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Emerging 21st Century technologies: Is Europe still falling behind?

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Abstract

Firms and countries that specialise in emerging technologies tend to have a higher chance of becoming or remaining competitive in the future. This paper aims to analyse the most dynamic areas of technological competition between 2010 and 2019 and to identify which actors are leading in those areas. We analyse patenting dynamics in four major patent offices (USPTO, EPO, JPO, KIPO), to have a global landscape of technological dynamism, and we use the IPC patent classification system to proxy the technological areas. After examining patenting growth patterns in all 4-digit IPC classes, we built a score to classify the emergent technological areas across the four offices. Our results indicate twelve "emerging" IPC classes, which are related to software engineering, digital communication, IT methods for management, medical technology, pharmaceuticals, energy conservation, games, biotechnology and semiconductor devices. We find that European firms do not hold a leading share in any of these IPC classes. This is particularly true in emerging areas such as software engineering, energy conservation and semiconductor devices, which are likely to be critical to succeed in the new techno-paradigms related to digitalization and clean energy.

Keywords: Emerging technologies; Technology policy; Technological competition; European Paradox; Matched patent-firm data

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1. Introduction

In the last decades, a vast literature has emphasised that economic growth and development are linked to increases in productivity, technological advantages and innovation. Thus, it is important to analyse the patterns of technological specialisation at a global level, as this can reveal the capacity of different countries, regions and companies to compete. Understanding why certain areas of technological knowledge grow faster than others is of key importance because they indicate what areas are governing the Schumpeterian dynamics of "creative destruction", with the firms and countries leading on those technological areas eventually being those that will earn higher economic returns in the near future (Rosenberg, 1976; Schumpeter, 1942). It is well established now that developing countries that enter early on in the new key technologies of each historical period are the ones that are most successful in catching up, with the mastering of the emerging technologies accounting for changes in industry leadership (Fagerberg and Godinho, 2004; Lee and Lim, 2001; Lee and Malerba, 2017).

In this paper we identify the emerging technology areas of the 21st century, and we ask if European firms are specialised in those emerging areas in relation to other regions. If technological competition and innovation are at the heart of economic performance, then it becomes evident that learning which areas of technological knowledge grow faster than others is relevant to understand how innovation capacity and competitive positioning will progress (Dosi, 1982; Verspagen, 2007). Successful technological competitors are the ones that react to technological change (Cantner et al., 2009; Schiavone, 2011). Thus, national governments may find it useful to monitor the global technological frontier for changes that may be important to their countries' technological standing and anticipate social, political, or economic effects.

To understand this technological competition and which technological fields are growing faster, we need to look at technology domains and assess each domain for its potential (Cantner et al., 2009; Malerba, 2002). In this context, patents are valuable resources to analyse technological competition in technological fields (Farmer and Lafond, 2016; Magee et al., 2016; Singh et al., 2020). Patent data not only allow tracking development trends of technology, but also help in identifying the main competitors, assess the capabilities needed for technological innovation and are helpful in defining an intellectual property rights strategy.

In what's next in this paper, we will first frame our research question, analyse what the most dynamic areas of technological competition are between 2010 and 2019, and identify which actors (countries and firms) are becoming specialised in those areas. We will focus on patenting dynamics in four major patent offices (EPO, JPO, KIPO, USPTO)[1] by using 4-digit IPC (International Patent Classification) patent classification

[1] EPO – European Patent Office; JPO – Japanese Patent Office; KIPO – Korean Intellectual Property Office; USPTO – United States Patent and Trademark Office.

system[2] as indicators of technological areas. We will address particularly how European firms are performing in the context of the most relevant emerging technologies.

2. Background

2.1. Technological competition, R&D and Europe

Many scholars have studied the impact of R&D, knowledge production, patenting activity and innovation systems on the international competitiveness of both countries and industries (Breschi et al., 2000; Dosi et al., 1990; Fagerberg and Srholec, 2008; Freeman et al., 1982; Nelson and Winter, 1982). This work clearly shows a positive relationship between R&D, patenting activities and international competitiveness. This literature extends the pioneering work of Posner (1961), who considered that a country's comparative advantage emerged from its relative position in some technological activities vis-à-vis its competitors.

Following this Schumpeterian/evolutionary perspective, technological asymmetries between countries result from different product and process innovation capacities, with cost advantages and international competitiveness arising from the technological knowledge generated by innovation activities (Fagerberg, 1987; Fagerberg and Godinho, 2004; Verspagen, 1991). At the same time, it is well known that countries' technological capabilities are not equally and randomly distributed among all possible technological areas, but instead tend to be relatively concentrated in specific areas (Archibugi and Pianta, 1992; Evangelista et al., 2018). This is mainly because innovation processes tend to be cumulative, knowledge spillovers and interactions tend to be localised, which tend to result in technological accumulation developing along with sticky and spatially bounded specialisation patterns (Cowan et al., 2000; Jaffe et al., 1993; Maurseth and Verspagen, 2002). Therefore, different countries and regions have different competitiveness levels, stemming from different innovation competencies and profiles of technological specialisation.

Overall, more industrialised countries distribute their innovative activities among a broader set of technologies, while developing countries specialise in areas far from the technological frontier (Archibugi and Pianta, 1992; Malerba and Montobbio, 2003; Urraca-Ruiz, 2019). If this asymmetry is maintained, particularly if there are no technological discontinuities (Perez and Soete, 1988), the technological gap will remain and differences in productivity across countries tend to be maintained (Brezis et al., 1993; Verspagen, 1991). Thus, under a competitive environment, the leading countries seek to preserve their competitive advantages in markets of their interests. However, historically, there were "windows of

[2] The IPC is an internationally uniform classification of patent documents, and its primary purpose is the establishment of an effective search tool for the retrieval of patent documents by intellectual property offices and other users (WIPO, 2020). Another important purpose of this classification is that it serves as a basis for the preparation of industrial property statistics which in turn permit the assessment of technological development in various areas.

opportunity" for industrial leadership to change and catch-up cycles[3] to happen in several sectors (Landini et al., 2017). The concept of "windows of opportunity" was first used by Perez and Soete (1988) to refer to the role of the rise of new techno-economic paradigms in the leapfrogging of latecomers who take advantage of a new paradigm and overtake incumbents. According to Lee and Malerba (2017), there are three types of "windows of opportunity". One dimension is related to changes in knowledge and technology (e.g., a new technology or radical innovation is introduced, and the incumbent leader fails to change its technological capabilities and is locked-in to the existing technology). The second dimension pertains to changes in demand of users and consumers (e.g., leaders do not respond to a new demand because they are successful within their existing markets and customers). And finally, the third includes changes in institutions and public policy (e.g., government interventions like the establishment of R&D programs that affect the accumulation of domestic firms' capabilities and create "disadvantages" for incumbent firms).

In our work, we will focus on "windows of opportunity" related to changes in technology and how industry leaders are adapting to them, particularly in Europe. These dynamics of change make sense in the perspective of successive techno-economic paradigms (Freeman and Louçã, 2002; Freeman and Perez, 1988) or even in the perspective of the four industrial revolutions (von Tunzelmann, 2003), in which England gave way to the USA (United States of America) leadership, which in turn competed with Europe in the second industrial revolution (chemical and automobile), while Japan and Korea had their catching-up processes in the third industrial revolution (electronics and computing) (Lee and Lim, 2001).

Concerns with the possibility of Europe falling behind technologically are not new. Already in the 1960s that was the topic of the highly influential book "Le Défi Américan" (Servan-Screiber, 1967). Careful observation in the 1980s led however to the conclusion that there was "no justification for assuming general European technological backwardness" nor there was "convincing evidence that Western Europe is relatively backward in converting technology into economically efficient innovation" (Patel and Pavitt, 1987). Later, in the early 2000s, it was believed that Europe could become the "most dynamic knowledge economy in the world", in the sequence of the proposals put forward at the European Council summits held in Lisbon (March 2000) and Barcelona (March 2002) (Archibugi and Coco, 2005). Moreover, there was a general perception that institutional innovation, with the creation of the European single currency, could help in creating the proper framework for European larger technology-intensive companies thriving in the most dynamic global markets.

Currently, technological competition between China, Europe, Japan, South Korea and the USA is intensifying. Since 2000, total global R&D expenditures have more than tripled in current dollars, from

[3] Process of closing the gap in global market shares between firms in leading countries and firms in latecomer countries.

$676 billion to $2.0 trillion in 2018 (OECD, 2021). In 2000, China accounted for nearly 5% of global R&D, joining the USA, Japan, South Korea, and the European Union (EU) as the largest funders of R&D. From 2000 to 2018, while China's share of global R&D rose from 5% to 26%, the USA share fell from 40% to 28%, EU share fell from 25% to less than 20%, Japan's share fell from 15% to 8%, and South Korea share grew from 4% to 5%.[4] In relative terms, in 2000, the EU allocated 1.67% of its GDP to R&D (GERD), almost double that of China (0.89%). Since then, though, China's commitment to R&D spending has been persistent, overtaking the EU bloc in 2012. In 2018 China spent 2.14% of its GDP in R&D, the USA 2.83%, Japan 3.28%, South Korea 4,5% and the EU only 2,03% (OECD, 2021).

The share of business R&D as a total of R&D expenditure is also lower in the EU (at 67%) than in the USA (73%), or China, Japan and South Korea (78% to 80%). According to a recent report by EIB (2021) the private sector is driving the rapid increase in R&D expenditure in China and South Korea and the decline of the EU, USA and Japan. Although the EU does still have a number of global tech firms, the share of EU firms in the top 2500 R&D investors has fallen over time (Grassano et al., 2020). This fall is mostly attributable to the emergence of Chinese firms. While the USA remains an innovation leader, the number of Chinese companies included on the list of big R&D spenders has risen fast – from 0.5% in 2006 to 20% in 2018 – and is now higher than the number of EU companies (EIB, 2021).

When thinking about a European strategy for innovation, it should be remembered that the continent has vast regional disparities, and that they are much wider in terms of scientific and technological competencies than in other aspects of economic life such as income or trade (Archibugi and Coco, 2005). For example, in 2019, the EU country with the highest level of GERD, Sweden, displays an R&D intensity that is seven times higher than the country with the lowest, Romania (OECD, 2021). In order to develop an appropriate innovation strategy, Europe must acknowledge that it is an agglomeration of different innovation systems with each one of them retaining substantial autonomy. What the old continent gains in variety and diversity, it loses through a lack of cohesion and central policy decision-making (Archibugi and Coco, 2005). This leads to potential trade-offs between the use of resources for the diffusion of knowledge in the peripheral parts of the region (widening) or for generating new knowledge in the core countries (deepening). Usually, EU policy has tried to deal with this trade-off by prioritising funding schemes that require the involvement of firms and institutions from several member countries (e.g. Framework Programmes), or by developing strategies, such as smart specialization, that emphasizes the need for regions and countries to prioritize selected vertical areas (specialization) by building on existing strengths and assets (smart) as a base for innovation-driven growth (Foray et al., 2009).

[4] https://fas.org/sgp/crs/misc/R44283.pdf

Nevertheless, R&D investment is getting more and more concentrated, with a small number of companies, sectors and countries accounting for a large share of business R&D expenditure (Pellens et al., 2018). The emergence of a "superstar effect", which sees most of the gains of this new era captured by a small number of strong companies, raises the stakes even higher for Europe to rise to the innovation challenge (Autor et al., 2020; Bughin et al., 2019). Although the EU still hosts large incumbent R&D leaders, it seems to be less well placed to host entrepreneurial talents riding on new technology shifts to displace incumbents and take up new leading R&D positions (Veugelers, 2018). With the USA, and more recently China, hosting most of the new R&D leaders, especially in digital sectors but also in other sectors, the weaker creative-destruction power of the EU corporate R&D system could contribute to a shifting regional R&D capacity to Europe's detriment. In this context, it has been argued that the EU should steer public support to set up a few large corporations in the areas of greater scientific and technological opportunity (Archibugi and Mariella, 2021).

2.2. Emerging technologies

There is a broad interest in emerging[5] technologies. As argued before, the rise of disruptive technologies allows certain companies, regions and countries to take advantage of windows of opportunity to catch up with the technological leaders, as those newcomers specialise in the novel key technologies (Brezis et al., 1993; Lee and Malerba, 2017; Perez and Soete, 1988). However, there is no agreed conceptual definition of what an "emerging technology" is. For example, Porter et al. (2002) define emerging technologies "as those that could exert much enhanced economic influence in the coming (roughly) 15-year horizon." Cozzens et al. (2010), on the same line of thought, argue that it is "a technology that shows high potential but hasn't demonstrated its value or settled down into any kind of consensus." Hung and Chu (2006) perspective, centred on the importance and economic impact and competition brought by new technologies, builds upon a broader view such as the one provided by Martin (1995), who discusses technological competition in the context of its extensive societal impacts.

