Growth Welfare Innovation Productivity

Working Paper

Does value chain integration dampen producer price developments? Evidence from the European Union

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EXPLORING THE SEEDS OF THE FOURTH INDUSTRIAL REVOLUTION: THE EMERGENT TRAJECTORIES OF INDUSTRY 4.0 TECHNOLOGIES

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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, the asks 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.

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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 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 '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 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 integrate a review of industry reports and market data with in-depth analyses of patent records with the aim 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, their relations, similarities and use, including an econometric analysis of the GPT characteristics (generality, originality, and longevity) of the technologies. 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.
<< INSERT FIGURE 1 ABOUT HERE >>

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. 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. 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).

We now provide a brief overview of each group of technologies.

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). Also 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 in general microelectromechanical systems. More specifically, within these core technologies, IoT devices incorporate 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 (IoT). Investments in these technologies are driven by private companies. IBM, Google, Samsung, SAP, Dell, Siemens and Intel seem to be the companies investing more (IoT Analytics cited in eWeek, 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 signalled by the acquisition of Nest and CSR by Google and Qualcomm (FTI Consulting, 2016).

2.2 Big Data/Industrial Analytics

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 (Durdianovic and Lee, 2004). 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.

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. In 2001, Doug Laney, then an analyst at consultancy Meta Group (Gartner, 2019) expanded the notion of big data to also include increases in the variety of data being generated by organizations and the velocity at which that data was being created and updated. Separately, 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 of 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, energy companies and other mainstream enterprises. While we do not have precise data on R&D expenditure on manufacturing Big Data tools, the growth of patenting activities in this area indicates a rapid increase in commercial interest in this field (Ardito et al., 2018).

2.3 Cloud Manufacturing

Cloud manufacturing is a new set of IT service delivery models. It 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.[1]

The field is a combination of applied research on virtualization, fast Internet, memory computing, and firewall technologies. Bloomberg and Red Monk report some figures on the R&D expenditure of cloud computing companies.[2] 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

[1] For an extensive analysis of Cloud Manufacturing see: Adamson et al. (2013), Caldarelli et al. (2016), Bughin et al., (2010), Wei et al., (2013), Wu et Al., (2015), Wu et al. (2013), Macia et al. (2012), Tao et al. (2011), (2014), Putnik (2012), Hashem et al. (2014), Mezgar, (2011), Park and Jong (2013), Ren et al. (2014), Zhang and Chai, (2010), Hossain, (2013), Majhi and Shial, (2015), Givehci, (2012), Givehu et al. (2013), Panetto and Molina, (2008).

[2] https://redmonk.com/rstephens/2017/09/26/cloud_rd/; https://iot-analytics.com/industrial-technology-trends-industry-40-patents-12x/; https://www.reddie.co.uk/2015/08/28/cloud-computing-patents-and-the-art-of-semantics/.

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.[3]

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 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.

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

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 signalling 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 start-up 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). 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 (2019 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 61,772 patents: of which 28,525 (46.18%) related to Robotics, 13,919 (22.53%) related to Artificial Intelligence, 7,932 (12.84%) related to 3D Printing, 4,586 (7.42%) related to IoT, 3,588 (5.81%) related to Robotics, and 3,22 (5.22%) related to Cloud. The bar chart in Figure 2 shows a significant increase over time in the total number of patents filed each year. Plotting the 3-year average growth rates of patent grants indicates a decade of positive growth from the beginning of the 2000s onwards, with the only interruption caused by the 2008 Financial Crisis.

<< INSERT FIGURE 2 ABOUT HERE >>

Table 2 highlights differences in the number of patents and average growth rates over five periods (1990-1995; 1996-2000; 2001-2005; 2006-2010; 2011-2014) and across technologies. There are large variations across periods, but the data indicate strong growth for all technologies in the most recent period of the times series.

<< 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 with low level of concentration of innovative activities, high entry rates and turbulence in the ranking of innovators (Breschi, Malerba and Orsenigo, 2000; Malerba and Orsenigo, 1996a; 1996b; 1997). Figure 3 displays the evolution of the concentration of the innovative activities in each enabling technology as measured by the C4 indicator and 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 indicates a general reduction in concentration levels, according to standard theory. The most significant falls in the indices throughout the whole period concern Cloud, Big Data and IoT. AI and Robotics display the steadiest patterns, while innovation in 3D printing becomes gradually less concentrated over time. Robotics and 3D printing are the technologies with the lowest concentration of innovation activities in the most recent period, which indicates the persistent presence of a high 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 4 shows some differences among the six technologies under examination. Big Data and IoT show consistently high stability over time. AI and Cloud displayed relatively low stability (i.e. higher turbulence) from 1995 to 2005, but their stability overall increased from 2005 onwards due to consolidation of technology leadership in these fields. 3D printing displays somewhat volatile patterns, with steady increases, indicating more stability in the group of top investors, over the last few years.

