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AI and Robotics Innovation: a Sectoral and Geographical Mapping using Patent Data

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AI and Robotics Innovation: a Sectoral and Geographical Mapping using Patent Data

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Abstract

Economic activities based on the invention, production and distribution of artificial intelligence (AI) technologies have recently emerged worldwide. Yet, little is known about the innovative activities, location and growth performance of AI innovators. This chapter aims to map and analyse the global innovative landscape of AI by exploring 155,000 patents identified as AI-related by means of text-mining techniques. It highlights the emergence and evolution of AI technologies and identifies AI hotspots across the world. It explores the scale and pervasiveness of AI activities across sectors, and evaluates the economic performance of AI innovators using firm accounting information. Finally, it assesses recent trends in venture capital investments towards AI as financial support to promising AI startups.

Findings of this chapter reveal a tremendous increase in AI patenting activities since 2013 with a significant boom in 2015-2016. While most of AI patenting activities remain concentrated in the sectors of software programming and manufacturing of electronic equipment and machinery, there are clear signs of cross-fertilisation towards (non-tech) sectors. The market of AI patenting firms is very vibrant and characterised by a large increase of new and small players with economic performances above industry average. This trend is also reflected by the recent increase in venture capital towards AI startups.

JEL Classification: O31, O33
Keywords: Artificial intelligence, innovation, patents, robotics.

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1. Introduction

There is a consensus in academic and public discussions that the diffusion of artificial intelligence (AI) technologies has a fundamental impact on the economy and society. As a recent MIT Sloan Review article pointed out - based on a survey of company executives - AI is "expected to be the single most disruptive" of the new technological capabilities (Bean 2017). Similar to electricity or the internet, AI is a general-purpose technology; it is difficult to imagine an industry that will not be affected by it (WIPO 2019). A significant degree of uncertainty surrounds any newly emerging technology, especially with regards to how much impact it will have on overall economic growth and, on changing economic and social structures, or the policy challenges it creates (EC 2018a). While it is only vaguely possible to estimate the future potential of this new technology at this point in time, it should already be possible to estimate the innovative and economic importance of AI, as significant commercial applications of the technology have been introduced in many industries. Examples of commercialized AI technologies abound, but there is surprisingly little systematic evidence available on the location, innovative activities and growth performance of AI innovators. This chapter aims to fill this gap by providing an overview of past growth trajectory and by taking stock of the current scale of AI as an economic activity. By doing so, it helps bringing somewhat closer down to earth an activity that often creates fear or excessive optimism in its observers.

Scientific and technological discoveries in the field of AI have been around since the 1950s; their widespread application as a business activity in the real economy is nevertheless only a recent development, evidenced by the strong decline in the publications to patents ratio (WIPO 2019). Accordingly, increasing attempts have been made in recent years to shed light on AI's expected transformative impact on society. This is far from an easy task, given the numerous perspectives from which the transformative nature of AI can be explored. Some authors approached the impact of AI from a legal or ethical perspective (e.g. Müller 2016; Russell et al. 2015). Others explored the financial aspect by evaluating the rise of global equity investments towards AI (e.g. Roland Berger 2017). Arguably, the most intensive academic debate concerns the labor market effects of the diffusion of robotization and automation (e.g. Acemoglu and Restrepo 2017, 2019; Agrawal et al. 2018; Arntz et al. 2017; Autor 2015; Autor and Salomons 2018; Chiacchio et al. 2018; Dauth et al. 2017; Frey and Osborne 2017; Graetz and Michaels 2018).

This line of research typically identifies a positive impact of robotization and AI on labor productivity and total factor productivity, coupled with distributive consequences on the

composition of employment, adversely affecting low-skilled workers. That being said, the emerging evidence on most labor market outcomes is rather conflicting. A couple of examples, far from being comprehensive of the growing number of studies, illustrate the variety of findings. First, focusing on aggregate employment and wage effects, a number of empirical studies based on historical data indicates that the diffusion of robot and AI is associated with decline in both employment and wages (Acemoglu and Restrepo 2019), and decline in employment while unrelated to changes in wages (Chiacchio et al. 2018). At the same time, the use of industrial robots was found to be unrelated to changes in employment and associated with rises in wages (Graetz and Michaels 2018), and unrelated to changes in employment and associated with falls in wages (Dauth et al. 2017). Different effects are consistent with economic theory. The direct substitution of workers with machines may or may not be compensated by increasing labor demand resulting from AI adoption and the associated creation of new types of jobs and demand for new types of skills in the labor market (Autor 2015, Acemoglu and Restrepo 2017). Second, estimates about the number of workers most likely to be displaced in the coming years due to the diffusion of AI diverged substantially. For instance, based on different assumptions on the extent to which AI technology substitute human work, the estimated risk of displacement due to automation in the US ranges between 38% (Frey and Osborne 2017) and 9% (Arntz et al. 2017) of today's jobs. Furthermore, it is not only the magnitude of job displacement, but also the speed of AI's diffusion in the economy is uncertain, generating concerns on the potential impact on work and ultimately social cohesion.

Such wider impacts of AI described in the paragraphs above remain outside the scope of this chapter. By applying an undoubtedly narrower focus, this study analyzes a different type of economic impact of AI. It aims at better understanding the importance of AI in the economy from the perspective of innovators, developers and merchants of this technology. It should be kept in mind that the study is only meant to provide a narrower picture by not considering spillovers or other indirect effects of AI. It is nevertheless a crucial initial step to estimate the direct employment and growth effects of AI. In doing so, it contributes to an emerging literature of studies aiming at mapping the innovative landscape of AI across time and space (e.g. Cockburn et al. 2019; Fujii and Managi 2018; Keisner et al. 2015; WIPO 2019). All these studies, even if adopting different definitions and measurement techniques, provide evidence for the fast-growing scientific and technological activity associated to the domain of AI.

Typically, emerging economic activities are characterized by turmoil, in the sense that technology and market shares are widely distributed among many actors, the entry and exit of

companies is more frequent than in mature industries, radically new technological solutions compete to become standards as institutional structures are in the formation. Schumpeterian economists have identified similar trends in the life cycle of virtually all technologies and industries (Klepper 1997; Malerba and Orsenigo 1996; Nelson 1994; Utterback and Abernaty 1975). This tradition provides a useful compass to navigate the changing techno-economic landscape, and puts trends in a broader context.

The exploratory analysis in this chapter focuses on two main crosscutting issues. The first one is the organization of the industry, which refers to the nature of the key industrial players and the overall competitive landscape, as well as the scale, the geographic and sectoral distribution of innovative activities. The second, to a certain extent overlapping, issue is the race for technological and market leadership. Among the many applications of AI, cybersecurity and other military uses make the technology particularly relevant for governments. Many countries have already devised AI strategies to domestically secure key capabilities (EC 2018a). Mastering these new transformative technologies is expected to give considerable advantage over competitors. First movers building technological capabilities in a newly emerging industry can gain considerable advantages given their power on resources- and product-markets. These comparative advantages may translate into technological leadership and lead to sustainable cost reductions. Hence, these forces are expected to trigger a fierce competition for leadership in AI.

This chapter attempts to shed more light on AI as an economic activity by addressing the following questions: Who are and where are the main innovators? What organizations and companies are the leading players in AI, in which economic sectors are they active, how has their global distribution changed over time, and how do they perform with respect to the rest of their industry?

In order to do that, the study will address a number of challenges. The first one concerns the identification of AI technology and its key components. AI refers to a broad and rapidly expanding field of technologies, so it is not surprising that there is no single, ready-made definition. Section 2 aims at explaining the notion of Artificial Intelligence and provides a definition for AI as used throughout this chapter. The main theoretical foundations and the proposed approach of identifying AI based patents are discussed in sections 3 and 4, alongside the description of its technology base.

A related challenge is the identification of key innovator organizations in the field of AI. This is done based on a careful analysis of the owners of AI patents, in a way to make it possible

to describe their geographic location and, as much as possible, their economic activities in terms of sales and employment. A main contribution of this study is the analysis of the performance of innovators at the company level – also discussed in section 3. This allows not only a more targeted focus on the innovators than more aggregated (sector-level) approaches, but it also makes it possible to compare the performance of AI innovators with their peers in the same industry (section 6). While many of the AI inventors turn out to be large firms with multiple divisions, as strategy is usually devised at the corporate level, the identification of the top industry actors (section 5) gives an overview of who shape the future of the industry.

The remainder of the chapter is organized as follows. The race for global leadership in AI – discussing 'where' and 'who' are the key innovators – is presented in section 5. The economic performance of the innovators is discussed in section 6. Section 7 investigates the key players of the future, by looking at startup activity in terms of venture capital funding. Section 8 summarizes the findings.

2. What is artificial intelligence?

A common challenge to all the studies investigating AI is how to define the notion of artificial intelligence. In many cases, AI is associated with the attempt of imitating and surpassing a peculiarity of humans, namely their natural intelligence, through logical and rational calculations or through a cognitive modelling approach of human consciousness itself. In this respect, introductory books to artificial intelligence classify AI definitions in different categories. AI can refer to both systems that are able to think humanly (reasoning perspective) as well as to act humanly (behavioral perspective) with the aim of obtaining rational outcomes (Ertel 2018; Russell and Norvig 2016).

According to the OECD, Artificial Intelligence (AI) "is a term used to describe machines performing human-like cognitive functions (e.g. learning, understanding, reasoning or interacting)" (OECD 2017, p. 22). In line with this definition a recent Joint Research Centre (JRC) report from the European Commission refers to AI as "machines or agents that are capable of observing their environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions" (EC 2018a, p. 19). While there seems to be a consensus that AI relates to the creation of machines that work and react like humans, the boundaries of technologies that belong to this economic activity remain elusive.