In a comprehensive literature review, Rotolo et al., (2015) made an effort to combine different pieces and define what an emerging technology is. In their work they highlighted five main attributes: i) radical novelty, technologies that "fulfil a given function by using a different basic principle as compared to what was used before to achieve a similar purpose"; ii) fast growth, technologies that "show relatively fast growth rates compared to non-emerging technologies"; iii) coherence, technologies that "have acquired a certain identity and momentum from those still in a state of flux and therefore not yet emerging"; iv) prominent impact, technologies that exert significant influence "on the socio-economic system by

[5] The word 'emerging' or 'emergent' means "the process of coming into being, or of becoming important and prominent" (New Oxford American Dictionary).

changing the composition of actors, institutions, patterns of interactions among those, and the associated knowledge production processes"; and v) uncertainty and ambiguity, technologies that "are characterised by uncertainty in their possible outcomes and uses, which may be unintended and undesirable, as well as by ambiguity in the meanings different social groups associate with the given technology." Although some of these attributes are easier to operationalise empirically than others, this multidimensional characterisation is very useful for studying and classifying emerging technologies.

In the literature, we can find basically two types of approaches to evaluate emerging technologies: 1) qualitative evaluation by experts; and 2) quantitative evaluation based on data. On the qualitative side, various methods have been adopted to identifying promising technologies, such as the analytic hierarchy process, Delphi exercises, roadmaps, and foresight (e.g. Song et al., 2018). However, as the complexity of technology increases and the scope of technological applications expand, the validity of qualitative evaluation by experts may be limited. To complement expert decision-making, quantitative approaches have been developed. One of the most commonly adopted approaches is patent analysis (e.g. Arora et al., 2012; Farmer and Lafond, 2016). Patent documents contain semi-structured bibliographic information in addition to the descriptive information that explains the technological components, principles, and benefits in detail. Patent data are easy to assess, open to the public, and have been accumulated for several decades.

2.3. **Patenting dynamics**

Patent-based indicators have been widely used as an innovation output measure for several decades (Griliches, 1990; Schmookler, 1950). There are numerous reasons why this is approach is so enduring. There is a recognition that patent analysis allows for tracking the growth of new technologies. Patent databases give easy access to information and enable comparison between countries being therefore suitable for analysing long-term cross-sector technology trends (e.g. Acs et al., 2002; Hu and Mathews, 2005; Kleinknecht et al., 2002). Given this potential, patent based indicators have been widely used to track the innovative performance of countries, regions and companies (e.g. Buesa et al., 2010; Godinho and Ferreira, 2012; Griliches, 1990; Nagaoka et al., 2010; Pavitt, 1985).

Nevertheless, it has also been recognized that patents as an innovation indicator have shortcomings. The intensity of patent demand varies widely across sectors, patent usage depends on national laws, the scope of protection and patent quality vary across different patent offices, patents only reflect technological innovation, and not all patents lead to innovation (Archibugi, 1992; Cohen et al., 2000; Griliches, 1990; Pavitt, 1985). One possibility to overcome some of these shortcomings, which is explored in this paper, is to use composite measures as proxies for innovation outputs, such as an aggregate measure of patenting

across the main patent offices worldwide. Such an approach is also justifiable since the studies that rely on counts of patents filed at one single office often suffer from selection bias (de Rassenfosse et al., 2014).

According to the WIPO's 2019 report (WIPO, 2019), patent grants have been growing worldwide every year since 2004 and reached 1.42 million in 2018. In 2018, the largest number of patents in force was recorded in the USA (3.1 million), followed by China (2.4 million), Japan (2.1 million) and South Korea (1 million). Asia's share of all grants filed worldwide increased from 52.4% in 2008 to 57.1% in 2018, being the only world region, whose share of all grants increased substantially between the two periods.

In terms of dynamism in relation to technological areas, a recent report by Breitinger et al. (2020) used patent families to identify what they called "cutting-edge technologies". Their approach first identifies "world class patents" using an indicator of "patent quality" based on market coverage (number of offices which the same priority was filed) and technological relevance (forward citations). Then, after identifying a restricted set of "world class patents", they identify 58 "cutting-edge technologies" (divided in ten broad areas) using an ad-hoc combination of patent classes and subject-specific keywords: **Environment** (waste management, sustainable packaging, water treatment, carbon capture, recycling), **Energy** (battery technologies, biofuels/biomass, energy-saving procedures, energy conversion, geothermics, photovoltaics, solar thermal energy, hydropower, wind energy), **Nutrition** (biocides, fertilizers, functional food technologies, green biotech, precision farming), **Infrastructure** (5G, Internet of things, construction, smart city, smart grids, smart home), **Digitalization** (big data, blockchain, cloud computing, artificial intelligence, quantum computing, virtual/augmented reality), **Security** (cyber security, fintech and payment, network security, product security, defense), **Materials** (carbon-graphene, functional materials, advanced coatings, nanomaterials, quantum tech, composites), **Health** (digital medtech, diseases, gentech, vaccines, precision medicine, rational drug discovery), **Mobility** (autonomous driving, drones, electric vehicles, smart traffic, air and space tech), **Industry** (additive manufacturing, process automation, robotics, smart factory).

In our work, instead of relying on manual keyword search, we will use the established 4-digit IPC classes growth trends to identify what can be considered "emergent technologies". Based on Rotolo et al., (2015) we will use three indicators to measure three of the "emergent" attributes he identified: i) relatively fast growth (growth rate of IPC total share of grants in each office from 10-14 to 15-19); ii) coherence (growth rate of absolute IPC grants in each office from 10-14 to 15-19); and iii) prominent impact (IPC total share

of grants in each office in 15-19). The attributes "radical novelty"[6] and "uncertainty and ambiguity"[7] will not be retained in our analysis due to data limitations. Because in most previous literature related to technology emergence, the analytical results are usually binary (yes or no), the multidimensional character of our approach to generate an "emergent technology score" could be a promising method (Daim et al., 2006).

[6] Radical novelty, is characterized as an attribute of a technology that "fulfils a given function by using a different basic principle as compared to what was used before to achieve a similar purpose" (Rotolo et al., 2015). In its simplest form, novelty detection is sometimes operationalized by the emergence of a new term, or a new combination of terms, within the text of patent document. More recently, radical novelty has been operationalized by Verhoeven et al. (2016) by using patent classification and citation information to classify ex-ante a certain invention (patent) along three dimensions of novelty (new recombination of IPC's in a certain patent, new recombination between the IPC codes of a certain patent and an IPC code from its referenced patents, new recombination between an IPC-code of a certain patent and a scientific field from its referenced scientific publications).

[7] Some studies have examined news articles, editorials, review and perspective articles on professional and academic journals to qualitatively assess the degree of uncertainty and ambiguity associated with an emerging technology as well as to identify possible multiple visions of the future associated with the technology.

3. Data and Methods

3.1. Data

Our primary source of data is ORBIS-IP[8], a large data set provided by the Bureau Van Dijk. ORBIS-IP is a recently released data set combining rich firm-level and patent-level information for more than 300 million companies and more than 110 million patent records (Benassi et al., 2020). Certain types of patent indicators are more appropriate for certain uses, and careful consideration of the research objective is needed to select the most appropriate indicator. For instance, national data provided by the USPTO are widely used to study inventive activity in the USA. However, national databases suffer from geographical bias since applicants from the USA, and neighbouring countries, are more prone to apply to the USPTO. Two ways to avoid the geographic bias are either to count 'international' patents filed under the Patent Cooperation Treaty (PCT), or to count applications filed simultaneously at several national offices (e.g., the 'triadic families'). Yet, these indicators are very exclusive since they count patent applications having an international market perspective, with very high costs, which are often owned by large firms with a substantial patenting budget (De Rassenfosse et al., 2013). Since we intend to analyse technological competition and patenting dynamics worldwide in recent years, we focus on patent grants independently conceded at four of the largest intellectual property offices in the world between 2010 and 2019: EPO[9], JPO, KIPO and USPTO. We decided to exclude the patents in the China National Intellectual Property Administration (CNIPA) because the way patent examiners classify patents in CNIPA by IPC code is substantially different from the other offices (Meguro and Osabe, 2019), and this would make comparability difficult. Still, we believe our approach is comprehensive enough to cover the vast majority of all patenting activity worldwide and allow us to grasp to what extent there are heterogeneous technological dynamics in different regions. Regarding the reference date, we choose to analyse patent grants instead of priorities/applications/publications because different offices provide applicants with a number of choices regarding procedures and timelines, which could impact significantly our results. In all four offices, the date of grant effectively terminates prosecution of a specific application and establishes the date upon which infringement may be charged. This choice allows us comparability between offices.

Another crucial decision in our work is how to classify patents in groups of "technologies". Several patent classifications have been used by different institutions for many years such as the International Patent Classification (IPC), Cooperative Patent Classification (CPC), WIPO Technology Classification or the US

[8] https://www.bvdinfo.com/en-gb/our-products/data/international/orbis-intellectual-property

[9] An important issue when analysing patent grants from the EPO is that there are patents being granted in EPO offices (e.g. Germany, Spain, etc.) that don't go through EPO system. Still, we think that using EPO grants by 4-digit IPC is a good proxy for technological dynamism in the European area.

Patent Classification. In our work, we decided to use the 4-digit IPC codes because it is a classification that is standardized across the four offices and is a classification that, at any single moment in time, the patents are classified according to a coherent, up-to-date taxonomy[10]. The IPC system is considered the "lingua franca" of the patent classification, and many other authors (e.g. Dibiaggio and Nesta, 2005; Jaffe, 1986) have used IPC codes as a proxy for technological competencies of firms/countries in specific sectors. IPC codes are assigned by patent examiners from the intellectual property office(s) publishing the patent document, and are used to retrieve patent documents and other relevant documents when searching for prior art. According to Adams (2001), there are two major advantages in the use of the IPC classification in relation to other methods to classify technologies (e.g. keywords). One, it enables a single inventive concept (code) to be represented concisely and unambiguously (keywords might relate to different technologies); two, since the IPC is published in many different languages, it allows cross-country comparisons (keywords need to be translated). IPC is a hierarchical classification system, divided into eight technological sections, covering approximately 70,000 subdivisions. In our main analysis, we will use the 4-digit sub-classification which cover 650 IPC codes. We will also perform a robustness check with the 35 WIPO technological classes (Schmoch, 2008), which will also be used to contextualise some of our descriptive findings. In order to reduce noise, some of the analysis in this paper are shown for two 5-year windows starting in 2010 and ending in 2019.

3.2. Method to identify emergent technologies

After identifying our "technologies" (4-digit IPC codes), the next challenge is to select which theoretical elements of the various definitions of technical emergence are possible to operationalize empirically. Since our major objective is to compare technological dynamics in different offices, and since some of those patent offices don't have organized information about the references and text of each patent grant, the most reliable information we could retrieve from ORBIS-IP was the number of grants by year and IPC code for each patent office. As argued in section 2.3. the theoretical components we were able to operationalize using this data for all 4-digit IPC codes in all four patent offices were:

1) Relative fast growth – The growth rate of the total share of patent grants from an IPC in an office from 10-14 to 15-19. This indicator allows us to differentiate emerging trends of a specific technology (IPC) against the overall increasing trends;

2) Coherence – The growth rate of the absolute value of patent grants from an IPC in an office from 10-14 to 15-19. This property is usually operationalized by looking at the scientific discourse around a specific

[10] Observers at different points in time have a different idea of what is a consistent classification of the past, even when classifying the same set of past patents. The classification system cannot be well understood as a system in which categories are created once-and-for-all and accumulate patents over time. Instead, it is better understood as a system that is constantly re-organized (Lafond and Kim, 2019).

technology or by identifying emerging communities of inventors or researchers. Here we just assume that if a certain IPC code is getting more patent grants than others, it is becoming more coherent/established.

3) Prominent impact – Total share of patent grants from an IPC in an office in 15-19. Scientometric methods have troubles in identifying the impact of a technology in society due to a lack of data on societal needs. Here we assume if a certain IPC code is the one with more grants in our latest period of analysis, it is because it is the IPC code (technology) that has the greatest impact in the country of a certain office.

After defining which indicators to use as properties of an emerging technology, we computed a principal component analysis (Jackson, 1991) to reduce the three dimensions of analysis in all four offices to one component ("emergent technology score") that preserves data's variation as possible. We followed the next steps:

- For the selected indicators and office, we calculated z-scores (to allow comparability between indicators);
- We computed a principal component analysis (PCA) using all indicators in each period of interest, and we forced the PCA to estimate only one component (eigenvalues and eigenvectors can be provided upon request);
- We predicted the scores for all 4-digit IPC codes, and we analysed their distribution using histograms;
- We classified an IPC code as emergent by analysing its distance to the mean score (0). All IPC codes that scored 2 standard deviations above the mean score, were classified as emergent.

We end up with a list of 4-digit IPC codes that are classified by an emergence score, which can subsequently be used to analyse if specific firms/countries are more or less specialised in those technologies.