<< 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. With the exception of IBM's performance in Big Data and AI, where the company is among the highest ranked players in both periods (and it reaches leadership in Cloud in the second period), the top positions are in the long run rather precarious. The field of AI saw Google, Microsoft and Amazon inherit the top ranks from Hitachi, Mitsubishi and Matsushita in the top four. Beside IBM, SAP, Oracle and Dell take leadership in Big Data. In Cloud, we see among the top performers in the first period the US Navy and the University of California (this hints at the role of mission-oriented and fundamental research, respectively, in this particular field. In the second period Microsoft, Google and Oracle take top positions after IBM. Intel takes leadership over competitors in IoT, followed by telecommunications companies LG, Ericsson and Qualcomm. In 3D printing, two universities (University of Texas and MIT) are overtaken by specialist 3D manufacturer Stratasys and orthopaedics company Conformis, and large electronics conglomerates (GE and Siemens). Automotive companies Toyota and Ford take leadership in Robotics from robotics manufacturer Fanuc and Honda, followed by Google (this is the company's third appearance in the top innovators after AI and Cloud) and Intuitive Surgical (whose entry in the top four ranks complements Conformis' performance in 3D printing in indicating the growing role of medical applications).

From a geographical point of view, we observe in Table 3 a very high concentration of activities in the United States, with Japanese companies losing top positions in AI, Big Data, and IoT. 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 35% of the set, increasing to 41% in the period 2010-2014.[4]

<< 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 between complementary technologies. Figure 5 shows that the share of entrants from another technology is overall increasing over time. Cloud and IoT attract the largest share of entrants from related technologies, Robotics the lowest, followed by AI. Note, however, that for AI this share increases over time.

3.3. 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, Vereyen and Schmoch (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.

[4] 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 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 computers, communication equipment, and office machinery. 3D Printings and Robotics display different industrial knowledge bases, including manufacturing of medical equipment and manufacturing of metal forming machinery and machine tools (both important for the two technologies) and more field-specific capabilities (e.g. Rubber and Plastics for 3D printing and Motor vehicles and Instruments for Robotics).

<< INSERT FIGURE 6 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 6 presents the evolution of the cosine similarity in the used industrial knowledge base over time and across technologies. AI, Big Data and Cloud 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 falling trend (but always higher relative to 3D printing and Robotics) in the levels of similarity with AI, Big Data and Cloud. The second apparent trend is the increased convergence of 3D printing and Robotics.

<< 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 information is useful to identify the industrial classes of application of inventions developed within an 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. Robotics also contributes to computer manufacturing, but shares with 3D printing medical device manufacturing as top field. The comparison of the C4 and HHI indicators presented in Table 4 and Table 5 indicates that industrial application is much more concentrated than the industrial knowledge bases, and concentration of industrial applications is always highest for Big Data and Cloud.

<< INSERT FIGURE 7 ABOUT HERE >>

Figure 7 reports the evolution of cosine similarity measures in the application industry. After an initial period of turbulence, as we saw for the technological knowledge bases the strongest similarities are between AI, Big Data, and Cloud. In this case, however, we also note similarity in industrial use between Cloud and IoT, which is consistent with qualitative evidence of joint deployment of Cloud and IoT. 3D Printing displays again patterns of complementarity in knowledge use with Robotics, with a marked decrease in the last two years of the period. Both 3D printing and Robotics appear to be diverging from all other technologies, and to find over time more specific areas of knowledge use.

3.4. 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 8 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 9 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 8 and 9 ABOUT HERE >>

AI, 3D Printing and Robotics seem to be the technologies characterised by more independent development, with shares of self-citations constantly well above the 70% mark for both backward and forward citations. Big- Data, Cloud and IoT display more varied dynamics, indicating a more integrated position in the technological system. Big data tend to display patterns of cross-fertilising above all with AI. Cloud displays a variety of cross-technology citations, but a field becomes more self-referential in the most recent years, when within-field citations account for approximately 80% of total citation. IoT follows a similar pattern to Cloud with increased within-technology citations over time, with the exception of the last two years, which display more variety.

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

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? To empirically address this question, we follow the approach used by Moser and Nicholas (2004) in their study of Electricity as a GPT. We use regression analysis to examine how Industry 4.0 patents score on three patent indicators – generality, originality, and longevity – generally associated with GPTs, as compared to other technologies.

The generality index (*GENERALITY*) captures the range of later generations of inventions that have been promoted by a patent, by measuring the breath of technological classes citing that patent (Trajtenberg, Jaffe, and Henderson, 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 larger the value of the index, the more technologically widespread the effect of a patent, in line with the definition of a GPT (Hall and Trajtenberg, 2004).

The originality index (*ORIGINALITY*) 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, Jaffe, and Henderson, 1997). The more diverse the technological base upon which a patent is built, the more potential for novel 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 captures the high technological dynamism that is typical of GPTs (Trajtenberg, Jaffe, and Henderson, 1997; Moser and Nicholas, 2004). 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 average lag (in years) between the year of patent grant and the year of the latest forward citation (*AV_LONGEVITY*).[5] All three indicators have been calculated using the EPO-PATSTAT Database (Autumn 2019 version).

