THE ENABLING TECHNOLOGIES OF INDUSTRY 4.0: EXAMINING THE SEEDS OF THE FOURTH INDUSTRIAL REVOLUTION

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ABSTRACT

Technological revolutions mark profound transformations in socio-economic systems. They are associated with the diffusion of general purpose technologies that display very high degrees of pervasiveness, dynamism and complementarity. This paper provides an in-depth examination of the technologies underpinning the 'factory of the future' as profiled by the Industry 4.0 paradigm. It contains an exploratory comparative analysis of the technological bases and the emergent patterns of development of Internet of Things (IoT), big data, cloud, robotics, artificial intelligence and additive manufacturing. By qualifying the 'enabling' nature of these technologies, it explores to what extent their diffusion and convergence can be configured as the trigger of a fourth industrial revolution, and identifies key themes for future research on this topic from the viewpoint of industrial and corporate change.

KEYWORDS: Industry 4.0; technological paradigm; enabling technology; general purpose technology; disruptive innovation.

JEL CODES: O33; O31; L01.

1. INTRODUCTION

Technological revolutions are associated with the emergence of “constellation of innovations” that profoundly transforms the economy, and more broadly social systems (Freeman and Louçã, 2001; Perez, 2002; 2010). Examples of these technologies are water-powered energy and the steam engine, which shaped the British Industrial Revolution, then electricity, automotive technologies and more recently information and communication technologies (ICTs). Observation of such cyclical revolutions has provided the basis for the development of a theory of long cycles in economic growth where spells of high and low growth are tied to the rise and fall of waves of technical change (Freeman and Louçã, 2001). The economic literature has also linked this uneven development path to the emergence of a specific class of technologies, general purpose technologies (GPTs), characterised by pervasiveness, high dynamism and strong complementarities (Bresnahan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005; Bresnahan, 2010).

Understanding the effects of technological transformation requires opening up the "black box" of technology and explaining how, where and why they emerge and evolve (Rosenberg, 1982). Unique patterns of technical change develop through complex interactions of technical factors (e.g. characteristics of artefacts, their specifications and performance measures), the science base, and the broader institutional and economic context (Rosenberg, 1982, 1994). Dosi’s (1982) concepts of technological paradigms and trajectories provide an ideal framework for the study of innovative activities encompassing cognitive, technical, institutional and economic dimensions. While technological paradigms characterise and bind the potentially unlimited research space of a technology, technological trajectories identify local, cumulative, and irreversible patterns of development through time. This overarching framework is extremely useful to study emergent general purpose technologies and integrate contextual elements of institutional analysis into this approach.

This is important because the identification, measurement and characterisation of technological paradigms not only help us understand the knowledge bases of economic systems, but also make it possible to study the effects different paradigms may have for the patterns of industrial dynamics and competitiveness (Schumpeter, 1942; Malerba and Orsenigo,1996; Breschi, Malerba and Orsenigo, 2000). The potential for disruptive change specifically related to the development of GPTs has major implications for barriers to entry, market concentration, and the organisation of value chains between incumbents and new entrants (Tushman and Anderson, 1986; Christensen, 1997). The expanding processes of digitalization and automation in manufacturing and services (Teece, 2018) make this kind of analysis all the more urgent because of their effects on productivity, wages and employment (Frey and Osborne, 2017; Acemoglu and Restrepo, 2017).

There is yet no consensus as to whether we are observing the onset of a Fourth Industrial Revolution and whether this coincides with the Industry 4.0 paradigm. They are not synonyms. Industry 4.0 is the qualification of the 'factory of the future', shaped by policy interventions that have fostered the adoption of smart manufacturing technologies in Europe, and resulting from the convergence of a new wave of operational technologies with Internet-driven IT (Kagermann et al., 2013). This might be a fundamental component of a Fourth Industrial Revolution, but does not coincide with it because of its still relatively limited scale and scope. A similar difference exists, as Teece (2018) points out, between the notions of *general purpose* technology vis-à-vis *enabling* technology. Contrary to the concepts of technological paradigm (Dosi, 1982) and general purpose technology (Helpman, 1998), the concept of 'enabling technologies' has not been well defined in the academic literature because it has emerged in the policy arena to profile groups of technologies that can contribute to innovation and productivity growth in many sectors of the economy (Commission of the European Communities, 2009), and therefore identified primarily as industrial policy targets (European Commission, 2017). Paradigm changes and GPTs are much rarer than enabling technologies, but some enabling technologies may become GPTs (Teece, 2018) and trigger paradigmatic change. This may happen with Industry 4.0 technologies due to transformative potential of current trends in digitization and automation, and in particular the convergence (or recombination) of some incumbent and some rapidly developing new manufacturing technologies.

This paper provides an in-depth examination of the enabling technologies underpinning the Industry 4.0 paradigm. It contains an exploratory comparative analysis of the technological bases and the emergent patterns of production and use of *Internet of Things (IoT), big data, cloud,* *robotics, artificial intelligence and additive manufacturing.* We rely on primary and secondary data sources to reflect on the development of these technologies. One of the problems faced in empirical research on these topics is the lack of systematic information on the adoption of new technologies. This is a major drawback considering that the revolutionary potential of new technologies resides in their use, diffusion and adaptation. However, and despite well-known limitations, patents are a powerful instrument to study of the sources and flows of technological knowledge. We therefore use them to identify the emergent features of the six enabling technologies.

The paper is structured as follow. In the next section contains a brief overview of the Industry 4.0 (I4.0) technological context. Section 3 presents extensive patent analyses of the distribution of inventive efforts, their patterns of accumulation, and their relations and similarities. This includes an evaluation of the characteristics of GPTs of the enabling technologies, their knowledge bases and their use. Section 4 discusses the complex dynamics characterising the diffusion of Industry 4.0. Section 5 draws the contribution to a close.

2. THE TECHNOLOGICAL BOUNDARIES OF 'INDUSTRY 4.0'

Industry 4.0 is not a single technology but rather appears as a cluster of different technologies that are de facto agglomerated together by technological leaders, pivotal users, system integrators and government policy makers. Figure 1, synthetises the concept by illustrating the core technologies of Industry 4.0, with cloud manufacturing connecting industry devices through sensors and digital twins, and manufacturing execution systems (MES) that keep control of the whole factory streams through manufacturing analytics. It is clearly a complex architecture characterized by old technologies paired with new ones, all interconnected by cloud-based Internet. In more detail, the technologies are:

- IoT. IoT entails devices with self-identification capabilities, localisation, diagnosis status, data acquisition, processing, implementation that are connected via standard communication protocols. IoT technologies are used in I4.0 manufacturing applications, and in many others (housing and construction, automotive, environment, smart city, agriculture, health, etc.). In relation to the Industry 4.0, IoT applications are specific of the so called "industrial Internet".

- Big Data/Industrial Analytics. This includes methods and tools to process large volumes of data for manufacturing, supply chain management and maintenance. The data can come from IoT systems connected to the productive layer (for example with sensors and associated equipment), or the exchange between IT systems for production and warehouse management. Specific applications in this area are machine learning tools for planning and forecasting, predictive maintenance, and simulation.
- Cloud Manufacturing. Cloud Manufacturing encompasses the application in manufacturing of cloud technologies, with widespread access, easy and on-demand IT services – infrastructure, platform or application – to support production processes and supply chain management. Cloud manufacturing ranges from the virtualization of physical resources necessary for factory equipment to applications, data and processes across platforms and execution-and-collaboration tools, and hosted in the Cloud.
- Robotics. The robotics cluster includes SCARA, Articulated, Cartesian, Dual Arm and Co-bots (see section 2.4 for precise definitions) as different ways to automate production tasks. Advanced automation encompasses the latest developments in production systems with improved ability to interact with the environment, self-learning and automatic guidance, the use of vision and pattern recognition.
- Artificial Intelligence (AI). It concerns the knowledge and techniques developed to make machines 'intelligent', that is to say able to function appropriately also through foresight in their environment of application. Industrial AI refers to the computer science-based technologies which, coupled with machine learning, are used to generate intelligent sensors, edge computing, and smart production systems.
- Additive Manufacturing, also known as 3D Printing. It consists in the production of objects by depositing layer upon layer of material in exact geometric shapes. Additive Manufacturing finds application in the prototyping (to support the product development process, static simulation and wind tunnel, etc.), manufacturing (direct production of products), maintenance & repair and modelling phases.[1]

We now a brief overview of each group of technologies.

[1] The US International Standard Organization defines the following seven categories of additive manufacturing processes: Binder Jetting, Directed Energy Deposition, Material Extrusion, Material Jetting, Powder Bed Fusion, Sheet Lamination and Photo polymerization (as per ISO TC 261, 2011).

2.1 IoT

The concept of IoT was introduced in the 1980s at Carnegie Mellon where a modified Coke dispenser was made able to report its inventory and signal whether newly loaded drinks were cold through the Internet. IoT became popular in 1999 in the Auto-ID Center at MIT, with Radio-frequency identification (RFID) (Zhang et al., 2011; Chopra and Sodhi, 2007; Kubac et al., 2013; Liu and Chen, 2009). Several companies then introduced correlated concepts, including Olivetti, Xerox, IBM and universities such as Carnegie Mellon and MIT itself, but it was Siemens who introduced a machine-to-machine (M2M) GMS connected system in 1995 (Benrachi-Maassam, 2012; Kima et al., 2017). Open source dynamics, like in many other IT segments, often pushed the development of IoT, as clearly illustrated by the adoption in 2003 of the (open source-based) JXYA standard as a universal peer-to-peer standard to connect electronic things. After that, diffusion of the technology was boosted by the introduction of a low price, single board, electronic things controller, which originated in 2005 from the Interaction Design Institute Ivrea through the open-source electronics platform Arduino. Through this, IoT has progressively become a relevant offering for chip players as well as sensors producers, gateways hardware producers and software and machine developers for IoT platforms.