AI refers to a wide range of software technologies such as machine learning, neural networks, logic programming, and speech recognition, among others. Many studies consider robotics as an integral part of AI technologies for the simple reason that the use of robots makes the AI techniques practically applicable (EC 2018a; Fujii and Managi 2018; WIPO 2019). The implementation of AI techniques in robots allows them to autonomously carry out a range of tasks. Accordingly, the European Commission (EC 2018b, p.1) stipulates that "AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications)." Subscribing to this perspective, in this chapter, the term AI refers to the combination of software and hardware components, including robotics.

3. Data and methods

The objective of this chapter is to assess the global innovative landscape of AI. This is primarily done by analyzing patent activities related to AI. Patents are of course not the only outputs of scientific and technological research carried out in public and corporate R&D labs or through "citizen science". Other relevant outputs include scientific publications and software codes for algorithms; however many of them remain closely held secrets. While various studies rely on different innovative outcomes such as publications (e.g. EC 2018a; Klinger et al. 2018; WIPO 2019), patents are an appealing source of data as they allow tracking and analyzing the use and diffusion of AI technologies in the economy across time and space, and identifying the main innovators behind these patents. Although patents are the most commonly used means of protecting technical inventions, young firms may not be at the stage of patenting, or may use other intellectual property rights. To this purpose, the AI patent investigation of this chapter is complemented with an analysis of private equity funding in AI startups in section 7.

In line with a recent study of WIPO (2019), patent analyses are performed on patent families. Patents referring to the same invention that are filed in various patent offices are reported as being part of the same patent family. Main advantages of using patent families comprise capturing the most valuable inventions and avoiding problems of double counting of similar inventions. Patent data are extracted from the patent collection processed by Tools for Innovation Monitoring (TIM), which is an analytics tool developed by the Joint Research Centre to support policy-making in the field of innovation and technological development. TIM provides access to patent documents of the PATSTAT database from the European Patent Office. It contains patents

from more than 90 patent authorities including all the major patenting countries. The patent documents are then grouped per patent family when at least one of the members of the family is in English.

One of the main difficulties is identifying which patents from a patent collection relate to AI technologies. AI cuts through multiple, constantly evolving and overlapping technology fields, and there is no established definition for its composition and perimeter. Researchers therefore typically apply one or a combination of the following two approaches to identifying AI patents, as summarized in Table 1. A first approach is a keyword-based search of patents (search for specific terms identified relevant by experts in titles, abstracts, or keywords of patents (e.g. EC 2018a; De Prato et al. 2018). A second approach relies on expert selection of specific Intellectual Property Classes (IPC) mapped to AI technology areas (e.g. Inaba and Squicciarini 2017; Fujii and Managi 2018; OECD 2017). Some studies combined the two approaches (e.g. Cockburn et al. 2019; Keisner et al. 2015; WIPO 2019).

Table 1 Methods used to identify patent applications related to AI in recent studies

Study	Approach used to identify patent applications related to AI	Details
Keisner et al. 2015	Combined approach	Pre-selected set of IPC and CPC codes complemented with keywords (robot, robotics, and robotic) search in patents' title and abstract; Applied to robotics only
De Prato et al. 2018 EC 2018a	Keyword approach	Applied to patents as well as to business registers, scientific and trade publications and industrial associations records
OECD 2017	Selection of IPC codes approach	Selected IPC classes are a subset of those selected by Inaba and Squicciarini (2017) to identify ICT patents; Applied to ICT
WIPO 2019	Combined approach	Both keywords and IPC classes selection are based on the Association for Computing Machinery Computing Classification Scheme; Keywords also used to map publications
Fujii and Managi 2018	Selection of IPC codes approach	IPC classes listed in the Appendix of the study
Cockburn et al. 2019	Combined approach	Keywords search in the title of patents falling in pre-selected USPC codes; Keywords listed in the Appendix of the study; Keywords also used to map publications; Applied to specific fields: robotics, learning systems and symbol systems

This study uses a keyword-based approach to select AI patents. The list of keywords takes stock of the findings of prior scientific literature and is displayed in Table 2. Over 155,000 patent families could be identified worldwide for the period 2000-2016 with the help of TIM's text-mining techniques to retrieve these keywords in either the patent title or the abstract. For patent families, information is available on the priority date, the current outcome of the application process (as of

December 2018), and the applicants' name, country and organization type. While the priority date is available for all patent families, information on the country, the type and the name of the applicant is available respectively for about 77%, 73% and 86% of all patent families. The number of applications measures the quantity of patenting, which may be seen as a limitation. Future studies could opt for using more refined measures of patent quality – i.e., counting only PCT patent applications or applying weights based on forward citations. However, due to the inherent lags, such a choice reduces the timeliness of statistics, which would be another important limitation for analyzing an emerging technology domain.

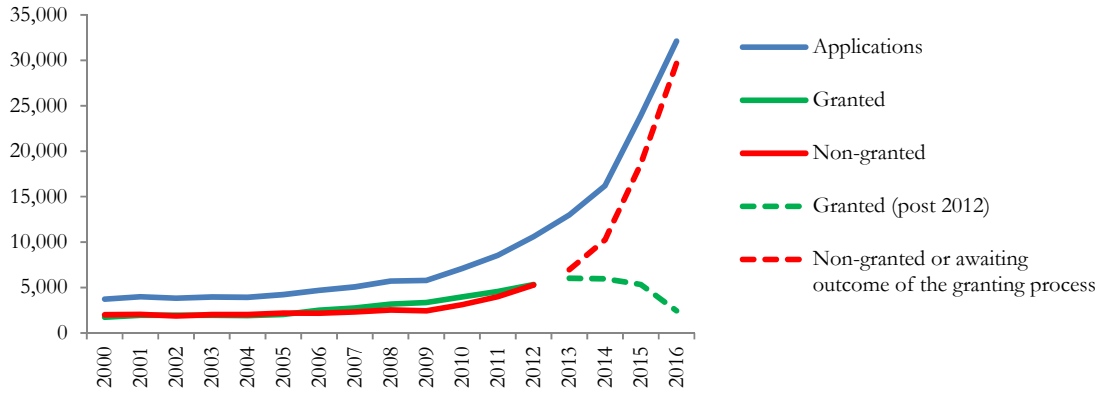
Table 2 List of keywords related to Artificial Intelligence

Keywords related to artificial intelligence		
Artificial intelligence	Face recognition	Random Forest
Artificial intelligent	Facial recognition	Reinforcement learning
Artificial reality	Gesture recognition	Robotics
Augmented realities	Holographic display	Self driv
Augmented reality	Humanoid robot	Sentiment analysis
Automatic classification	Internet of things	Smart glasses
Autonomous car	Knowledge Representation	Speech Recognition
Autonomous vehicle	Machine intelligence	Statistical Learning
Bayesian modelling	Machine learn	Supervised learning
Big data	Machine to machine	Transfer Learning
Computational neuroscience	Mixed reality	Unmanned Aerial Vehicle
Computer Vision	Natural Language Processing	Unmanned aircraft system
Data mining	Neural Network	Unsupervised learning
Data science	Neuro-Linguistic Programming	Virtual reality
Decision tree	Object detection	Voice recognition
Deep learn	Predictive modeling	
Evolutionary Computation	Probabilistic modeling	

Figure 1 presents the number of AI patent applications by year and granting outcome in the period 2000-2016. It shows a rising trend across time and an accelerating pace of growth. It is possible to split the period in three sub-periods according to rates of growth. On average, about 4,500 AI patent families were filed each year between 2000 and 2009, 11,000 between 2010 and 2014. In 2015 and 2016 alone, about 24,000 and 32,000 patent families were filed. Correspondingly, a moderate increase is observed up to 2009 – with an average yearly change equal to 5% –, followed by strong increases between 2010 and 2014 (56%) – with an average yearly change equal to 23% – and a boom in 2015 and 2016 when applications doubled since 2014 – with yearly changes equal to 48% and 34% respectively. Just 36.4% of all patent families have been granted, but the rate increases to about half (52%) of the families between 2000 and 2012, with broadly stable shares across years ranging from a minimum equal to 46% in 2000 to a maximum of 58% in 2009. The

shares of granted patents declines substantially in the last four years of the period up to 8% in 2016, reflecting the time lag required by patent offices to carry out the evaluation and granting process. The distributions by country and type of applicants are also broadly similar between granted and non-granted patent families up to 2012. Though some differences are observable, with a greater success rate in the patent granting process if the applicant is a single company or based in China, South Korea or the United States, these differences are relatively small (as shown in Table 3). The analysis of inventive activity therefore relies on all applications independently on their granting outcome, which allows considering also the most recent years when the boom of patent applications is observed.

Figure 1 Number of AI patent applications by year and granting outcome, 2000-2016



Source: Authors' calculations based on JRC TIM / EPO PATSTAT data

Table 3 The distribution of AI patent applicant(s) by country, organization type and the outcome of the granting process, 2000-2012 (in percentage points)

Applicant	Total	Granted	Non-granted	Difference (Granted - Non-granted)
By Country				
Japan	29.4	26.3	33.2	-6.9
South Korea	19.9	20.9	18.7	2.2
United States	17.9	19.5	15.9	3.6
China	16.7	18.8	14.3	4.4
European Union	9.6	7.7	11.9	-4.2
Rest of the world	6.4	6.8	5.9	0.9
By organization				
One company	75.0	80.6	70.6	10.0
Two or more companies	3.5	3.4	3.6	-0.2
One university	13.7	10.7	16.1	-5.4
Two or more universities	0.2	0.1	0.2	0.0
One (or more) research centre(s)	5.6	3.5	7.3	-3.8
Company(ies) with university(ies) and/or research centre(s)	1.6	1.4	1.9	-0.5
Other	0.4	0.3	0.4	-0.1
Total	100.0	100.0	100.0	0.0

Source: Authors' calculations based on JRC TIM/ EPO. *Note:* The last 4 available years were dropped from our full dataset in order report only applications where the evaluation and granting process has been concluded.