3.3. Method to identify applicants

Our next step is to identify who are the main applicants that are specialised in our emergent technologies. ORBIS-IP provides a firm/entity[11] identifier, called "bvdid", which uniquely identifies each company present in the data set (as previously mentioned, ORBIS-IP collects most of all incorporated firms in the world). Besides general information on applicants (e.g. bvdid, names and countries of origin), ORBIS-IP also indicates, for each patent application, the grant date, IPC code (s), patent office, number of claims, number of citations, among other information. Since some patents have more than one applicant and IPC codes, we had to make some decisions for our analysis. We choose to investigate only the first applicant

[11] ORBIS-IP also gives a "bvdid" to other types of entities such as universities or public research institutes. In this paper, when we refer to firms/entities, we are referring to all types of entities that have a "bvdid".

(bvdid) and IPC code in each patent.[12] Given that we are dealing with large numbers, this should not be a source of bias. Another important issue is that many companies have several subsidiaries. We used a correspondence table provided by ORBIS-IP, to combine all patents granted to subsidiaries with patents granted to the parent company. This allowed us to generate a dataset that includes information at the company level on the number of patent grants, IPC codes, year, office, firm nationality, among other info. In table 1 we present the descriptive statistics of our dataset for all patent classes and firms for which info is available. The office with best info at firm level in our dataset is the EPO. In this office, only 4% of all patent grants don't have firm identifiers. The office with the worst info is KIPO, where 25 % of patents don't have reliable firm info.

Table 1. Descriptive statistics on patent grants and firm numbers by office during 2010-2019

Office	Num patents	Num Firms	% patents with no firm info
USPTO	1960419	121969	13%
KIPO	1527879	87907	25%
JPO	1652017	40545	10%
EPO	797318	68902	4%

3.4. Approach to compare different countries regarding their specialisation in emerging technologies

As argued before, one of the main interests of this paper is to understand to what extent European firms have technological capabilities in emerging IPC classes. In order to do that, we use our "emergency technology score" to define which are the emerging IPC classes, and then we observe patent trends and relative technological specialisation of all companies from each region (all 38 member states of the EPO, Japan, Korea and USA) combined in all offices

First, we calculate how many patent grants all companies from a region have in all offices (EPO, JPO, KIPO, USPTO) in our emerging IPC classes. Second, we calculate the share of patents belonging to firms from a specific region in all offices combined. Then, since different regions have different specialisation patterns, we will also compute relative specialisation indexes (RSI) to assess the relative specialisation of firms from a region in a given IPC emergent between 2010 and 2019. We will do this by computing the revealed comparative index (Balassa, 1965):

$$RSI_{ri} = \frac{P_{ri}/\sum_i P_{ri}}{P_i/\sum_i P_i} \qquad (1)$$

[12] In our sample, 3.4% of all patents have more than one bvdid, and only 0.6% have more than two applicants.

where P is the number of patent grants from firms in a region ***r*** in a IPC class ***i*** in all four offices***.*** This index can be interpreted as a "comparative advantage". If a region ***r*** has a relative specialisation in IPC class ***i,*** it means that ***r*** has more patent grants on a certain emergent IPC class than the world average (RSI > 1).

The definition of the index implies that its value is necessarily null or positive but is not bound by an upper limit. For this reason, we will standardise this measure by forcing the RSI index to take values between -1 and +1 by computing the ratio of RSI minus one over RSI plus one:

$$NRSI = \frac{(RSI - 1)}{(RSI + 1)} \qquad (2)$$

The threshold value of the normalised relative specialisation index (NRSI) remains zero, but the asymptotic limits are now ±1.

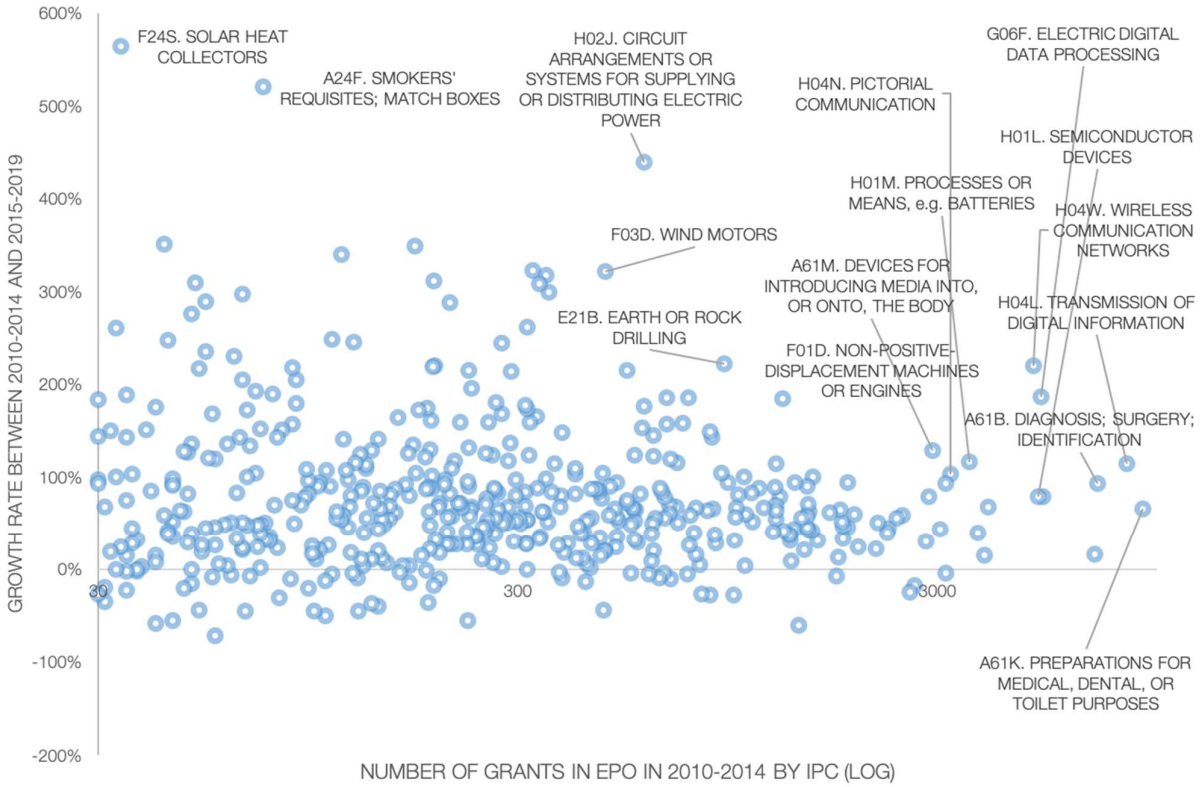
4. Results

4.1. Emerging IPC classes in EPO, JPO, KIPO and USPTO

4.1.1. European Patent Office (EPO)

In the EPO, the growth rate in number of grants between 2010-2014 and 2015-2019 was 63%. Applicants from the EPO region[13] filed 44% of the total number of grants in 2015-2019, while non-residents filed the remaining 56%. EPO applicants share decreased from 47% in 2010-2014 to 44% in 2015-2019. Fig. 1 shows the logarithm of patent grants by 4-digit IPC in 2010-2014 (x-axis) versus the growth rate of patent grants per 4-digit IPC between 2010-2014 and 2015-2019 (y-axis) in the EPO.

Figure 1. Most dynamic IPC patent classes between 2010-2014 and 2015-2019 in the EPO



Source: ORBIS IP
Note 1: In this graph, we only included 4-digit IPC classes with more than 0.01% of total patent grants in 2010-2014 to avoid extreme growth rate outliers.

We find that some of the IPC categories with more patent grants in 2010-2014 are related to medical technology and pharmaceuticals (e.g. A61B - diagnosis; surgery; identification; A61K - preparations for medical, dental, or toilet purposes; and A61M – devices for introducing media into, or onto, the body). Medical technology covers, for example, vaccination instruments, prostheses, surgical robots, computed

[13] The EPO has 38 member states: https://www.epo.org/about-us/foundation/member-states.html

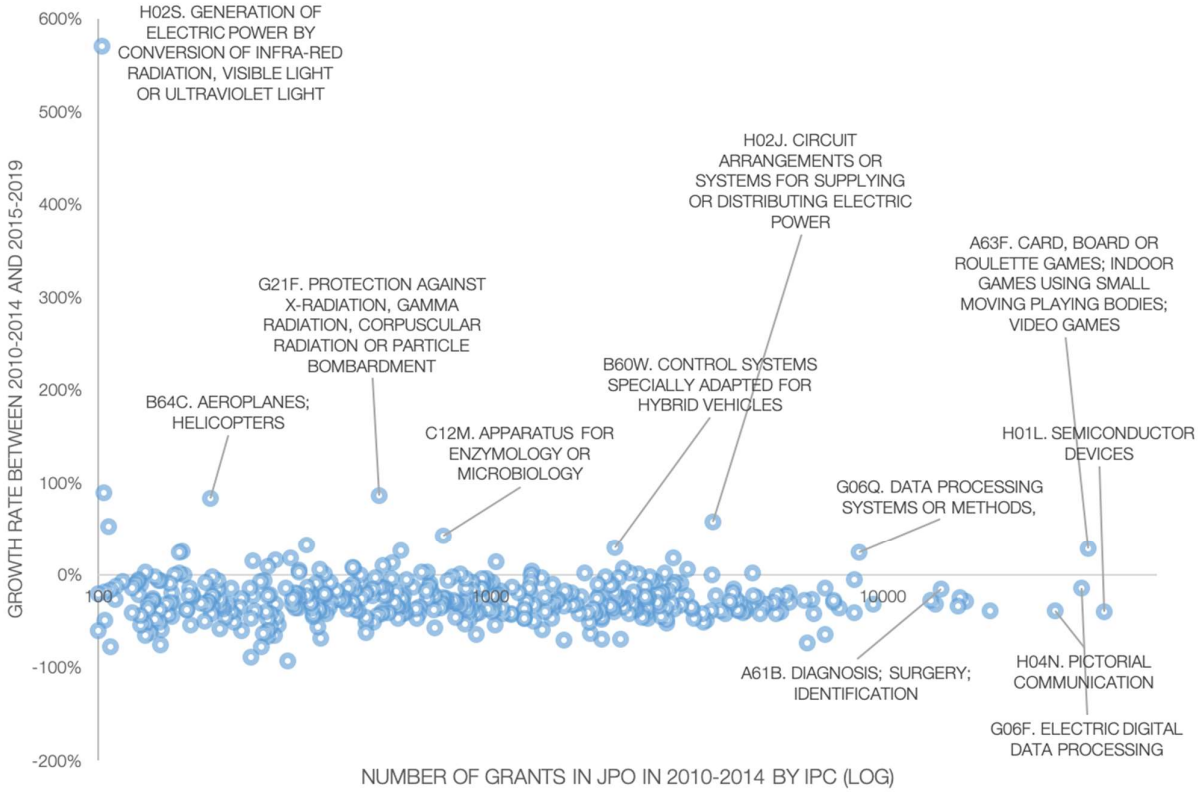
tomography and pacemakers. In one of those classes (A61B), we find that the top5 largest patent applicants are not only European firms (e.g. Johnson & Johnson and Royal Philips) but also foreign firms such as Medtronic[14], Olympus and Boston Scientific Corp.

Two other expanding IPC categories are H02J (circuit arrangements or systems for supplying or distributing electric power) and F03D (wind motors) which are included in the "IPC green inventory"[15] and are related to power supply circuitry and wind energy respectively.

4.1.2. Japanese Patent Office (JPO)

In the JPO, the growth rate in number of grants between 2010-2014 and 2015-2019 was -22%. It is the only office from the four where the growth rate has been negative, arguably as a result of a persistent fall in resident applications (WIPO, 2019). Applicants from Japan filed 84% of the total number of grants in 2015-2019, while non-residents filed the remaining 16%. Japanese applicants share decreased from 92% in 2010-2014 to 84% in 2015-2019.

Figure 2. Most dynamic IPC patent classes between 2010-2014 and 2015-2019 in the JPO



Source: ORBIS IP
Note 1: In this graph, we only included 4-digit IPC classes with more than 0.01% of total patent grants in 2010-2014 to avoid extreme growth rate outliers.

[14] Medtronic is headquarted in Ireland although it was founded in the USA.
[15] https://www.wipo.int/classifications/ipc/green-inventory/home

In Fig. 2 one of the IPC classes growing substantially between the two periods is A63F (card, board or roulette games; indoor games using small moving playing bodies; video games). The two companies with more patents granted in this class are Sankyo and Kyoraku, which are some of the major pachinko machine[16] manufacturers in Japan, which is a recreational arcade game frequently used as a gambling device, comparable to that of the slot machine in Western gambling.

Two other growing IPC categories, related to power supply circuitry and energy conservation, are H02J (circuit arrangements or systems for supplying or distributing electric power) and B60W (control systems specially adapted for hybrid and electrical vehicles). Japan (and Republic of Korea) are leading countries in the global battery technology race. According to EPO (2020), Japan was already a leader in the 2000s, but now Japanese-based companies (e.g. Panasonic and Toyota) and inventors generated more than one third of all international patent families related to battery technologies.

