2005 and 2014

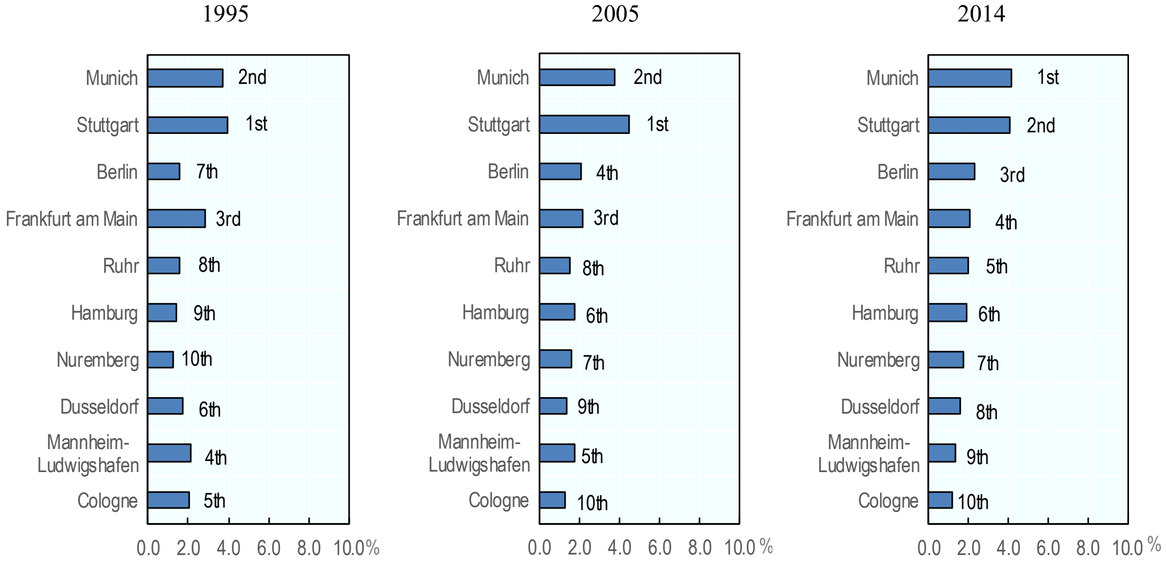
Share of United Kingdom's patent applications



Note: Cities (FUA) selected correspond to the top 10 in patent applications in 2014.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Figure 5. Ranking and share of top 10 cities in patent applications, Germany, 1995, 2005 and 2014

Share of Germany's patent applications

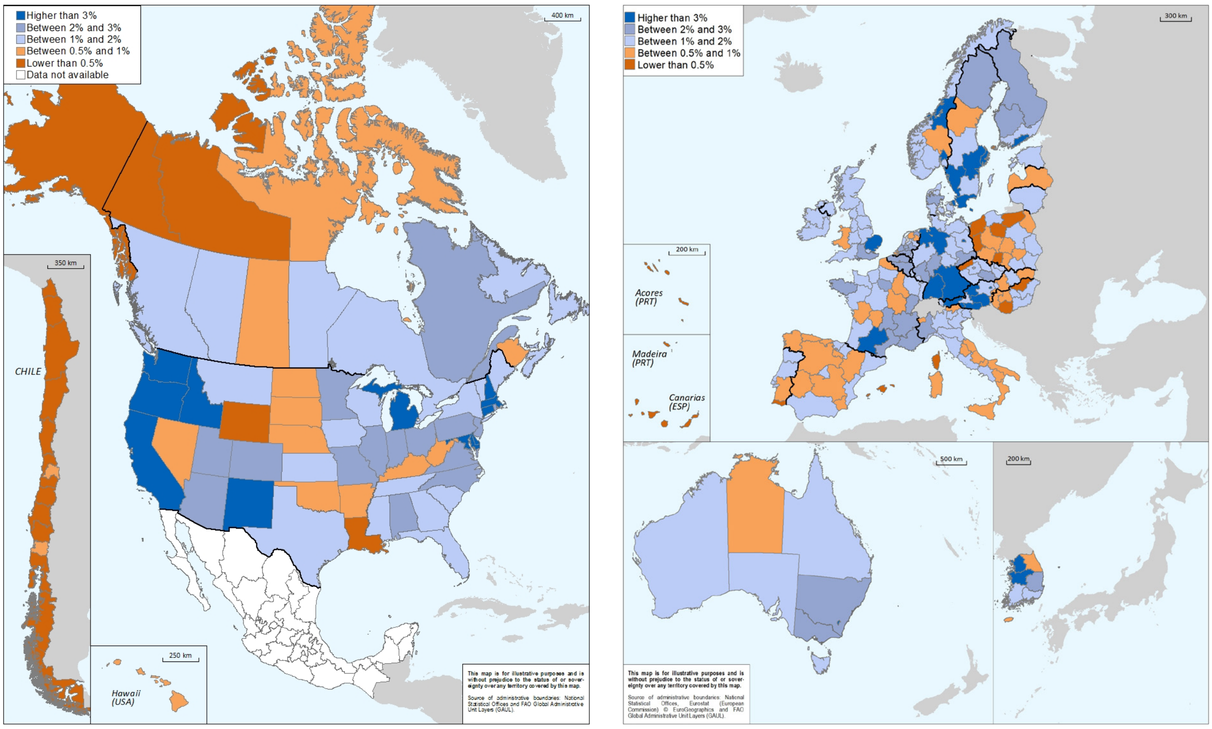


Note: Cities (FUA) selected correspond to the top 10 in patent applications in 2014.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

The concentration of patenting in top cities reflects well-known disparities in innovation capacities across regions within and across countries. Figure 6 shows the divergence in regional R&D intensities in OECD countries. Indicators of business R&D investments (Figure 7) and venture capital show a similar picture of concentration. Across the OECD area, the share of the top 20% regions in BERD was of 45% in 2013 (OECD, 2016a). Venture capital funding is also strongly concentrated. For instance, the top region in the United States (California) was host to almost half of all VC invested in 2014 (OECD, 2016a).

Figure 6. Regional R&D intensity in OECD countries, 2015

Gross domestic R&D expenditure as % of GDP, TL2 regions

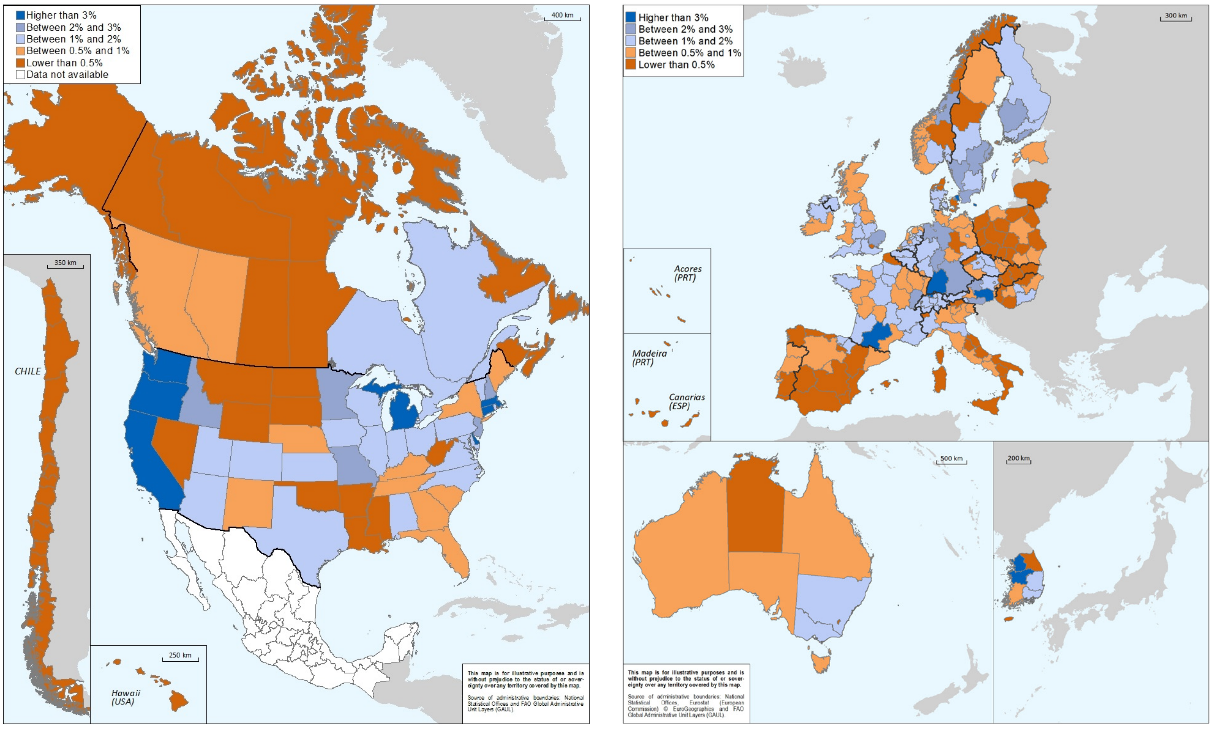


Note: Regions within OECD countries are classified on two territorial levels reflecting the administrative organisation of countries. The OECD large (TL2) regions represent the first administrative tier of subnational government, for example, the Ontario Province in Canada. Countries where only governmental R&D expenditures are available are depicted in grey (Greece, Israel, Japan, Turkey).

Source: Calculations by E. Gonnard based on OECD Regional Statistics, https://doi.org/10.1787/region-data-en

Figure 7. Regional business R&D expenditure, 2015

Business expenditure on R&D (BERD) as % of GDP, TL2 regions



This map is for illustrative purposes and is without prejudice to the status of or sovereignty over any territory covered by this map.

Source of administrative boundaries: National Statistical Offices and FAO Global Administrative Unit Layers (GAUL).

This map is for illustrative purposes and is without prejudice to the status of or sovereignty over any territory covered by this map.

Source of administrative boundaries: National Statistical Offices, Eurostat (European Commission) © EuroGeographics and FAO Global Administrative Unit Layers (GAUL).