In order to analyze the economic performance of AI innovators, patent applicants are linked to the ORBIS data, which are commercialized by Bureau van Dijk Electronic Publishing (BvD). ORBIS includes multiple databases. The ORBIS Patent database was used to establish a link between patent families identified in the keyword search and the current owners (reflecting the state of December 2018). Current owner identifiers served to retrieve financial and detailed location information on owners of AI patents from the ORBIS Companies database. Over 13,400 unique patent owners could be identified in the ORBIS Companies database, accounting for 62% of the AI patent families. While information on contact details and therefore location is available for all owners, financial information could be retrieved for 10,727 patent owners accounting for 50% of the AI patent families. For these owners, financial information based on balance sheets and income statements has been collected from the first year onwards in which the owner filed an AI patent.

Finally, the exploration of the private-equity investment landscape towards AI startups has been performed with the help of Venture Source data. This database is owned by Dow Jones and provides global information on private equity-backed companies, including detailed investment figures over time. Using a similar AI dictionary as above and applied on firm descriptions in the database, a total of 3,459 AI startups could be identified in Venture Source.

4. The building blocks of AI technologies

This section characterizes the pool of patent families in the sample in terms of the underlying technologies as captured by the international patent classification (IPC) system. As one or more IPC classes are assigned to every family, it is possible to analyze the most frequently occurring IPC classes in AI and their change over time between 2000 and 2016. The aim of the analysis is to describe the main technological building blocks constituting AI and their evolution. Consistently with this goal, the analysis focuses on the IPC classes at the 3- and 4-digit levels of aggregation. While finer granularities are also available, they would provide minuscule details, which are beyond the scope of this study.

Table 4 provides descriptive statistics about the 15 three-digit-level IPC technology classes most frequently used in AI patent families. Overall, these IPC classes account for 90% of all AI patent families in the sample. The most frequently used IPC classes in patent families related to AI include both transversally applicable technologies (such as computing, measuring, controlling or signaling, etc.) as well as more applied ones (such as those related to the medical, aeronautics, vehicles, sports and games fields). As expected, IPC classes referring to more transversally applicable technologies are typically related to a larger number of patent families, with the notable exception of the hand tools-manipulators (B25) class. The number of patent families increased throughout the period in all classes, yet at a largely different pace.

The class of computing, calculating and counting (G06) has been the leading technology class contained in about 30% of all the patents filed in the field over the period 2000-2016. It is not only associated with a large number of patent families in all sub-periods, but also shows a relatively strong growth moving from accounting for about 26% of patent families in 2000-2005 to 32% in 2011-2016. Jointly with other sizeable classes such as controlling (G05), measuring (G01) and signaling (G08), the G06 class encompasses transversally applicable technologies associated with science and engineering tasks strictly related to improvements in computers capacity. The strong link to increasing capabilities of machines and computers is also shown by many of the 4-digits classes contained in the largest number of patent families – namely electric digital data processing (G06F, contained in 24,992 families), recognition and presentation of data (G06K, 9,643), data processing systems or methods (G06Q, 9,458), image data processing or generation (G06T, 9,254), systems for controlling/regulating non-electric variables (G05D, 6,936), control or regulating systems (G05B, 6,897) and computer systems based on specific computational models (G06N, 6,395).

The next two largest 3-digit classes – hand tools-manipulators (B25) and electric communication techniques (H04) – account for about 17% and 15% of all families. Jointly with the G06 class, they are contained in more than half (about 56%) of patent families over the 2000-2016 period. The B25 class, as said, is the largest one referring mostly to an applied field, namely the manufacture of robots. While it remained sizeable throughout the period and the number of patent families containing it increased by a nearly three-fold rate between 2000-2005 and 2010-2016, their relative share declined significantly over time (from 23% in 2000-2005 to 15% in 2010-2016), testifying the widening of developments and applications occurred in recent years in AI technologies. The size and strong increase in the 2011-2016 period of the H04 class (in particular the transmission of digital information H04L and pictorial communication subclasses), coupled with the relative maturity of the acoustics class (G10, mostly in the speech analysis and synthesis subclass G10L, which is crucial for natural language processing technologies) are at the root of fundamental changes in machine-machine and human-machine interfaces and are likely to lead to substitution of human intermediation (i.e., "middleman") tasks in such communications.

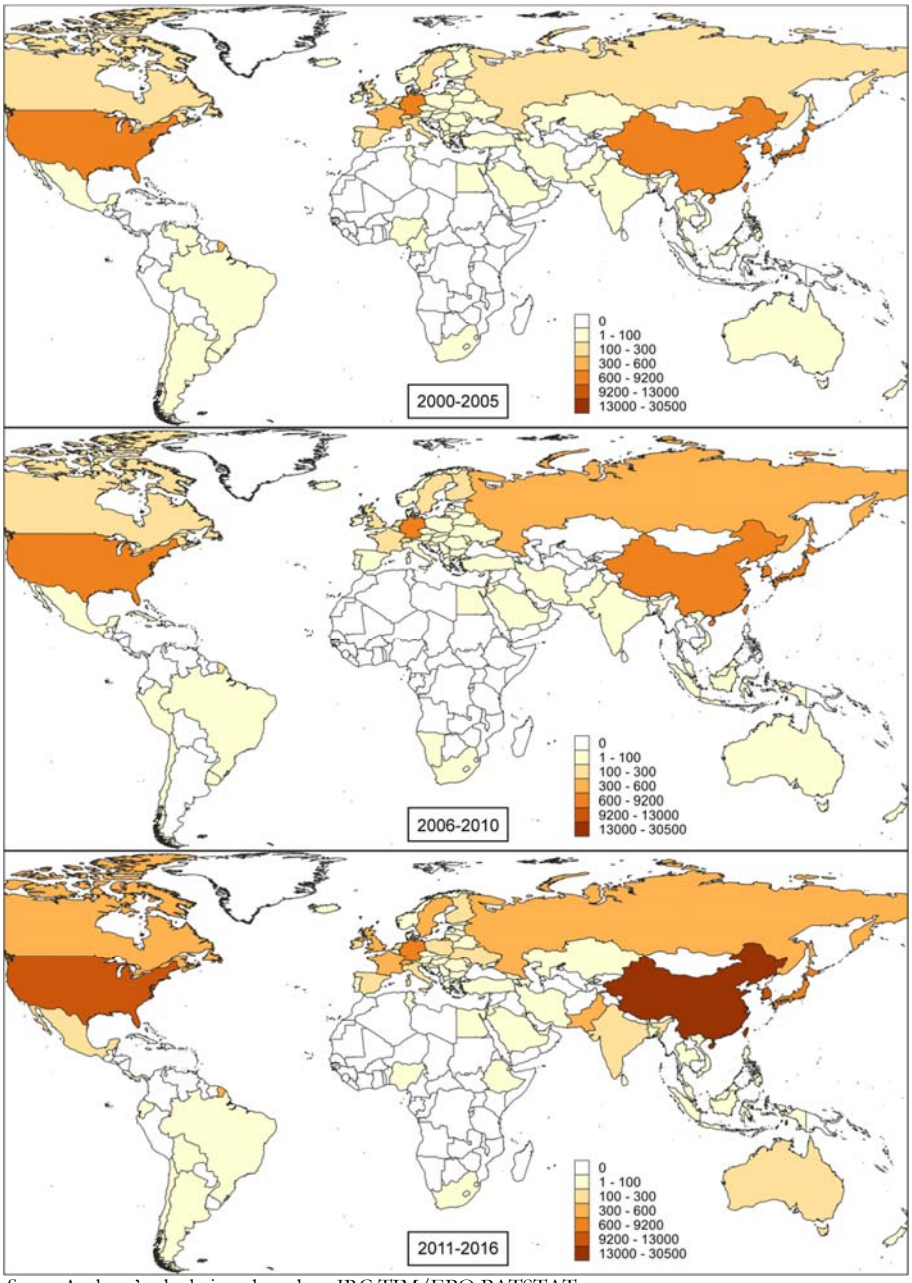
At the same time, sharp increases are evident in classes related to specific areas of application. Such increases, albeit less significant in comparison with what was observed for transversally applicable technologies, are important as they demonstrate the diffusion of the use of AI technologies in commercial products and services. The aerospace (B64) class emerged from a nearly negligible to a significant patent filing sector after 2010. Mostly a result of the diffusion of unmanned aeronautical vehicles (UAVs, or drones), this growth is particularly remarkable, given that the sector historically used secrecy and the high capital intensity as barrier to protect its intellectual property (Vertesy 2015). The agricultural (A01), electricity distribution and storage (H02, especially H02J) and medical (A61) classes are further examples of swiftly growing fields of application, where patenting increased well above the average rates. Although not among the fastest growing ones, vehicles (B60) – think of the diffusion of self-maneuvering capabilities – and conveying, packaging, storing technologies (B65) have remained among the most important domains of AI application – possibly linked to the growth of e-commerce.