The basic disciplines at the roots of IoT are computer science, communication and information technology and electronics. The core technologies needed to build an IoT device are semiconductor technologies, internet, sensor technologies and more generally microelectromechanical systems. Within these core technologies, IoT incorporates Bluetooth technologies, low consumption battery technologies, laser technologies, smart cameras technologies, smart meters and sensors for energy consumption. Within this heterogeneous assemble of different devices and solutions there are at least three technological clusters: devices, software platforms, and gateways and other networking elements. IoT technologies are still in an early stage of development and consequently characterized by an unstable competitive and technological environment. Technical challenges of this kind of environment include: data exchange among large scale heterogeneous networks elements, integration and interaction adaptation of uncertain information, service adaptation in dynamic system environment.

There are structured data on R&D spending specific to IoT, and we do not have any specific on the subsystem of Industrial IoT (IIoT). Investments in these technologies are driven by private companies. IBM, Google, Samsung, SAP, Dell, Siemens and Intel seem to be the companies investing more (Lueth, 2015), but it is very difficult to identify a clear technology leader in both devices and platforms, also due to the vast number of different technologies and sectors involved. Interestingly, the growing interest of large companies in acquiring IoT capabilities seem to be driving a wave of consolidation in the industry, as signaled by the acquisition of Nest and CSR by Google and Qualcomm respectively.

2.2 Big Data/Industrial Analytics

Big data analytics is the process of examining large and varied data sets to uncover hidden patterns, unknown correlations, market trends, customer preferences and other useful information that can help organizations make more-informed business decisions. The term big data was first used to refer to increasing data volumes in the mid-1990s, and later expanded to also capture increases in the variety of data and the pace at which they were generated. A manufacturing analytic system starts out with a data acquisition system that can either be built-in by the original equipment manufacturer (OEM) or a third-party provider. Using appropriate sensor assemblies, various signals such as vibration, pressure, temperature, etc. can be recorded. The types of signal and data acquisition parameters are determined by the application and the failure modes of the asset being monitored. Communication protocols, such as MT Connect and OLE-DB Process Control or OPC, can help users to acquire process or controller signals. Such data can provide context as to the type of action/function the machine was performing when sensor data was being collected. The aggregation of all information results in "Big Data" because of the volume of data collected, velocity by which data is being received and variety of data that are being collated. Such phenomenon requires new analytical approaches in place of standard statistical process control or other traditional techniques.

Several components are at play in this space: an integrated platform, predictive analytics and visualization tools. The deployment platform is selected based on several factors such as speed of computation, investment cost, and ease of deployment for scaling purposes and update. The actual processing or transformation of big data into useful information is performed by utilizing predictive analytics such as the tools found in the Watchdog Agent toolbox that has been developed by researchers at the National Science Foundation (NSF) Industry/University Research Cooperative Center (I/UCRC) for Intelligent Maintenance Systems (IMS) since 2001. There are also other commercial predictive analytic providers such as IBM, Hadoop, SAS, and SAP. The Watchdog Agent algorithms exemplifies the working of this technology. It can be categorized into four sections, namely: signal processing and feature extraction, health assessment, performance prediction and fault diagnosis. By utilizing visualization tools, health information such as current condition, remaining useful life estimation, root cause, etc., can be effectively conveyed using radar charts, fault maps, risk charts and even health degradation curves. The calculated health information can then be forwarded or made available to existing company management systems such as enterprise resource planning system (ERP), manufacturing execution system (MES), supply chain management system (SCM), customer relation management system (CRM), and product lifecycle management system (PLM) to achieve overall enterprise control and optimization.

The Hadoop distributed processing framework was launched as an Apache open source project in 2006, planting the seeds for a clustered platform built on top of commodity hardware and geared to run big data applications. Initially, as the Hadoop ecosystem took shape and started to mature, big data applications were primarily used by large internet and e-commerce companies, such as Yahoo, Google and Facebook, as well as analytics and marketing services providers. In ensuing years, though, big data analytics has increasingly been embraced by retailers, financial services firms, insurers, healthcare organizations, manufacturers, and energy companies. While we do not have precise data on R&D expenditure on manufacturing Big Data tools, the growth of activities in this area indicates a rapid increase in commercial interest in the field (IDC, 2018).

2.3 Cloud Manufacturing

Cloud manufacturing is a new set of IT service delivery models. It can be can be divided into two categories. The first category is concerned with the deployment of manufacturing software on the Cloud, i.e. a “manufacturing version” of computing. The second category has a broader scope, cutting across production, management, design and engineering abilities in a manufacturing business. Unlike with computing and data storage, manufacturing involves physical equipment, monitors, materials, etc. In this kind of Cloud Manufacturing system, both material and non-material facilities are implemented on the Manufacturing Cloud to support the whole supply chain. In Cloud Manufacturing System, various manufacturing resources and abilities can be intelligently sensed and connected through the Internet, and automatically managed and controlled using IoT technologies (e.g., RFID, wired and wireless sensor network, embedded system).

Several industrial players developed products in this space. In 2006 Amazon introduced its Elastic Compute Cloud. Microsoft Azure was announced as "Azure" in 2008 and released in 2010 as Windows Azure, before being renamed to Microsoft Azure in 2014 (for a time, Azure was on the TOP500 supercomputer list, before it dropped off it). In July 2010, Rackspace Hosting and NASA jointly launched an open-source cloud-software initiative known as OpenStack. The OpenStack project intended to help organizations offering cloud-computing services running on standard hardware. The early code came from NASA's Nebula platform as well as from Rackspace's Cloud Files platform. In 2011, IBM announced the IBM Smart Cloud framework to support Smarter Planet. Among the various components of the Smarter Computing foundation, cloud computing is a critical part. In 2012, Oracle announced the Oracle Cloud. While aspects of the Oracle Cloud are still in development, this cloud offering is poised to be the first to provide users with access to an integrated set of IT solutions, including the Applications (SaaS), Platform (PaaS), and Infrastructure (IaaS) layers. In April of 2008, Google released Google App Engine in beta. In 2012, Google Compute Engine was released in preview, before being rolled out into General Availability in 2013.[2]

The field is a combination of applied research on virtualization, fast Internet, memory computing, and firewall technologies. Red Monk (2017) report some figures on the R&D

[2] For extensive analyses of Cloud Manufacturing see: Caldarelli et al. (2016), Wei et al., (2013), Wu et Al., (2015), Putnik (2012), Hashem et al. (2014), Ren et al. (2014).

expenditure of cloud computing companies.[3] From 2014 to 2017, in percentage terms over their total R&D expenditure, IBM grew from 5% to 6%, Amazon from 8% to 12.5%, Microsoft from 13% to 15% Google from 12,5% to 16% and Oracle from 13% to 16%. In absolute terms, the available data show a substantial gap between the top-tier cloud providers (Amazon, Microsoft, and Google) and their competitors.

2.4 Robotics

Since the invention in 1954 of George Devol's first digitally operated and programmable robot, sold to General Motors in 1960, the advancements of robotics are well documented in the literature since the field is well established and commercial and industrial robots are in widespread use. Robots are used in manufacturing, assembly and packing, transport, earth and space exploration, surgery, weaponry, laboratory research, and mass production of consumer and industrial goods. With recent advances in computer hardware and data management software, artificial representations of humans are also becoming widely spread, and artificial intelligence and machine learning are contributing to the development of modern flexible robots. Fundamental components of the robotic industry are sensors, actuators, power conversion units, manipulators, and software. Relative to other fields, we have much better data on R&D expenditures and markets. As far as R&D expenditures are concerned, the three major spenders (KUKA, ABB and YASKAVA) account for more than 70% of sales, and increasing investments.[4]

Industrial robots are typically classified in the following groups: SCARA, Articulated, Cartesian, Dual Arm and Co-bots. SCARA (Selective Compliance Assembly Robot Arm) is a type of robot which moves an "arm" on the horizontal plane and an outlet that can rise and fall in the vertical one. This type of robot was developed for high speed and repeatability in series assembly, such as Pick-and-Place from one place to another. An *Articulated robot* is a robot with rotary joints (e.g. a legged robot or an industrial robot), that can range from simple two-jointed structures to systems with ten or more interacting joints. They are

[3] https://redmonk.com/rstephens/2017/09/26/cloud_rd/.

[4] Figures have been obtained from the three companies' 2018 Annual Reports.

powered by a variety of means, including electric motors. A *Delta robot* is a type of parallel robot. It consists of three arms connected by universal joints to the base. The key feature of the design is the use of parallelograms in the arms, which maintain the orientation of the end device. Delta robots are usually used in picking and packaging in factories because they are fast enough to run more than 300 outlets per minute. *Cartesian robots (or Gantry robot)* are used for pick-and-place work, application of sealant, assembly operations, handling machine tools and arc welding. They are robots whose arms have three prismatic joints, and axes are coincident with a Cartesian coordinator. *Dual Arm* robots are robots in which each of a pair of robotic arms has an anthropomorphic elbow, and configurations with six joints: there are three joints at the wrist that support the gripper (the end-effector) and the arm itself has three more joints to position the wrist at the desired location. Finally, *Cobots* or co-robots (from collaborative robot) are robots designed to physically interact with humans in a shared workspace. This is in contrast with other robots, designed to operate autonomously or with limited guidance, which is what most industrial robots were up until the 2010s.

To date, the world market for industrial robots is worth about 11B$ (on a total of 27B$) with steady, if not especially fast, growth rates (International Robotic Federation, 2017). The market appears to be highly concentrated (in 2014 the top four manufacturers delivered robot units amounted to approximately 70% of the total robot units delivered worldwide in that year) and is signaling faster growth in easy-to-use collaborative robots, and a growing presence, through acquisitions, of new Chinese producers.

2.5 Artificial Intelligence

Attempts to mechanise human intelligence have a relatively long history (Nilsson, 2010), but the development of modern AI – the term was coined back in 1954 by John McCarthy as the topic of a conference at Dartmouth – is intimately related to progress in computing technologies and to recent advancements in machine learning and predictive processes. AI includes various areas of research and it is often difficult to draw precise boundaries. Its core components can however be identified with machine learning, deep learning, NLP (natural language processing) platforms, predictive APIs (application programming interface), image recognition and speech recognition.