To assess the extent to which the technologies included in the Industry 4.0 paradigms are GPTs, we compare our set to patents to a control group. We select the control patents by randomly matching each patent in our set to up to five USPTO granted patents (without replacement) that are not related to one of the technology under examination (and neither is part of the same DOCDB

[5] Note that Moser and Nicholas (2004) measure longevity also as the maximum lag (in years) between the year of patent grant and the year of the latest forward citation. While we present the result using the average longevity, we also run the analysis using the maximum longevity and the results are qualitatively (i.e. sign and significance) similar.

family).[6] This matching procedure ensures that the joint distribution of primary technological class, grant years, assignee type is balanced in the two samples. This control set does not provide an estimate of the exact counterfactual outcome. However, these comparison groups yield an estimate of the "average outcome" in a set of patents with similar characteristics.[7] To complete the analysis, we also include two other variables that are the number of citations received by the patents in the first five years after the granting (*FORW_CIT_5Y*) and the number of IPC-classes listed in the patent document (*NUM_IPC_CLASS*).[8]

<< INSERT TABLE 6 HERE >>

Table 6 reports the results from nonparametric Mann-Whitney rank-sum tests of the null hypothesis that the median characteristics of patents related to Industry 4.0 are identical to the control sample. These tests show that patents related to Industry 4.0 are significantly less original and general than their controls. Conversely, patents related to Industry 4.0 are cited over longer periods, receive more citations in the 5 years after the application, and have a broader scope than the control patents.

<< INSERT TABLE 7 HERE >>

To confirm whether the difference in the generality indicator persists while controlling for some patent characteristics, we run a regression exercise. Table 7 reports three sets of results for different models' specifications and the three dependent variables (i.e. generality, originality and average longevity). The main variable of interest is the dummy variable *INDUSTRY_4_0*, which takes value one if the patent is related to one of the six enabling technologies under examination, and zero if the patent is a matched control. The first three columns of each table panel present the results for the whole sample, while the last three focus on the subsample of patents whose

[6] The matching of at least one control patent was successful for 54,109 patents out of 61,322 starting set (88.2%), with the matching of 5 controls 87.6% of all the starting set.

[7] See Appendix A for the descriptive statistics of the sample.

[8] See Appendix A for a summary table of the variables used.

dependent variable is above the sample median. The top panel presents the results for *GENERALITY* where the dummy *INDUSTRY_4_0* is always negative and significant, indicating that the patents in our sample are significantly less general than a comparable sample. The middle panel presents similar results for *ORIGINALITY*, where the dummy *INDUSTRY_4_0* is either negative or insignificant. Finally, the bottom panel shows the results for *AV_LONGEVITY,* which confirms the finding of table 6. The dummy *INDUSTRY_4_0* is always positive and significant, indicating that the patents in our sample are cited significantly longer than a comparable sample. All in all, even though these results are not clear cut, they provide some indication that the technologies under examination are not yet a GPTs.

Following these results, in order to explore possible differences between the six technologies, we run the same regressions on each technology group. Figure 10 reports these results together with the estimate of the *INDUSTRY_4_0* effect for the pooled sample.[9] Figure 10(a) displays all the estimates for the technology dummy, indicating that for all technologies, except for Big Data, the patents are not more general than the matched controls. Also Figure 10(b) displays some heterogeneity, indicating that only AI and Big Data are more original than the matched controls. Finally, Figure 10(c) shows that all the technologies included in our sample are cited for longer timespans than the controls. However, when we focus the analysis on the longest-lived patents – the results on the patents whose longevity is above the median, some differences emerge. Patents related to Cloud technologies display lower longevity than the controls. This difference is statistically significant, while there is no statistically significant difference for AI and IoT relative to the counterfactuals.

Taken together, these results have at least two interesting implications. First, they confirm the existence of significant heterogeneity between the technologies under investigation. Second, only Big Data and to a lesser extent AI shows the emergent characteristics of a GPT in terms of generality and originality, whereas the other technologies under examination are better framed – at least at this point in time – as enabling technologies rather than GPTs, despite the strong

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[9] The complete estimation results of the split-sample analysis are available upon request.

longevity performance recorded for the most mature technology, that is 3D printing. There are two caveats. The first is that these enabling technologies might well develop into independent GPTs in the future.[10] The second is that the test we have applied is rather strict in the identification of the control group, drawn from the same primary patent class as the focal sample. The results should therefore be interpreted as evidence that – with the exceptions of Big Data and AI – there is no strong indication across the board that these technologies are a dramatic departure from the ICT paradigm is which they operate.

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 8 and 9 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

[10] Note that regression analysis run over the six period we previously used (see table 2) shows that these results are consistent over the period under examination.

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[11], 850,000 industrial robots (including all robotic technologies), and 600.000 3D printers installed.[12] 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).[13]

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 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 recently carried out by the Italian Ministry of Industry and Economic Development (MISE, 2018) illustrates the very slow uptake of Industry 4.0

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

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

[13] 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.

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[14], the segment is highly unstable 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

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

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 (Catinean, 2013). 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).[15] 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.[16] 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 another domain strongly affected by the availability of standards or lack thereof. Cloud interoperability is a major issue (Dillon 2010), 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

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

[16] As noted by Weber (2011), there will be a need for extreme transparency in tracing the flows and type of data transmitted.

ITU).[17] 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 (REF). 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 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.

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

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 in some detail 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. At the moment, the two technology groups that give the strongest indication of following a trajectory leading to a GPT are Big Data and AI.

It is , however, important to remember that 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.

REFERENCES

Acemoglu, D., Restrepo, P. (2017) 'Robots and Jobs: Evidence from US labor markets' NBER Working Paper No. 23285.

Breschi, S., Malerba, F. and Orsenigo, L. (2000), 'Technological regimes and Schumpeterian patterns of innovation', Economic Journal 110(April), 388–410.