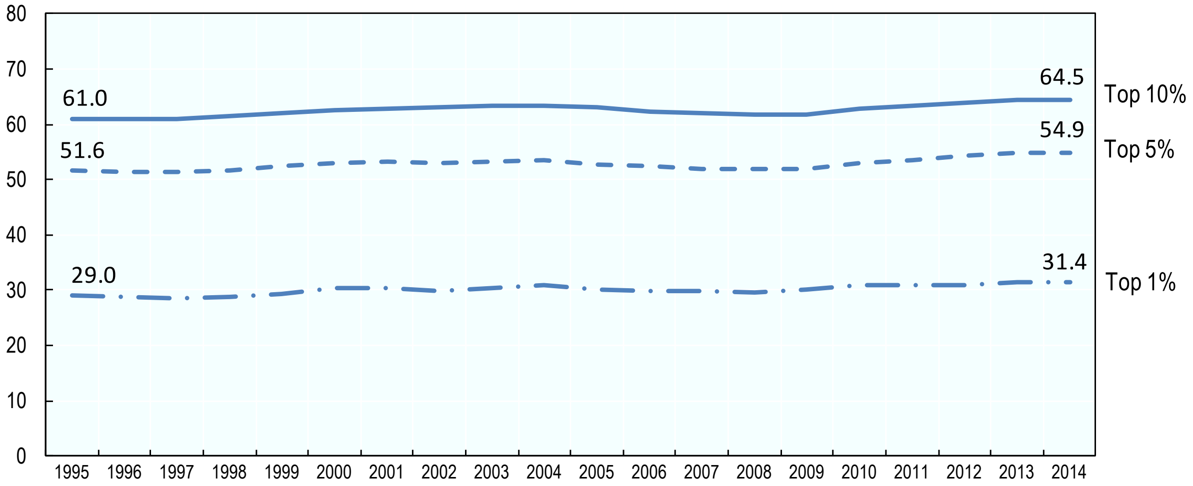
Note: Countries where only governmental R&D expenditures are available are depicted in grey (Greece, Israel, Japan, Turkey).

Source: Calculations by E. Gonnard based on OECD Regional Statistics, https://doi.org/10.1787/region-data-en

Fact 2: At the global level, the share of the top cities in total patenting has been stable over 1995-2014.

Figure 8 shows that the share of the top global cities in total global patenting stayed fairly stable from 1995 to 2014. There was a moderate increase over the 20-year period we cover, with a 3.5 percentage point increment among the top 10% (from 61% to 64.5%) and a similar trend for the top 5%, while that of the top 1% was lower. That is, the past two decades have not seen a fundamental change in the concentration of patenting applications in the aggregate. This may point to the continued benefits concentration offers to facilitate patenting.

Figure 8. Share of top 10%, 5% and 1% global cities in patent applications, 1995-2014



Note: Patent applications include all applications by the 30 OECD countries to the EPO.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Fact 3: Persistence and change characterise top cities over 1995-2014.

When it comes to mobility among the top 10 global cities, there is an interesting mix of persistence but also change. Some of the top cities globally (Tokyo, San Francisco, Higashiosaka, Paris and New York) have been stable over the past two decades (Figure 9). Seoul, Seattle and San Diego show the most important increases in the global ranking (from 37th, 34th and 17th positions in 1995 to 2nd, 9th and 6th positions in 2014), while Minneapolis and Philadelphia are those with most important relative decreases (from 9th and 13th positions in 1995 to 16th and 20th in 2014).

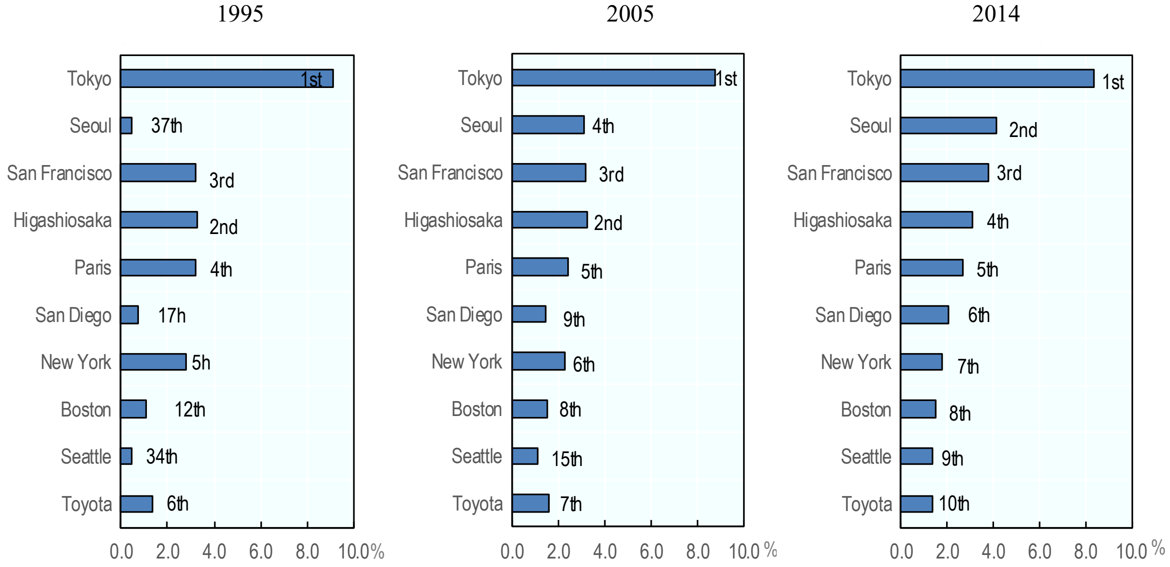
Interestingly, in 2014 there were 5 US cities and 3 Japanese cities in the global top 10 cities in terms of patenting, but only 1 European city (Paris) (Figure 9). In the ranks 10-20 for 2014, there were 5 European cities (Munich, Stuttgart, Eindhoven, Stockholm and Berlin), 5 US cities (Chicago, Los Angeles, Minneapolis, Houston and Philadelphia), and 1 Japanese city (Toyota).

The country rankings for 1995, 2005 and 2014 show similar persistence of cities at the top, although relative weights have generally changed. There is also some mobility in other cities (see Figures 1- 5 above).

In the US, San Francisco and New York were the top 2 cities in 1995 (accounting for 12% and 10.4% of total patent applications). Over time, the relative weight of New York has declined and that of San Francisco has significantly increased, while San Diego has seen a spectacular increase in share over the years (from 9th position in 1995 to 2nd in 2014). In 2014, it accounted for 8% of total patent applications (and 1% of total population). Seattle has also seen an important increase (from 15st to 5th). Most other cities are quite stable, with some slightly increasing their share of total patent applications (Houston and Boston) or slightly decreasing (Minneapolis and Los Angeles) (Figure 1).

Figure 9. Ranking and share of top 10 global cities in patent applications, 1995, 2005 and 2014

Share of global patent applications



Note: Cities (FUA) selected correspond to the global top 10 in patent applications in 2014.
Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

In France, the concentration of patenting in Paris has decreased over time (from 57.6% in 1995 to 46.7% in 2014), while Grenoble (which accounts for only 1% of the country population) is the city with the highest increase in patenting, from 8.1% of total patents in 1995 to 11.4% in 2014. Others remain quite stable (Figure 2).

In Japan, patent applications are highly concentrated in Tokyo – a trend that seems to be slightly increasing over time (from 52% in 1995 to 53.6% in 2014). Higashiosaka and Toyota are the 2nd and 3rd cities in terms of patenting and remain relatively stable over time at around 20% and 8-9% of total patents, respectively (Figure 3).

In the United Kingdom, the concentration in London has increased over time, from 15% in 1995 to 18% in 2014. Cambridge, Rushmoor and Oxford (in the 2nd, 3rd and 5th position in 2014) have remained relatively stable, while Derby has seen a significant increase, from 0.6% of total patents (20th position) in 1995 to 5% (4th position) in 2014 (Figure 4).

In Germany, Munich and Stuttgart have remained stable as top cities in terms of patenting, at around 4% of total patent applications each. Berlin (2.3%) and Frankfurt (2.1%) are 3rd and 4th in the ranking, with increasing shares over time in the case of the former (from 1.6% in 1995 to 2.3% in 2014) and decline in the case of the latter (from 2.9% to 2.1%). Cologne and Mannheim have also reduced their shares over time (Figure 5).

4. Empirical facts about digital technology and the geography of innovation

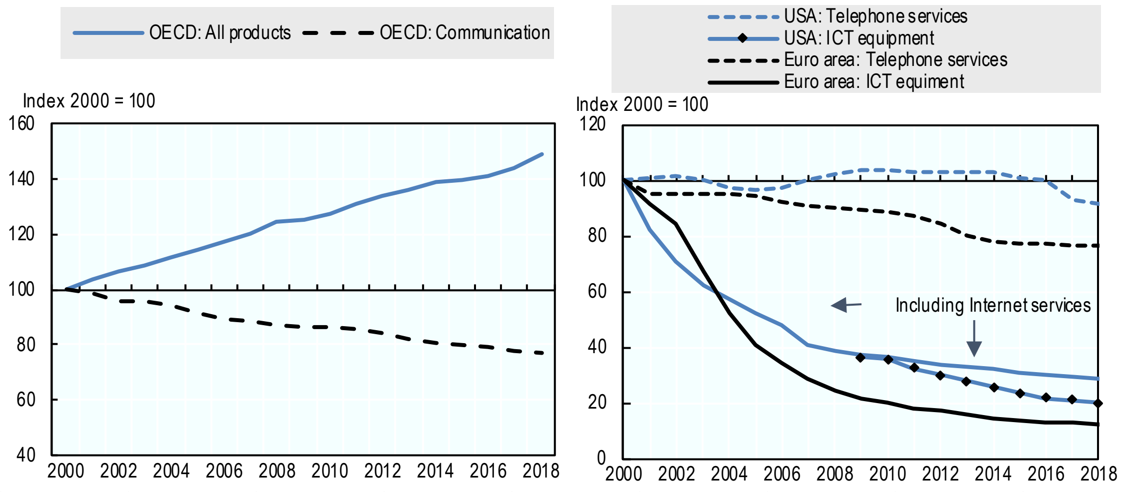
The purpose of this section is to discuss how the geography of innovation relates specifically to digital technology. The geography of innovation itself – and the features outlined in the empirical facts section – is the outcome of various trends, including globalisation and global value chains, different trends of industrial sectors that affect regions according to their respective specialisations and changes in policy, including efforts aimed at wider decentralisation.