Global R&D spending in AI is fast increasing, both in the form of internal research in large tech firms' labs (i.e. Goole and Baidu), but also through VC-backed start-ups, often financed by corporate investments. Investments appear to be in the order of $25 to $35 billion (MGI, 2018). Machine learning is the largest recipient of funds. Lee et al. (2018) note that the success of AI in industrial applications has so far been quite limited. However, industrial AI is fast improving as a systematic field of research, focused on developing, validating and deploying reliable machine learning algorithms for industrial applications. Demand for is also expected to growth significantly over the next few years, with early industrial adopters clustered in the finance and banking, retail and manufacturing sectors. Industrial applications have so far been concentrated in autonomous robots, digital assistants, neurocomputers, machine monitoring and control systems, and expert systems such as healthcare decision and smart grid systems.

2.6 Additive Manufacturing

In 1981, Hideo Kodama of Nagoya Municipal Industrial Research Institute published his account of a functional rapid prototyping system using photopolymers. A solid, printed model was built up in layers, each of which corresponded to a cross-sectional slice in the model. Then, the invention of stereolithography in 1984 let designers create 3D models with digital data, which could then be used to create tangible objects. The key to stereolithography is a kind of acrylic-based material known as photopolymer. The process starts with a hit on a vat of liquid photopolymer with a UV laser beam, so that the light-exposed portion turns into solid piece of plastic, and is then molded into the shape a 3D-model design. Interestingly, in that same decade (the 1980s) 3D printing crossed path with the open-source movement and this interaction continued over time until in 2005 Adrian Bowyer's RepRap Project launched an open-source initiative to create a 3D printer that could essentially build itself, or at least print most of its own parts. The first 3D printing machine became commercially viable in 2006, and this opened the door to on-demand manufacturing of industrial parts. 3D-printing startup Objet (now merged with Stratasys) built a machine that could print in multiple materials, which allowed a single part to be fabricated in different versions and with different material properties. With the entry of MakerBot, an open-source DIY kit became available for makers to build their own 3D printers and products. With open source kits the barriers to entry for designers and inventors started to fall. While the price of 3D printers has fallen rapidly in recent years, the accuracy of 3D printing has significantly improved, and designers are no longer limited to printing with plastic.

The field of 3D printing has been growing rapidly for years. It has applications in many sectors as diverse as healthcare, aerospace, and parts replacement. This is an industry with large commitment to R&D with three-year average year (2014-2017) spend of $309 million for all top six companies (Stratasys, Renishaw, 3D Systems, Organovo, ExOne, Arcam)[5]. Interestingly, Arcam has recently been acquired by General Electric for its multiple potential applications, ranging from aircraft components and medical equipment, to oil and gas equipment).

3. THE KNOWLEDGE BASES OF I4.0 ENABLING TECHNOLOGIES

Having profiled the boundaries and building blocks of Industry 4.0, we now turn to an in-depth analysis of the knowledge bases of these technologies. We collected patent data for each enabling technology under examination. The main questions to be concern the distribution of inventive efforts, their patterns of accumulation, and their relations and similarities.

3.1. Data and sample construction

Data were retrieved from the EPO-PATSTAT database (2018 Autumn Edition) but limitedly to granted United States Patent and Trademark Office (USPTO) patents filed between 1990 and 2014. Because of the relevance of the US market and the global nature of the actors involved, this choice does not introduce any significant home bias effects. We sampled patent records by following the search strategies documented in the literature and fully illustrated in Table 1, which also reports all the specific sources.

<< INSERT TABLE 1 ABOUT HERE >>

The final dataset includes 363,803 patents: of which 188,319 (51.8%) related to IoT, 130,604 (35.9%) related to Big Data, 17,732 (4.9%) related to Robotics, 15,480 (4.3%) related to 3D

[5] Figures from the companies' Annual Reports.

Printing, 5,930 (1.6%) related to Artificial Intelligence, and 5,738 (1.6%) related to Cloud. The bar chart in Figure 1 shows an increase over time in the total number of patents filed each year, even though at variable rates. The line graph in Figure 2 captures the 3-year average growth rate of patent numbers, indicating almost a decade (from 1997) of positive but decreasing growth rate.

<< INSERT FIGURE 2 ABOUT HERE >>

Table 2 highlights some differences in the number of patents and average growth rates over five periods and across technologies. Cloud and IoT are the technologies with more systematic high growth, that is to say that they grew more than the total in every period (except for Cloud in 1996-2000). However, after 2005, also Robotics and AI display high rates of growth clearly indicating increased innovative efforts in these areas. Conversely, 3D printing displays a dynamic more in line with a mature technology with decreasing levels of opportunities over time.

<< INSERT TABLE 2 ABOUT HERE >>

3.2. Geographical and organisational distribution of patents

Patents carry essential information on who are the innovators and their geographical location. The strong technological opportunities that characterise emerging technologies are generally associated to low level of concentration of innovative activities, high entry rates and turbulence in the ranking of innovators (Breschi et al., 2000; Malerba and Orsenigo, 1996a; 1996b; 1997). Figure 3 displays the evolution of the concentration of the innovative activities in each enabling technology measured using the C4 indicator and the Herfindahl–Hirschman Index (HHI).

<< INSERT FIGURE 3 ABOUT HERE >>

C4 measures the share of patents filed by the top 4 innovators; whereas, HHI index captures the dispersion of these shares. Figure 3 reveals that Cloud is the technology where inventive activities are more concentrated; however, a relatively higher level of the HHI index indicates that these inventors are relatively larger than in the other technologies. The other five technologies display more similar patterns, featuring a modest increase in the share of top inventors (especially for Robotics and Big data) coupled with a somewhat stable presence of a large number of smaller size players.

<< INSERT FIGURE 4 ABOUT HERE >>

Figure 4 reports the evolution of the Spearman correlation for the ranking of the top 20 inventors. The Spearman correlation picks up the extent to which two variables have similar ranks. It varies between -1 and 1, moving from an opposed to identical correlation. Spearman correlation can therefore be used to capture the degree of technological turbulence in a field. Figure 3 shows some differences among the six technologies under examination. Differently from the other technologies, Cloud and Robotics show a marked increase in the stability of inventors over time. This result, coupled with the previous, suggests a pattern of consolidation of technological leadership in Cloud technology. Conversely, AI shows a very low level of stability, denoting high mobility within the group of top inventors.

<< INSERT TABLE 3 ABOUT HERE >>

Besides these general trends, it is interesting to zoom into each technology and identify the top inventors. Table 3 reports the list of the top 4 inventors in each technology for the period 1990-1995 and the period 2010-2014. The most striking result is that IBM is the only company able to maintain the technological leadership in four out of the six technologies (i.e. AI, Big Data, Cloud, and IoT). Even in technologies characterised by an overall low level of instability, the top positions are in the long run rather precarious. Interestingly, the most patent-active companies in the two periods are very different also as far their sector of reference is concerned. While in the period 1990-1996, technological leadership is held by either hardware, cars, and telephone manufacturers; in the second period companies are more focused on software and services. This transition is also true for IBM, a company that over the years has changed considerably its core businesses away from hardware manufacturing and towards information services.

From a geographical point of view, we observe in Table 3 an increasing concentration of activities in the United States, with Japan losing significant technological opportunities. Table 3 also reveals that technological leaders tend to overlap across the six enabling technologies.

Strong complementarities in use could explain the tendency of these companies to develop technological capabilities that strand across all enabling technologies. The percentage of inventors active in more than one technology in the period 1990-1995 is 39% of the set, increasing to 44% in the period 2010-2014. Unreported graphs (available upon request) of the distribution of patent portfolio size by number of technologies show that a limited group of very large multi-technology firms drives this trend.

<< INSERT FIGURE 5 ABOUT HERE >>

Different patterns of entry can trigger different technological dynamics. While we observe an increasing number of inventors in each technology, it is important to distinguish whether they are really new entrants or they just enter in a technology field while being active already in another technological space. An increase in the latter category can indicate patterns of consolidation bewteen complementary technologies. Figure 5 shows that the share of entrants from another technology is overall increasing over time. AI and Cloud attract the largest share of entrants from related technologies, pointing to their key integrating role among the six enabling technologies.

3.3. 'Enabling' or 'general purpose' technologies?

The six enabling technologies we examine in this paper are often bundled together in the characterisation of the factory of the future. However, the extent to which these technologies are similar to one another can to be subjected to an empirical test. In this section, we evaluate the extent to which the six enabling technologies can be considered as general purpose technologies (GPTs). Bresnahan and Trajtenberg (1995) define GPTs as technologies characterised by i) pervasiveness (i.e., with a broad range of possible application sectors), ii) high technological dynamism (i.e., significant potential for increasing efficiency), and iii) the ability to generate complementarities (i.e., their adoption stimulates rapid technical progress in the application sectors). How do our six enabling technologies fare against these three criteria?

Following the literature, we examine how these technologies score on three patents indicators generally associated with GPTs: generality, originality, and longevity. The generality index is used to assess the range of later generations of inventions that have been promoted by a patent, by measuring the range of technological classes that cite that patent (Trajtenberg et al., 1997). This indicator is based on the HHI index and relies on information about the number of forward citations and their distribution across International Patent Classification (IPC) technology classes. It ranges from 0 (when all the citations received from the patents are from the same technological classes) to 1 (when all the citations are equally spread across different technological classes). The rationale of this indicator is that the larger it is, the more technologically widespread is the effect of a patent, which is consistent with the definition of a GPT (Hall and Trajtenberg, 2004).