Bresnahan, T. F. and Trajtenberg, M., (1995). General purpose technologies 'Engines of growth'?, Journal of Econometrics, 65(1), 83-108.

Bresnahan, T. (2010), General purpose technologies, in Hall, B.H. and Rosenberg, N. (eds.) *Handbook of the Economics of Innovation*, Elsevier, Vol. 2, pp. 761-791

Christensen, C.M., 1997. *The Innovator's Dilemma*. Harvard Business School Press, Cambridge.

European Commission, 2017. Horizon 2020 Work Program 2018-2020 Part 5: Leadership in Enabling and Industrial Technologies. European Commission Decision C(2017) 7124 of 27 October 2017. https://ec.europa.eu/programmes/horizon2020/sites/horizon2020/files/h2020-wp1820-leit_en.pdf.

Frey, C. B., Osborne, M. A. 2017. The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114: 254-280

Hall, B.H., and M. Trajtenberg (2004), "Uncovering GPTS with Patent Data", NBER Working Papers, No. 10901, National Bureau of Economic Research, Inc., www.nber.org/papers/w10901.

Helpman, E. (Ed.), 1998. General Purpose Technologies and Economic Growth. Cambridge, MA, MIT Press. Commission of the European Communities, 2009. Preparing for Our Future: Developing a Common Strategy for Key Enabling Technologies in the EU. Document 52009DC0512. http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52009DC0512.

Jaffe, A., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. American Economic Review 76, 985–1001.

Jaffe, A., 1989. Characterizing the 'technological position' of firms, with application to quantifying technological opportunity and research spillovers. Research Policy 18, 87–97.

Kagermann, H., Wahlster, W., Helbig, J. 2013. Securing the future of German manufacturing industry: Recommendations for implementing the strategic initiative INDUSTRIE 4.0. *Final report of the Industrie 4.0 Working Group*, available at: http://alvarestech.com/temp/tcn/CyberPhysicalSystems-Industrial4-0.pdf

IDC, 2018. Worldwide Semiannual Artificial Intelligence Systems Spending Guide, available at https://www.idc.com/getdoc.jsp?containerId=IDC_P33198.

Lee, J., Davari, H., Singh, J, Pandhare, V. 2018, Industrial Artificial Intelligence for industry 4.0-based manufacturing systems, Manufacturing Letters 18: 20–23.

Malerba, F. and Orsenigo, L. (1996a), 'The dynamics and evolution of industries', Industrial and Corporate Changes 5(1), 51–87.

Malerba, F. and Orsenigo, L. (1996b), 'Schumpeterian patterns of innovation are technology specific', Research Policy 25(3), 451–478.

Malerba, F. and Orsenigo, L. (1997), 'Technological regimes and sectoral patterns of innovative avtivities', Industrial and Corporate Change 6(1), 83–118.

McKinsey Global Institute, 2017. Artificial intelligence: the next digital frontier?, Discussion Paper, June, available at: https://www.mckinsey.com/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.ashx.

Ministero dello Sviluppo Economico, 2018. La Diffusione delle Imprese 4.0 e le Politiche: Evidenze 2017, available at: http://www.industriequattropuntozero.it/files/2018/07/Rapporto-MiSE-MetI40.pdf.

Moser, Petra, and Tom Nicholas. 2004. "Was Electricity a General Purpose Technology? Evidence from Historical Patent Citations." American Economic Review, 94 (2): 388-394.

Nilsson, N. 2010. The Quest for Artificial Intelligence: A History of Ideas and Achievements, Cambridge: Cambridge University Press.

Rosenberg, N., 1982. Inside the Black Box: Technology and Economics. Cambridge University Press, Cambridge (UK) and New York.

Rosenberg, N., 1994. Exploring the Black Box: Technology, Economics and History, Cambridge University Press, Cambridge (UK) and New York.

Squicciarini, M., H. Dernis and C. Criscuolo (2013), "Measuring Patent Quality: Indicators of Technological and Economic Value", OECD Science, Technology and Industry Working Papers, 2013/03, OECD Publishing. http://dx.doi.org/10.1787/5k4522wkw1r8-en

Teece, D. 2018. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world, *Research Policy* 47(8): 1367–1387

Trajtenberg, M, Jaffe, A., and R. Henderson (1997). "University versus Corporate Patents: A Window on the Basicness of Inventions", Economics of Innovation and New Technology, 5(1): 19-50.

Tushman, M., Anderson, 1986. Technological discontinuities and organisational environments. Adm. Sci. Q. 31, 439–465.

Van Looy B., Vereyen C., and U. Schmoch (2015). "Patent Statistics: Concordance IPC V8 - NACE Rev. 2 (version 2.0)", Eurostat Working Paper. Available at: https://circabc.europa.eu/d/d/workspace/SpacesStore/d1475596-1568-408a-9191-426629047e31/2014-10-16-Final%20IPC_NACE2_2014.pdf

Webb, C., H. Dernis, D. Harhoff and K. Hoisl (2005) "Analysing European and International Patent Citations: A Set of EPO Patent Database Building Blocks", STI Working Paper 2005/9, OECD, Paris.