4.1.3. Korean Intellectual Property Office (KIPO)

In the KIPO, the growth rate in number of grants between 2010-2014 and 2015-2019 was 14%. Applicants from South Korea filed 65% of the total number of grants in 2015-2019, while non-residents filed the remaining 35%. South Korean applicants share decreased from 70% in 2010-2014 to 65% in 2015-2019.

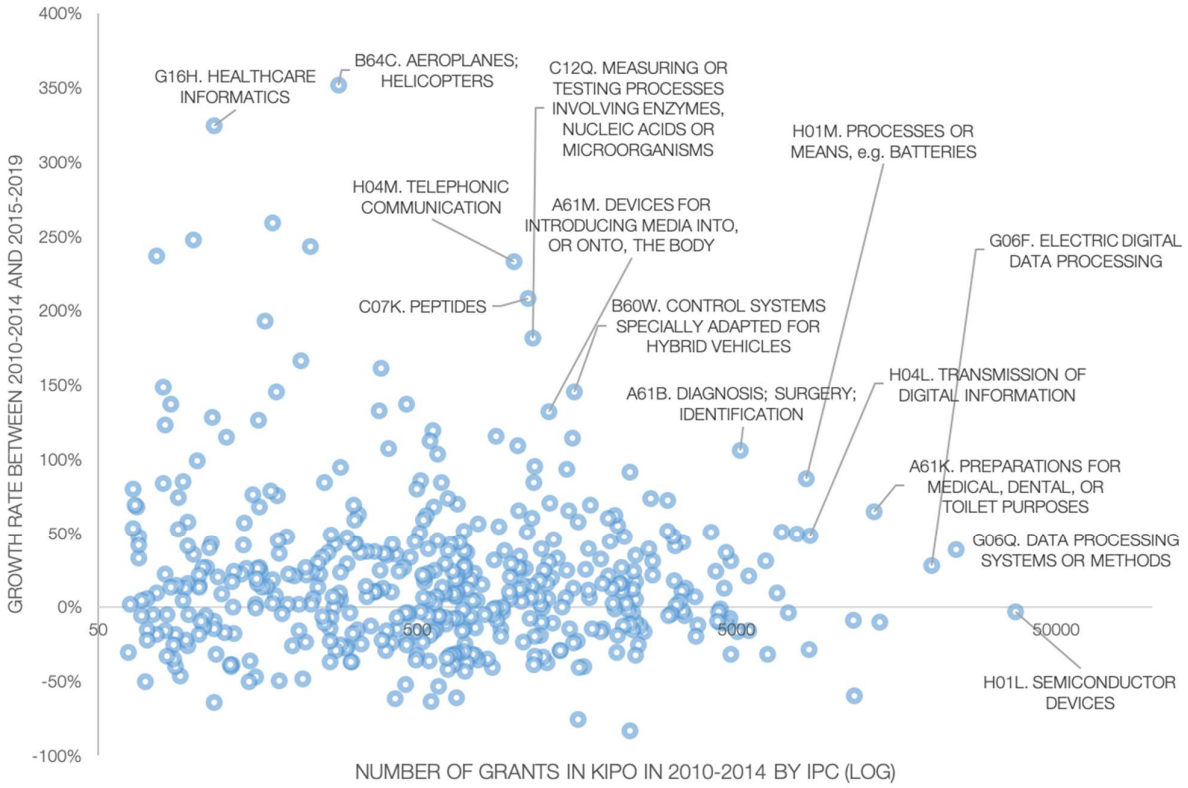
In Fig. 3, one class in the northwest hemisphere is related to the development of systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes (G06Q - data processing systems or methods). Another is about specific computational models and information technologies for data processing (G06F - electric digital data processing).

Other group relates to medical technology and pharmaceuticals (A61B - diagnosis; surgery; identification; A61K - preparations for medical, dental, or toilet purposes; A61M – devices for introducing media into, or onto, the body; and G16H – healthcare informatics). Digital health is a major trend in Korea with a diverse range of synonyms such as smart health, ubiquitous health (u-Health)[17], and medical artificial intelligence. This was an area strongly incentivized by Korean governmental agencies, with many projects focusing on creating foundational components-such as core technologies, standardization, communications, equipment which allowed significant technological progress in this broad area (Lee and Chang, 2012; Shin, 2019). Some of the top applicants in Korea are Amorepacific Corporation, Samsung and LG Household & Health Care.

[16] https://en.wikipedia.org/wiki/Pachinko

[17] u-Health focuses on ubiquitous computing applications that can provide healthcare to people anywhere and anytime using broadband and wireless mobile technologies.

Figure 3. Most dynamic IPC patent classes between 2010-2014 and 2015-2019 in the KIPO



Source: ORBIS IP
Note: In this graph, we only included 4-digit IPC classes with more than 0.01% of total patent grants in 2010-2014 to avoid extreme growth rate outliers.

Two other growing IPC categories related to storage of electrical energy and fuel cells are H01M (processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy) and B60W (control systems specially adapted for hybrid and electrical vehicles). According to EPO (2020), the Republic of Korea has a very strong relative specialisation in this domain, with companies like LG Electronics, Samsung and Hyundai leading the way. The Republic of Korea has a significant electric car market which helps the development of these battery technologies but is also a leader in stationary batteries for utility-scale power grid services and behind-the-meter applications in buildings (EPO, 2020).

4.1.4. United States Patent and Trademark Office (USPTO)

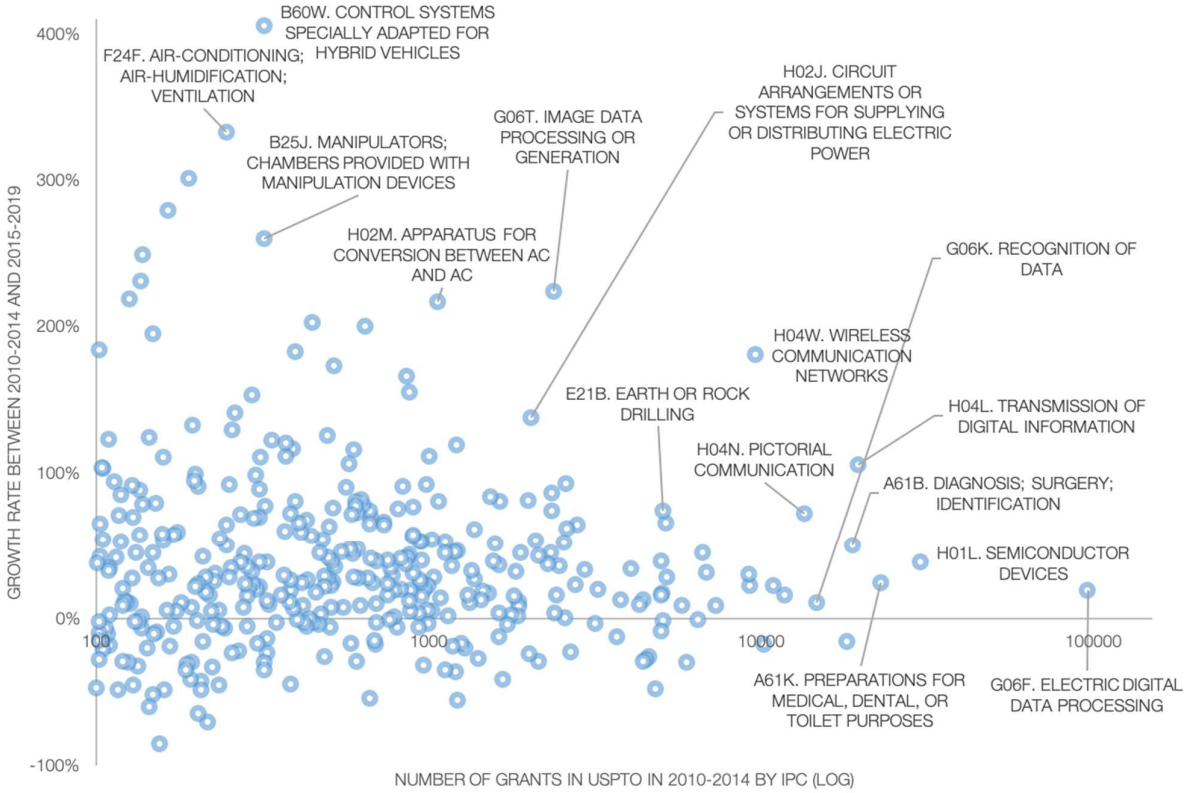
In the USPTO, the growth rate in number of grants between 2010-2014 and 2015-2019 was 30%. Resident applicants filed 75% of the total number of grants in 2015-2019, while non-residents filed the remaining 25%. USA residents share increased from 72% in 2010-2014 to 75% in 2015-2019.

In Fig. 4, the distribution of patent grants in the USPTO per 4-digit IPC code is substantially skewed with 12% of all patent grants in 2010-2014 being attributed to G06F (electric digital data processing). This code

includes technologies related to software engineering, digital computing, databases information retrieval, security arrangements for protecting computers, etc, and the applicants with more grants are big digital tech conglomerates in the USA such as IBM, Microsoft and Google. In 2018, the USA represented 71% of R&D expenditure among the leading companies in software and computer services, compared with 7% for the EU, 14% for China, and 3% for Japan and South Korea. Similarly, the USA accounted for 42% of R&D expenditure among leading companies producing technology hardware and electronic equipment, compared with 13% for the EU, 21% for Japan and South Korea, and 15% for China (EIB, 2021).

Two other G06 (computing, calculating or counting) 4-digit IPC codes also have a considerable share (G06K – recognition of data) and growth levels (G06T – image data processing). Here the driving factor for growth was the increase in patent applications related to machine learning and pattern recognition, image data processing and generation, and data retrieval.

Figure 4. Most dynamic IPC patent classes between 2010-2014 and 2015-2019 in the USPTO



Source: ORBIS IP
Note 1: In this graph, we only included 4-digit IPC classes with more than 0.01% of total patent grants in 2010-2014 to avoid extreme growth rate outliers.
Note 2: We added labels to the 4-digit IPC classes that we classified as emergent for this office in 4.2.2.

Another group of codes with substantial share and growth are related to digital communication (H04L - transmission of digital information; H04W - wireless communication networks; and H04N – pictorial

communication). The importance of these classes highlights their key role in driving the digital transformation that is permeating all sectors and industries. It includes technologies of high geostrategic importance and competition such as fifth-generation (5G) wireless networks.

Overall, we found that the IPC classes that are expanding are not exactly the same in every office. The same finding can be observed when performing the same analysis using the 35 WIPO technological categories (see Figure A.1 in appendix). There are some communalities, but in the previous analysis it is difficult to identify which are the IPC classes emerging across all offices.

4.1.5. Emergent Technology Score

In order to combine this information and generate an "emergent technology score" that allow us to identify which IPC codes rank substantially higher than others in all four offices combined (USPTO, EPO, JPO, KIPO), and therefore can be considered as emergent according to the three components we discussed in section 3.2., we decided to run a PCA using three different indicators in all offices: relative fast growth (growth rate of total share of patent grants from an IPC in an office from 10-14 to 15-19), coherence (growth rate of absolute value of patent grants from an IPC in an office from 10-14 to 15-19, and prominent impact (total share of patent grants from an IPC in an office in 15-19).[18]

The descriptive statistics of this "emergent technology score" coming from the 349 (out of 637) 4-digit IPC codes that surpass our threshold can be found in table A.1 in the appendix. We also display in the appendix a histogram (Fig. A.2) with the distribution of the same score. This histogram allows us to see that there are 12 IPC codes that score two standard deviations above the average. Those 12 IPC codes are shown in table 1 with their respective score.

Table 2. Emergent 4-digit IPC codes for all 4 offices combined

4-digit IPC code	Emergent technology score
G06F. electric digital data processing	17.4
H04W. wireless communication networks	11.8
H04L. transmission of digital information	11.2
H01L. semiconductor devices	9.2
A61B. diagnosis; surgery; identification	8.5
A61K. preparations for medical, dental, or toilet purposes	8.0
H01M. processes or means, e.g. batteries	6.8
G06Q. data processing systems or methods	6.7
A63F. card, board or roulette games; video games	5.9
H02J. circuit arrangements (…) for supplying or distributing electric power	5.3
H04N. pictorial communication, e.g. television	5.1
G01N. investigating materials by determining their chemical or physical properties	5.1

Source: Own calculation

The most noticeable "emergent technology score" between 2010-2014 and 2015-2019 is observed for G06F (Electric digital data processing). This is an IPC class that represents a substantial share of all patents in each one of the four offices and as expanded considerably during the two periods of our analysis. G06Q

[18] As previously we excluded all 4-digit IPC codes with less than 0.01% of total patent grants in 2010-2014 to avoid extreme growth rate outliers that would generate noisy PCA results.

is the other emergent **software engineering** class, which is considered a WIPO technological field per se, namely "IT methods for management". Webb et al. (2018) also documented a continued dramatic increase in software patents during the course of the twenty-first century. The other classes in our top12 emergence score can be gathered in 6 groups. First, we have "**digital communication**" (H04L - transmission of digital information; H04W - wireless communication networks; and H04N – pictorial communication) – these three classes are the only components of the "digital communication" WIPO technological field. Second, related to **health** we have a "medical technology" WIPO class (A61B - diagnosis; surgery; identification) and a class related to "pharmaceuticals" (A61K - preparations for medical, dental, or toilet purposes). Third, two "green" classes related to **energy conservation** (H02J - circuit arrangements or systems for supplying or distributing electric power and H01M - processes or means, e.g., batteries, for the direct conversion of chemical energy into electrical energy). Forth, we have **games** (A63F - card, board or roulette games; indoor games using small moving playing bodies; video games) – which is a substantial part of the WIPO class "furniture and games". Fifth, we have a class related to the "**biotechnology sector**"[19] (G01N - investigating or analysing materials by determining their chemical or physical properties) which is associated with the "analysis of biological materials" and "measurement" WIPO technological field. Finally, we find **semiconductor devices** (H01L) which is also a WIPO technological field called "semiconductors" per se.