The originality index is similar to the generality indicator, but it focuses on backward citations by measuring the range of technological classes that are cited by the patent (Trajtenberg et al., 1997). The more diverse the technological base upon which a patent is built, the more potential for new recombination. This indicator is also based on the HHI index and relies on information about the number of backward citations and their distribution across IPC classes. It ranges from 0 (when all the citations made by a patent are from the same technological classes) to 1 (when all the citations are equally spread across different technological classes). High originality correlates with the high technological dynamism that is typical of GPTs (Trajtenberg et al., 1997; Moser and Nicholas, 2004). Both the generality and originality indicators are retrieved from the OECD Quality database (Squicciarini et al., 2013). Finally, patent longevity measures the speed of obsolesce of a specific patent. As it was found for electricity (Moser and Nicholas; 2004), GPTs are expected to have lasting effects on subsequent technological development and therefore to become obsolete less fast. Following Moser and Nicholas (2004), we measure patent longevity as the maximum lag (in years) between the year of patent grant and the year of the latest forward citation. Longevity was calculated using the OECD Citations database (March 2018 version).

<< INSERT FIGURE 6 ABOUT HERE >>

In order to account for potential differences in the measure that might be due to specific technological characteristics, time trends, and vintage, we normalise them using the average of these indicators for patents filed in the same year in the same technological field. Figure 6 displays the evolution of these three indicators over time. Values are above the reference line indicates that patents have a higher average value than patents in the same technological field and filed in the same year. Figure 6(a) shows that AI, IoT, 3D Printing, and Robotics are more general than comparable patents. On the contrary, Big Data and Cloud are characterised by less widespread technological impact. Figure 6(b) shows that Cloud and Big Data have a comparably lower level of originality, but the latter is always above the reference line. Interestingly, AI displays a decreasing level of originality, perhaps suggesting a reduction over time in the scope of the recombined knowledge base. Finally, Figure 6(c) displays a more stable trend, almost always above the reference line, indicating that patents in the examined technologies have a low rate of obsolescence than comparable patents. All in all, we find evidence of heterogeneity in the pervasiveness, originality and longevity of the six I4.0 enabling technologies, despite their complementarity in use.

3.4. Sources and uses of technological knowledge

The previous section focuses on technological relations based on patent citations (both backward and forward) and IPC classes. IPC classes are very informative about patents technological domain, but they cannot be straightforwardly related to industries. The two concepts can be tightly interrelated when they are both defined at a low level of granularity; however, numerous technologies cut across several industries. This section presents two specular exercises. First, we examine the industrial knowledge base used by the six enabling technologies to uncover common roots. Second, we examine the industrial applications of these enabling technologies to uncover joint applications. To carry out these two analyses we use data on the industrial classification of both the cited and citing patents of enabling technologies. Van Looy et al. (2015) provides a concordance table between IPC classes and 2-digit NACE (Rev. 2), which makes it possible to associate any patent to one or more 2-digit NACE (Rev. 2) codes. The EPO-PATSTAT Database provides this information we use in this analysis.

<< INSERT TABLE 4 ABOUT HERE >>

Table 4 shows backward citations over NACE classes and the C4 and HHI indices to evaluate their relative importance, thus indicating the industrial knowledge base behind each enabling technology. Table 4 reveals the presence of three patterns of use. AI, Big Data, Cloud and IoT have strong commonalities rooted in the manufacturing of computer, communication equipment, and office machinery. However, the relative importance of these sources varies: for Cloud and IoT these represent more than 85% of the used industrial knowledge base; whereas, for AI and Big Data, these industries represent the 67.8% and 78.2%, respectively. 3D Printings and Robotics display completely different industrial knowledge, both between them, and between them and the other four technologies. These differences hint to a pattern of technological development running apart from, or in parallel to, the other enabling technologies.

<< INSERT FIGURE 7 ABOUT HERE >>

Another way to identify common patterns of development is measuring the similarity of technological domains used by each enabling technology. Cosine similarity, which has been extensively used to measure technological distance with patent data (Jaffe, 1986; 1989), can be fruitfully adapted to this context. Proximity between firms is typically measured by comparing vectors that represent firms' shares of patents in each patent class. In this case, the similarity in industrial knowledge bases can be measured by comparing vectors of the shares of cited industrial technological domain for each enabling technology in each year. Figure 7 presents the evolution of the cosine similarity in the used industrial knowledge base over time and across technologies. Cloud, Big Data and AI display remarkably stable patterns over time, which are rather similar to one another. This points to the presence of a long-term pattern of joint development between these three enabling technologies. IoT displays a similar trend but with consistently lower levels of similarity. Robotics has a less stable pattern of industrial use similarity characterised by convergence towards AI in the late 1990s. 3D Printing is the enabling technology with less similar industrial roots relative to the other technologies; it does, however, converges towards Robotics and diverges from Big Data.

<< INSERT TABLE 5 ABOUT HERE >>

Table 5 reports forward citations shares over NACE classes and the C4 and HHI indices to evaluate their relative importance. This indicates the industrial classes of application of the inventions developed within in enabling technology. AI, Big Data, Cloud and IoT appear to promote further technical advancement in the same industries, namely manufacturing of computer, communication equipment, and office machinery. The comparison of the C4 and HHI indicators presented in Table 4 and Table 5 indicates that industrial application is more concentrated than the industrial knowledge bases. In a nutshell, this suggests that the recombination of a broader industrial knowledge base is associated with a narrower range of industrial applications. This contrasts with the idea that that all these technologies should promote 'downstream' innovation in a wide range of industries.

<< INSERT FIGURE 8 ABOUT HERE >>

Figure 8 reports the evolution of cosine similarity measures in the application industry. Cloud, Big Data, and AI display a stable pattern of similar application. IoT also displays a comparable pattern of similarity, in contrast with what we found for the used industrial knowledge bases. This suggests that IoT recombines more diversified industrial knowledge bases that produce applications in a more similar group of technologies. 3D Printing displays a clear pattern of divergence from Robotics, coupled with a stable low level of application similarity to most of the other enabling technologies. Interpreting this result in the light of the content of Figure 6 suggests that 3D printing is diverging from Robotics in its industrial application, but is slowly converging with it in terms of their used industrial knowledge bases. Robotics shows a clearly decreasing trend in the knowledge application similarity with all the other enabling technologies.

3.5. The interrelation of knowledge bases

After examining the technological and industrial similarity of the six enabling technologies, we now assess whether and to what extent these technologies are interrelated, that is to say how these technologies cross-fertilise each-other, by using cross-citations between patents. While we based our previous analysis on citations made and received from the universe of USPTO granted patents, in this section we examine "internal" citations within patent sets. Figure 9 reports for each enabling technology the share of citations made to patents related to a focal enabling technology. The first category is always the share of "self-citations", i.e. citations between patents in the same enabling technology. Figure 10 reports similar graphs illustrating the shares of citations received by the enabling technologies. The comparison of the two figures provides information on the evolution of the reciprocal positions of these technologies in an interrelated technology system.

<< INSERT FIGURE 9 and 10 ABOUT HERE >>

Big Data, IoT, Robotics, and 3D Printing appear as technologies with a more independent development, with shares of self-citations constantly well above the 70% mark for both backward and forward citations. AI and Cloud display more varied dynamics indicating a more integrated position in the technological system. More specifically, AI decreases the share of self-citations made from a peak of about 80% in the late 90s to less than 30%in 2014. This fall in self citations is compensated by a steady increase in citations made to Big Data and IoT. While the total share of citations received by AI from AI, Big Data and IoT is similar to the total share of citations made, in the latter case, self-citations display a different pattern. They reach the minimum (less than 20%) in the early 2000s and doubled in 2014. This indicates that within AI there has clearly been a recent surge of internal technological development. Finally, Cloud is the technology that is less reliant on self-citations, displaying a large degree of integration with the IoT and AI domains.

4. An integrated approach to the adoption of Industry 4.0

Industry 4.0 is a combination of several technologies. The way in which the six enabling technologies might result in systemic disruptive change in the economy depends on how they will diffuse, more or less jointly, in adopting sectors, and on the way in which they will be adapted to different production and consumption needs as they diffuse. From the viewpoint of broad technological backgrounds, semiconductor and internet technologies, increasingly rich in AI content, are overall predominant components of Industry 4.0 systems. Given the information technology roots of these domains, it can be argued that so far we have been observing the continuation, or perhaps amplification, of the Third Industrial Revolution, rather than the clear-cut birth of a Fourth. It is however possible that we will soon see unprecedented and radically new uses of (combinations of) enabling technologies. Moreover, the most dramatic changes might not come from manufacturing at all but rather from the service sectors.

<< INSERT TABLES 6 and 7 ABOUT HERE >>

As far as manufacturing is concerned, it is difficult to find clear empirical evidence of a fundamental break between the adoption of ‘smart’ technologies and the adoption of ‘pre-smart’ technologies such as CAD/CAE/CAM. Overall the diffusion of Industry 4.0 appears to be patchy and heterogeneous across countries and sectors. After about four-five years from the introduction of all the major Industry 4.0 technologies, Table 6 presents estimates of the size of the markets for each enabling technology (note that artificial intelligence is here treated in its specific embodiment in advanced human-machine interfaces). The table shows that the largest market is by far Industrial IoT. Table 7 is an attempt to summarise what we know of the state of diffusion, with a synopsis of the major segments. It reports figures for: the worldwide installed base and/or percentage of adoption on the total target industry population; expected diffusion as per the latest growth rate estimates; diffusion by sector and geography; and key diffusion drivers. If we focus on the aggregate figures, there are around 2 billion IoT devices[6], 850,000 industrial robots (including all robotic technologies), and 600.000 3D printers installed.[7] In terms of growth rates (the growth of the installed base of systems and devices), there are clear indications of high growth in the IoT cluster and additive manufacturing, and slower growth in robots (a more mature segment) and advanced human-machine interfaces (a possible sign of the aforementioned difficulty to apply AI effectively to current production processes).[8]

Germany is at the frontier of Industry 4.0 and emergent evidence on this context of adoption provides very useful insights. A recent study of 128 adoption cases across 500 production sites (IoT Analytics, 2016) uncovered a clear dichotomy between large companies, which are the most advanced buyers and lead users, and small and medium sized firms, which are lagging behind, suggesting cost and absorptive capacity barriers to adoption. Moreover, the majority of firms seem to have privileged ‘single technologies’ adoption paths while only few companies are

[6] Note that this figure is somewhat ambiguous because it hides the relative weights of the different components of IoT systems.