LIST OF TABLES

Table 1 – Summary of the sampling strategy

Technology & References	CPC classes	Keywords
Internet of Things (IoT) 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	*Derived from keywords:* H04W4/70, Y02B70/3*, Y02B90/24, Y02D70/21	internet of \w1 thing\w*, IIoT, Io*T, ubicomp, ubiquitous computing, industrial internet, pervasive comput\w*, ambient intelligence, smarter planet, smart dust, smart \w1 device\w*, connected \w1 device\w*, networked \w1 device\w*, digital life, web of thing\w*, manchine to machine, M2M, smart meter\w*, smart grid\w*, smart home\w*, internet of everything\w*
Cloud computing Huang (2015), Dotsika (2017), IPO big data report (2014), Buyya et al. (2013)	*Derived from keywords:* G05B2219/32136	cloud comput\w*, cloud securit\w*, cloud technolog\w*, cloud serv\w*, cloud process\w*, cloud software\w*, cloud network\w*, cloud infrastructure\w*, cloud solution\w*, cloud system\w*, cloud data\w*, cloud storage\w*, cloud app\w*, public cloud\w*, private cloud\w*, hybrid cloud\w*, service orient\w*, web service\w*, utility orient\w*, utility comput\w*, cloud architectur\w*, \w*-as-a-service, Aneka, InterCloud, multitenan\w*, OpenStack, Microsoft Azure, Cloudera, Amazon Web Services, AWS, Google Cloud Platform
Big Data UK IP, 2014. Big Data & Energy Efficient Computing, UK Intellectual Property (IP)	*Conditional to keywords, from report:* G06F 17/3* (does not exist anymore, replaced by G06F 16/*), G06F 19/7* - G06F19/1* - G06F19/3* (do not exist anymore. Now, partially, G16Z 99* or G16B40/00, G16B50/00, G16H50/00, G16C20/70), G06Q 10/063*, G06Q 30/02*, G06F 17/50* (does not exist anymore, now G06F 30/*), G06N/* *Derived from keywords*: G06F16/2465, G06F16/283, G06F2216/03	big dat\w*, open dat\w*, data warehouse\w*, hadoop, aster, datameer, fico blaze, vertica, platfora, splunk, mapreduce, crowdsourcing, data mining, data fusion, spark, biometrics, cassandra, nosql, behavioral analytics, business intelligence, HANA, hive, flume, kafka, elasticsearch
Robotics UK IP Office, 2014.Eight great technologies: robotics and autonomous systems, UK Intellectual Property (IP) Office Available at. https://	*Derived from reports:* B25J9/16*, B25J9/20, B25J9/0003, B25J11/0005, B25J11/0015, B60W30/*, Y10S901/*, G05D1/0088, G05D1/02*, G05D1/03, G05D2201/0207, G05D2201/0212 *Derived from keywords:* G05B2219/40*, G05D2201/0217, A61B34/3*, B25J9/0006, B25J9/065, G05D2201/0217	robot\w*, cobot, self driving \w3 \w*car\w*, self driving \w3 vehicle\w*, self driving \w3 automobile\w*, self driving \w3 aircraft\w*, self driving \w3 airplane\w*, self driving \w3 aeroplane\w*, self driving \w3 \w*marine\w*, driveless \w3 \w*car\w*, driveless \w3 vehicle\w*, driveless \w3 automobile\w*, driveless \w3 aircraft\w*, driveless \w3 airplane\w*, driveless \w3 aeroplane\w*, driveless \w3 \w*marine\w*\, autonomous \w3 \w*car\w*, autonomous \w3 vehicle\w*, autonomous \w3 automobile\w*, autonomous \w3 aircraft\w*, autonomous \w3 airplane\w*, autonomous \w3 aeroplane\w*, autonomous \w3 \w*marine\w*, automated \w3 \w*car\w*, automated \w3 vehicle\w*, automated \w3 automobile\w*, automated \w3 aircraft\w*, automated \w3 airplane\w*, automated \w3 aeroplane\w*, automated \w3 \w*marine\w*, unmanned \w3 \w*car\w*, unmanned \w3 vehicle\w*, unmanned \w3 automobile\w*, unmanned \w3 aircraft\w*, unmanned \w3 airplane\w*, unmanned \w3 aeroplane\w*, unmanned \w3 \w*marine\w*

Table 2 – Summary of the sampling strategy (cont.)