Fact 1: Digital technology has become cheaper and more effective for the exchange of data and knowledge and for collaboration.

First, cost reductions associated with digital technology have been important over the 1995-2014 period, decreasing the costs of exchanges of information and knowledge across distances. From 2000 to 2018, while consumer prices increased by about 45% on average in the OECD area, the prices of communication-related products (i.e. excluding IT and media) decreased by more than 20%. ICT goods prices fell by 80% or more in the United States and Euro area and telecommunication service prices decreased by 10% to 25% (Figure 10).

Figure 10. Consumer price indices, all products and ICT goods and services, OECD, Euro area and United States, 2000-18

Index 2000=100, unweighted OECD average



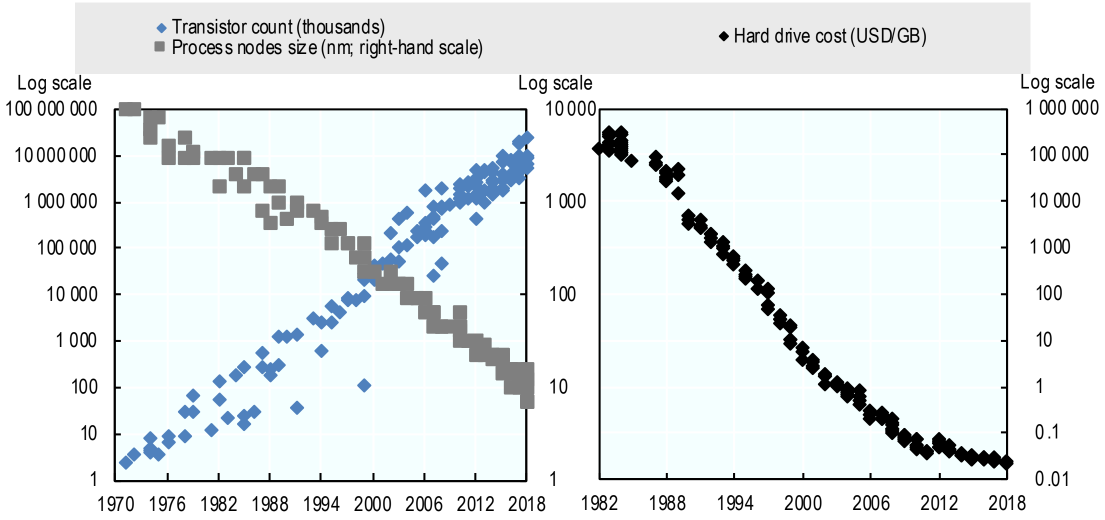
Note: For the OECD, the following data are not included in calculations: Canada (whole series), Iceland, Mexico and the United States (until 2002), Turkey (until 2004) and New Zealand (until 2007). National indices are used for Finland and the United States until 2009, Poland until 2005, the United Kingdom until 2004 and Hungary until 2006. Data for 2018 are limited to October. For the Euro area, data refer to Belgium, France, Germany, Italy, the Netherlands and Spain (representing 90% of the total Euro area) until 2014. Country and item weights were used for aggregations and estimations.

Source: OECD (2019c) based on OECD Consumer Price Indices (CPIs) Database; Eurostat, Harmonised Index of Consumer Prices (HICP) Statistics and United States Bureau of Labor Statistics, CPI-All Urban Consumers (Current Series), January 2019.

Second, quality improvements in computing capacity and storage (which are normally reflected in the "hedonic" price indices) have also been substantive over the 1995-2014 period, facilitating data analytics across multiple locations with quality infrastructure. Since the 1970s, the number of transistors per chip – a traditional way of considering improvements in computing power – has followed "Moore's law" by roughly doubling capacity every two years. This has been accompanied by concurrent miniaturisation: the length of the "transistor gate" is now around 7nm, 1 500 times smaller than in the early 1970s, resulting in increased processing speed and improved energy efficiency. Storage capacity has also increased enormously, with the commercial price per Gigabyte diminishing from about USD 10 in 2000 to below USD 0.3 in 2018 (Figure 11). The opportunity to create virtual spaces that contain large amounts of data has facilitated collaborations across different geographic locations, allowing joint work on large research project data (OECD, 2017a).

Figure 11. Computing power and cost of storage, 1970-2018 and 1982-2018

Number of transistors per central processing unit (CPU) microprocessor and process size (left-hand panel), cost of storage per GB (right-hand panel)



Note: The transistor count is the number of semiconductor devices on an integrated circuit (IC). Transistor count is the most common measure of IC complexity, although there are caveats. For instance, the majority of transistors are contained in the cache memories in modern microprocessors, which consist mostly of the same memory cell circuits replicated many times. The process node (also called the technology node, process technology or simply node) refers to a specific process in semiconductor manufacturing. The size of the elements of the structure of a chip are measured in nanometres.

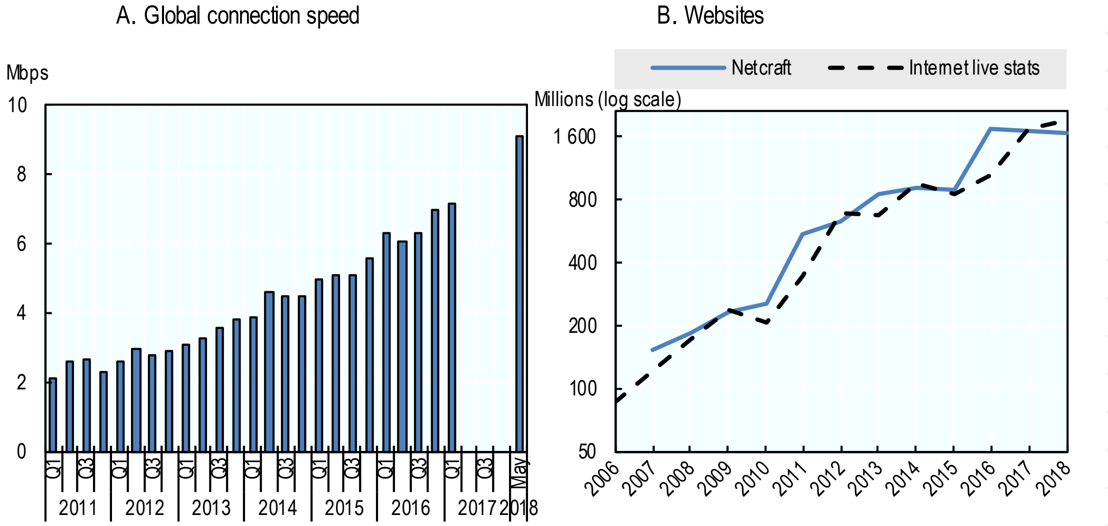
Source: OECD (2019c) based on Wikipedia, "Transistor count", www.wikipedia.org/wiki/Transistor_count; "A history of storage cost", www.mkomo.com/costper-gigabyte; "Disk drive prices 1955-2018", www.jcmit.net/diskprice.htm, January 2019.

Third, the quality of connectivity has also improved, with the launch of 3G at the beginning of the millennium and by the introduction of 4G in the early 2010s. This infrastructure facilitates new approaches to communication that simulate face-to-face interactions and allow for virtual discussions that are an improvement over phone conversations. According to commercial sources (Akamai and M-Lab), the average (fixed and mobile combined) global Internet connection speed increased from 2 Mbps to more than 9.1 Mbps between 2011 and 2018 (Figure 12).

Meanwhile, the total number of websites grew from about 100 million in 2006 to more than 1.6 billion in 2018, according to Netcraft, increasing the access to information sources available across all "connected" geographies (Figure 12). The latter is particularly important in view of increased opportunities for collaboration as more information on who is engaged in what innovation activities also becomes available, including via digital platforms, making it easier to establish research and innovation collaborations at regional, national and international levels.

Figure 12. The increasing capacity of Internet infrastructure, 2005-18

Speed in Mbps, 2011-18 (left-hand panel), Top-level domains in millions, 2005-18 (right-hand panel)



A. Global connection speed

B. Websites

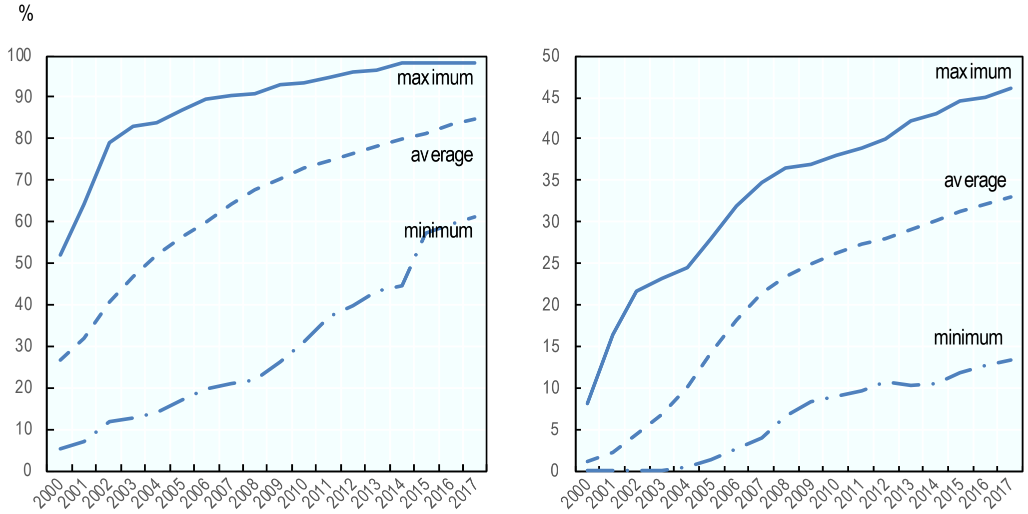
43Note: Speed data for 2018 refer to the period June 2017 to May 2018. Top-level domains data for 2018 are limited to October 2018.

Source: OECD (2019c) based on Akamai, MLAB, Netcraft and Internet live stats, January 2019.