Table 4 The 15 3-digit IPC technology classes with the largest number of patent families in AI, 2000-2016

IPC code	IPC name	Typical use	Number of AI patent families				% change between 2000-2005 and 2011-2016	% of total AI patent families			
			2000-2005	2006-2010	2011-2016	Total		2000-2005	2006-2010	2011-2016	Total
G06	Computing; Calculating; Counting	Transversal	6,147	7,714	33,617	47,478	447	26.5	27.4	32.3	30.5
B25	Hand Tools; Portable Power-Driven Tools; Handles For Hand Implements; Workshop Equipment; Manipulators	Applied	5,250	6,350	15,212	26,812	190	22.6	22.5	14.6	17.3
H04	Electric Communication Technique	Transversal	3,087	3,832	15,580	22,499	405	13.3	13.6	15.0	14.5
G05	Controlling; Regulating	Transversal	1,749	2,239	9,386	13,374	437	7.5	7.9	9.0	8.6
G01	Measuring; Testing	Transversal	2,105	2,566	8,603	13,274	309	9.1	9.1	8.3	8.5
G10	Musical Instruments; Acoustics	Transversal	4,080	2,478	4,603	11,161	13	17.6	8.8	4.4	7.2
A61	Medical Or Veterinary Science; Hygiene	Applied	768	1,265	4,123	6,156	437	3.3	4.5	4.0	4.0
G08	Signalling	Transversal	773	954	4,074	5,801	427	3.3	3.4	3.9	3.7
H01	Basic Electric Elements	Transversal	1,727	1,476	2,028	5,231	17	7.4	5.2	2.0	3.4
A01	Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing	Applied	430	749	3,981	5,160	826	1.9	2.7	3.8	3.3
B23	Machine Tools; Metal-Working Not Otherwise Provided For	Applied	1,103	1,034	2,700	4,837	145	4.7	3.7	2.6	3.1
B64	Aircraft; Aviation; Cosmonautics	Applied	145	276	3,867	4,288	2,567	0.6	1.0	3.7	2.8
B60	Vehicles In General	Applied	687	839	2,575	4,101	275	3.0	3.0	2.5	2.6
H02	Generation, Conversion, Or Distribution Of Electric Power	Applied	411	519	2,909	3,839	608	1.8	1.8	2.8	2.5
B62	Land Vehicles For Travelling Otherwise Than On Rails	Applied	414	715	2,393	3,522	478	1.8	2.5	2.3	2.3

Notes: The column 'Typical use' distinguishes transversally applicable core AI technologies from more specific application fields. The % displayed in the table's last four columns are computed using as denominators the following number of total patent families: 23,241 in 2000-2005, 28,183 in 2006-2010, 104,018 in 2011-2016 and 155,442 2000-2016.

Figure 2 Map of AI patent family applications by country and period



Source: Authors' calculations based on JRC TIM/EPO PATSTAT

5. The race for global leadership in AI inventions

5.1 Mapping inventors

Where are the inventors of AI technology? This section analyzes the geography of patenting and its evolution across time based on applicants' country. The analysis uses a full counting method, which considers more than once any family with multi-country applicants. However, since such patents represent merely 0.6% of all applications, their impact is marginal. Table 5 shows the number of patent families between 2000 and 2016 by applicant country for the largest players, while the results are also represented by period on a map in Figure 2.

The distribution concentrates around four global players – China, Japan, South Korea and the United States (US) – that alone account for more than 85% of all patent families worldwide. The performance of mainland China – which leads the ranking – is particularly striking when compared with Japan, its closest follower: applicants from P. R. China filed more than 11,000 (about 45%) more patent families than Japanese ones. The gap is comparatively narrow, by contrast, between the remaining three top applicant countries, as Japan leads by about 3,700 families over South Korean and the US.

The number of families drops sharply when moving further down the ranking. German applicants, who follow those from the US, filed just slightly more than one for every ten patent families applications by Chinese and about one for every five families applied by South Korean and US inventors. The European Union (EU) as a whole accounts for merely 7.7% of total patent family applications, which is less than half of the share of South Korea and the US. The performance of France and the UK appears surprisingly low, in view of the comparatively high technological advancement in these countries.

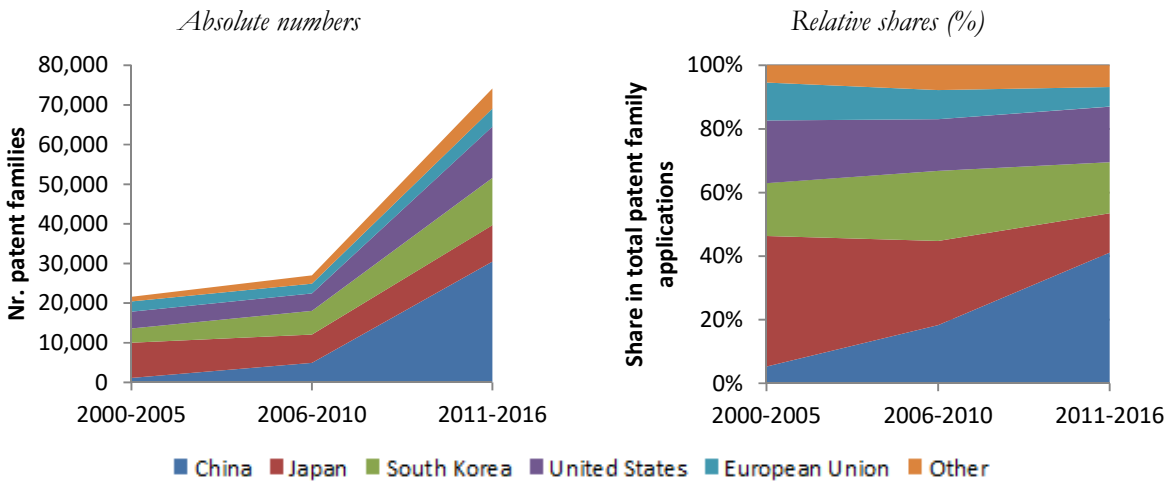
Table 5 AI patent families by country of applicant, 2000-2016

Total	**122,796**	**100.0**	**European Union**	**9,597**	**100.0**
China (mainland)	36,553	29.7	Germany	4,403	45.9
Japan	25,218	20.6	France	1,154	12.0
South Korea	21,453	17.7	United Kingdom	1,015	10.6
United States	21,614	17.6	Sweden	622	6.5
European Union	9,597	7.7	Netherlands	510	5.3
Taiwan	2,659	2.2	Italy	296	3.1
Russia	1,007	0.8	Finland	285	3.0
Canada	926	0.8	Spain	215	2.2
Switzerland	655	0.5	Poland	157	1.6
Pakistan	552	0.4	Ireland	150	1.6
Other	2,562	2.0	Other EU MSs	790	8.2

Source: authors' calculations based on JRC TIM/EPO PATSTAT
Note: Information on the country of applicants is only available for about 77% of all patent families.

Figure 3 shows how the distribution of patent family applications evolved over time across the main applicant countries. The 2000-2016 period is split in three sub-periods of comparable length: 2000-2005, 2006-2010 and 2011-2016. The graph shows a change in inventive leadership between Japan and China over the period, most remarkably after 2010. China, which merely accounted for about 5% of AI patent family applications between 2000 and 2005, increased its share to about 41% between 2011 and 2016. An opposite trend is observed for Japan, the first mover in AI (and robotics in particular). While the number of patent family applications remained roughly constant (around 9,000) throughout the period, its global share fell from about 41% in 2000-2005 to about 12% in 2011-2016. South Korea and the US show a similar evolution over time: a considerable increase in the number of applications (from about 3,500-4,000 in 2000-2005 to 12,000-13,000 in 2011-2016) resulted "only" in maintaining broadly constant shares across time (ranging between about 16% and 22%). EU applicants also increased their output (from about 2,600 in 2000-2005 to 4,600 in 2010-2016), but their rate of growth was comparatively slower with respect to the major players, so their share gradually halved from about 12% to 6% of all patent families. These trends imply that more than half of the "boom" of patent family applications observed in recent years is explained by the increase in inventive performance of Chinese applicants. South Korean and US applicants also contributed to this growth, though to a lower extent, while the role of applicants from other parts of the world remained limited.

Figure 3 The evolution of the geographic distribution of AI patent families applications, 2000-2016



Source: authors' calculations based on JRC TIM/EPO PATSTAT

5.2 The leading inventors

Leading AI inventors are identified based on their patenting activity. Table 6 lists the 20 organizations with the highest number of patent family applications in 2011-2016, and shows the country of headquarters as well as their overall ranking across the three sub-periods 2000-2005, 2006-2010 and 2011-2016. A striking result is the strong performance of Chinese organizations in the list, occupying 3 out of the first 4 ranks and 11 out of the top 21 ranks (two organization rank equally at the 20th rank). The list also presents an interesting heterogeneity of organization types: leading Chinese AI inventors are universities and public research organizations, while Japanese, Korean and US entities are typically large corporations. The rise of Chinese originations in the rankings over the past decade is also remarkable. For example, the Chinese organization with the most applications in 2000-2005 – the Chinese Academy of Sciences – moved from filing just 66 patent families (ranking 38th in 2000-2005) to filing 1,347 patent families (ranking 4th in 2011-2016). The leading innovators are highly concentrated in the four countries mentioned above: surprisingly, no organization from other countries appears in the list.