[7] From IDC, Gartner, Morgan Stanley, and PWC latest market data.

[8] Regarding the geographical distribution of I4.0, it is interesting to notice in the figures for robotics that China is the largest adopter by absolute numbers, while South Korea, Japan and Germany are leading by intensity of adoption.

undertaking a systemic (multi-technology) approach. Italy provides interesting contrasting evidence: despite the role played by the manufacturing sector in the structure of its economy (including exports), it is a context where the process of diffusion of ‘pre-smart’ technologies (e.g. CAD/CAE/CAM) has not yet been completed and the adoption of ‘smart’ technologies started significantly later than in Germany. A survey of 23,000 companies carried out in 2017 for the Italian Ministry of Industry and Economic Development (MISE, 2017) illustrates the very slow uptake of Industry 4.0 technologies: only 8.4% of manufacturing companies (most of which large) have made investments in this space, and only 4.7% intend to do so in the next three years, against estimates that show positive returns to adoption. As in the German case, firms that adopt a multi-technology approach are a minority. The same data indicate as main drivers of adoption increased competitiveness through greater production efficiency (e.g. due to cost optimization, and greater flexibility), and product quality improvement through minimization of production errors. Instead, the application of new business models figures prominently in the preferences of smaller firms.

5. Drivers of industrial change: a discussion and research agenda

There are several unexplored aspects of I4.0 enabling technologies, whose study presents some of problems typically posed by emergent technologies. These include fluid boundaries and definitions, as well as fundamental uncertainty in their substantial patterns of growth and development. Despite difficulties in finding and structuring relevant data, there are (at least) three sets of questions of particular importance to gain better understanding of these enabling technologies and monitor their possible transformation in the general purpose technologies of a Fourth Industrial Revolution. The first questions concern the domain of industrial dynamics, the second standards, and the third government policy.

Industrial dynamics

The six enabling technologies display uneven patterns of concentration and market dynamics. IoT is probably the most important segment where industry dynamics will eventually influence the evolution of the whole Industry 4.0. Other than in sensors[9], the segment is highly unstable

[9] The sensors segment of the industry is relatively mature and will likely be driven by low energy consumption, smaller size, and cost minimisation objectives.

and paths largely unpredictable. While sensors producers and telecom providers are capable of covering only their key area of specialization, and neither have strong competences in machine and processes nor ownership of the data produced, competition seems to be driven by machine producers, lead users and software companies. A particular challenge is the ongoing competition between proprietary vs. open source architectures. Additive manufacturing and robotics markets are relatively more mature. Additive manufacturing is strongly segmented in two different compartments (business and consumers) with different technologies and players. However, despite high barrier to entry in both segments, and also despite the fact that both segments depend on the quality of extruding technologies (this determines printing quality), the sector is still decisively unstable: after the expiration of key patents in 2014-2015, new industrial research has marked the entry of traditional printer players (such as HP), services players (such as Amazon) or software players (such as Autodesk), which could radically change the competitive landscape. Robotics has instead received new impulse by the aggressive entry of Chinese producers as well as the introduction of new materials, and advances in AI and its latest applications to human-machine interfaces. In turn, these are directly related to fast progress in big data and manufacturing analytics. Big data analytics features some of the major ICT players such as IBM (U.S.), General Electric (U.S.), Microsoft (U.S.), Oracle (U.S.), PTC Inc. (U.S.), SAP SE (Germany), Cisco (U.S.), Hewlett Packard (U.S), Hitachi (Japan), and SAS (U.S.). Interestingly, most large organizations in North America are choosing on-cloud deployment because of cheaper installation and ease of data retrieval (anytime, anywhere). Cloud computing is itself fragmented in Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) markets, depending on the degree of outsourcing. Moving from the former to the latter, there is an increasing level of efficiency (in terms of cost reduction), but also less control over data and software (the customer would typically deploy its own software on the infrastructure and platform). The three tiers are also characterized by different barrier to entry: SaaS has the lowest and new entrants can take advantage of low required initial investment and quick time to market. For PaaS, in-house development and human capital constitute significant barriers, while IaaS requires substantial financial investment in order to build and support the Cloud infrastructure.

Overall, the patterns of entry and industry growth differ within and across sectors, and some of the key segments presents the typical turbulence of fluid phases of technology life cycles. The presence of large players (e.g. Google, IBM) in related segments and related enabling technologies could, however, limit entry by small innovative firms and provide scope for agglomeration and diversification strategies.

Industry standards

One of the most interesting areas for research, with implications for both industrial dynamics and the diffusion of I4.0 enabling technologies, is the problem of standards. Of paramount importance are *legal* standards for robotics and AI, and *technical* standards for the most highly networked technical systems, such as IoT and Cloud. The lack of standards is one of the most serious barriers to adoption. Beside the ethical issues of robotics and AI regulation, at the technology level the clearest tension is between the push for proprietary standards by early-stage global players, and the preference of adopters' consortia for more open standards (such as the RAMI 4.0 architecture elaborated by "Platform Industrie 4.0" and the IIRA of the Industrial Internet Consortium).

Standards allows interoperability in complex technical systems and this is precisely the problem faced by the IoT industry, where companies are joining different consortia and entering different alliances in order to generate the critical mass needed for the generation of voluntary de facto standards (among them, Auto-ID Lab and the Alliance for the Internet of Things Innovation (AIOTI), promoted by the European Commission). Other parts of the systems are under the control to standard setting bodies: RFID technologies, frequency and the format of data are under the remit of GS1, the European Telecommunications Standards Institute (ETSI) and ISO (Atzori et al. 2010).[10] The definition of standards is also related to broader regulatory issues. Firstly, competition, given the need to address new markets and their boundaries. Secondly, privacy, given the sensitive nature of the type of data smart objects will be able to gather. Thirdly, cyber security: as noted by Whitmore (2015), current approaches to cyber-security, mostly based on encryption, may not be feasible for smart objects with limited computing capabilities. Cloud is

[10] For the broader IoT architecture, ETSI is also play a role through its Machine-to-Machine Technical Committee.

another domain strongly affected by the availability of standards or lack thereof. Cloud interoperability is a major issue, but there is no agreement of how best to address the problem. For example, IBM subscribed to the Open Cloud Manifesto (2009), but Microsoft and Amazon did not. Parallel standardisation initiatives are proliferating, led both by businesses alliances and by the main international standard-setting organizations (e.g. ISO, IEEE and the ITU).[11] Moreover, the European Commission has specifically identified IoT and Cloud, together with cybersecurity and 5G communications) as essential technology building blocks of the Digital Single Market. In summary, (interrelated) standards races and de jure standardisation processes will play a fundamental role in shaping the competitive environment, but whether these processes will follow the same lines of development of previous ITC standard making experiences remains an open question. At the moment, the technical and legal complexities of the problem, appear to be very distinctive of this phase of industrial growth and will deserve careful study.

Government policy

Enabling technologies are fast becoming a central part of a new wave of industrial policies, many of which are specifically designed to foster the development and diffusion of Industry 4.0. The IPOL Study Group on Industry 4.0 (European Parliament, 2016) describes a series of interventions that can be classified as:

- integrated adoption processes and a strong cooperation between industry, trade unions and companies;
- more targeted approaches focussing on individual technologies;
- ‘neutral’ direct approaches (firms use subsidies but select their technology of choice);
- ‘neutral’ indirect approaches (more standard tax incentives).

Very often different policies coexist within the same country more or less coherently, and more or less related to a ‘mission-oriented’ approach to science and technology policy, or industrial policy more broadly. It is not clear which type of policy and which policy mixes will prove effective in supporting the competitiveness of different economies, especially if we consider that

[11] The European Commission is considering 5G communications, Cloud, IoT, (big) data technologies and cybersecurity as essential technology building blocks of the Digital Single Market.

the same interventions may produce very different effects on systems that are structurally different in their production and application of I4.0 enabling technologies. This is an essential area for further research, not least because this level of policy intervention is related to other policy domain (above all labour policy) directly called into question by the revolutionary nature of emergent general purpose technologies.

6. CONCLUSION

Industry 4.0 is complex and heterogonous cluster of emergent technologies that contain the seeds of, but do not yet coincide with, the Fourth Industrial Revolution. In this paper we have identified and examined the six main components of the new digital economy, which has been growing out of the established semiconductor-cum-internet paradigm. As far as manufacturing is concerned, it is helpful to remember that is not the first time we have seen an attempt to implement systemic approach to automation. In the early nineties, CIM (Computer Integrated Manufacturing) was a top-down approach to translate a classic information system methodology into production facilities. It was not a success. It remains an empirical question whether and to what extent Industry 4.0 will be radically different, or – put differently – how long it will take for enabling technologies to become fully fledged general purpose technologies and revolutionise production and consumption systems.

Many of the building blocks of Industry 4.0 have been around for many years: robotics and human-machine interfaces are based on the existing mechatronic industry; the use of sensors in machines has more than 20 years of history, and so do machines connected to computers; 3D printing is now more than 30 years old and even AI has been around for many years but has not had any obvious and fundamental impact on businesses. However, the introduction of complementary innovations are changing the potential application of known techniques: the introduction of low energy consumption in sensors, and their declining costs, are boosting their diffusion; advanced machine learning and deep learning are now beginning to drive automation; the introduction of cloud connectivity is delivering low cost processing power and pervasive interconnection; and finally, new ways to connect monitoring and management systems (the so ‘digital twins’). No easy prediction can be made about the aggregate outcomes of joint diffusion of complementary and incremental innovations. Much work remains to be done on heuristics at the base of the R&D processes in this space, their geographical and organisational distribution, the diffusion of technology, patters of concentration and industry dynamics (who will be the technology leaders of the future?), and their ultimate effects on growth, productivity and employment.