Connectivity is increasingly dense across OECD countries and beyond: 94.6% of firms in the OECD have a broadband connection, and 80% of OECD citizens have a broadband subscription in 2014 (OECD, 2016a). Two indicators of the adoption of digital infrastructure (the share of internet users in the total population and the number of broadband subscriptions by 100 inhabitants) show an upward trend for the 2000-2017 period (Figure 13). Interestingly, however, the average hides substantial variation in the rates among the advanced OECD countries, as indicated by the minimum and maximum values.

Figure 13. Internet users and fixed broadband subscriptions, 30 OECD countries, 2000-17

Share of internet users in total population (left-hand panel) and number of fixed broadband subscriptions by 100 inhabitants (right-hand panel)



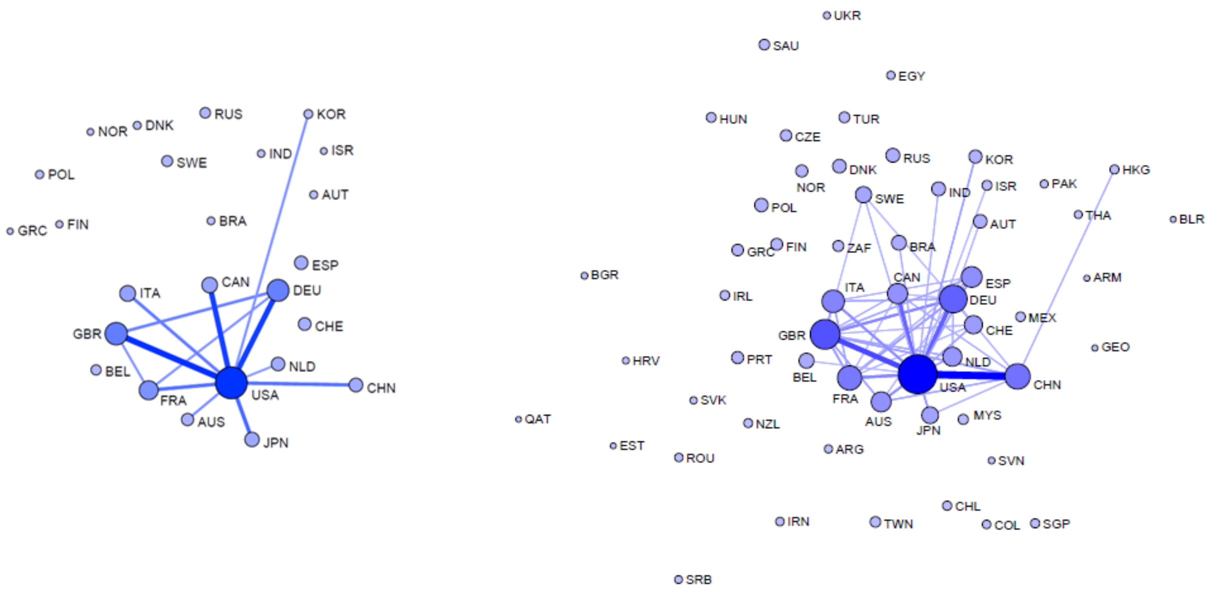
Source: ITU World Telecommunication, ICT indicators database.

Fact 2: Collaboration across geographic distance has increased, as reflected in intensified cross-border relations in scientific production.

There is also evidence of widening collaborations in innovation over the same period, possibly leveraging the opportunities offered by digital technology. One pertinent example is the production of scientific research, as judged from co-authored papers, which has shifted progressively from individuals to groups and from national to international collaborations. For instance, international collaborations on research papers has tripled between 2006 and 2016 (Figure 14). Flows of scientific knowledge, as measured by the international citation network, have also become more connected since the late 1990s (OCED, 2015c).

Figure 14. International collaboration networks in science, 2006 and 2016

Whole counts of internationally co-authored documents



2006

2016

Note: The position of selected economies (nodes) exceeding a minimum collaboration threshold of 10 000 documents is determined by the number of co-authored scientific documents published in 2016. A visualisation algorithm has been applied to the full international collaboration network to represent the linkages in a two-dimensional chart on which distances approximate the combined strength of collaboration forces. Bubble sizes are proportional to the number of scientific collaborations in a given year. The thickness of the lines (edges) represents the intensity of collaboration between countries (number of co-authored documents between each pair). The edges have a minimum threshold of 5,000 collaborations. The positions derived for 2016 collaboration data have been applied to 2006 values. New nodes and edges appear in 2016 as they exceed the minimum thresholds.
Source: OECD calculations based on Scopus Custom Data, Elsevier, Version 1.2018.

Fact 3: Communication & tech patent applications are more concentrated in top cities than patent applications in other technology fields.

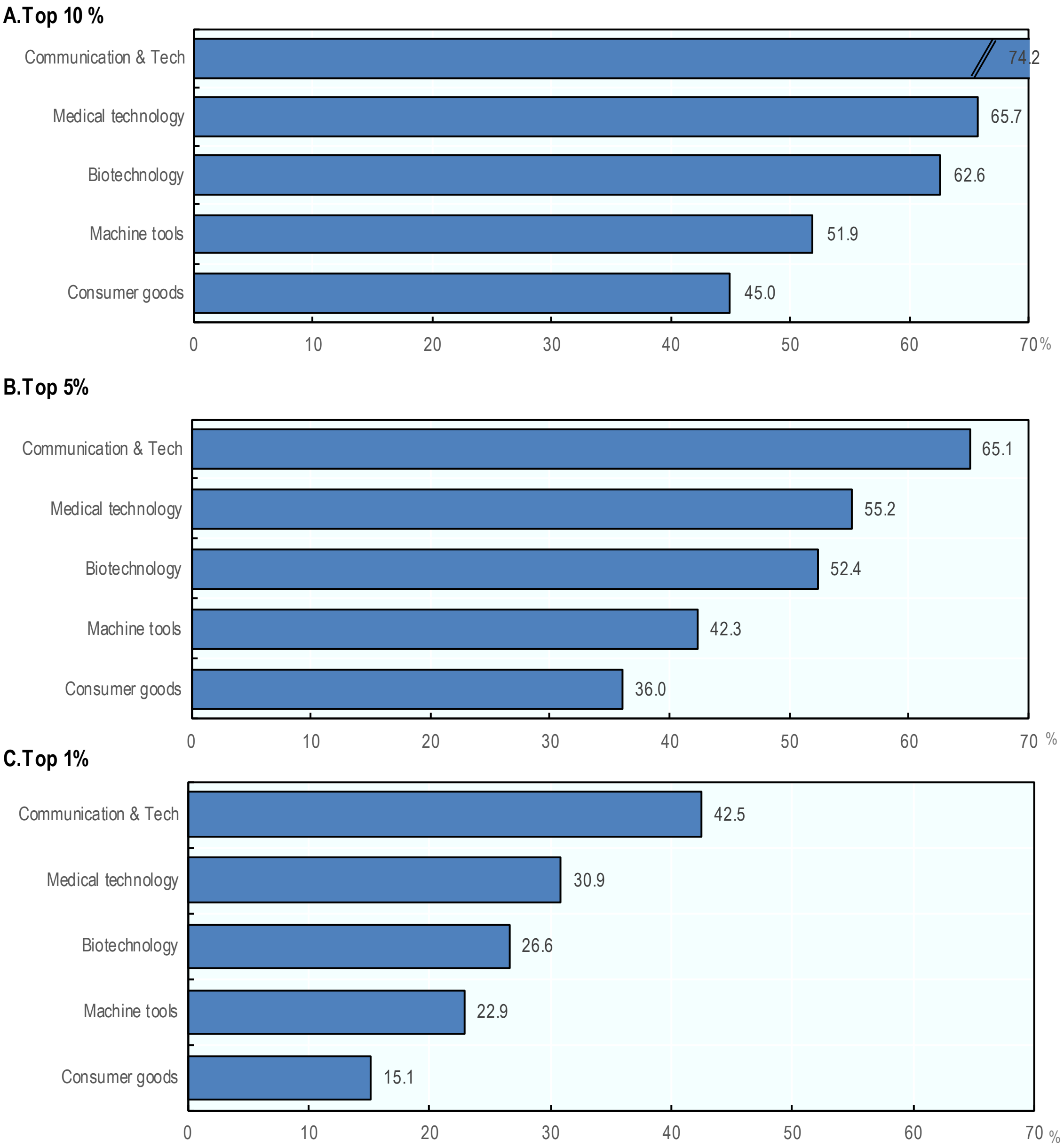
Interestingly, technology fields differ with regard to the geographic concentration of patent applications (Figure 15). Communication & tech lead the ranking in that 10%, 5% and 1% of the most active cities account for the biggest share in total patents. These shares – 74.2% of patent applications in the top 10% of cities, 65.1% in the top 5% and 42.5% in the top 1% – contrast with those associated to consumer goods that are much less concentrated (with 45% in the top 10%, 36% in the top 5% and 15.1% in the top 1%).

The technology fields with the highest concentration in almost all countries are also the most dynamic and recent ones and the most science-based: communication & tech, medical technology and biotechnology. This might have something to do with their closer connection with knowledge production (from universities or R&D labs) than with manufacturing production (factories), which entails a more important role for knowledge spillovers, hence generating different location patterns.

The same ranking holds across countries, with communication & tech patents being the most geographically concentrated (Figure 16). There are, however, some national specificities as to how technology fields rank with regard to geographic concentration. Japan is the country with highest concentration of communication & tech patents (with 90.3% of patent applications concentrated in top 10% of cities), followed by France (73.5%) and the USA (73.5%) (average for 1995-2014). The United Kingdom (46.6%) and Germany (42.3%) are those with lower concentration of communication & tech patents, being below the European average (59.3%). The biggest differences between patents in communication & tech and those in other technology fields are found in France (with 28 percentage points of difference between share of patents in communication & tech and those in consumer goods concentrated in the top 10% of cities), followed by the USA (24 percentage points between communication & tech and machine tools).