Table 6 The applicants with the largest number of patent families filed in 2011-2016

Applicant organization name	Country	2000-2016		2000-2005		2006-2010		2011-2016	
		Rank	Patent families	Rank	Patent families	Rank	Patent families	Rank	Patent families
China University of Mining & Tech.	CN	2	2,219	159	14	42	90	1	2,115
Tencent Technology	CN	4	1,721	343	6	57	70	2	1,645
Samsung	KR	1	2,990	1	724	1	872	3	1,394
Chinese Academy of Sciences	CN	5	1,629	38	66	14	216	4	1,347
Seiko-Epson	JP	7	1,551	20	152	11	245	5	1,154
State Grid	CN	11	1,125	4894	0	861	3	6	1,122
IBM	US	3	1,731	5	436	16	207	7	1,088
Semiconductor Manufacturing Int'l Co.	CN	9	1,204	106	21	30	118	8	1,065
LG	KR	6	1,625	3	529	4	418	9	678
Collaborative Innovation Center of Chemical Science and Engineering	CN	25	656	916	2	206	17	10	637
Source Photonics	US	29	622	916	2	479	6	11	614
Google Inc.	US	27	639	251	8	71	55	12	576
Canon Inc.	JP	14	1,016	11	250	15	211	13	555
Toyota Motor	JP	8	1,494	9	304	2	651	14	539
Microsoft	US	12	1,031	15	208	6	300	15	523
Tsinghua University	CN	20	729	45	56	20	171	16	502
Elect & Telecom Research Institute	KR	15	916	28	103	5	316	17	497
Zhejiang University	CN	28	634	174	13	25	138	18	483
Harbin Institute of Technology	CN	32	584	343	6	36	105	19	473
Beihang University	CN	26	641	295	7	21	164	20	470
Led One	CN	34	489	408	5	242	14	20	470

Source: authors' calculations based on JRC TIM/EPO PATSTAT

Looking at not just the leading, but the entire sample of organizations reveals more information about the type of innovators and their collaborative patterns. Table 7 shows the distribution of patent families by applicant type. The majority (about 71%) of families have been

filed by a company, either alone (66%) or jointly with other companies, universities and/or research centers. Yet, the share of families involving a company substantially declined across time, falling from about 91% in 2000-2005 to 65% in 2011-2016. Universities constitute the second largest share among applicants, being involved in 24% of families. In contrast to the time trend observed for companies, the share of universities experienced a substantial rise across time from about 6% in 2000-2005 to 29% in 2011-2016. A slight increase over time is also observed for research centers, which are involved in a limited share of patent families (about 7% in 2011-2016). Most of the applicants filed their applications in isolation. Yet, while multi-country AI patents are very rare, collaboration between innovators in the same country is somewhat more pervasive. The share of families with multiple applicants – involving organizations either of the same or different type – increased throughout the period from about 4% in 2000-2005 to 7% in 2011-2016. The increase in collaboration in AI patenting involving different organization types (i.e., between public and private actors) is remarkable as licensing or other agreements are preferred over co-ownership given its legal complexity.

Table 7 AI patent families across time by applicant type, 2000-2016

Applicant type	All		2000-2005		2006-2010		2011-2016	
	Nr.	%	Nr.	%	Nr.	%	Nr.	%
By applicant type								
One company	74,860	65.5	14,824	86.4	15,883	72.3	44,153	58.8
Two or more companies	4,382	3.8	569	3.3	721	3.3	3,092	4.1
One university	24,232	21.2	899	5.2	3,418	15.6	19,915	26.5
Two or more universities	385	0.3	11	0.1	41	0.2	333	0.4
One (or more) research centre(s)	7,346	6.4	651	3.8	1,392	6.3	5,303	7.1
Company(ies) with university(ies) and/or research centre(s)	2,403	2.1	142	0.8	427	1.9	1,834	2.4
Other	601	0.5	56	0.3	78	0.4	467	0.6
Total	114,209	100.0	17,152	100.0	21,960	100.0	75,097	100.0
By number of applicants								
Single applicants	106,656	93.4	16,406	95.7	20,719	94.3	69,531	92.6
Multiple applicants of the same type	4,884	4.3	583	3.4	777	3.5	3,524	4.7
Multiple applicants of different type	2,669	2.3	163	1.0	464	2.1	2,042	2.7
Total	114,209	100.0	17,152	100.0	21,960	100.0	75,097	100.0

Source: authors' calculations based on JRC TIM/EPO PATSTAT

Note: Information on the type of applicants is only available for about 73% of all patent families.

Table 8 AI patent applications by global players and applicant type, 2000-2016

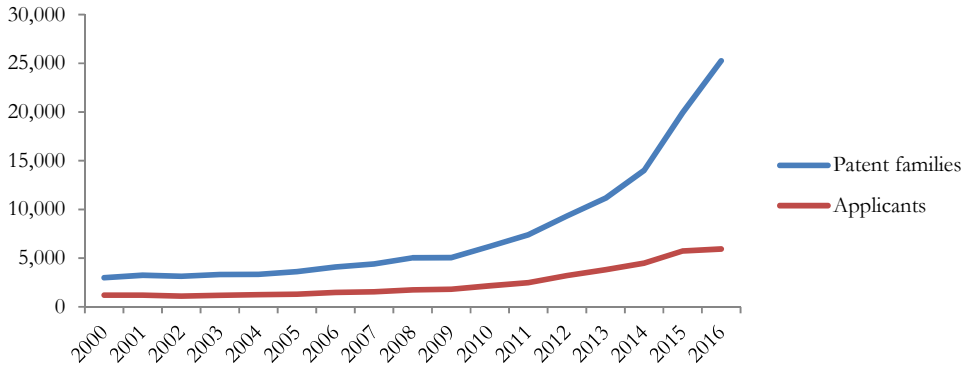
Applicant type	Total		China		Japan		South Korea		United States		European Union		Other	
	Nr.	%	Nr.	%	Nr.	%	Nr.	%	Nr.	%	Nr.	%	Nr.	%
One company	64,945	65.0	9,411	26.9	21,267	90.0	12,041	81.0	13,476	89.3	5,610	84.9	3,140	66.0
Two or more companies	4,449	4.5	1,889	5.4	1,209	5.1	509	3.4	468	3.1	280	4.2	94	2.0
One university	21,250	21.3	18,290	52.3	295	1.2	633	4.3	719	4.8	371	5.6	942	19.8
Two or more universities	287	0.3	196	0.6	4	0.0	11	0.1	36	0.2	23	0.3	17	0.4
One (or more) research center(s)	6,283	6.3	3,703	10.6	456	1.9	1,316	8.9	171	1.1	177	2.7	460	9.7
Company(ies) with university(ies) and/or research center(s)	2,247	2.2	1,274	3.6	372	1.6	289	1.9	169	1.1	100	1.5	43	0.9
Other	471	0.5	217	0.6	23	0.1	71	0.5	55	0.4	45	0.7	60	1.3
Total	99,932	100.0	34,980	100.0	23,626	100.0	14,870	100.0	15,094	100.0	6,606	100.0	4,756	100.0

Source: authors' calculations based on JRC TIM/EPO PATSTAT
Note: Information on the country and the type of the applicants is only available respectively for about 77% and 73% of all patent families.

The increasing share of universities and research centers among AI patent applicants over time, as opposed to the decline of companies' importance, is linked to the emergence of Chinese applicants as global leaders in AI patent applications. Table 8 cross-tabulates the type and country of applicants. Universities are involved in more than half (56%) of patent applications with a Chinese applicant, and the share increases to 67% when also research centers are considered. Companies, by contrast, are involved in just 36% of patent applications with a Chinese applicant. The distribution of applicants by type of organization observed in China sharply differs from what is observed in the other countries. The share of applications in other countries involving at least one company among the applicants is always above 85% – ranging between 86% in South Korea and 97% in Japan, while intermediate shares are observed in the EU (91%) and the US (94%).

The sample of patent family applications with valid information on organization names (this represents 84% of all AI patent families) indicates that 24,301 different organizations were applicant for at least one patent family. Each organization filed on average 5.4 patent families in the period 2000-2016. The average number of families per applicant increased from 2.5 in 2000 to 4.3 in 2016, as the growth of the number of applications outpaced the number of applicants (Figure 4). Japan shows the largest average number of patent families per applicant in the period (12.9), as it has the lowest number of applicants. China follows (9.2), due to its large number of patent families. South Korea (5.9), the US (4.4) and the EU (2.9) have much lower averages.

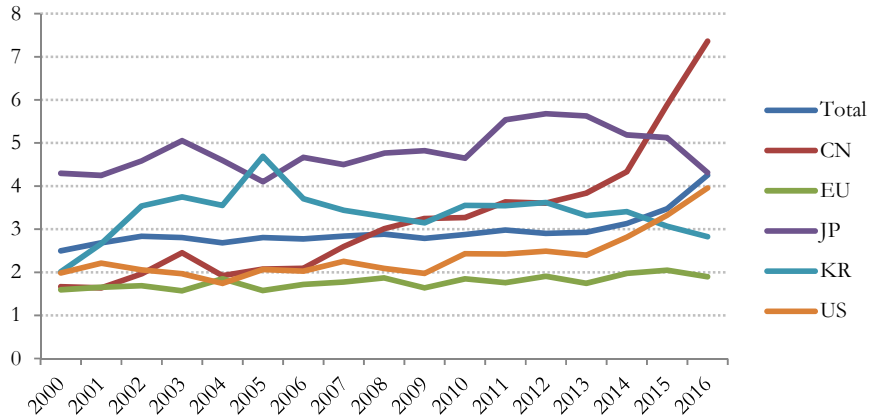
Figure 4 Patent families and applicants by year, 2000-2016



Source: authors' calculations based on JRC TIM/EPO PATSTAT

As shown in Figure 5, the rising global trend in the average number of families per applicant is driven by China and, to a lower extent, the US. In China, in particular, the average number of patent families per applicant started increasing in the second half of the 2000s and accelerated further in 2015 and 2016. A similar pattern, though with a slower pace of growth, is observed in the US. Japan and South Korea, by contrast, show fluctuating patterns throughout the period, and a moderate fall in recent years. Concentration in the EU, finally, does not show any change across time.

Figure 5 The average number of patent families per applicant by country and year, 2000-2016



Source: authors' calculations based on JRC TIM/EPO PATSTAT

6. The economic performance of inventors

Today's artificial intelligence market and economic performance is not easy to quantify. One of the reasons is that applications and developments in AI have cross-cutting potential for all

economic activities, being valuable in virtually all possible sectors. Inventions in AI go hand in hand with the adoption of AI as tools to improve existing technologies and to detect new market opportunities. In this respect, it is a plausible assumption that the higher will be the degree of AI adoption across sectors, the higher will be the sectoral spread of AI inventions and patenting activities. Despite the recognized and tremendous potential of AI in the near future, both the adoption and inventions in this field are probably still in their infancy. Firms active in AI patenting remain concentrated to a handful of sectors.

This section consists of two parts. First, it provides a sectoral analysis and describes main trends in economic performance for the global AI industry, including sectoral differences across global competitors. Second, it presents the economic performance of European AI companies in particular.