Technology & References	CPC classes	Key-words
3D printing 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	*New class:* B33Y: additive manufacturing *Derived from report*: B29C67/0051* (does not exist anymore), B22F3/1055, B22F 2003/1056, B22F 2003/1057, B22F 2003/1058, B22F 2003/1059, B23K9/04*, B23K10/027, B23K11/0013, B23K15/0086, B23K20/1215, B23K25/005, B23K26/34, B23K26/342, *Additional, from keywords:* B29C64/*, Y02P10/29*	3D \w1 print\w*, additive \w1 manufactur\w*, additive \w1 fabrication, 3D \w1 manufactor\w*, 3D \w1 fabrication, rapid \w1 prototyp\w*, rapid \w1 manufact\w*, selective laser deposition\w*, selective laser manufactur\w*, laminate object manufactur\w*, fuse deposition model\w*
AI Webb, N. Short, N. Bloom and J. Lerner (2018) "Some Facts of High-Tech Patenting", NBER Working Paper 24793	*Derived from WIPO report and keyword search (intersection):* Y10S706/*, G06N20/*, G06N7/02*, G06N7/005, G06N3/02, G06T2207/20081, G06T2207/20084, G06T3/4046, G06T9/002, G05B13/027, G05B13/0275, G05B13/028, G05B13/0285, G05B13/029, G05B13/0295, G10L15/16, Y10S128/924, Y10S128/925, F02D41/1405, B29C66/965, B29C66/966, F03D7/046, F05B2270/707, F05B2270/709, F16H2061/0081, F16H2061/0084, G10K2210/3038, G10L25/30, G10L25/33, H04N21/4666	artific\w* \w1 intelligen\w*, computation\w* \w1 intelligen\w*, neural \w1 network\w*, bayesian \w1 network\w*, chatbot\w*, data \w1 mining\w*, decision \w1 model\w*, deep \w1 learn\w*, genetic \w1 algorithm\w*, inductive \w1 logic \w1 programm\w*, machine \w1 learn\w*, natural \w1 language \w1 generation\w*, natural \w1 language \w1 process\w*, reinforcement \w1 learn\w*, \w*supervised \w1 learn\w*, \w*supervised \w1 train\w*, swarm \w1 intelligen\w*, connectionis\w*, expert \w1 system\w*, fuzzy \w1 logic\w*, transfer \w1 learn\w*, learning \w3 algorithm\w*, learing \ w1 model, support vector machine\w*, random forest\w*, decision tree\w*, gradient model boosting, xgboost, adaboost, rankboost, logistic regression\w*, stochastic gradient descent, multilayer perceptron, latent semantic analysis, latent dirichelet allocation, multi agent system\w*, hidden markov model\w*

Table 3 - Number of patents and growth rate by technology

	1990-1995		1996-2000		2001-2005		2006-2010		2011-2014	
	NUM PATENTS	AV. GROWTH RATE	NUM PATEN TS	AV. GROWTH RATE	NUM PATENTS	AV. GROWTH RATE	NUM PATENTS	AV. GROWT H RATE	NUM PATENT S	AV. GROWT H RATE
AI	2415	13%	2202	0%	2010	-2%	2780	8%	4512	24%
BIG_DATA	39	81%	437	54%	838	3%	972	4%	1302	21%
CLOUD	7	0%	12	78%	65	57%	703	60%	2435	26%
IOT	57	40%	187	39%	352	7%	624	28%	3366	54%
PRINTING_3D	580	26%	1039	11%	1721	6%	1987	4%	2605	22%
ROBOTICS	2887	5%	3601	10%	5013	4%	6787	7%	10237	20%
TOTAL	4197	14%	6288	11%	9999	3%	13853	9%	24457	24%

Table 4 - Top Innovators over time and technology

	Top Innovators (1990-1995)			Top Innovators (2010-2014)		
	country	company	share	country	company	share
AI	JP	HITACHI	4.97%	US	IBM	9.50%
	JP	MITSUBISHI	4.75%	US	GOOGLE	6.12%
	US	IBM	4.71%	US	MICROSOFT	4.86%
	JP	MATSUSHITA	2.79%	US	AMAZON	2.13%
BIG_DATA	US	IBM	47.37%	US	IBM	13.86%
	US	RCA	10.53%	DE	SAP	5.48%
	JP	FUJITSU	5.26%	US	ORACLE	3.76%
	US	MICROSOFT	5.26%	US	DELL	3.76%
	US	HONEYWELL	5.26%			
CLOUD	US	US NAVY	25.00%	US	IBM	13.82%
	US	UNIVERSITY OF CALIFORNI	25.00%	US	MICROSOFT	5.71%
	US	HEWLETT PACKARD	25.00%	US	GOOGLE	3.68%
	DE	SIEMENS	25.00%	US	ORACLE	2.92%
IOT	US	ACRES GAMING	10.53%	US	INTEL	12.34%
	US	XEROX	8.77%	KR	LG	9.64%
	US	TEXAS INSTRUMENTS	7.02%	SE	ERICSSON	5.99%
	JP	RICOH	5.26%	US	QUALCOMM	4.01%
	US	MOTOROLA	5.26%			
	US	QUALCOMM	5.26%			
PRINTING_3D	US	3D SYSTEMS	10.38%	US	STRATASYS	4.38%
	US	UNIVERSITY OF TEXAS	3.85%	US	GENERAL ELECTRIC	2.42%
	SW	CIBA	3.46%	US	CONFORMIS	2.19%
	US	MIT	3.27%	DE	SIEMENS	2.19%
ROBOTICS	JP	FANUC	4.82%	JP	TOYOTA	5.21%
	US	HONDA	3.25%	US	FORD	4.26%
	US	MITSUBISHI	2.29%	US	GOOGLE	2.85%
	US	HITACHI	2.26%	US	INTUITIVE SURGICAL	2.64%