To check the robustness of these results, we also computed this PCA "emergent technology score" for each one of the four offices independently. In table A.2 (in appendix) we present the 4-digit IPC codes that scored two standard deviations above average in each office. Overall, although there are differences between offices, the results seem to mirror the results from table 1. One surprising fact is that G06F (Electric digital data processing) doesn't appear in the USPTO top emergence scores. Since it is the IPC code with more grants ("prominent impact") in the USPTO, it would be expected that this class would be considered an emergent code. However, this can be explained by the fact that the growth rate of this IPC is smaller than the average in the USPTO ("coherence"), and there is also a decline in the growth rate of the total share of patent grants between 2010-2014 and 2015-2019 ("relative fast growth"). This is interesting and also provides some clues about the growth dynamics of IPC codes between offices. G06F seemed to have emerged first in the USPTO, and now the expansion of patent grants on that class seems to happen in different offices.

[19] https://ec.europa.eu/eurostat/cache/metadata/Annexes/pat_esms_an2.pdf

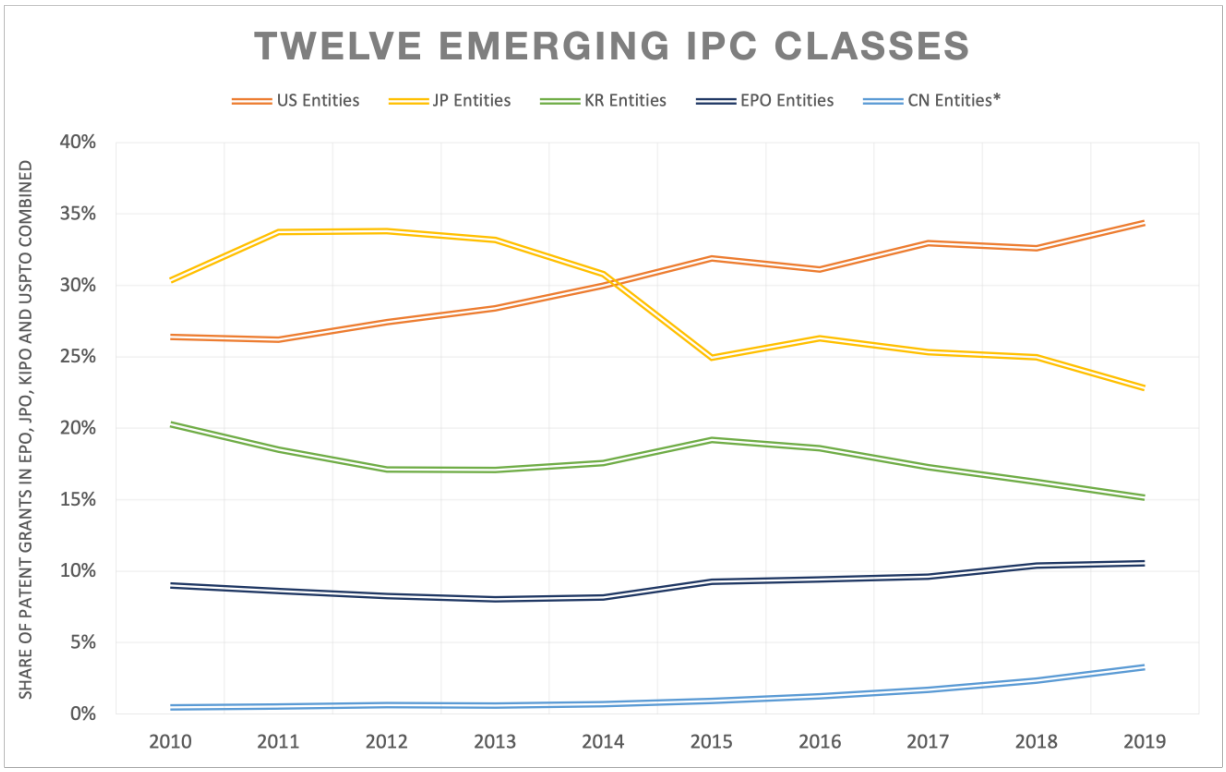
4.2. How do different regions fare on emerging classes?

In this section our aim is to understand how European firms compare against Japanese, Korean and USA firms in the emerging classes we identified before. In order to do that, as mentioned in section 3.3., we combine all firm identifiers from one of the four regions (European region includes all EPO member countries combined), during 2010-2019, and check the share of patent grants they applied for in all four offices combined.[20] Subsequently, we analyse the technological comparative advantage of each of those four regions.

Using this approach, the region with more patent grants in our twelve emerging IPC classes was the USA, followed by Japan (JP), South Korea (KR), the EPO region (all EPO member countries combined) and China (CN). The USA share increased by around 10% during this period, while JP and KR both decreased by more than 5%. In contrast, the EPO region countries, despite faring below the other three regions, remained relatively stable, with around 10% of all patent grants in these emerging classes over the period 2010-2019. It is relevant to emphasize, that these four regions have different sizes in terms of population or market size. In the last decade, the USA has around three times the population of JP and more than six times the population of KR. All EPO 38 member states combined have around twice the population of USA. Therefore, EPO's countries share of patent grants per capita is much smaller than the other regions, and consequently, the region has weaker technological capacity in emerging areas then Figure 8 seems to suggest. We also included CN in Figure 5, although their results are not entirely comparable since we are not counting patent grants in their home office (CNIPA). Still, we can observe that during the last 5 years there has been a sustained rise of patent grants from CN entities, which is mostly related to Huawei development of technological capacities in areas related to wireless networks and transmission of digital information (see Fig. 6 and Fig. A.3 in appendix).

[20] A limitation of this approach is that we are probably double counting the same patent in different offices as there will be cases where a patent with a certain priority date is conceded in several offices. However, these patents also indicate that those inventions have extra "value", since obtaining patent protection in different offices is costly and time consuming which should, in principle, filter lower impact inventions.

Figure 5. Regional share of patents across all offices combined in emerging IPC classes. 2010-2019

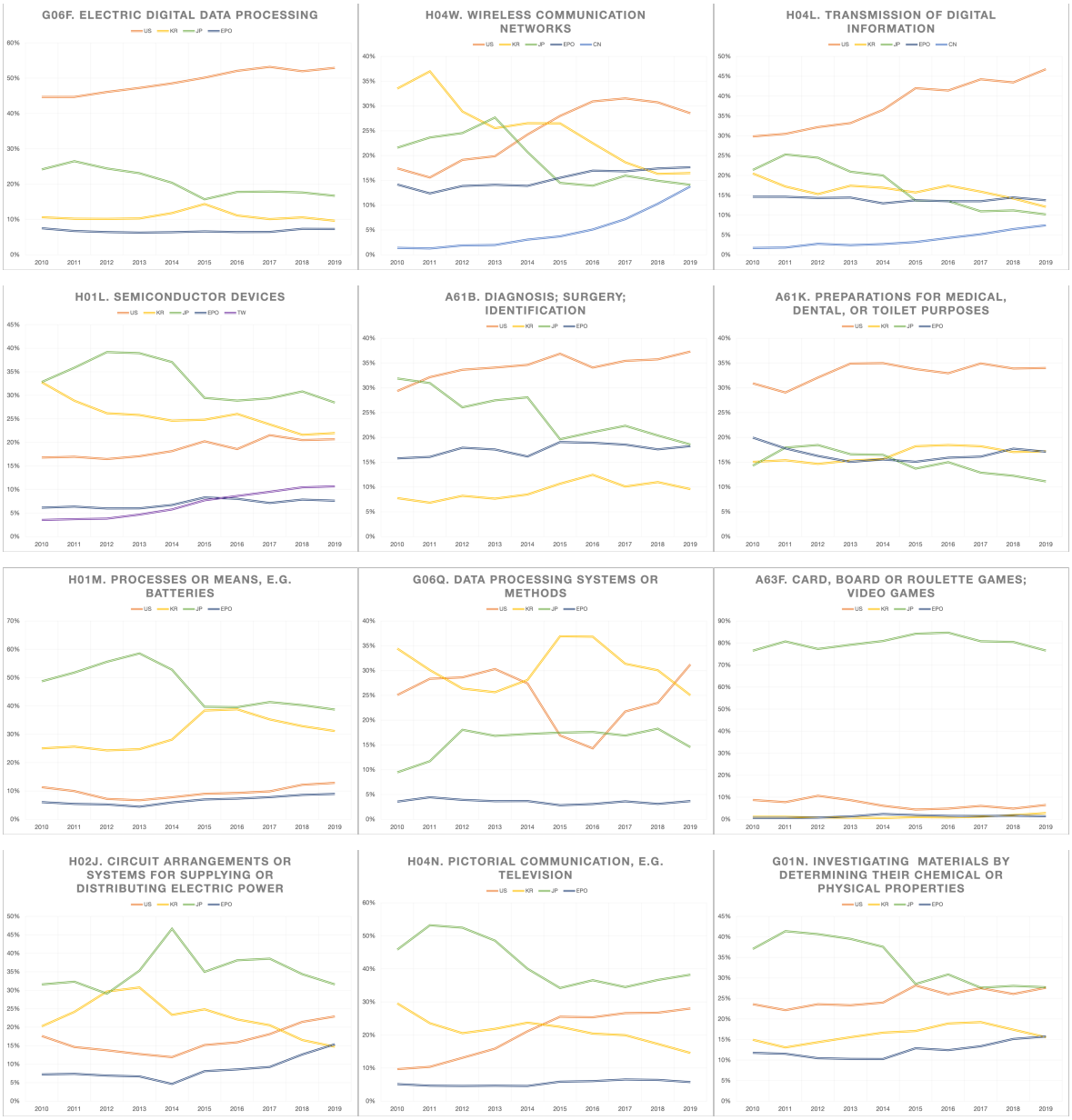


Source: Orbis IP
Note: Chinese number of patent grants is not exactly comparable to the other regions since we are not counting their home office patent grants and ORBIS IP firm identifiers for Chinese entities is not as good as for the other regions analysed.

The values in Fig. 5 comprise all 12 classes combined. In order to have a better understanding of these trends at the IPC class level we display the same analysis in Fig. 6 but this time by IPC class.

An important conclusion from the charts displayed in Fig. 6 is that the EPO region firms are not leading in any of the twelve emerging IPC classes. This is particularly evident in class G06Q (data processing systems or methods), which is dominated globally by USA and KR firms (e.g. IBM, Alphabet, Amazon, Samsung). This weak technological strength in "software" related areas has historical roots, as previously noted by Patel and Pavitt (1987) or Archibugi and Coco (2005). Firms in the EPO region are relatively stronger in medical technologies and pharmaceuticals (A61B and A61K).

Figure 6. Regional share of patent grants in the twelve emerging IPC classes, 2010-2019



Source: Orbis IP

Notes: Patent shares are calculated across all offices (EPO, JPO, KIPO, USPTO); each chart shows the regions with shares above 5% in 2019, which means that China and Taiwan also show up in some charts; charts are ordered by "emergent technology score".

Another important finding is that USA firms lead in seven out of our twelve emerging areas and are increasing their dominance during the last decade. This is particularly true for G06F (electric digital data processing), but also for digital communication technologies (H04L - transmission of digital information; H04W - wireless communication networks); health related classes (A61B - diagnosis; surgery; identification; A61K - preparations for medical, dental, or toilet purposes). At the beginning of the decade,

Korean firms (e.g., Samsung and LG) were leaders in H04W (wireless communication networks) and G06Q (data processing systems or methods) but have been losing that dominance to USA firms.

As for the JP firms, they are outstanding in A63F (card, board or roulette games; indoor games using small moving playing bodies; video games), and are leaders in five out of the twelve classes (in H01L - semiconductor devices, H01M - processes or means, e.g. batteries, H02J - circuit arrangements for supplying or distributing electric power, H04N - pictorial communication, e.g. television, and G01N - investigating materials by determining their chemical or physical properties). Some top applicants in JP such as Canon, Panasonic, Toyota and Mitsubishi Electric have a strong presence in more than one class.