As introduced earlier, analyses in this section are carried out based on ORBIS Companies data. This source provides detailed financial information about companies, complementing the patent applicants' data used in the preceding section. The main reason for focusing the analysis on Europe in section 6.2 is the fact that the company data coverage in ORBIS is most complete for Europe compared to other continents, particularly in the context of smaller and medium-sized firms that are typically important actors in emerging industries. While the findings in this section reveal clear indications towards cross-fertilization across (non-tech) sectors and highlight promising growth trends, the real boom in AI is still yet to come.

6.1 Scaling the global AI economy

6.1.1 Sector analysis

Starting with a sector analysis, Table 9 presents the distribution of AI patenting firms across main sectors in the economy in the overall ORBIS sample. The sectors presented in the table refer to the primary economic activity of the firms, excluding any secondary sector to which a firm may belong. Firms patenting in AI are active in all sectors, including the primary, secondary and tertiary sectors, although the distribution is fairly skewed. A bit less than half of the firms are active in manufacturing industries, with a majority of them in manufacturing of electronic equipment (20%), machinery (10%) and cars and transport equipment (5%). The most prominent service sectors comprise information and communication (19%), professional and scientific activities (12%) and wholesale and retail trade (8%). The remaining 20% is spread out over all other sectors and

industries. Not surprisingly, the manufacturing of mineral products, and services related to transportation, accommodation, and food are among the least represented economic activities.

Table 9: Distribution of patenting AI firms across main sectors in the economy, 2000-2016

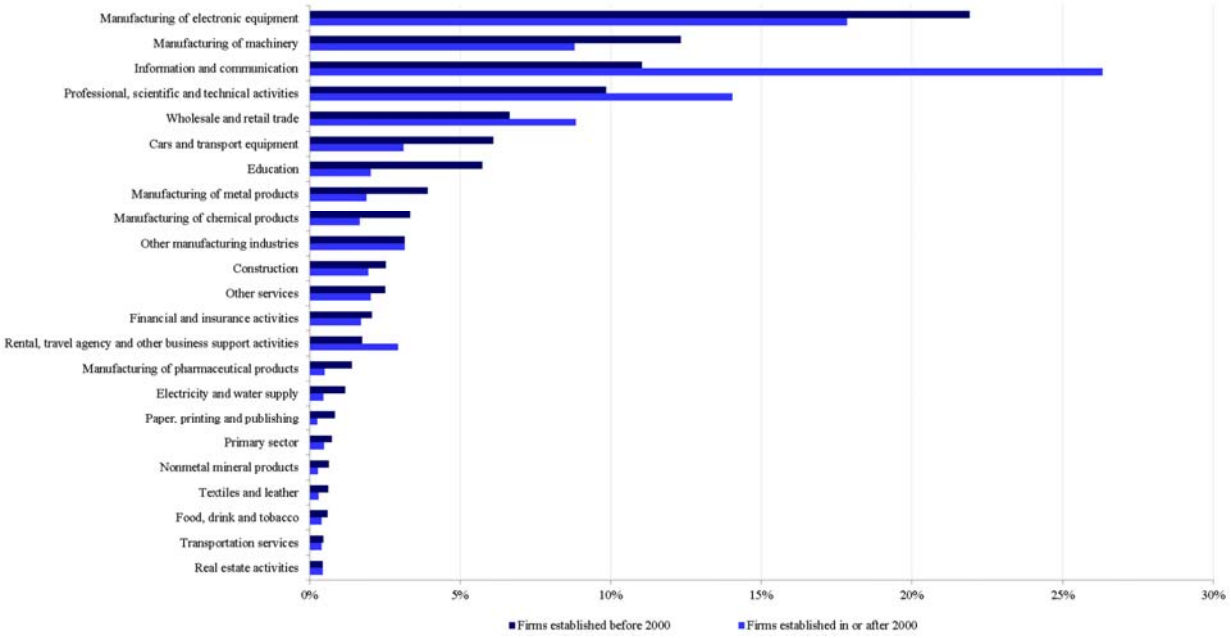
Sectors	AI firms	
	Numbers	Percentage
Manufacturing of electronic equipment	2,274	19.5
Information and communication	2,172	18.62
Professional, scientific and technical activities	1,385	11.88
Manufacturing of machinery	1212	10.39
Wholesale and retail trade	905	7.76
Cars and transport equipment	527	4.52
Education	509	4.36
Other manufacturing industries	363	3.11
Manufacturing of metal products	336	2.88
Other services	293	2.51
Manufacturing of chemical products	287	2.46
Rental, travel agency and other business support activities	271	2.32
Construction	262	2.25
Financial and insurance activities	218	1.87
Manufacturing of pharmaceutical products	109	0.93
Electricity and water supply	94	0.81
Primary sector	83	0.71
Paper, printing and publishing	70	0.6
Food, drink and tobacco	56	0.48
Real estate activities	54	0.46
Textiles and leather	53	0.45
Nonmetal mineral products	53	0.45
Transportation services	51	0.44
Accommodation and food service	25	0.21
Total	11,662	100.0

Source: authors' calculations based on ORBIS data

To evaluate structural changes over time, Figure 6 presents the sectoral distribution across firms that have been established before and after the year 2000. Some interesting patterns emerge in terms of sector dynamics. AI firms established before 2000 were mainly active in hardware sectors related to the manufacturing of electronic equipment and machinery, as well as information and communication services. While the two above-mentioned manufacturing sectors slightly decreased in importance in the sectoral distribution, the most prominent increases are observed in the sector of information and communication, mostly related to computer programming and software publishing activities. The increase of software firms is a natural step given that most of AI applications find their strength in the combination of hardware and software components. Another remarkable increase is observed in professional, scientific and technical activities. This rising trend highlights the greater relevance of engineering activities and experimental research for

the rapid development of AI technologies. Finally, the increasing number of AI firms active in wholesale and retail trade and rental or travel agencies is in line with the recent booming of ecommerce and online renting marketplaces.

Figure 6: Evolution of the sectoral distribution of patenting AI companies, 2000-2016



Note: Roughly, half of the sample of AI patenting firms has been established before 2000. Includes all countries in the ORBIS sample.

Turning to the geographical distribution of AI firms across the main global competitors and sectors as presented in Table 10, the US and South Korea seem to outperform the European Union, Japan and China in terms of total number of firms (however, the number of AI firms in China may not fully reflect reality due to a lower coverage of companies in ORBIS). The European Union's most prominent sector is the service provision of professional, scientific and technical activities, while it records a more balanced coverage across manufacturing of electric equipment, machinery, and information and communication services. Differences in the other global competitors are more outspoken. Both the US and South Korea seem to have a comparative advantage in information and communication, and to a lower extent also in manufacturing of electronic equipment. China and Japan have relative strength in manufacturing of electronic equipment, while the latter country records also a relatively high share in manufacturing of machinery.

Table 10: Geographical distribution of patenting AI firms across main sectors in the economy, 2000-2016

Sectors	EU		US		China		South-Korea		Japan	
	Numbers	Percentage	Numbers	Percentage	Numbers	Percentage	Numbers	Percentage	Numbers	Percentage
Manufacturing of electronic equipment	240	12.1	465	17.0	473	26.0	565	21.6	243	20.3
Information and communication	322	16.3	644	23.5	204	11.2	708	27.1	98	8.2
Professional, scientific and technical activities	375	19.0	375	13.7	175	9.6	154	5.9	52	4.3
Manufacturing of machinery	296	15.0	157	5.7	158	8.7	320	12.2	203	16.9
Wholesale and retail trade	120	6.1	214	7.8	161	8.8	174	6.7	121	10.1
Cars and transport equipment	67	3.4	99	3.6	99	5.4	130	5.0	81	6.8
Education	83	4.2	115	4.2	149	8.2	30	1.2	52	4.3
All sectors	1978	100.0	2738	100.0	1822	100.0	2614	100.0	1200	100.0

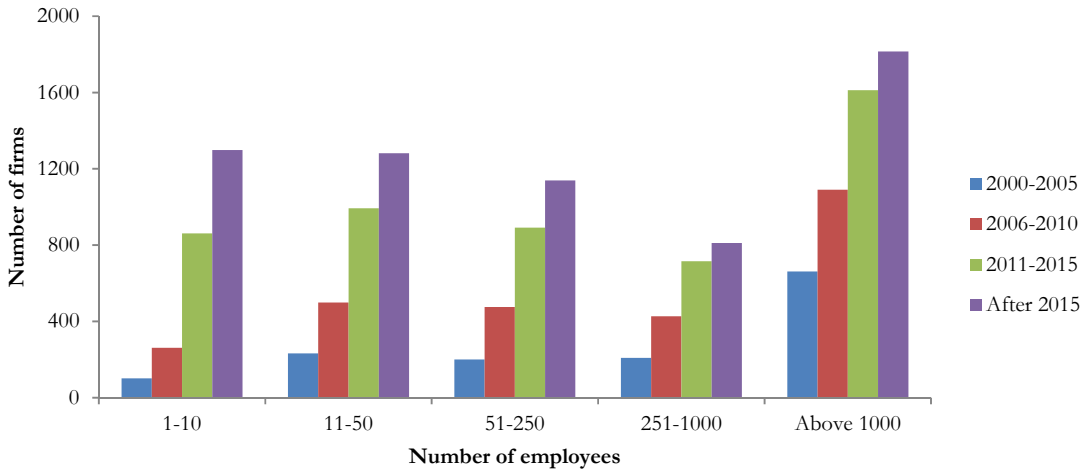
Source: authors' calculations based on ORBIS data

6.1.2 Economic performance

This section provides an overview of the economic performance of AI innovators in terms of employment and turnover levels and growth, and highlights comparisons across global competitors.