Table 5 - Top used industrial knowledge base domain

		USING INDUSTRIAL KNOWLEDGE DOMAIN	Share	C4	HHI
AI	26.2	Manufacture of computers and peripheral equipment	40%	0.200	0.701
	26.3	Manufacture of Communication Equipment	13%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	12%		
	62	Computer Programming, Consultancy and Related Activities	5%		
BIG_DATA	26.2	Manufacture of computers and peripheral equipment	64%	0.437	0.911
	26.3	Manufacture of Communication Equipment	12%		
	62	Computer Programming, Consultancy and Related Activities	10%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	5%		
CLOUD	26.2	Manufacture of computers and peripheral equipment	59%	0.407	0.922
	26.3	Manufacture of Communication Equipment	24%		
	62	Computer Programming, Consultancy and Related Activities	6%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	3%		
IOT	26.3	Manufacture of Communication Equipment	50%	0.291	0.784
	26.2	Manufacture of computers and peripheral equipment	19%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	6%		
	26.5	Manufacture of Instruments and Appliances for Measuring, Testing and Navigation; Watches and Clocks	4%		
PRINTING_3D	32.5	Manufacture of medical and dental instruments and supplies	25%	0.097	0.495
	22	Manufacture of Rubber and Plastic Products	11%		
	26.1	Manufacture of Electronic Components and Boards	7%		
	28.4	Manufacture of Metal Forming Machinery and Machine Tools	6%		
ROBOTICS	32.5	Manufacture of medical and dental instruments and supplies	30%	0.120	0.540
	29.1	Manufacture of Motor Vehicles	9%		
	26.5	Manufacture of Instruments and Appliances for Measuring, Testing and Navigation; Watches and Clocks	8%		
	28.4	Manufacture of Metal Forming Machinery and Machine Tools	8%		

Table 6 – Top sourced industrial knowledge base domain

		USED INDUSTRIAL KNOWLEDGE DOMAIN	Share	C4	HHI
AI	26.2	Manufacture of computers and peripheral equipment	36%	0.179	0.692
	26.3	Manufacture of Communication Equipment	12%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	12%		
	62	Computer Programming, Consultancy and Related Activities	8%		
BIG_DATA	26.2	Manufacture of computers and peripheral equipment	67%	0.479	0.954
	62	Computer Programming, Consultancy and Related Activities	13%		
	26.3	Manufacture of Communication Equipment	12%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	4%		
CLOUD	26.2	Manufacture of computers and peripheral equipment	44%	0.341	0.906
	26.3	Manufacture of Communication Equipment	38%		
	62	Computer Programming, Consultancy and Related Activities	5%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	4%		
IOT	26.3	Manufacture of Communication Equipment	35%	0.194	0.763
	26.2	Manufacture of computers and peripheral equipment	22%		
	28.23	Manufacture of Office Machinery and Equipment (Except Computers and Peripheral Equipment)	10%		
	32	Other Manufacturing	10%		
PRINTING_3D	32.5	Manufacture of medical and dental instruments and supplies	21%	0.096	0.542
	22	Manufacture of Rubber and Plastic Products	15%		
	28.9	Manufacture of Other Special-Purpose Machinery	9%		
	26.1	Manufacture of Electronic Components and Boards	8%		
ROBOTICS	32.5	Manufacture of medical and dental instruments and supplies	28%	0.111	0.502
	26.2	Manufacture of computers and peripheral equipment	9%		
	29.1	Manufacture of Motor Vehicles	7%		

26.5	Manufacture of Instruments and Appliances for Measuring, Testing and Navigation; Watches and Clocks	7%

Table 6 – Mann-Whitney test

Variable	H0: Industry_4_0=Control
ORIGINALITY	54.178***
GENERALITY	3.214***
AV_LONGEVITY_Y	-27.926***
MAX_LONGEVITY_Y	-28.652***
FORW_CIT_5Y	-51.332***
NUM_CLASS	-44.721***

Legend: *** Statistically significant at the 1%

Table 7 – Regression results

DV: GENERALITY						
	FULL SAMPLE			GENERALITY ABOVE THE MEDIAN		
	(1)	(2)	(3)	(4)	(5)	(6)
INDUSTRY_4_0	-0.013***	-0.008***	-0.008***	-0.028***	-0.020***	-0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FORW_CIT_5Y		-0.001***	-0.001***		-0.003***	-0.003***
		(0.00)	(0.00)		(0.00)	(0.00)
NUM_CLASS		-0.004***	-0.003***		-0.006***	-0.005***
		(0.00)	(0.00)		(0.00)	(0.00)
NUM_CLAIMS		-0.000***	-0.000***		-0.001***	-0.001***
		(0.00)	(0.00)		(0.00)	(0.00)
Constant	0.092***	0.111***	0.119***	0.142***	0.175***	0.227***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
YEAR DUMMY	YES	YES	NO	YES	YES	YES
MATCHED GROUP FIXED EFFECT	NO	NO	YES	NO	NO	NO
Observations	323652	323652	323652	161781	161781	161781
R-square	0.0243	0.0354	0.211	0.0366	0.0644	0.373

DV: ORIGINALITY						
	FULL SAMPLE			ORIGINALITY ABOVE THE MEDIAN		
	(1)	(2)	(3)	(4)	(5)	(6)
INDUSTRY_4_0	-0.018***	-0.011***	-0.011***	-0.004***	0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FORW_CIT_5Y		-0.000***	-0.001***		-0.001***	-0.001***
		(0.00)	(0.00)		(0.00)	(0.00)
NUM_CLASS		-0.006***	-0.005***		-0.008***	-0.007***
		(0.00)	(0.00)		(0.00)	(0.00)
NUM_CLAIMS		-0.000***	-0.001***		-0.000***	-0.001***
		(0.00)	(0.00)		(0.00)	(0.00)
Constant	0.155***	0.184***	0.140***	0.198***	0.230***	0.205***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
YEAR DUMMY	YES	YES	NO	YES	YES	YES
MATCHED GROUP FIXED EFFECT	NO	NO	YES	NO	NO	NO
Observations	323652	323652	323652	161814	161814	161814
R-square	0.0186	0.0506	0.243	0.00662	0.0230	0.337