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LIST OF TABLES

Table 1 – Summary of the sampling strategy

TECHNOLOGY	SELECTION STRATEGY		
	IPC	KEYWORDS	SOURCES
CLOUD	NO	Cloud comput%, cloud securit%, cloud technolog%, cloud serv%, cloud process%, cloud software, cloud networking, cloud infrastructure, cloud solution, cloud system%, cloud data%, cloud storage, cloud app%, public cloud, private cloud, hybrid clouds, virtuali%ation, data warehouse, distributed comput%, cloud based, grid comput%, parallel comput%, concurrent comput%, parallel software, parallel process, cluster comput%, data portability, service orient%, service-orient%, web service%, utility orient*, utility comput%, cloud architectur%, MapReduce, Hadoop, VMware, hypervisor%, Hyper-V, % as-a-service, Aneka, InterCloud, multitenan%, multi-core	Huang (2015), Dotsika (2017), IPO big data report (2014), Buyya et al. (2013)
IOT	G05B19/418 G06F15/16 G08C17/02 H04B7/26 H04L12/28 H04L29/06 H04L29/08 H04W4/00 H04W72/04 H04W84/18	NO	Ardito, D'Adda, Messeni Petruzzelli (2018) "Mapping innovation dynamics in the Internet of Things domain: Evidence from patent analysis", Technological Forecasting & Social Change, 136, 317-333 on the basis of UK IP Office, 2014. The Internet of Things: A patent overview, UK Intellectual Property (IP) Office
ROBOTICS	B25J 9/16 B25J 9/18 B25J 9/20 B25J 9/22 B60W 30/00 B60W 30/02 B60W 30/04 B60W30/045 B60W 30/06 B60W 30/08 B60W30/085 B60W30/09 B60W30/095 B60W 30/10 B60W 30/12 B60W 30/14 B60W30/16 B60W30/165 B60W30/17 B60W 30/18 B60W30/182 B60W30/184 B60W30/186 B60W 30/188 B60W30/19 B60W 30/192 B60W 30/194 B60W30/20 G05D1/02 G05D1/03	self –driving, driverless, autonomous, automated, unmanned) in proximity to (car, motorcar, vehicle, automobile, aircraft, airplane, aeroplane, submarine, marine)	UK IP Office, 2014.Eight great technologies: robotics and autonomous systems, UK Intellectual Property (IP) Office Available at. https://
3D PRINTING	B23K9/04 B23K26/34 B23K26/342 C08L101/00 C08L101/02 C08L101/04 C08L101/06 C08L101/08 C08L101/10 C08L101/12 C08L101/14 C08L101/16 B22F%	NO	UK IP Office, 2013.3D printing: a patent overview, UK Intellectual Property (IP) Office Available at. https://www.gov.uk/government/publications/3d-printing-a-patent-overview
BIG DATA	G06F 17/30 G06F19/10 G06F19/12 G06F19/14 G06F19/16 G06F19/18 G06F19/20 G06F19/22 G06F19/24 G06F19/26 G06F19/28 G06Q 30/02 G06F 17/50 G06N*	NO	UK IP, 2014. Big Data & Energy Efficient Computing, UK Intellectual Property (IP)
AI	NO	machine learning, supervised learning, SVM, support vector machine, neural network, Artificial Intelligence, Data Mining, Machine Learning, Expert Systems, Machine Intelligence, Intelligent Machines, Artificial Thinking	Webb, N. Short, N. Bloom and J. Lerner (2018) "Some Facts of High-Tech Patenting", NBER Working Paper 24793

Table 2 - Number of patents and growth rate by technology

	1990-1995		1996-2000		2001-2005		2006-2010		2011-2014	
	NUM PATENTS	AV. GROWTH RATE	NUM PATENTS	AV. GROWTH RATE	NUM PATENTS	AV. GROWTH RATE	NUM PATENTS	AV. GROWT H RATE	NUM PATENTS	AV. GROWT H RATE
AI	1118	13%	1133	4%	1139	-2%	1197	0%	1343	15%
BIG DATA	9421	18%	19268	15%	28050	6%	36714	4%	37151	4%
CLOUD	205	33%	398	10%	667	18%	1825	19%	2643	11%
IOT	4861	34%	19618	31%	42400	9%	54823	6%	66617	9%
3D PRINTING	3425	10%	3819	4%	4012	-8%	2002	-4%	2222	5%
ROBOTICS	1976	13%	2661	6%	3222	2%	3578	6%	6295	25%
TOTAL	21006	19%	46897	18%	79490	6%	100139	5%	116271	8%

Table 3 - Top Innovators over time and technology

	Top Innovators (1990-1995)			Top Innovators (2010-2014)		
	country	company	share	country	company	share
AI	US	IBM	0.052	US	IBM	0.083
	JP	HITACHI	0.034	US	MICROSOFT	0.067
	JP	TOSHIBA	0.026	US	GOOGLE	0.059
	JP	PANASONIC-MATSUSHITA	0.026	US	QUALCOMM	0.028
BIG DATA	US	IBM	0.073	US	IBM	0.121
	JP	HITACHI	0.027	US	GOOGLE	0.069
	JP	FUJITSU	0.014	US	MICROSOFT	0.044
	JP	TOSHIBA	0.013		SAP	0.020
	US	MOTOROLA	0.013			
CLOUD	US	IBM	0.149	US	IBM	0.227
	US	DEC	0.077	US	RED HAT	0.041
	JP	HITACHI	0.072	US	MICROSOFT	0.040
	JP	FUJITSU	0.053	US	INTEL	0.032
	US	THINKING MACHINES	0.053			
IOT	US	IBM	0.098	US	IBM	0.048
	US	MOTOROLA	0.067	KR	LG	0.035
	JP	NEC	0.052	US	QUALCOMM	0.033
	SE	ERICSSON	0.035	US	GOOGLE	0.028
3D PRINTING	SW	CIBA	0.025	US	BAKER HUGHES	0.025
	JP	SUMITOMO	0.024	US	GE	0.023
	US	GE	0.016	JP	HITACHI	0.021
	US	MINNESOTA MINING & MANUFACTURING	0.015	DE	SIEMENS	0.020
ROBOTICS	JP	FANUC	0.032	JP	TOYOTA	0.059
	US	EATON	0.029	US	FORD	0.051
	JP	HONDA	0.027	US	GOOGLE	0.037
	JP	HITACHI	0.020	US	DIEBOLD	0.029
	US	CATERPILLARD	0.020			

Table 4 - Top used industrial knowledge base domain

	USED INDUSTRIAL KNOWLEDGE DOMAIN	Share	C4	HHI
AI	Manufacture of computers and peripheral equipment	38.7%	0.678	0.188
	Manufacture of Communication Equipment	11.3%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	11.1%		
	Manufacture of Instruments and Appliances for Measuring, Testing and Navigation; Watches and Clocks	6.7%		
BIG DATA	Manufacture of computers and peripheral equipment	49.2%	0.782	0.278
	Manufacture of Communication Equipment	15.7%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	7.1%		
	Computer Programming, Consultancy and Related Activities	6.2%		
CLOUD	Manufacture of computers and peripheral equipment	56.3%	0.858	0.361
	Manufacture of Communication Equipment	19.5%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	5.3%		
	Computer Programming, Consultancy and Related Activities	4.7%		
IOT	Manufacture of Communication Equipment	55.0%	0.908	0.384
	Manufacture of computers and peripheral equipment	27.7%		
	Computer Programming, Consultancy and Related Activities	4.3%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	3.8%		
3D PRINTING	Manufacture of Basic Chemicals, Fertilisers and Nitrogen Compounds, Plastics and Synthetic Rubber in Primary Forms	26.4%	0.500	0.102
	Manufacture of Basic Metals	8.6%		
	Manufacture of Other Special-Purpose Machinery	8.0%		
	Forging, Pressing, Stamping and Roll-Forming of Metal; Powder Metallurgy	7.0%		
ROBOTICS	Manufacture of Motor Vehicles	12.7%	0.406	0.064
	Manufacture of Instruments and Appliances for Measuring, Testing and Navigation; Watches and Clocks	11.8%		
	Manufacture of General-Purpose Machinery	9.8%		
	Manufacture of computers and peripheral equipment	6.3%		

Table 5 – Top sourced industrial knowledge base domain

	USED INDUSTRIAL KNOWLEDGE DOMAIN	Share	C4	HHI
AI	Manufacture of computers and peripheral equipment	39.6%	0.718	0.200
	Manufacture of Communication Equipment	11.9%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	11.5%		
	Computer Programming, Consultancy and Related Activities	8.8%		
BIG DATA	Manufacture of computers and peripheral equipment	54.0%	0.842	0.330
	Manufacture of Communication Equipment	16.9%		
	Computer Programming, Consultancy and Related Activities	6.9%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	6.5%		
CLOUD	Manufacture of computers and peripheral equipment	62.2%	0.928	0.438
	Manufacture of Communication Equipment	21.1%		
	Computer Programming, Consultancy and Related Activities	7.1%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	2.4%		
IOT	Manufacture of Communication Equipment	54.6%	0.935	0.403
	Manufacture of computers and peripheral equipment	32.0%		
	Computer Programming, Consultancy and Related Activities	4.5%		
	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	2.5%		
3D PRINTING	Manufacture of Basic Chemicals, Fertilisers and Nitrogen Compounds, Plastics and Synthetic Rubber in Primary Forms	21.9%	0.438	0.080
	Manufacture of Other Special-Purpose Machinery	7.7%		
	Manufacture of medical and dental instruments and supplies	7.6%		
	Manufacture of Electronic Components and Boards	6.6%		
ROBOTICS	Manufacture of computers and peripheral equipment	12.2%	0.383	0.064
	Manufacture of Instruments and Appliances for Measuring, Testing and Navigation; Watches and Clocks	9.3%		
	Manufacture of Motor Vehicles	8.8%		
	Manufacture of Communication Equipment	7.9%		