Figure 7 presents the distribution of AI firms across size classes and time periods. A firm can change size class over time due to variations in its employment growth. The number of firms in each size class increases monotonically over time, indicating the steady entry of newcomers active in AI patenting activities. Over time, the highest proportional increases in number of firms are observed for SMEs (i.e. firms up to 250 employees), suggesting a vibrant changing landscape in AI due to new and small players in the market. A strong increase is also observed for large firms above 1000 employees, representing the largest size class in all sub-periods. A dominance of large firms is not surprising in view of a common patenting strategy in which firms belonging to a large corporation assign their patents to the ultimate owner.

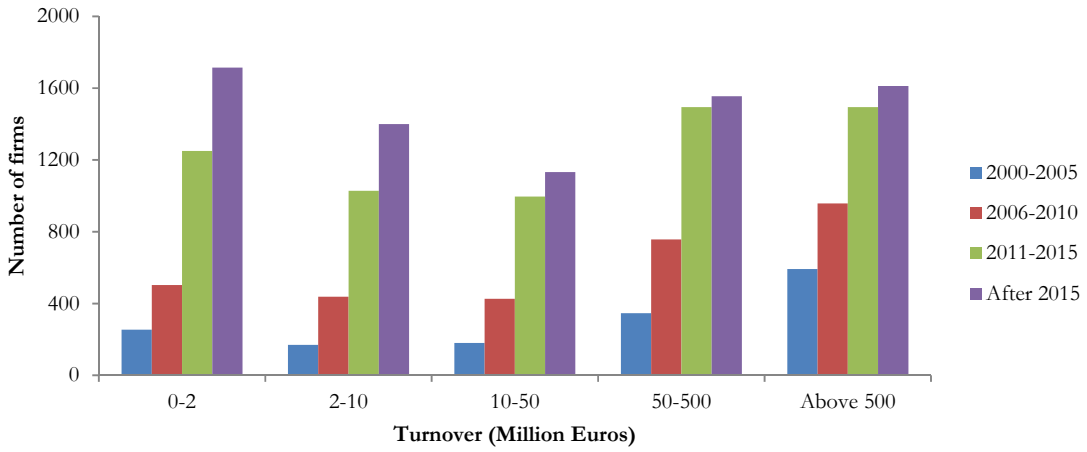
Figure 7: Distribution of firms over time and across size classes, 2000-2016



Source: authors' calculations based on ORBIS data

Figure 8 presents the distribution of AI firms across turnover classes and time periods. In the same vein as for Figure 7, a relatively high increase can be observed in the number of firms with turnover levels below 50 million euros. Not surprisingly, the proportion of firms with turnover levels above 50 million euros constitute a large part of the sample as these firms represent large holdings and mother companies active in AI patenting activities.

Figure 8: Distribution of firms over time and across turnover classes, 2000-2016



Source: authors' calculations based on ORBIS data

Patenting activities are an important driver for the economic performance of firms, both in terms of employment and turnover growth (Van Roy et al. 2018). The net impact of innovative activities on the economic performance is not linear but depends on the nature and value of the patenting activities of firms. In a preliminary analysis, Table 11 compares the average annual employment and turnover growth across firms with only non-granted patent applications and those with at least one granted patent in the time period 2000-2016. To minimize the effect of extreme values and outliers, the top and bottom 1% of the distribution of growth values has not been taken into account in the growth analyses of the remainder of this chapter. For the total sample of AI firms as for AI SMEs, firms with at least one granted patent perform significantly better in terms of employment growth. A similar pattern is observed for turnover growth in AI SMEs, while in the total sample no significant difference could be found.

Table 11: Distribution of employment and turnover yearly growth rates across firms with granted and non-granted patent applications

AI patenting firms	Percentage growth	
	Employment	Turnover
Total sample		
Only non-granted patent applications	2.9	9.6
At least one granted patent	3.6*	9.5
SMEs		
Only non-granted patent applications	3.3	14.5
At least one granted patent	4.6*	15.9*

Note: Percentage growth values with an asterisk indicate that the percentage growth for firms with at least one granted patent is significantly higher than the growth rate for firms with only non-granted patent applications.

6.2 The performance of European AI companies

Table 12 presents the average annual percentage growth in employment, turnover and labor productivity of AI patenting firms across the top sectors in the European Union. Positive and relatively high annual growth rates are recorded in all sectors, revealing prosperous economic opportunities for AI firms in the period 2000-2016. Annual employment growth rates oscillate between two and five percent, while turnover growth lie between 5 and 15 percent. The highest growth rates in employment, turnover and labor productivity (turnover divided by employment) are recorded in information and communication, which mainly refers to computer programming and software publishing activities.

Table 12: Distribution of employment, turnover and labor productivity yearly growth rates per sector in the EU, 2000-2016

Sectors	Percentage growth		
	Employment	Turnover	Labour productivity
Manufacturing of electronic equipment	2.9	9.0	5.4
Information and communication	5.3	15.6	8.7
Professional, scientific and technical activities	3.7	13.2	8.7
Manufacturing of machinery	3.6	9.4	6.6
Wholesale and retail trade	1.6	4.7	6.5
Cars and transport equipment	1.7	9.6	6.2
Education	2.4	6.2	7.2
All sectors	2.5	9.8	6.9

Source: authors' calculations based on ORBIS data

In order to explore the performance of the sample of AI patenting firms in EU across time and compare their performance with the industry average, Table 13 displays average annual growth rates of employment, turnover and labor productivity of the sample and industry across the top sectors and for three reference periods. In several sectors – particularly wholesale and retail trade and education – performance statistics for the sample of AI firms in the first reference period

(2000-2005) are based on limited amount of firms due to a lower historical coverage of financial information in ORBIS. In general, the performance of AI firms is higher than the industry average, both for top sectors individually as for all sectors together. The economic rise that can be observed in most of the top sectors can be seen as a reassuring signal in the current debate of job losses. At the same time, it may also signal the presence of a tight labor market for specific skills increasingly demanded due to the rise of AI and, possibly, some shortages from the labor supply side.

The boost of economic growth due to increasing jobs and higher productivity in existing and upcoming AI firms could potentially outperform the losses in jobs due to automation. In this respect analyses of a recent study in the UK reveal that AI would create more jobs than it displaces (PWC, 2018). Yet, it is too early to tell the actual scale of the transformation in the economy, including the magnitude of the educational and training challenge of transforming and supplying skills to meet the needs of an AI-based economy.

In terms of job creation in AI firms of the European Union, the most impressive and continuous increases over time are observed in the sectors of communication and information and manufacturing of machinery and electronic equipment. In contrast to these trends, increases in the industry averages remain steadier over time. Patterns of productivity growth in AI are more volatile over time but remain predominantly positive and substantially higher than industry averages. Similar trends can be observed for the labor productivity growth.

Table 13 Distribution of employment, turnover and labor productivity yearly growth rates per sector and period in the EU, 2000-2016

Sector	Employment growth						Turnover growth						Labour productivity growth					
	2000-2005		2006-2010		After 2010		2000-2005		2006-2010		After 2010		2000-2005		2006-2010		After 2010	
	Sample	Industry	Sample	Industry	Sample	Industry	Sample	Industry	Sample	Industry	Sample	Industry	Sample	Industry	Sample	Industry	Sample	Industry
Manufacturing of electronic equipment	0.1	-2.0	2.0	-2.0	3.6	-0.5	10.1	-0.3	8.0	0.7	9.2	0.4	4.5	1.8	6.6	2.6	5.2	0.8
Information and communication	2.1	1.3	4.8	1.1	5.9	1.8	24.2	4.6	8.3	2.3	16.8	3.2	19.6	3.2	6.5	1.2	7.9	1.4
Professional, scientific and technical activities	3.7	2.7	2.8	2.3	4.0	2.1	7.5	4.7	12.9	3.2	13.9	3.7	5.9	2.0	10.1	0.8	8.5	1.6
Manufacturing of machinery	-1.1	-1.3	2.0	-1.2	4.3	1.1	5.9	2.9	6.7	2.3	10.7	4.0	12.4	4.3	4.1	3.3	7.1	2.8
Wholesale and retail trade	-4.9	0.9	0.7	0.5	2.8	0.0	-0.9	3.9	5.8	2.0	4.9	2.5	5.9	3.0	4.2	1.4	7.1	2.5
Cars and transport equipment	-0.6	-1.1	0.9	-2.0	2.3	2.0	7.1	3.3	7.2	1.8	11.1	5.9	5.1	4.4	5.1	3.9	6.8	3.8
Education	-4.7	1.1	5.1	1.1	1.7	0.5	0.9	4.7	18.5	3.3	3.1	2.3	9.4	3.5	16.5	2.2	3.2	1.8
All sectors	0.2	-0.1	2.1	-0.4	3.8	0.1	8.7	3.4	8.2	2.2	10.6	2.4	7.8	3.5	6.8	2.6	6.8	2.3

Source: authors' calculations based on ORBIS (Sample) and Eurostat National Accounts (Industry) data

7. The future shakers: venture capital and startups in AI

Although the field of artificial intelligence is recognized to be in a nascent stage of development, the previous patent analysis predicts a flourishing future in a wide range of segments and application areas. Nevertheless, reflections based on patenting activities may only provide a partial picture of reality. Many AI startups are still in their infancy and may not have reached the stage of patenting their cutting-edge and emerging technologies. Alternatively, they may rely on other means of intellectual property rights such as copyrights, secrecy, or may opt for open source strategies often used in software programming. To gain more detailed insights in the global AI startups ecosystem, this section complements the chapter with an analysis of venture-backed AI firms.