In order to analyse if there are other countries that also have strong technological capabilities in these emerging classes, in Fig. 6 we also included countries with firms that account for more than 5% of all patent grants in the last year (2019). By following this approach, we found that CN appears to be gaining technological importance in digital communication (H04L - transmission of digital information; H04W - wireless communication networks) and Taiwan in H01L (semiconductor devices). According to the Economist[21] "The Semiconductor Industry Association, an American trade body, reckons that 80% of global chipmaking capacity now resides in Asia" and a chip making company from Taiwan (Taiwan Semiconductor Manufacturing Company) recently increased its planned capital spending for 2021 from $17.2bn to as much as $28bn, in anticipation of strong demand. That is one of the largest budgets of any private firm in the world and indicates it will probably continue to develop and potentially dominate technological capacity in the semiconductor industry.

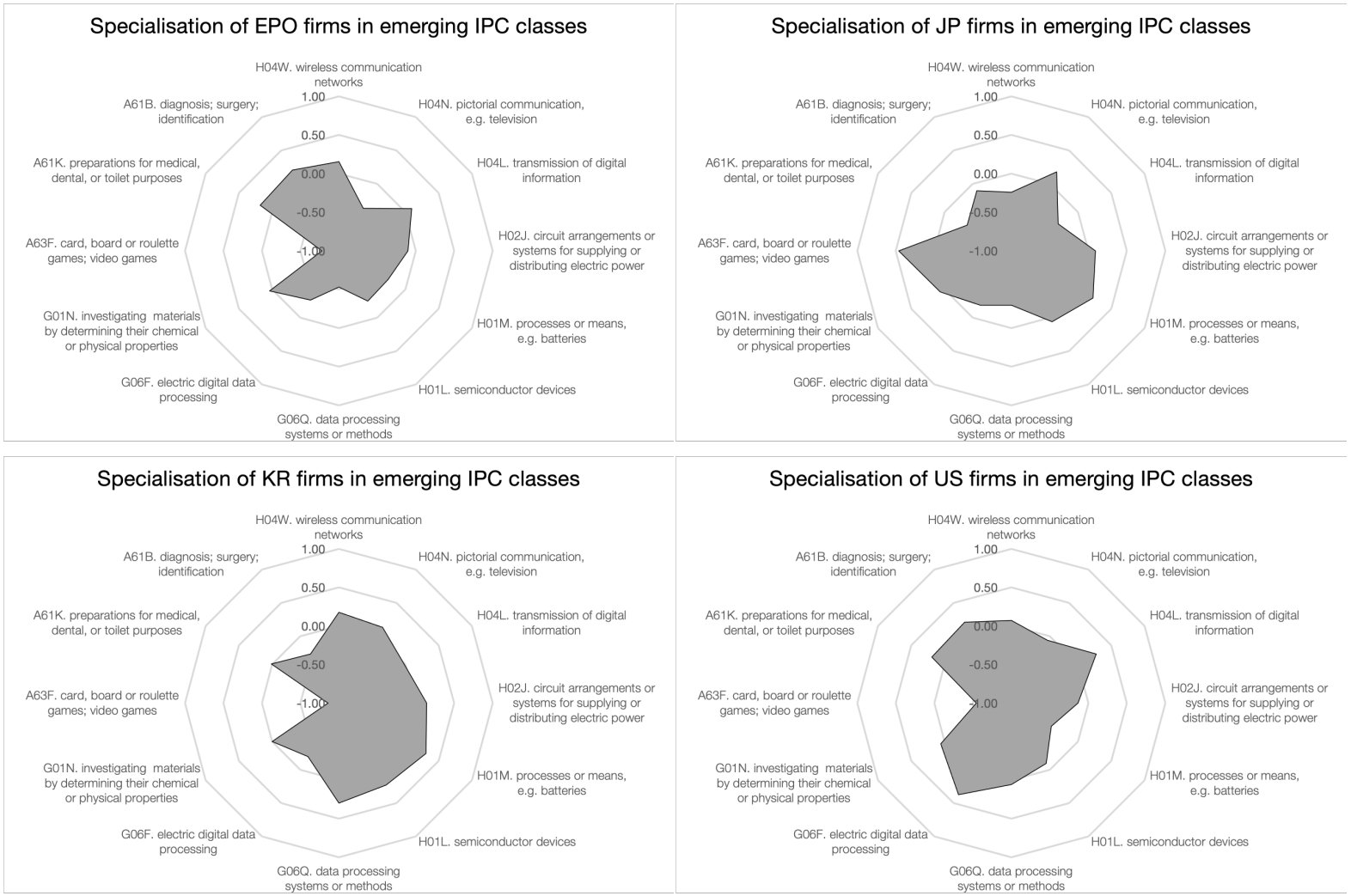
While Fig. 6 allowed us to compare the shares and assess the technological leadership across regions, it didn't tell us exactly to what extent are those regions specialised in specific emerging IPC classes in relation to the World. This type of analysis indicates which relative technological strengths and weaknesses each region has. In order to do that, we applied the method explained in section 3.4 to our four regions in Fig. 7 (and Table A.3 in appendix) and calculated relative specialisation indexes for each IPC class.

All values above 0 indicate that a certain region is relatively specialised in this IPC class in relation to the World average. For the EPO region firms this happens with medical technologies and pharmaceuticals (A61B; A61K), and to a certain extent with digital communication technologies (H04L; H04W) and biotechnology (G01N). The specialisation of EPO firms is particularly low (below 0) in G06Q (data processing systems or methods), G06F (electric digital data processing), A63F (card, board or roulette games; indoor games using small moving playing bodies; video games) and H04N (pictorial communication, e.g. television). Among the four regions analysed, the EPO region is the one whose graphs below have the smallest area, thus clearly indicating it is the region that is relatively less specialised in our emerging classes.

[21] https://www.economist.com/business/2021/01/23/chipmaking-is-being-redesigned-effects-will-be-far-reaching

JP firms are highly specialised in games (A63F), and relatively specialised in energy conservation technologies (H01M, H02J), pictorial communication (H04N), semiconductors (H01L) and biotechnology (G01N). KR firms are highly specialised in IT methods for management (G06Q), energy conservation technologies (H01M, H02J), semiconductors (H01L) and relatively specialised in digital communication technologies (H04N, H04L, H04W). Finally, in the USA, firms seem to be mostly specialised in medical technologies and pharmaceuticals (A61B; A61K), digital communication technologies (H04L; H04W) and computing related IPC classes (G06Q – data processing systems or methods, G06F – electric digital data processing). It is argued that the rising importance of intangible assets (such as R&D, patents, software and databases, etc.) in combination with network effects in ICT sectors and possible declines in knowledge diffusion (e.g. due to strategic behaviour reflected in patent thickets) may favour a polarisation of firm competitiveness in these sectors, that reduces the chances to leapfrog leaders, potentially reducing incentives to innovate and compete (Akcigit and Ates, 2021; Haskel and Westlake, 2018).

Figure 7. Relative specialisation of EPO, JP, KR and USPTO firms in emerging IPC classes (Radar graph). 2010-2019



Source: Orbis IP

4. Conclusion

In this paper, our objective has been to analyse the most dynamic areas of technological competition between 2010 and 2019 using patent data and to identify which actors (firms and countries) are becoming specialised in those areas. Our point of departure is that the actors that specialise in emerging technologies will become or remain competitive in the future, and therefore governments must understand how their countries are performing in those technologies.

We analyse patenting dynamics in four major patent offices (USPTO, EPO, JPO, KIPO) to have a global landscape of technological dynamism, and we use the 4-digit IPC patent classification system as a proxy for technological areas. We first analyse growth patterns in patent grants across offices in all IPC classes, and what firms own a significant share of patents in expanding technological areas. Our descriptive results indicate that some IPC classes are more prominent across the four patent offices (e.g. G06F – electric digital data processing; H04W – wireless communication networks; H04L – transmission of digital information). However, we also identify substantial differences between offices, thus indicating that there is no geographic homogeneity regarding the most dynamic technologies.

Then, we propose a method to classify and score emergent technological areas (4-digit IPC classes) across the four offices, and we analyse if European firms are falling behind in those areas compared to other regions. The IPC classes that seem to be emerging across all offices are related to software engineering, digital communication, IT methods for management, medical technology, pharmaceuticals, energy conservation, games, biotechnology and semiconductor devices. We find that European firms do not lead (in terms of patent share across offices) in any of these "emerging" IPC classes, although they seem to be relatively specialised globally in medical technologies, pharmaceuticals and digital communication.

All firms from EPO countries combined accounted for around 10% of all "emerging" patent grants in the four offices, between 2010-2019. This share has remained stable during the decade, while the USA firms share has increased from 25% to 35% during the same period. USA firms lead in seven out of the twelve emerging areas that were identified. This is particularly true for G06F (electric digital data processing), which is the IPC class with a higher emergent technology score according to our approach, but also for the digital communication technologies and the health-related emerging classes. As for Japanese firms and Korean firms, we found a decrease in their global patent shares during this period (30% to 23% for Japan, and 20% to 15% for Korea), though both countries still rank above the European region countries, which overall have a much larger population or GDP. Japanese firms lead in five out of the twelve classes, in areas related to games, semiconductors, energy conservation, electronics and biotechnology. Korean firms together don't lead in any emerging technological area but are relatively specialised in IT methods for management, semiconductor devices, energy conservation, digital communication and electronics. In

parallel, our data confirm the take-off of China in some of the emerging technologies (which would only be clearer have we dealt with application rather than grant data).[22]

Our findings indicate that European firms have not been at the forefront of technological competition since 2010, and we don't observe any signs of dynamic changes. This is particularly true in emerging areas such as software engineering, energy conservation and semiconductor devices, which will potentially be critical in the future for new techno-paradigms related to digitalization and clean energy. Whilst European companies still account for 20% of total industrial R&D in the world (Grassano et al., 2020), over the past ten years USA companies have continued to increase their share and reinforced their leadership position, while China has been catching up. Such trends might challenge the ability of Europe to sustain its growth model over the long term.

While no silver bullet exists for Europe to address its structural scale disadvantages related to the amount of frontier tech investment, political fragmentation, lack of superstar firms and digital platforms, it seems evident that leaving technological development in the hands of the market alone will not restore the edge that European firms have been losing (Archibugi et al., 2020; Bughin et al., 2019). Research and innovation policies in Europe should target emergent technologies and invest in its capacity to activate its entrepreneurial culture to generate the next generation of new leading firms (Veugelers, 2018).

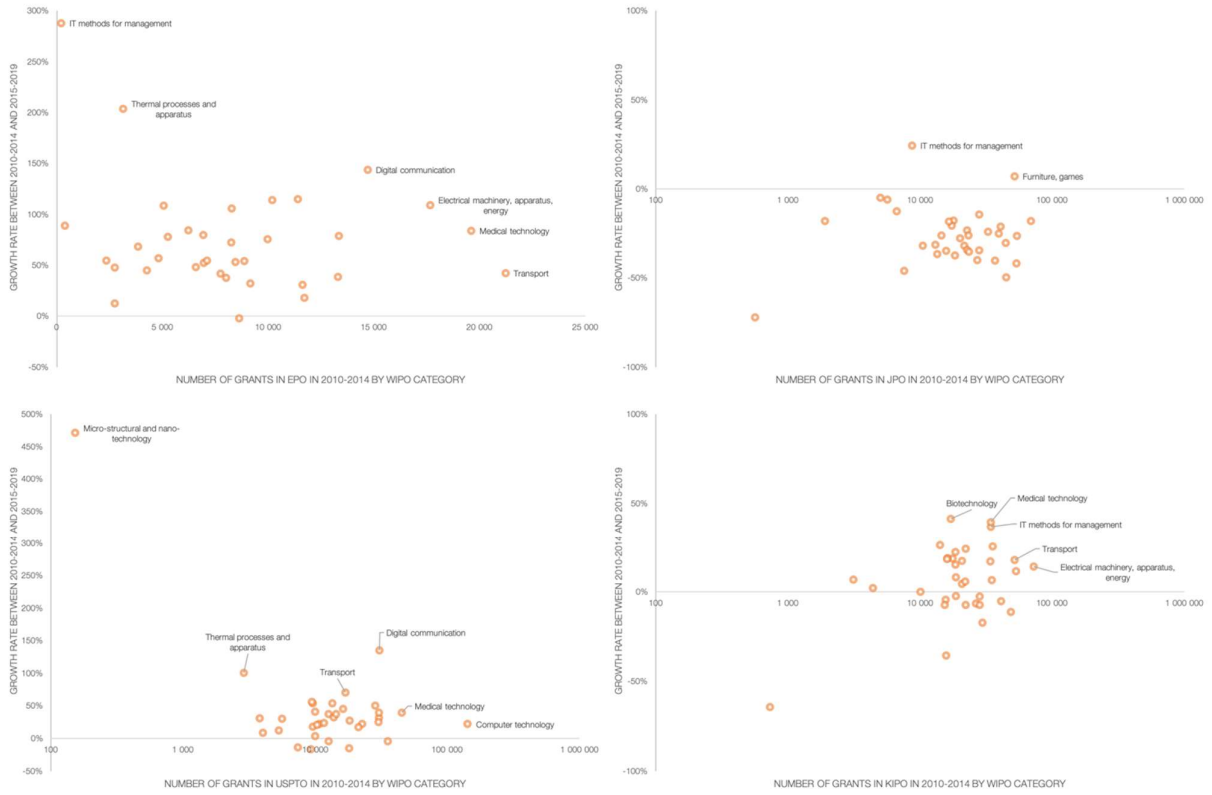
Several caveats must be kept in mind with regard to our study. First, we are working with patent grants instead of applications. Since the time window between applications and grants can be quite considerable, working with applications could give us more recent patterns of technological specialisation. However, we believe that working with grants is an adequate option since we leave out low value patent applications (which don't get granted) and differences between the two approaches would be marginal. Second, although IPC classes are standardized across offices, different patent offices have different scopes of eligibility. For example, the USPTO accepts software patents (computer programs without technical embeddedness) while in the EPO software patents are only conceded if there is an inventive technical contribution. Therefore, our results might be affected by these different scopes. Third, since our unit of analysis is the patent office (region) we are omitting differences within regions. Since it is well known that there are substantial geographical disparities in terms of innovation activities both in the USA and in Europe, this type of analysis is omitting these differences. Fourth, other studies use a diversity of approaches to identify "coherent" emergent technologies such as keyword searches (e.g. Joung and Kim, 2017), machine learning (e.g. Kwon et al., 2019), topic modelling (e.g. Porter et al., 2019), among others.