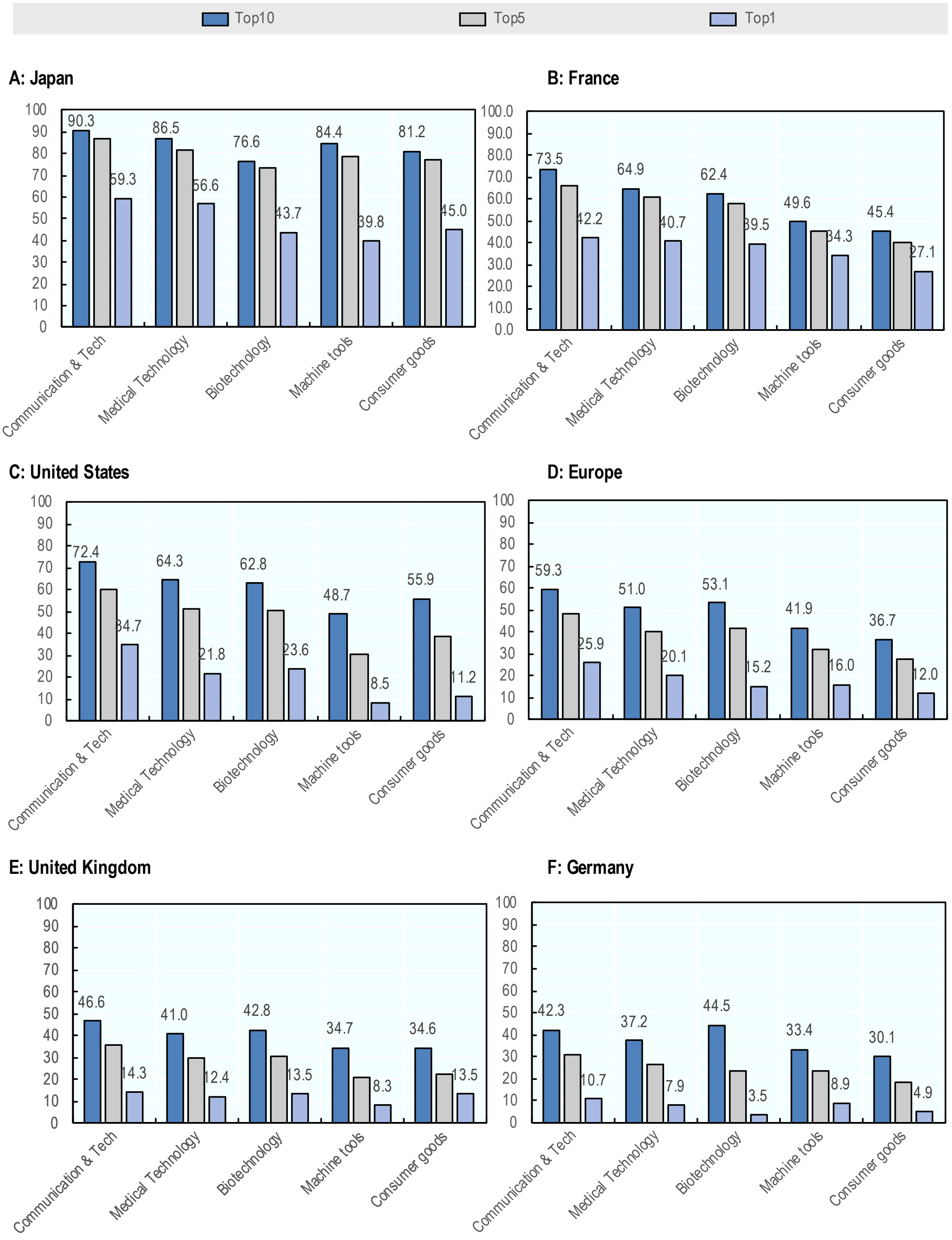
Over time, the concentration of patents in cities increased more in the ICT sector (with an increase at the top 10% of cities of 4.5 percentage points between 1995 and 2014) than in other technology fields that registered more moderate increases of between 3.5 percentage points and 1.2 percentage points (Figure 17). Concentration at the top 1% of cities has also increased more in the case of communication & tech patents (with an increase of 4 percentage points between 1995 and 2014) than other technology fields (with an increase of 3.3 percentage points in biotechnology and a decrease of 1.7 percentage points in medical technologies; machine tools and consumer goods remained quite stable).

Figure 15. Share of the top cities by patent application technology, average for 1995-2014



Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

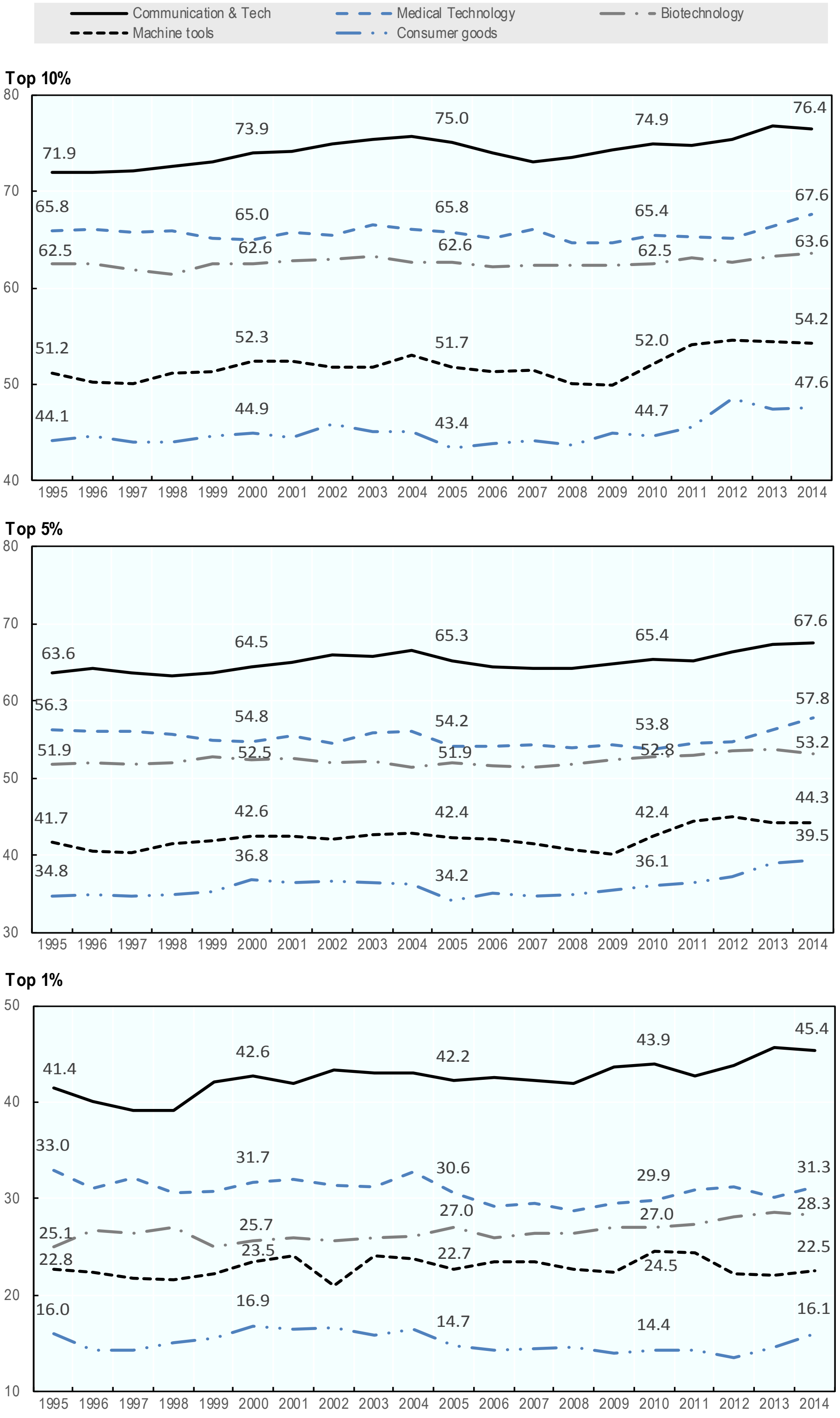
Figure 16. Concentration of patent applications by technology domain for selected countries and for Europe, averages for 1995-2014



Note: Technology fields are ordered by the level of concentration at the top 10% of cities at the global level for ease of comparison across countries. Countries are ordered by the level of concentration of communication & tech patents at the top 10% of cities.

Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Figure 17. Evolution of the share in patent applications of the top cities by technology domain, 1995-2014

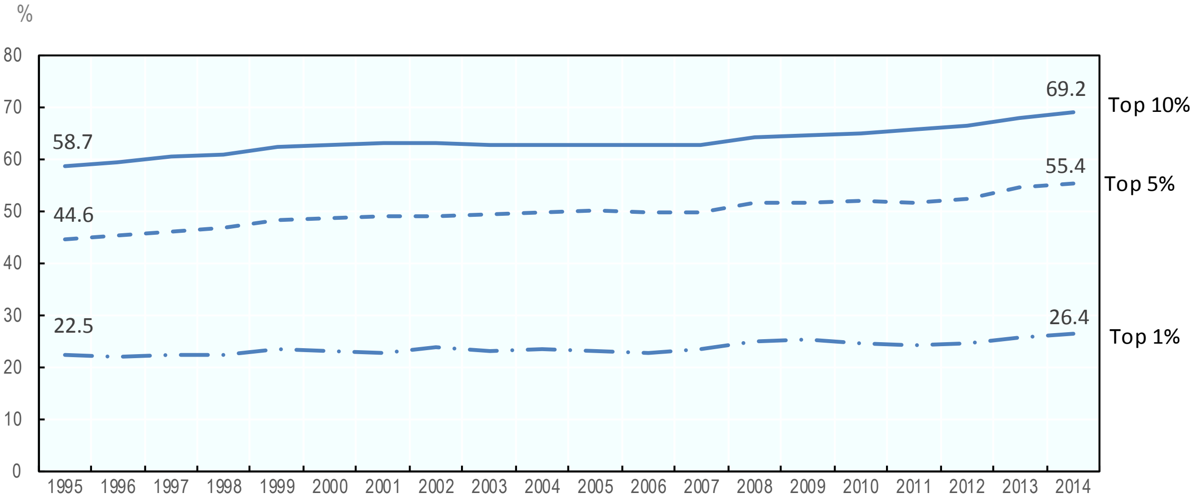


Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Fact 4: The United States has experienced a more important increase in the share of its top cities compared to Japan and Europe.