Venture Source – a private equity funding database owned by Dow Jones – is used as a source of information for this analysis. This database provides comprehensive data on venture-backed and private equity-backed companies in every region, industry sector and stage of development throughout the world. Startups are identified as being active in AI by using a similar dictionary and text-mining technique as for the collection of AI patents. If one of the key words in the dictionary is found in the firm description in Venture Source, the firm is classified as an AI startup. This key-word matching procedure resulted in the identification of 3,459 AI startups in Venture Source, being mainly in line with prior attempts to quantify the emerging AI players across the world using venture capital data (McKinsey 2017; Roland Berger 2017).

Table 14 presents the geographical distribution of AI startups across continents and across the top countries within each continent. In terms of number of AI players, US is taking the lead with 1,406 startups or almost 41% of AI startups, while the European Union ranks second with nearly 20%, slightly followed by China at the third place with 18%. Looking at individual countries within the European Union AI startups ecosystem, the United Kingdom is leading with 7%, followed - with a considerable gap - by France (3%) and Germany (2%). While the European Union as a whole exhibits a strong AI startup ecosystem, each of its individual countries may be of little weight on the international scene as compared to US and China.

Table 14 Geographical distribution of AI startups across continents and top-ranked countries, 2000-2018

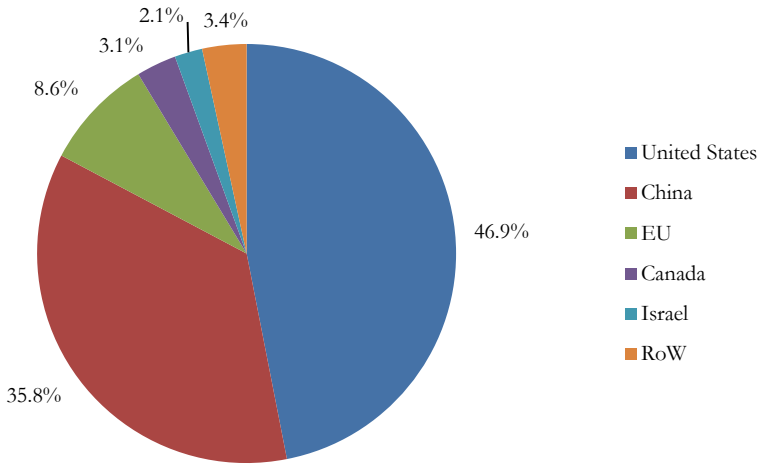
Region	AI startups	
	Numbers	Percentage
European Union	689	19.9%
United Kingdom	242	7.0%
France	112	3.2%
Germany	72	2.1%
Sweden	54	1.6%
Spain	44	1.3%
Rest of Europe	79	2.3%
North-America	1518	43.9%
United States	1406	40.6%
Canada	112	3.2%

Region	AI startups	
	Numbers	Percentage
Asia	1191	34.4%
China	628	18.2%
Japan	173	5.0%
India	125	3.6%
Israel	112	3.2%
South-Korea	79	2.3%
Latin-America	21	0.6%
Oceania	30	0.9%
Africa	10	0.3%

Note: All percentages in the table are calculated across the total number of AI startups identified in Venture Source.

To measure investment in the development and deployment of new AI technology, Figure 9 presents the distribution of VC funding raised across regions with the highest funding figures. In terms of raised VC funding US and China are clearly one step ahead at the moment. US dominates the picture with 50 percent of funding raised, followed by China with 35 percent, while the European Union reports only 9 percent of funding raised.

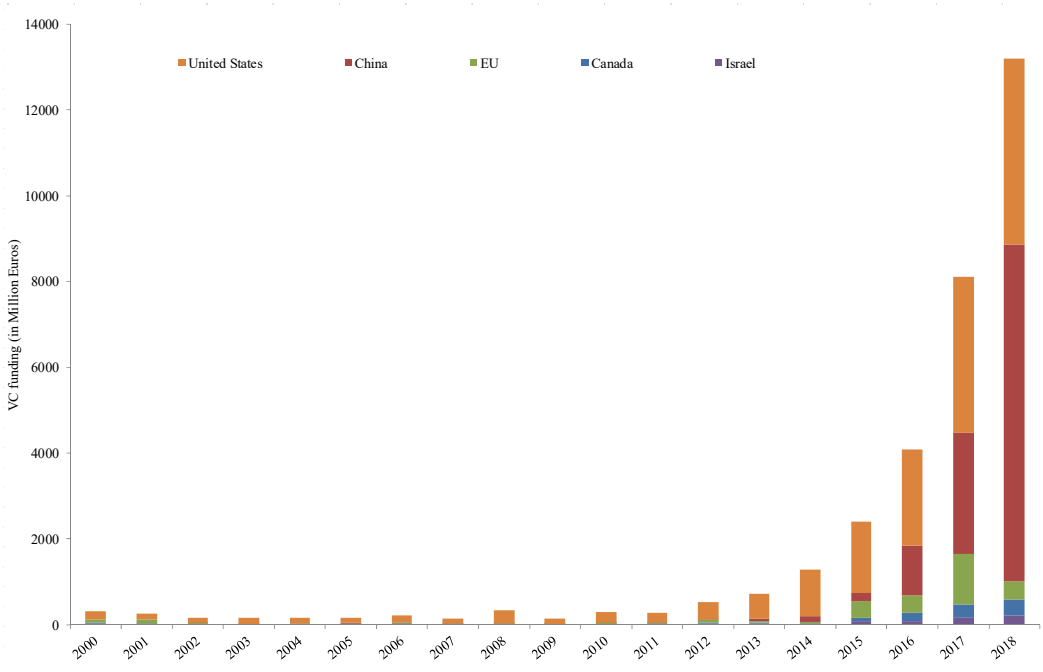
Figure 9 Distribution of total VC funding across selected regions, 2000-2018



While aggregated figures across the period 2000-2018 highlight a dominant position of the US, the distribution of raised VC funding per region and year as illustrated in Figure 10 reveals that China has gained momentum since 2015 and even surpassed the US in 2018 in terms of raised VC funding. In general, the amount of VC funding raised remained relatively stable from the early

2000s until 2012. The real take-off of VC funding can be observed from 2012 onwards with raising trends in nearly all regions.

Figure 10 Distribution of total VC funding across selected regions, 2000-2018



8. Summary

This chapter makes an attempt at estimating the current scale and growth trends of artificial intelligence. In a sense, it aims at contextualizing artificial intelligence by proposing a methodology to identify current and emerging AI technology developments and their innovators using patent family data. Employing a dictionary of AI-related keywords, a global set of 155,000 AI patents could be identified in the period 2000-2016.

While patenting activities in AI knew a moderate start in the earlier years up to 2009, the real take-off took place between 2010 and 2014 while it boomed from 2015 onwards. Remarkably, the boom in the latest years is mainly driven by the dramatic increase of AI patents in China. Besides having a relatively high patent propensity, China also differentiates itself from its global competitors by the composition of its patent applicants. Almost half of the Chinese patent applicants are universities, while Japan, South-Korea, US and EU have relatively large shares – above 85 percent – of companies as applicants. The observed high concentration of AI intellectual property rights to a few countries and organizations at a time when the technology is still in its

emerging phase raises many questions for future research – for instance, concerning the information and power asymmetries between developers and users of the technology, and between incumbents and possible new entrants.

Analyses of the underlying technologies of AI patents provide an indication of the direction in which AI is heading. Patents with transversally applicable technologies are generally the most diffused ones. High-tech sectors such as medicine, aeronautics and vehicles are among the main users of this emerging technology, but AI patents seem to rapidly grow in traditionally less technology-intensive fields, such as agriculture. While the fields of machine tools or acoustics have lost relative importance, the majority of fields seem to continuously grow over time; a trend that can be expected to continue in the future.

The very nature of AI as a transversally applicable technology is reflected in the sectoral distribution of AI firms. Although most of the AI firms remain concentrated in the sectors of manufacturing of electronic equipment, machinery and software programming, there are clear signs of cross-fertilization towards (non-tech) sectors. To further increase the breakthrough of AI technologies, governments should facilitate and promote the adoption and production of AI across all industries. This would allow industries to adapt to the next wave of technological developments and to increase their performance on the international AI scene.

Undoubtedly, the global AI landscape is already vibrant and characterized by a large increase of new and small players in the market over time. Even though the real boom is yet to come, AI firms are experiencing a flourishing economic performance, exhibiting on average positive employment, turnover and labor productivity growth rates across all global competitive regions. Having compared economic performance in AI firms to industry averages in the EU, it turns out that the former ones largely outperform industry growth rates. While these micro-level signals indicate that the opportunity offered by this new technology has larger ignited changes in the economy, it is too early to foresee the economy-wide impacts of AI on employment.

Opportunities for AI startups are also reflected in the rise of financial support. In this respect, venture capital investments raised by US AI firms steadily increased over the last decade, while the highest balance shift in venture capital is most apparent for China, recording dramatic increases in recent years. While venture capital is present in the European Union, it lacks sufficient depth and impact and remained relatively stagnant over time.

To conclude, the possibilities that AI is offering are immense and the revolutionizing process of AI is still ahead of us. AI brings along a wide range of challenges as well as opportunities. In this respect, global competitors should not necessarily aim at winning or losing the current AI race (EC 2018a), but should also focus on strengthening the necessary conditions to develop a stable and vibrant AI ecosystem. While most of the societal consequences of AI's diffusion are yet to be seen, the ongoing rapid progress and accelerating speed in the development of its constituent technologies implies that the right time to anticipate upcoming challenges is now. This calls for policy actions in coordination with research centers and businesses to advance efforts in identifying policy needs to prepare for the future of artificial intelligence. Accordingly, many global players, such as the US (National Science and Technology Council 2016, US Department of Defense 2019), China (State Council 2017) and the EU (EC 2018b) are currently developing strategic plans to define the role of governments in supporting AI development. The specific contexts of AI applications will warrant most of the attention. Nevertheless, one of the main building blocks common to all these strategic plans - and to which this chapter aimed to contribute - is the continuous monitoring of the innovative landscape of Artificial Intelligence.

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