[22] This trend has been confirmed with regard to other patent indicators. Overall, China, with 58,990 applications filed in 2019 via WIPO's Patent Cooperation Treaty (PCT) procedure, became the biggest user of the PCT system, recording a 200-fold increase in only twenty years. The top 10 list of PCT applicants includes four companies from China, with Huawei in position #1, while only two European companies feature in that top 10 (WIPO, 2020).

Finally, it is relevant to mention that the technology "war" should not be just about chasing after technological trends set by others and random "frontiers". R&D investments, innovations and the development of technological capabilities must also be aligned with the challenges arising in our societies such as climate change.

5. Appendix

Figure A.1. Most dynamic WIPO technological classes between 2010-2014 and 2015-2019 in the EPO, JPO, KIPO and USPTO

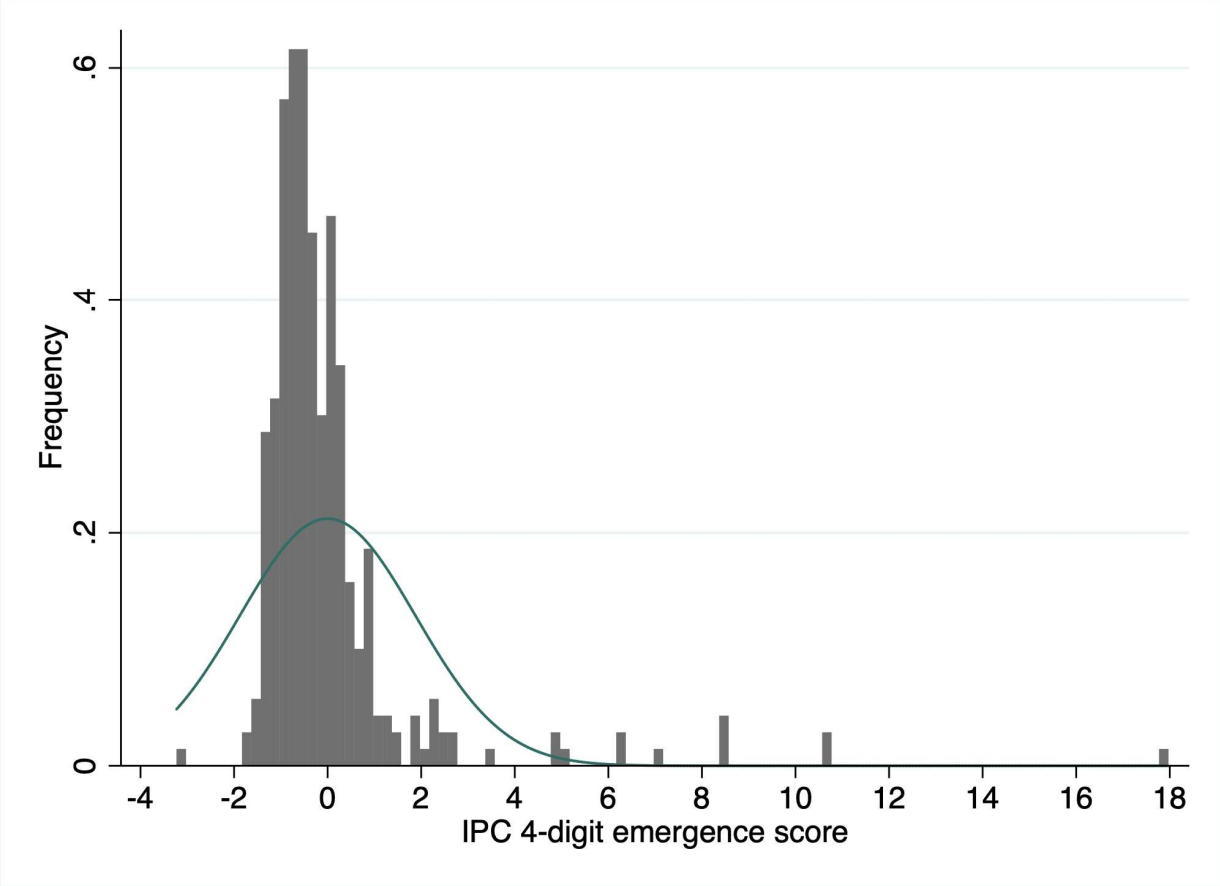


Source: ORBIS IP

Table A.1. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Emergence Score	349	2.19E-09	1.96	-3.24	18.92

Figure A.2. IPC 4-digit scores after PCA



Source: Own calculation
Note: We only included 4-digit IPC classes with more than 0.01% of total patent grants in 2010-2014, for all IP5, to avoid extreme growth rate outliers.

Table A.2. Emergent 4-digit IPC codes in each office

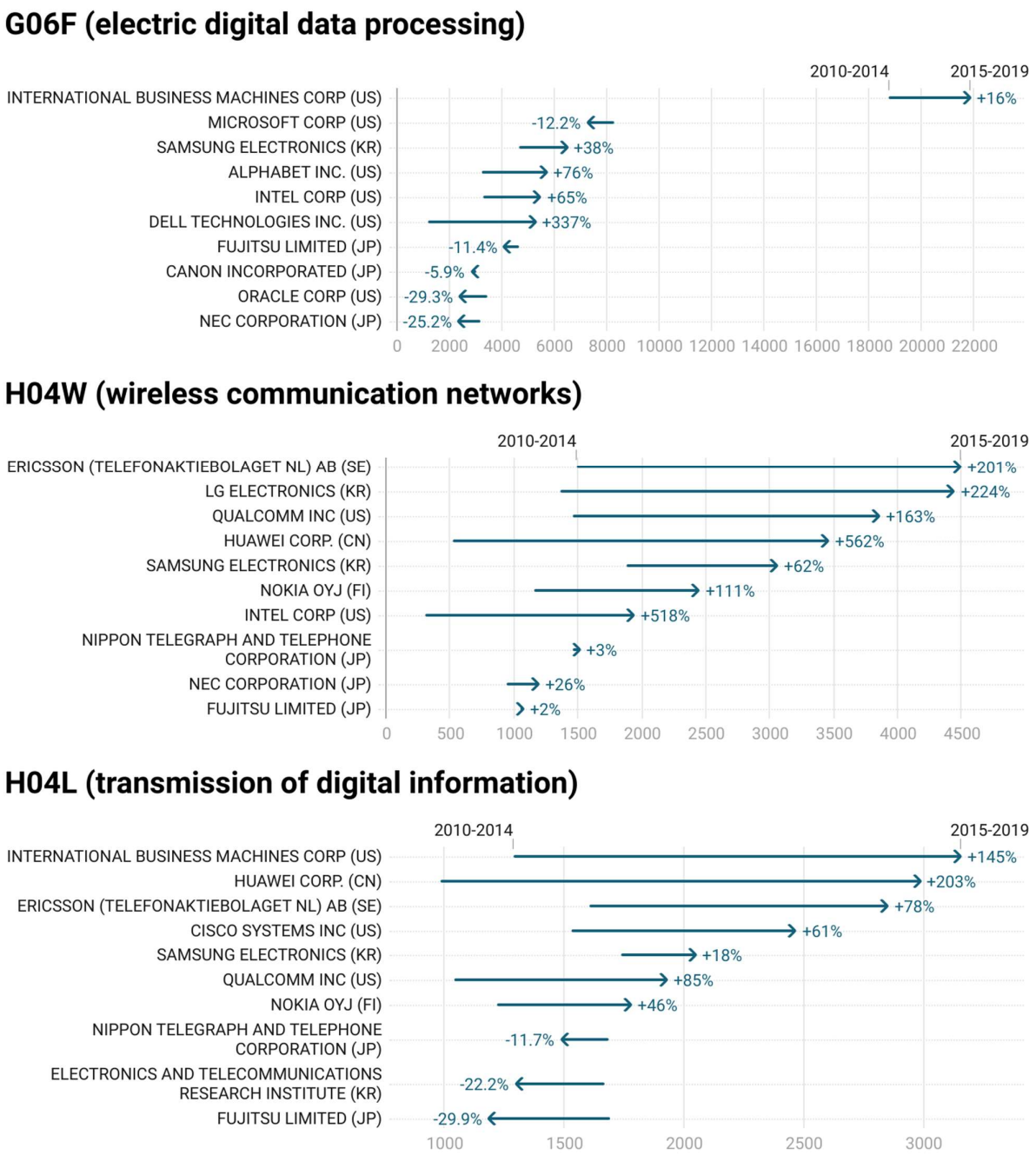
USPTO		EPO		JPO		KIPO	
IPC code	**Score**	**IPC code**	**Score**	**IPC code**	**Score**	**IPC code**	**Score**
H04W	8.6	**H04W**	13.1	**A63F**	19.4	**G06Q**	8.1
H04L	7.9	**G06F**	11.0	H02S	7.7	**A61K**	7.6
B60W	4.6	**H04L**	8.9	**G06F**	6.3	**H01M**	6.6
G06T	4.3	**A61B**	5.4	**G06Q**	5.1	**A61B**	5.3
F24F	3.6	**H02J**	5.2	**H02J**	3.8	**G06F**	4.8
C09J	3.2	**H01M**	3.9	**A61B**	2.6	B64C	4.5
A61J	3.2	A61M	3.7			H04M	4.2
H04N	3.1	**A61K**	3.5			C07K	3.9
H02M	2.9	F03D	3.1			G16H	3.7
A24F	2.9	F24S	3.0			**H04L**	3.6
B25J	2.8	A24F	3.0			C12Q	3.4
G10K	2.5	F01D	2.9			**G01N**	3.4
G08G	2.3	E21B	2.9			B60W	3.1
		G01N	2.9			A23L	3.1
		H01L	2.8			B01L	3.0
		H04N	2.8			F01D	2.9
						B64F	2.7
						A61M	2.5
						G04G	2.5

Source: Own calculation
Note 1: We only included 4-digit IPC classes with more than 0.01% of total patent grants in 2010-2014, in each patent office, to avoid extreme growth rate outliers. Only IPC classes with emergent scores two standard deviations above the office average are included.
Note 2: In bold we show the IPC codes that also appear in table 2

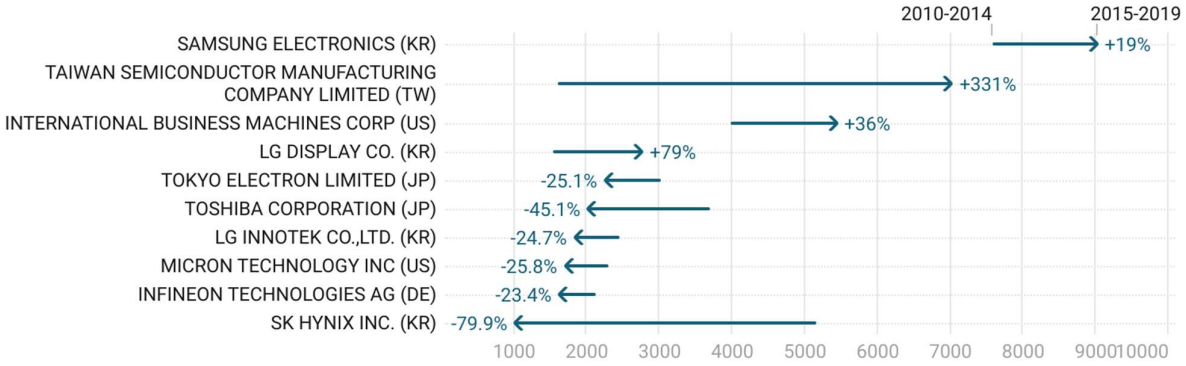
Table A.3. Relative specialisation of EPO, JP, KR and USPTO firms in emerging IPC classes. 2010-2019