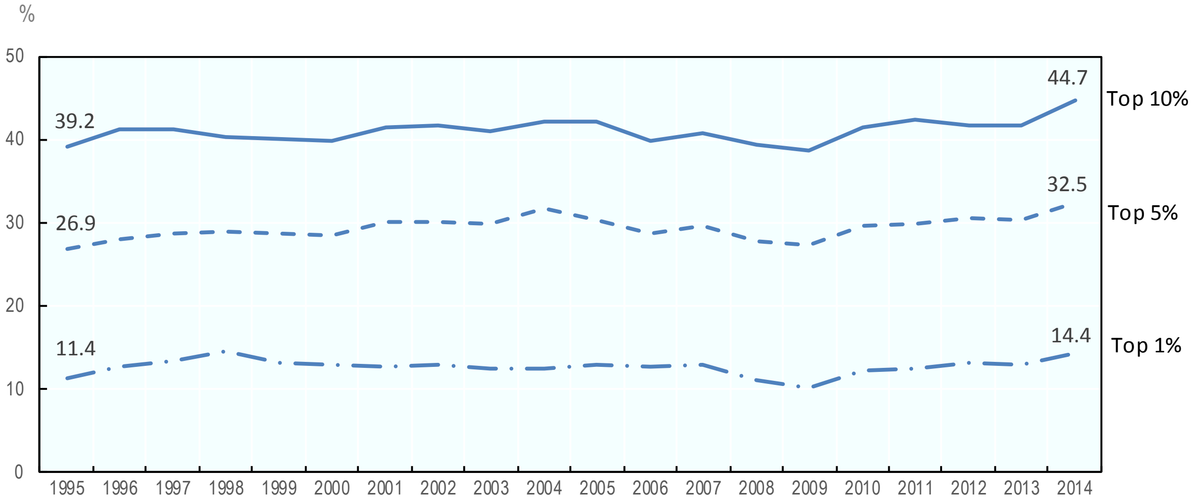
The share of patent applications filed in top cities in the United States has increased more than the global average over the two decades we analyse (Figure 18 and Figure 8). In the United States, the shares increased by more than 10 percentage points from 1995 to 2014 for the top 10% and 5% of cities, respectively, and by 4 percentage points for the top 1% (Figure 18). Such increases are higher than those experienced in Japan and in European countries. In Japan, concentration increased by 5.4 percentage points for the top 10% of cities, although starting from significantly higher levels of concentration (82% of patents were filed in top 10% of cities in 1995). The European average has remained quite stable, with around 50% of patent applications filed in the top 10% of cities over the period. This is also the case of the two large economies of France (with 61% of patents filed in top 10% of cities) and Germany (with around 40% of patents filed in top 10% of cities and only a decrease of 1.4 percentage points from 1995 to 2014) (Figure 21). In the United Kingdom, concentration at the top 10% of cities increased by 5.4 percentage points, from 39% in 1995 to 45% in 2014 (Figure 19).

Figure 18. Share of patent applications of the top 10%, 5% and 1% cities in the United States, 1995-2014



Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Figure 19. Share of patents of the top 10%, 5% and 1% cities in the United Kingdom, 1995-2014

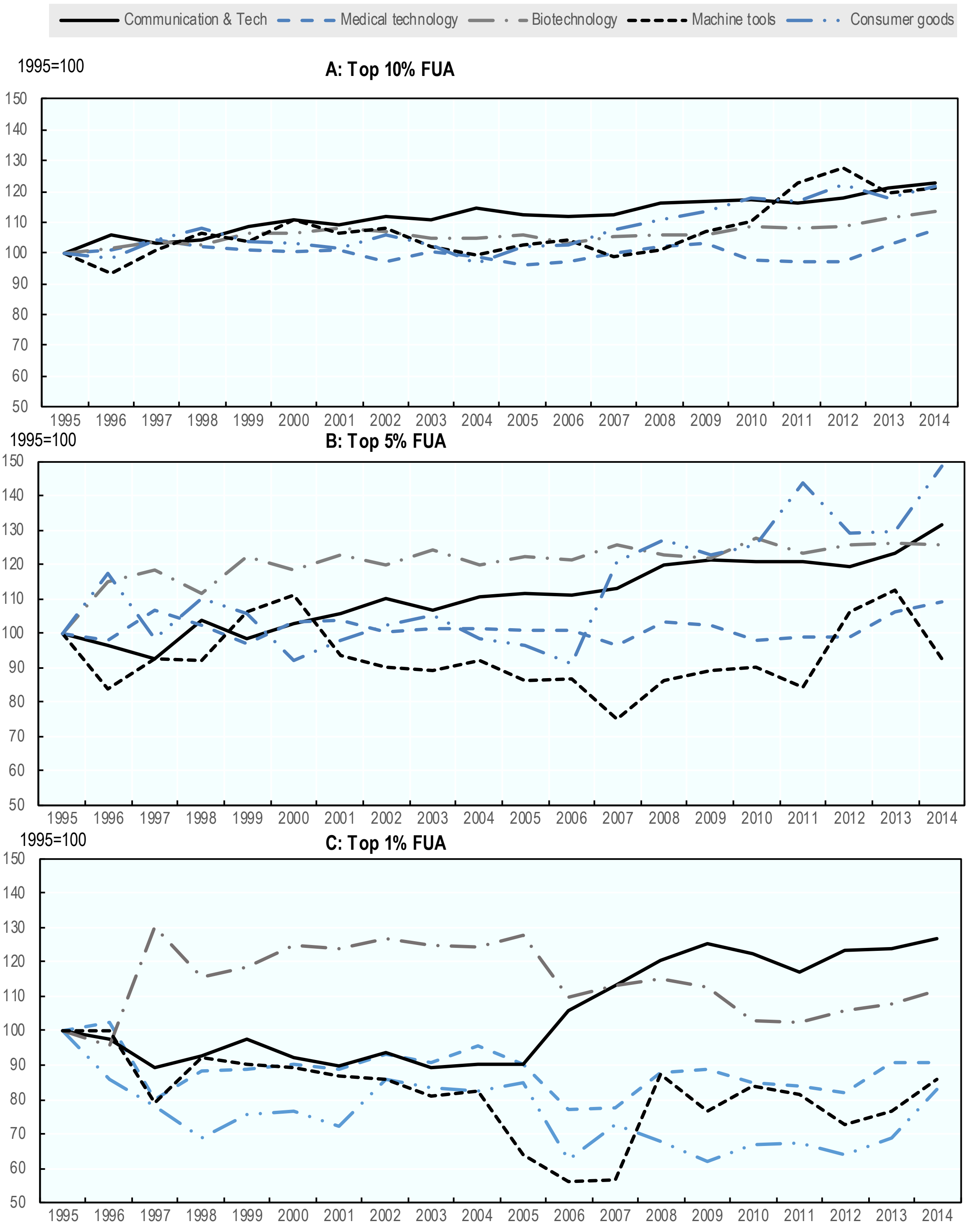


Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Looking at trends across technology fields, the share of communication & tech filed in top 10% cities has experienced a constant increase, jointly with important increases from the second half of the 2000s in machine tools and consumer goods (Figure 19). However, differently from communication & tech patents (which concentrated already 65% of patents in top 10% cities in 1995), the machine tools and consumer goods categories started off from more modest levels of concentration (45% and 52% of patents filed in top 10% of cities in 1995, respectively). Consequently, the additional increase in communication & tech stands out, pointing to the possible role of digital technologies in concentration, as the United States has had a leading position in this field.

Figure 20. Evolution of the top cities in patent applications in the United States, 1995-2014

1995=100



Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

5. The geography of innovation and digital technology in Germany

Different dynamics shape the geography of innovation across countries. This section focuses on Germany, a country characterised by less pronounced geographic concentration of patent applications compared to other OECD countries. As shown in Table 2 above, Germany has a lower geographical concentration in patenting among the top 10%, 5% and 1% of cities compared to other OECD countries, such as Japan, the United States, France and the United Kingdom. What is true for the top of the distribution also holds for the concentration of patenting across all cities as measured by the Gini index – a widely used inequality measure. The measure –which ranges from 0, that would indicate full equality among cities with regards to patent applications, to 1 that would reflect maximum inequality – shows that concentration in Germany has remained fairly stable (Table 3), as is the case of the share of top cities in patenting (Figure 21).

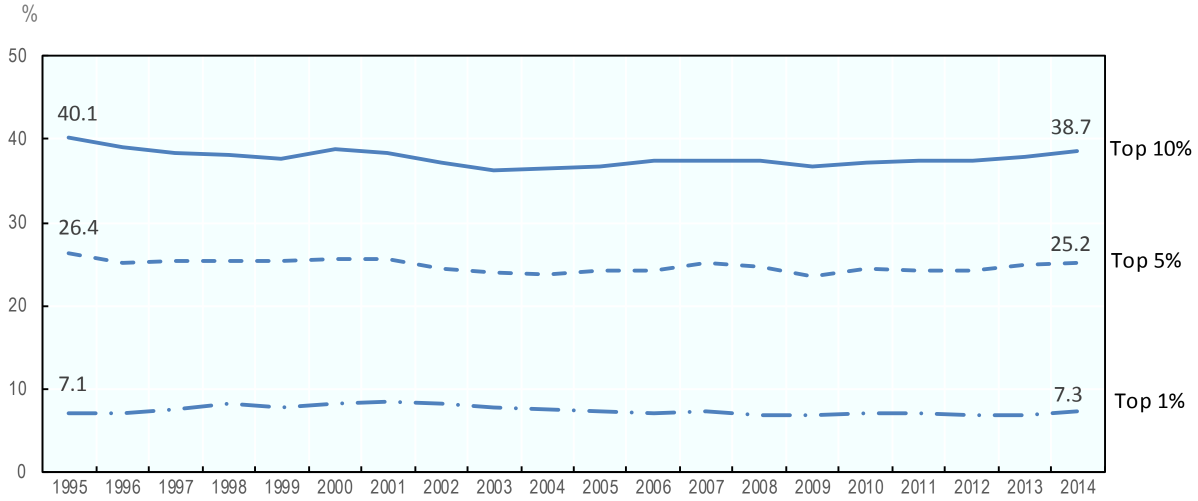
Table 3. Evolution of Gini coefficient of patent applications for selected countries

	1995	2005	2014
Japan	0.88	0.89	0.89
France	0.86	0.85	0.86
Total*	0.81	0.83	0.84
United States	0.79	0.81	0.83
Europe	0.77	0.77	0.78
United Kingdom	0.63	0.67	0.67
Germany	0.66	0.64	0.64

Note: The Europe sample includes the following 23 countries: Austria, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom. Total* refers to all 30 countries in our database.

Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

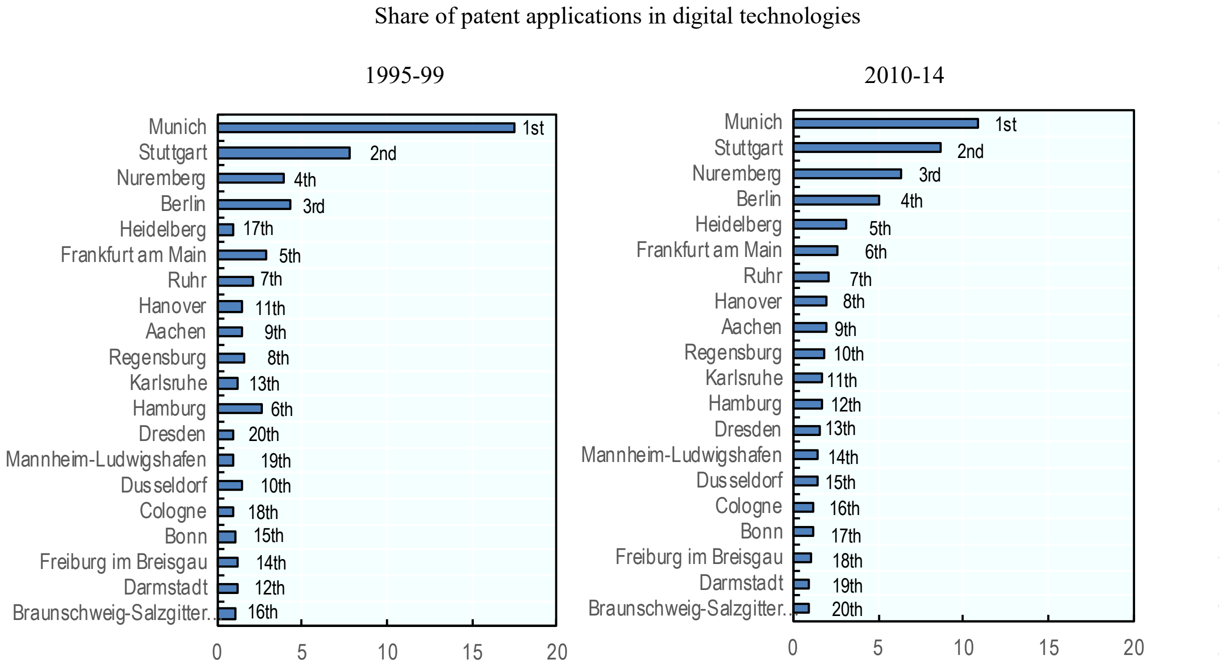
Figure 21. Share of top 10%, 5% and 1% of cities in patent applications, Germany, 1995-2014



Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

Patenting in digital technologies is jointly with biotechnology the most concentrated in Germany, with the top 10% cities accounting for around 41% and 45% of patenting in 2010-14, respectively. These shares are higher than the average across all technology fields over the entire period (Figure 21). As for digital technologies, Figure 22 shows that in line with the general trend (Figure 5), Munich and Stuttgart are the top 2 cities in terms of patenting in digital technologies. There has been some mobility over time, with Munich significantly decreasing its share from 17.4% of the total in 1995-99 to 10.9% in 2010-14. Nuremberg (in the 3rd position in 2010-14) and Heidelberg (5th position) are those with most important increases in shares over the period. Hamburg decreased from the 6th position in 1995-99 to the 12th position in 2010-14.

Figure 22. Ranking and share of top 20 cities in patent applications in digital technologies in Germany, averages for 1995-99 and 2010-14



Note: The cities (FUA) selected correspond to the top 20 in patent applications in Communications and Technology in 2010-14. Digital technologies are defined following the J-Tag taxonomy proposed by Inaba and Squicciarini (2017).

Source: Authors' calculations based on the PATSTAT database (2018, autumn version). Section 3 describes the database.

6. Econometric analysis

Initial econometric exploration

To understand how digital technologies may have influenced the geographic concentration of patenting in leading urban areas, we conduct a first exploration by investigating how the number of patents at city-level relates to digital technologies. For this purpose, we first implement the following specification for the period 2000-2014:

$$patents_{fct,j-dig} = \alpha + \beta^{dig} * dig_{patents}{}_{fct-1} + \beta^{pop} * PopSize_{ft} + \gamma_f + \upsilon_{jt} + \lambda_{ct} + \varepsilon_{fjct} \tag{1a}$$

where $patents_{fct,j-dig}$ are the number of patents per city *f* and per technology domains *j* located in country *c* in year *t,* except for communication & tech patents ($dig\_patents_{fct}$).

Our variable of interest, $dig\_patents_{fct-1}$, is the number of communication & tech patents of cities *f* located in country *c* in year *t-1*. This measure indicates the extent to which city *f* has engaged in patenting in digital technologies and can be seen as an indicator of the extent to which the city engages with digital technologies and develops local applications. The home bias of technology adoption (as discussed in the framework and literature review section) also justifies using this localised measure of adoption rather than a more global indicator of digital technology adoption.

This specification controls for factors other than digitalisation that may drive the number of patent applications of cities in different technology domains. Population size controls for differences in population growth across cities over time. City fixed effects (γ_f) control for time-invariant city features that explain differences in innovation capacities such as, for instance, the sectors of activity, the presence of industry clusters, multinationals and research institutions, the inclusion in global value chains, etc. We also include country-year fixed effects (λ_{ct}) to control for the impacts of globalisation, trade openness, competition, macroeconomic conditions and other country differences. In addition, we introduce technology domain-year fixed effects (υ_{jt}) to control for any systematic differences in patenting across technology domains, including differences in the use of patents across those technologies and shocks to individual technology domains at time *t*. Finally, we cluster standard error at city level (Moulton, 1990).

Results reported in Table 4 show that the number of patent applications by city *f* in all technology domains except for communications & tech (column 1) is positively correlated with cities' digital patent applications in specifications that control for city, technology and country-year fixed effects. The results also hold for our preferred specification that includes technology-domain-year fixed effects (column 2). This evidence suggests cities benefit from positive dynamics from engaging with digital technology.

Table 4. Linear regression of cities' patent applications and patent applications in Communications & Technology

Dependent variable:	Number of patent applications per city and technology field				
	(1)	(2)	(3)	(4)	(5)
Patent applications per city in Communications & Tech (f,t-1)	0.009***	0.009***	0.006***	0.007***	0.008***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Patent applications per city in Communications & Tech (f,t-1) * Top 10% (c,1995)			0.020***		
			(0.006)		
Patent applications per city in Communications & Tech (f,t-1) * Top 5% (c,1995)				0.031***	
				(0.010)	
Patent applications per city in Communications & Tech (f,t-1) * Top 1% (c,1995)					0.036
					(0.025)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Technology domain fixed effects	Yes	No	No	No	No
Technology domain-year fixed effects	No	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,655,495	2,655,438	2,655,438	2,655,438	2,655,438
Adjusted R-squared	0.274	0.275	0.275	0.275	0.275

Note: Standard errors clustered at the city level are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Next, we implement modified regressions that include an interaction term between the digitalisation measure and a measure, $topCity_f$, which indicates the position of the city among the top patenting cities at country-level in 1995, the first year that our database provides. The purpose of this specification is to understand whether leading cities in the pre-period benefit more than other cities from digital patents. The measures we use are dummies that equal to 1 if the city is in the top 10%, 5% and 1% in terms of total patents at country-level. The estimated equation is the following:

$$patents_{fct,j-dig} = \alpha + \beta^{dig^I} * dig\_patents_{fct-1} + \\ + \beta^{topDig} * dig\_patents_{fct-1} * topCity_f \\ + \beta^{pop} * PopSize_{ft} + \gamma_f + \upsilon_{jt} + \lambda_{ct} + \varepsilon_{fjct} \tag{1b}$$

where all variables are as before. β^{topDig} would be positive if digital patents are associated with more patenting for the top ranked cities than for others.

Table 4 shows results from interactions of our variable of interest with the top city dummies. Findings in columns (3), (4) and (5) suggest that cities among top 10%, 5% or 1% of cities in terms of patent applications at the country-level in the initial period benefited more than those that were further behind.

Main analysis and findings

One limit of these regressions is that the indicator we used for our exploratory analysis is potentially endogenous to cities' overall patenting activities and may not be a good indicator of digital technologies' spread. Strong patenting activities in communications & tech may simply indicate the city is active in patenting more generally and consequently say little about the role of digital technology. Moreover, relying purely on patents to measure digital technology uptake may not proxy correctly the adoption of these technologies, which critically depends on infrastructure conditions and widespread uptake. In particular when it comes to the communication and exchange dimensions of digital technology, a critical mass of users is needed for these technologies to have expected benefits.

We consequently use an alternative approach that has been used extensively in empirical analysis, following Rajan and Zingales (1998), notably Nunn (2007), Chor and Manova (2012) and Paunov (2016). We measure digitalisation by an indicator of technology-reliance on digital patents *(j)* that is interacted with an indicator of digital infrastructure, $digInfra_{ct-1}$, by country and year (*ct*).

As measures of digital infrastructure adoption we apply two alternative indicators: i) the number of fixed broadband subscriptions per capita and ii) the Internet adoption rate, for country *c* in year *t-1* (Figure 13 above). Our indicator of reliance of patents of technology field j, computed at 4-digit IPC codes, on digital technologies is obtained by computing the share of patents in the specific technology field *j* that have a technology field code belonging to the group of digital patents as identified in Inaba and Squicciarini (2017). The digitalization index can hence be constructed as follows:

$$dig_{jct} = \theta_{ct} * \left(\frac{\sum_{i=1}^{N} \gamma_i}{N}\right)_j$$

Where θ_{ct} represents the infrastructure measure (i.e. share of internet users and broadband subscriptions per capita), γ_i is the ICT class share in a patent *i* and *N* is the total number of patent applications. The ICT reliance component is computed as an average for the pre-period 1995-1999. We standardise the digitalisation index by demeaning and dividing by the standard deviation for ease of interpretation and comparability between results.