Table 6 - Industry 4.0 Worldwide turn over

	Industrial IoT	**Cloud Manufacturing**	**Manufacturing Analytics**	**Advanced Robotics**	**Advanced Human-Machine Int.**	**Additive Manufacturing**	**ICT Industry**
Turn Over (2015-2016)	200 B $ (on a total of 1,000 B$, savvy estimate)	8 B$, (on a total of 23 B $ including ERP and CRM Cloud)	3,2 B$ on a total of 17B$)	11B$ (on a total of 27B$)	1 B $ (on a total of 2,6 B$)	6 B $	3.5 T $
Expected 5 Yrs CAGR	25-30 %	25%	21%	5-8 %	8-9%	20%	2%
Sources	IDC, IC Market Drivers, IooT Analytics, Gartner	Gartner, IDC, Cisco	Markets and Market, IDC	BI Intelligenc e, World Robotics	Market and Markets, Grand View Research	Market and Markets, IDC	Gartner, IDC

Table 7 – Industry 4.0 diffusion

	IIoT	Cloud Manufacturing	Manufacturing Analytics	Advanced Robotics	Advanced Human Machine Interface	Additive Manufacturing
Installed base or % adoption	IIoT=2B devices on a total of 12B Installed devices (all IoT)	Global Cloud penetration is: 10% of companies are adopting private cloud and 20 % public cloud, driven by large companies (more than 30% overall adoption)	Statistic on different manufacturing analytics' global adoption: Inventory Management 20%, Plant Quality Management 7%, Plant Simulation 5%, Plant Analytics 10%, Predictive maintenance 7%	850 K installed devices	12 M devices (Industry only)	600 K Installed Base
Expected growth rate	30%	30%	30%	5%	10%	29%
Diffusion by Sector	IIoT about 25% of total installed base (Oil and Gas Leading) Overall: Connected Cities = more than 50% of total installed base	Manufacturing 15%,Aerospace 13%, Parma Consumer and Automobile each 13% penetration	NA	Automotive 50%, Electrical/Electronics 15% Metal/Machinery 10%	Automotive, Oil & Gas, Packaging, Aerospace and Defense, Food and Beverage,	Installed base distribution: Consumer Products 20% Automobile 20% Medical 15% Aerospace 15%
Geography	APAC=US =Europe	LATAM 40 %, APAC 30%, US 20 % Europe 15%	NA	Sales in 2015: China leading country 70 k, Korea, 35 k, Japan 35, US 27k, Germany 20 k	NA 40% APAC 30% Europe 20%, China and India fast growing countries	40% NA, 28% Europe, 27% APAC
Drivers	IIoT: Revenue Growth more than cost cutting Predictive maintenance Product Control	Search for more flexibility and scalability, Big Data, move to Opex, less important cost reduction	Search for New revenue streams and reduce cost. Pressure to increase customer satisfaction and product quality	Cost drivers, Unit price decrease, Product Quality improvements (Word Robotics 2016)	New industrial automation plants, operational efficiency	Prototyping, product Development, Increased efficiency, cost reduction
Sources	IDC, IC Market Drivers, IIoT Analytics, Gartner, Cisco	IDC, Morgan Stanley, 451 Group, TATA consulting Serv.	IDC for HP, Oracle	BI Intelligence, World Robotics	Markets and Market, Global Industry Analyst Inc.	IDC, Morgan Stanley, Wholers, Fathom Research

LIST OF FIGURES

Figure 1 - A Graphical Representation of Industry 4.0 (Source: Authors)

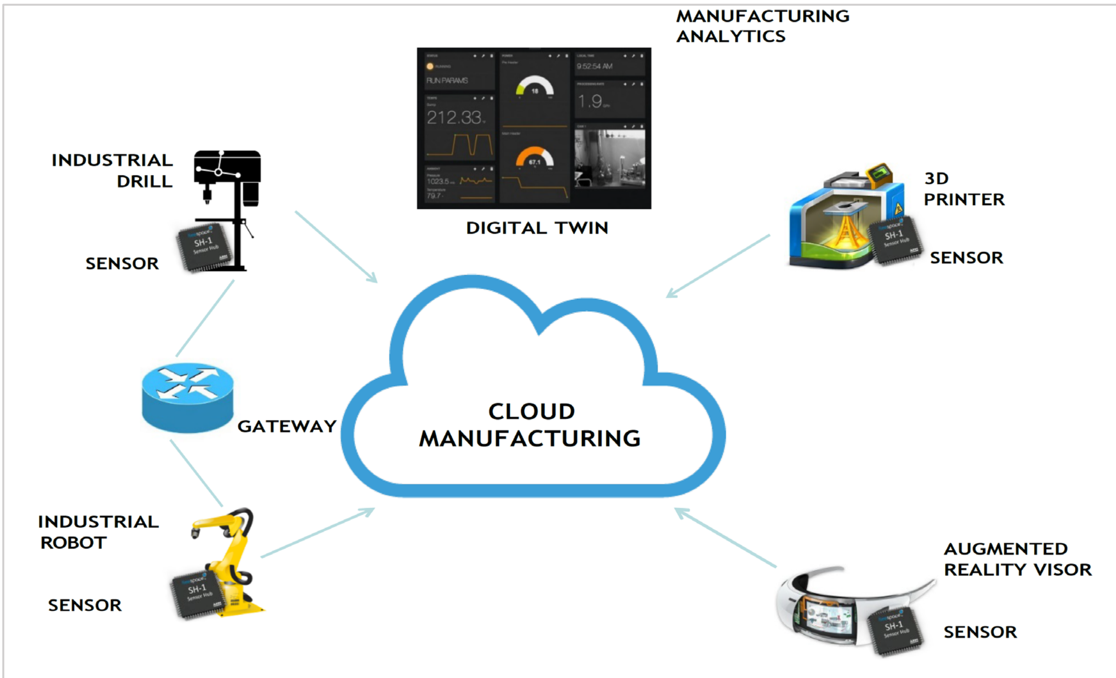
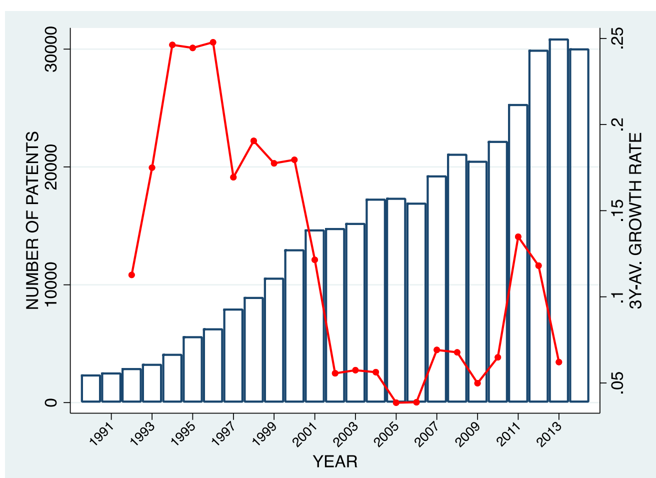
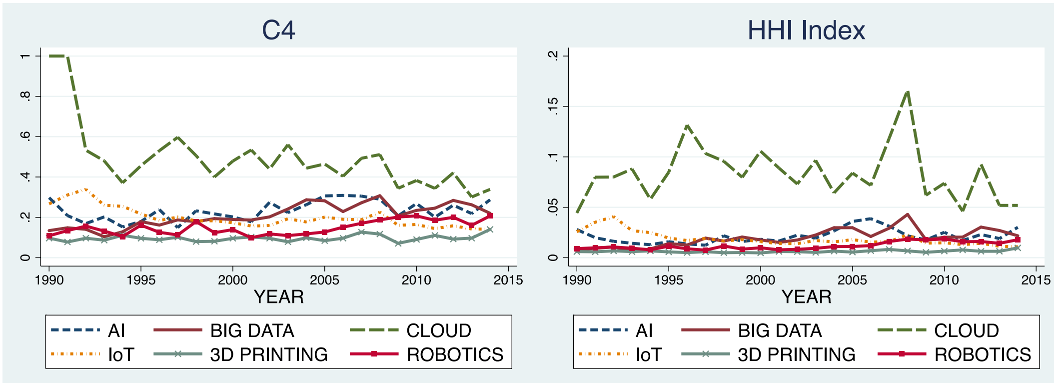


Figure 2 - Time evolution and growth rate



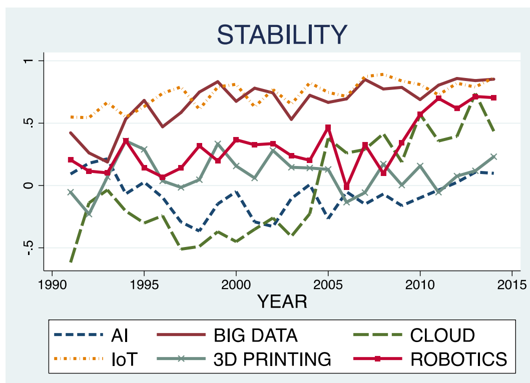
Source: Authors calculations

Figure 3 – Evolution of the concentration of innovative activities across technology