	EPO	JP	KR	US
H04W. wireless communication networks	0.15	-0.24	0.18	0.07
H04N. pictorial communication, e.g. television	-0.36	0.18	0.14	-0.06
H04L. transmission of digital information	0.09	-0.30	-0.01	0.27
H02J. circuit arrangements or systems for supplying or distributing electric power	-0.10	0.09	0.14	-0.13
H01M. processes or means, e.g. batteries	-0.26	0.22	0.31	-0.40
H01L. semiconductor devices	-0.25	0.06	0.23	-0.10
G06Q. data processing systems or methods	-0.53	-0.30	0.30	0.06
G06F. electric digital data processing	-0.26	-0.19	-0.20	0.37
G01N. investigating materials by determining their chemical or physical properties	0.04	0.07	0.00	0.06
A63F. card, board or roulette games; video games	-0.78	0.46	-0.86	-0.54
A61K. preparations for medical, dental, or toilet purposes	0.18	-0.34	0.01	0.19
A61B. diagnosis; surgery; identification	0.21	-0.10	-0.27	0.21
Other IPC classes combined	0.04	0.01	-0.02	-0.08

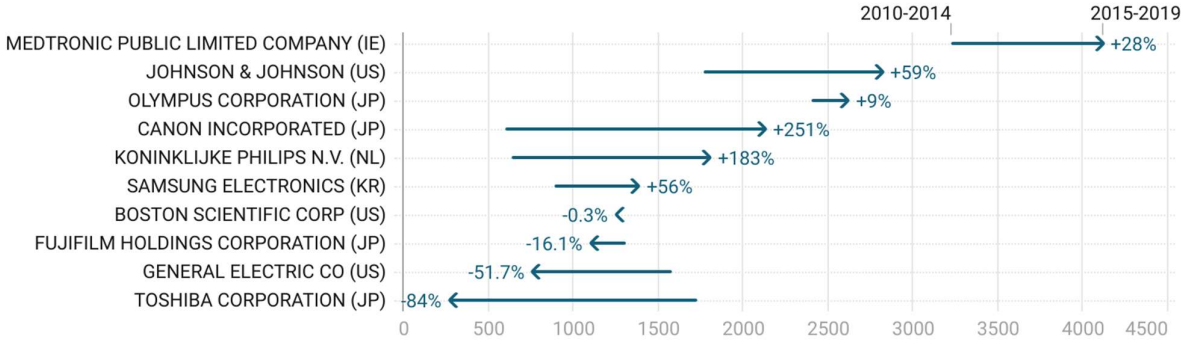
Figure A.3. Top10 patent applicants in emerging IPC classes in four patent offices combined (EPO, JP, KR and USPTO).



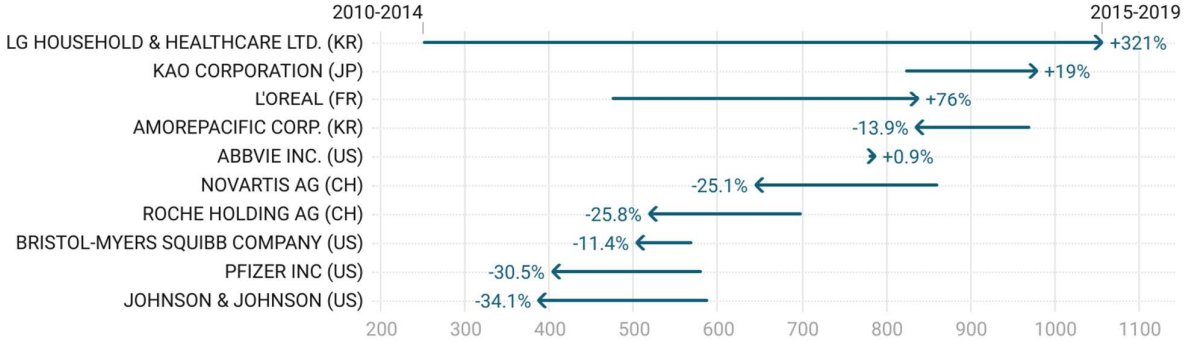
H01L (semiconductor devices)



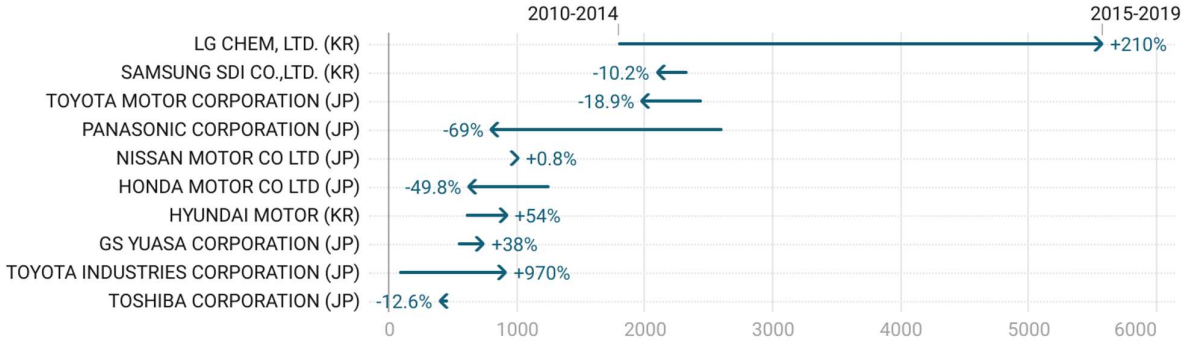
A61B (diagnosis; surgery; identification)



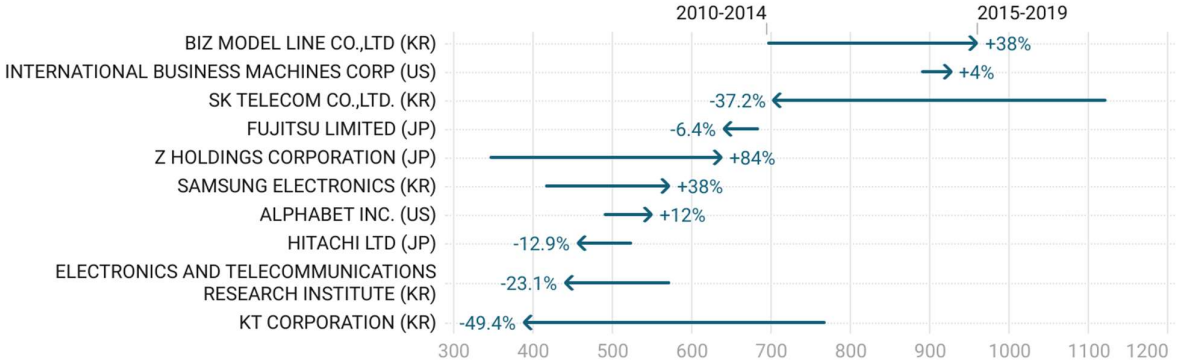
A61K (preparations for medical, dental, or toilet purposes)



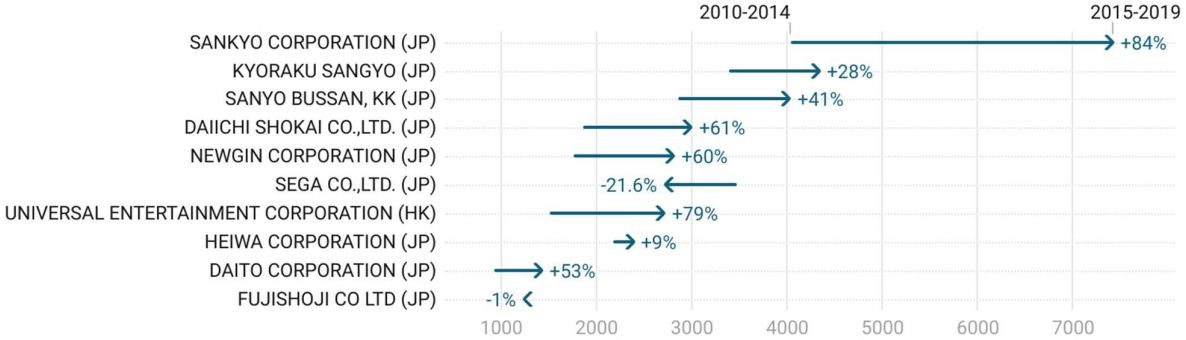
H01M (processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy)



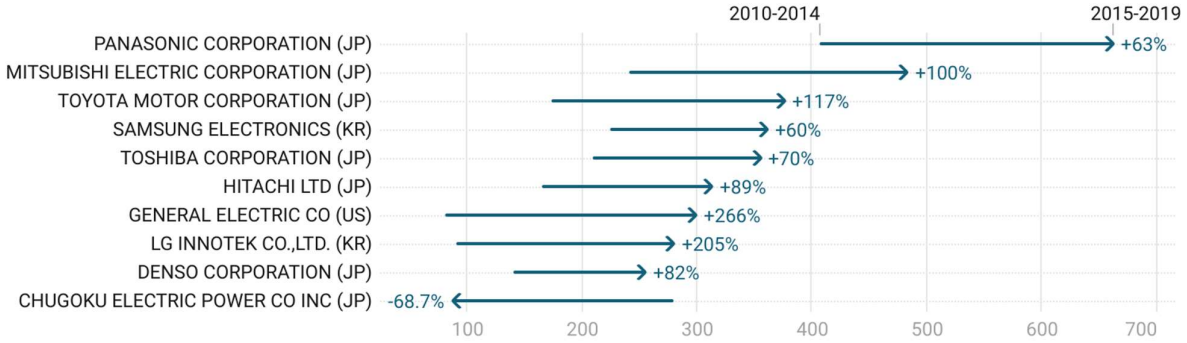
G06Q (data processing systems or methods)



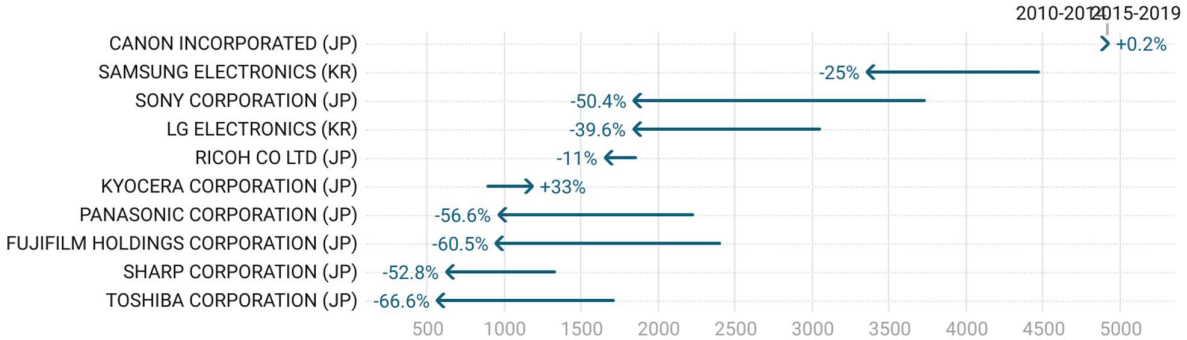
A63F (card, board or roulette games; video games)



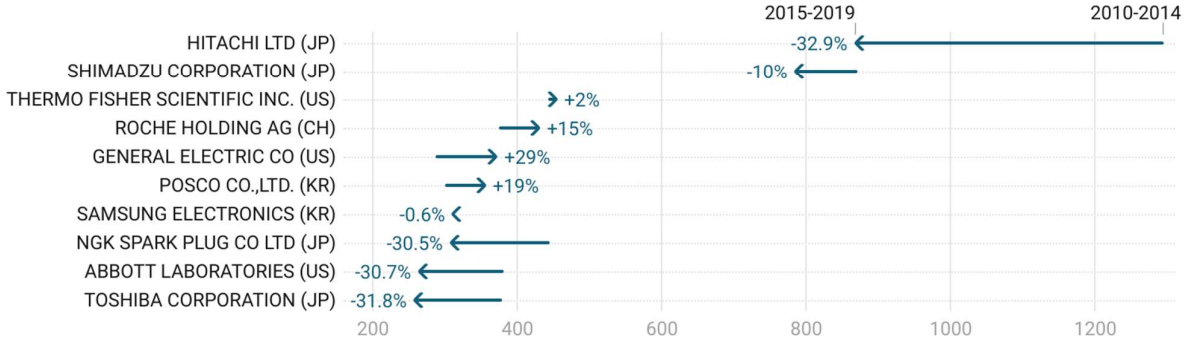
H02J (circuit arrangements or systems for supplying or distributing electric power)



H04N (pictorial communication, e.g. television)



G01N (investigating or analysing materials by determining their chemical or physical properties)



Source: Orbis IP

Notes: Charts are ordered by "emergent technology score", and companies are ordered by total number of patent grants in a certain IPC class in 2015-2019. The graphs also show what was the growth rate of patent grants of a company in a certain IPC class from 2010-2014 to 2015-2019.

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