Our main specifications are as follows:

$$patents_{fjct} = \alpha + \beta^{dig^{II}} * dig_{cjt-1} + \beta^{pop} * PopSize_{ft} + \gamma_f + \upsilon_{jt} + \lambda_{ct} + \varepsilon_{fjct} \tag{2a}$$

$$\begin{aligned} patents_{fjct} = \alpha + \beta^{dig^{II}} * dig_{cjt-1} + \\ + \beta^{topDig^{II}} * dig_{cjt-1} * topCity_f \\ + \beta^{pop} * PopSize_{ft} + \gamma_f + \upsilon_{jt} + \lambda_{ct} + \varepsilon_{fjct} \end{aligned} \tag{2b}$$

where our coefficient of interest, $\beta^{dig^{II}}$, captures the role of digital technologies in cities' patenting under the assumption that if those technologies have an impact on patenting it should be more pronounced for patents in those fields that are more affected by digital technologies than others. As in the previous specification, we include city population size and a battery of fixed effects including city fixed effects (γ_f), technology-year fixed effects (ν_{jt}) and country-year fixed effects (λ_{ct}). These ensure that our evidence does not pick up city differences, specific technology- and country-year shocks. Standard errors are clustered at country-technology level (Moulton, 1990).

Results for specification (2a) are shown in Table 5 below and show a positive significant effect for a baseline specification based on the indicator of the Internet adoption rate that uses technology and country-year fixed effects (column 1), adding city fixed effects (column 2) and also for our preferred set of fixed effects that includes technology-year fixed effects to take into account any shocks that vary across technologies in specific years (column 3). Column (4) shows results also hold for our alternative measure of digital infrastructure, broadband adoption.

Table 5. Regression results of the effects of digitalisation on cities' patent applications

Dependent variable:	Number of patent applications per city and technology field			
	(1)	(2)	(3)	(4)
Digitalisation Index - Internet (c,j,t-1)	0.017***	0.015***	0.074***	
	(0.004)	(0.004)	(0.008)	
Digitalisation Index - Broadband (c,j,t-1)				0.062***
				(0.006)
City fixed effects	No	Yes	Yes	Yes
Technology fixed effects	Yes	Yes	No	No
Technology-year fixed effects	No	No	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes
Observations	2,717,955	2,717,955	2,717,941	2,716,304
Adjusted R-squared	0.210	0.286	0.288	0.288

Note: Standard errors clustered at the country-technology level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Next, we explore to what extent top cities benefit more than others by interacting our digitalisation index with dummies for top 10%, 5% and 1% cities in the initial period (1995) at both country and country-technology-levels. Our results show that cities that are among the top gain more from digitalisation (Table 6a and b). Results of column (1) of Table 6a indicate that a one standard deviation increase in digitalisation is associated with a 10% higher gain in patent applications compared to cities outside of the top 10%. The premium is even higher (at 13% and 15% respectively) for the top 5 and 1% (columns 2 and 3 of Table 6a). Our results are confirmed using our alternative index, broadband adoption. As regards cities' rankings by technology, which extends to cities with leadership in specific technology fields but less strong leadership across other technologies, the same premium is of around 5% for top cities (Table 6b).

Table 6a. Regression results of the effects of digitalisation on top cities' patent applications, ranking at country level

Dependent variable:	Number of patent applications per city and technology field					
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalisation Index - Internet (c,j,t-1)	0.060***	0.063***	0.062***			
	(0.008)	(0.008)	(0.007)			
Digitalisation Index - Internet (c,j,t-1) * Top 10% (c,1995)	0.108***					
	(0.010)					
Digitalisation Index - Internet (c,j,t-1) * Top 5% (c,1995)		0.139***				
		(0.011)				
Digitalisation Index - Internet (c,j,t-1) * Top 1% (c,1995)			0.157***			
			(0.010)			
Digitalisation Index - Broadband (c,j,t-1)				0.046***	0.047***	0.050***
				(0.006)	(0.006)	(0.006)
Digitalisation Index - Broadband (c,j,t-1) * Top 10% (c,1995)				0.096***		
				(0.009)		
Digitalisation Index - Broadband (c,j,t-1) * Top 5% (c,1995)					0.124***	
					(0.010)	
Digitalisation Index - Broadband (c,j,t-1) * Top 1% (c,1995)						0.147***
						(0.010)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Technology-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,717,941	2,717,941	2,717,941	2,716,304	2,716,304	2,716,304
Adjusted R-squared	0.298	0.299	0.295	0.295	0.296	0.293

Note: Standard errors clustered at the country-technology level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6b. Regression results of the effects of digitalisation on top cities' patent applications, ranking at technology-country level

Dependent variable:	Number of patent applications per city and technology field					
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalisation Index - Internet (c,j,t-1)	0.075***	0.077***	0.074***			
	(0.008)	(0.008)	(0.008)			
Digitalisation Index - Internet (c,j,t-1) * Top 10% (c,j,1995)	0.059***					
	(0.010)					
Digitalisation Index - Internet (c,j,t-1) * Top 5% (c,j,1995)		0.065***				
		(0.010)				
Digitalisation Index - Internet (c,j,t-1) * Top 1% (c,j,1995)			0.048***			
			(0.006)			
Digitalisation Index - Broadband (c,j,t-1)				0.055***	0.063***	0.060***
				(0.007)	(0.007)	(0.006)
Digitalisation Index - Broadband (c,j,t-1) * Top 10% (c,j,199				0.046***		
				(0.009)		
Digitalisation Index - Broadband (c,j,t-1) * Top 5% (c,j,1995)					0.056***	
					(0.009)	
Digitalisation Index - Broadband (c,j,t-1) * Top 1% (c,j,1995)						0.046***
						(0.006)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Technology-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,717,935	2,717,935	2,717,935	2,716,298	2,716,298	2,716,298
Adjusted R-squared	0.291	0.290	0.289	0.290	0.290	0.289

Note: Standard errors clustered at the country-technology level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

7. Policy dimensions

What do these results imply for public policies? We take the perspective of national policy makers who ask about the optimal allocation of innovation-related resources across geographical areas. The objective function of such policies is twofold. One objective is to maximise aggregate efficiency, i.e. how much innovation can be achieved from public spending in support of innovation. The other objective is distributional: ensuring that all geographic areas are engaged in the innovation dynamics, as cities and regions critically shape engagement in and consequently benefits from innovation (OECD, 2017).

The extent to which these two objectives are coincident or contradictory depends on the relative strength of geographical concentration and dispersion forces. If the agglomeration forces of digital technologies outlined in the framework section are strong, then an efficient allocation of innovation across space will be unequal and may exclude some regions from the innovation dynamics, whereas the opposite might work in case forces in favour of more equal distribution are stronger.

Our empirical results as outlined in the previous section support the hypothesis that digitalisation tends to favour agglomeration more than dispersion, pointing to a trade-off between efficiency and equality in the geography of innovation across cities. Put differently, the most dynamic cities in terms of patenting benefit more in their patenting performance from digital technology. The implications on the geography of innovation, however, depend on the policy response provided. Investing more in digital technologies across cities is attractive to the extent that the cost of digital technologies continues to decrease while the quality of the services digital technology provides continues to improve. The benefits from those investments, however, require further empirical analysis as improvements may or may not change the relative importance of the agglomeration and dispersion dynamics outlined in the framework section. More investments across cities may, depending on the evolution of those dynamics, change little or much to the differential ways in which cities are engaged in innovation in the digital age.

With the objective of maximising the aggregate impact of public spending on innovation, some policies have (directly and indirectly) supported more concentration of innovation. Some countries have attempted to leverage the agglomeration advantages by providing more support to successful local ecosystems. The assumption is that due to stronger agglomeration gains, the return on public research spending will be higher in such places. For instance, the French “poles de compétitivité” allow firms located in certain selected places to get more public support for innovation than similar firms located elsewhere. Such policies obviously increase geographical polarisation, as it is their very objective. Moreover, regular innovation policies that are geography neutral might de facto also reinforce geographical polarisation. Resource allocation mechanisms which target the most effective prospective users (e.g. competitive research funding) will be geographically concentrated if the best laboratories are geographically concentrated. The “Matthew effect”, well known for researchers, might therefore also operate at the level of cities.

Are there ways to boost both aggregate efficiency of public spending in innovation while reducing the concentration in innovation? One such policy approach is called "smart specialisation". It argues that regions that are lagging in terms of innovation should embed innovation in existing economic activities and regional comparative advantages. Hence, most often, it will not be high tech, radical innovation, but the development of new products and processes based on existing know-how and established activities, or at least using these as the starting point for diversification. This sort of innovation typically does not result in patents and would not be detected in a setting as the one of this study, but it can nonetheless be a significant source of new jobs and income. This approach might also not require significant spending on R&D and would not therefore drain innovation-related resources, but it could have a high return locally. As it is better adapted to areas lagging behind, it might also reduce spatial inequalities. However, it would probably do little in terms of reducing concentration of innovation among top and second-tier cities.

Another important pre-requisite for regional participation in the digital age consists in providing for connectivity, access to data and strengthening linkages with top cities. Policies aimed at using innovation to boost the development of lagging regions should ensure, first, sufficient connectivity of the concerned regions (broadband access, etc.) and connection to regional, national and global platforms for innovation. Access to data is critical to innovation and consequently the capacity of cities to engage in digital innovation relies on having such access and the right infrastructure for data exploitation (Guellec and Paunov, 2019). Exploiting opportunities to connect to top cities also has to be part of the pre-requisites for other cities to catch-up. Mobility programmes for the highly skilled may help establish new collaborations with top cities, which, as shown in the descriptive sections, concentrate patenting activities at global and national levels. The extent to which those global collaborations alleviate regional disparities in patenting in the digital age and the extent to which such collaborations will be effective (compared to collaborations of the top with the top) remain open questions to be addressed in further research.

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