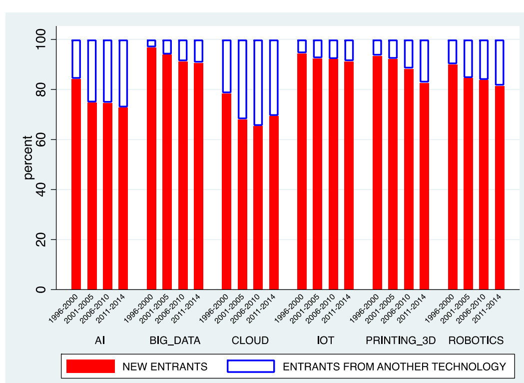
Source: Authors calculations

Figure 4 - Evolution of the stability of innovative activity across technology



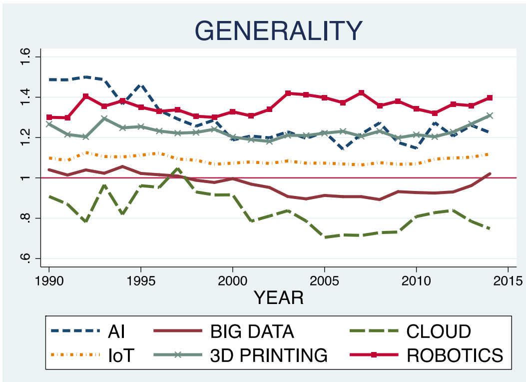
Source: Authors calculations

Figure 5 - Patterns of entry over time and across technology

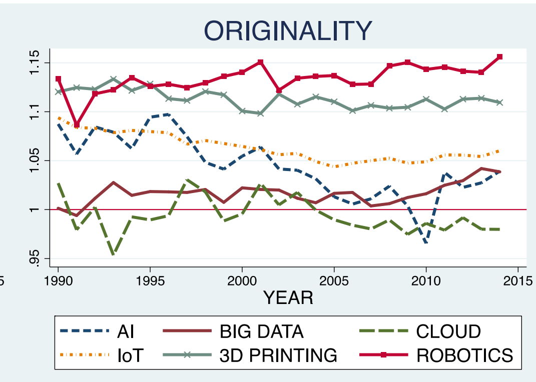


Source: Authors calculations

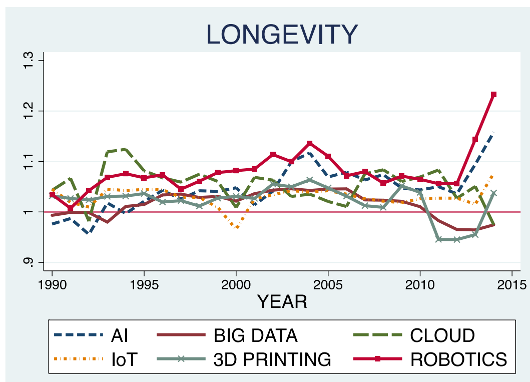
Figure 6 - Evolution of patent characteristics



(a)



(b)



(c)

Source: Authors calculations

Figure 7 - Similarity of used industrial knowledge base by technology

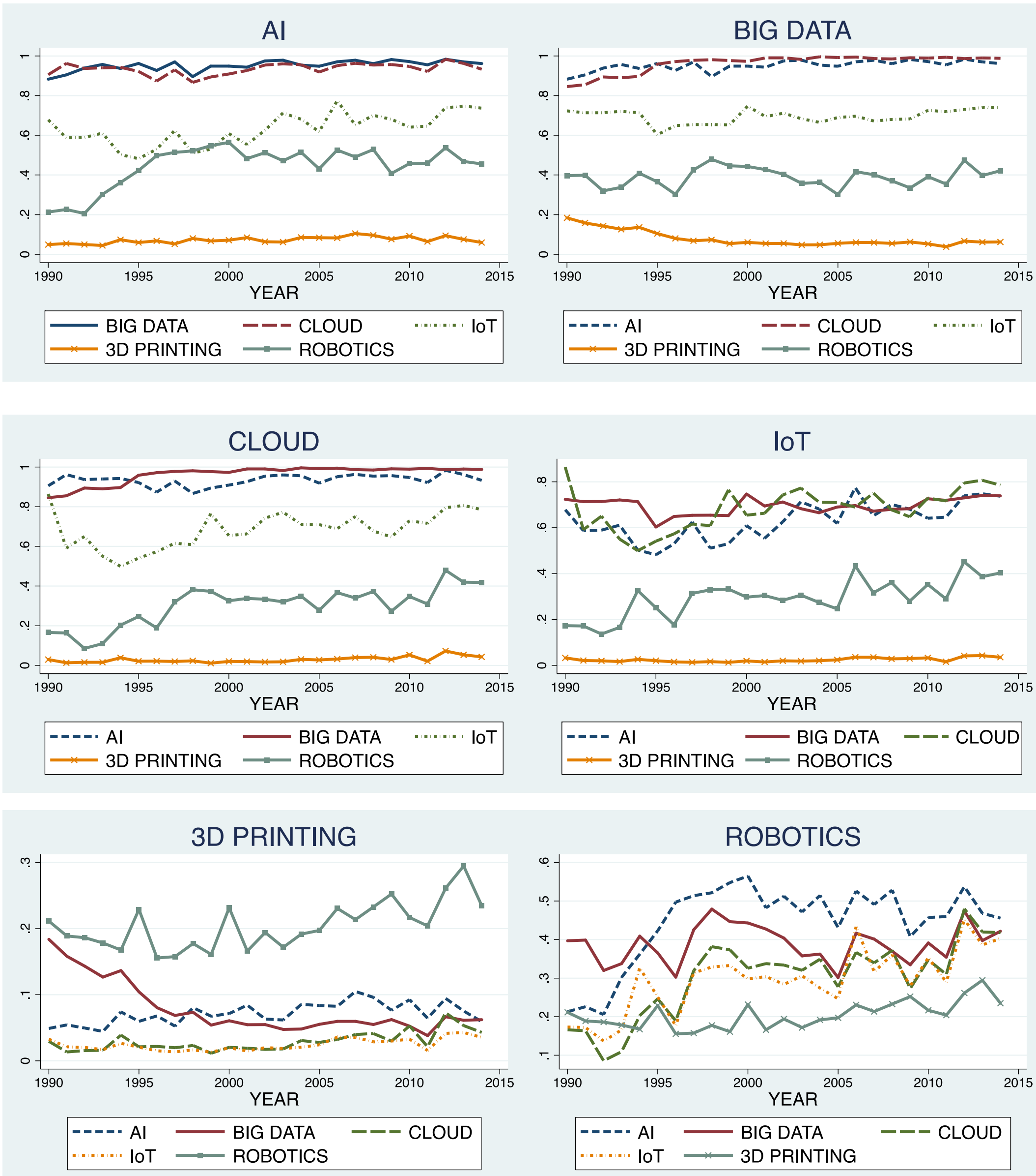


Figure 8 - Similarity of industrial application by technology

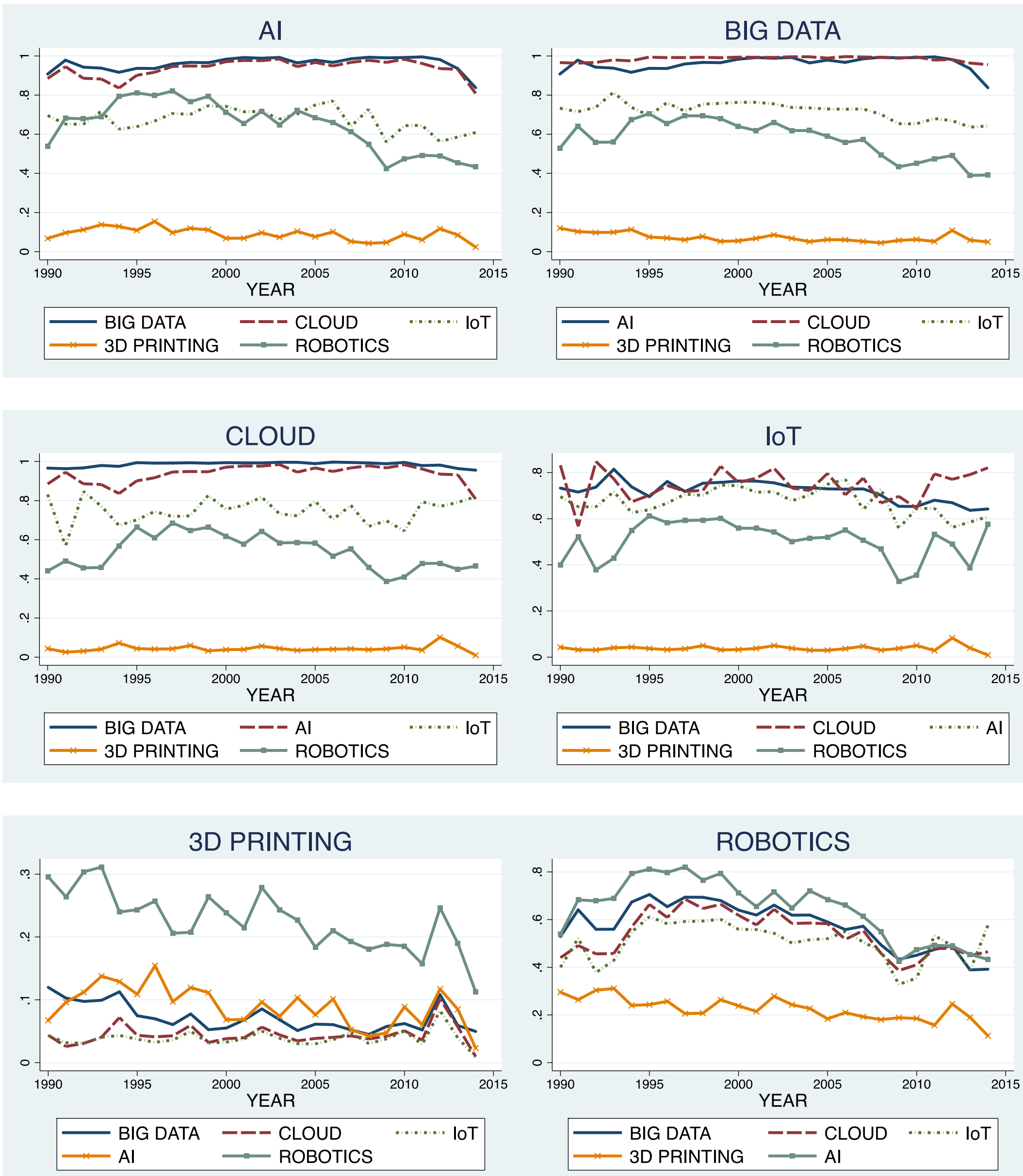


Figure 9 - Distribution of cited patents between enabling technologies