DV: LONGEVITY						
	FULL SAMPLE			LONGEVITY ABOVE THE MEDIAN		
	(1)	(2)	(3)	(4)	(5)	(6)
INDUSTRY_4_0	0.479***	0.428***	0.440***	0.263***	0.314***	0.344***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
FORW_CIT_5Y		0.030***	0.027***		-0.026***	-0.031***
		(0.00)	(0.00)		(0.00)	(0.00)
NUM_CLASS		-0.036***	-0.020***		-0.007***	-0.003
		(0.00)	(0.00)		(0.00)	(0.00)
NUM_CLAIMS		0.022***	0.013***		0.002***	0.004***
		(0.00)	(0.00)		(0.00)	(0.00)
Constant	11.585***	11.294***	3.778***	12.247***	12.357***	7.678***
	(0.08)	(0.08)	(0.01)	(0.07)	(0.07)	(0.01)
YEAR DUMMY	YES	YES	NO	YES	YES	YES
MATCHED GROUP FIXED EFFECT	NO	NO	YES	NO	NO	NO

Observations	323652	323652	323652	157802	157802	157802
R-square	0.608	0.617	0.729	0.520	0.526	0.657

Note: All the models are estimated using Ordinary Least Square. Robust standard errors in brackets. Legend: *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 8 - Industry 4.0 Worldwide turn over

	Industral 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 Intelligence, World Robotics	Market and Markets, Grand View Research	Market and Markets, IDC	Gartner, IDC

Table 9 – 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

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

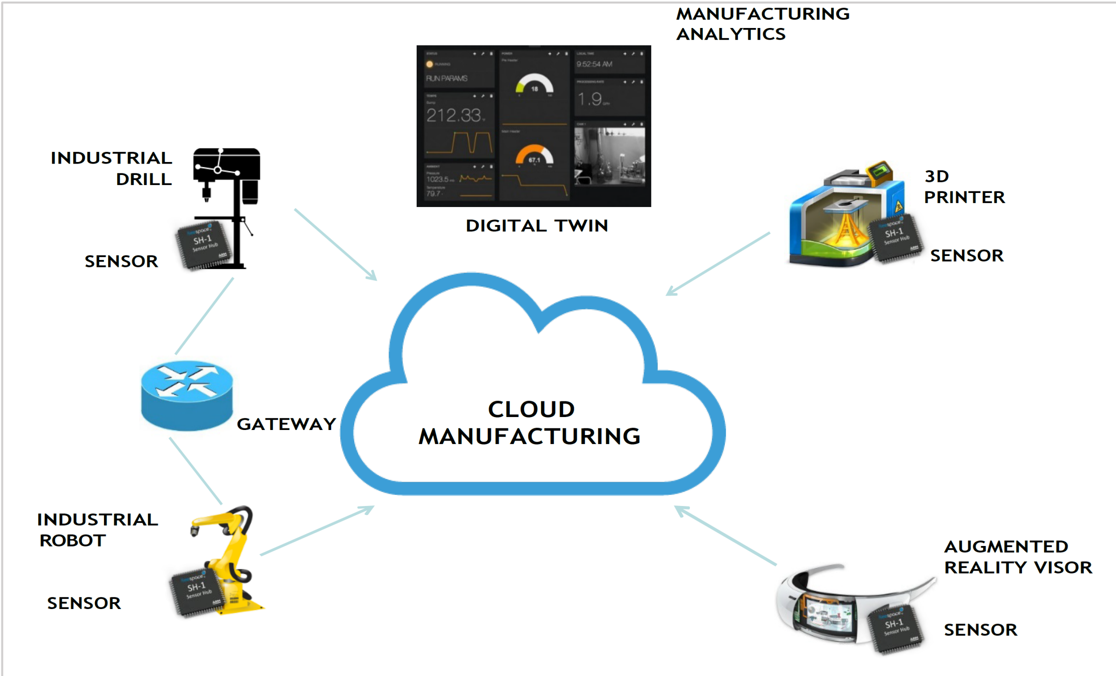
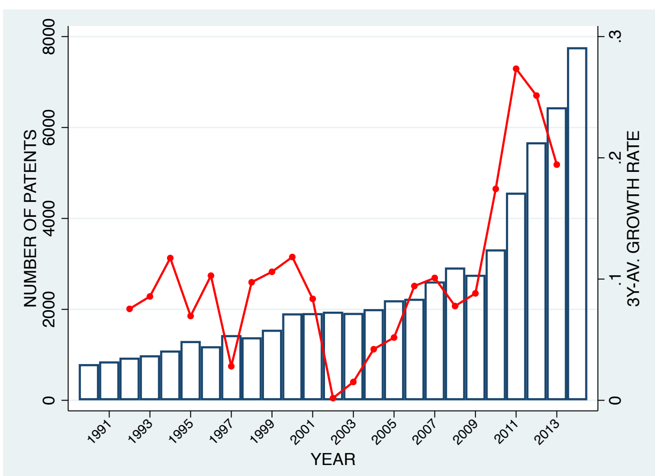
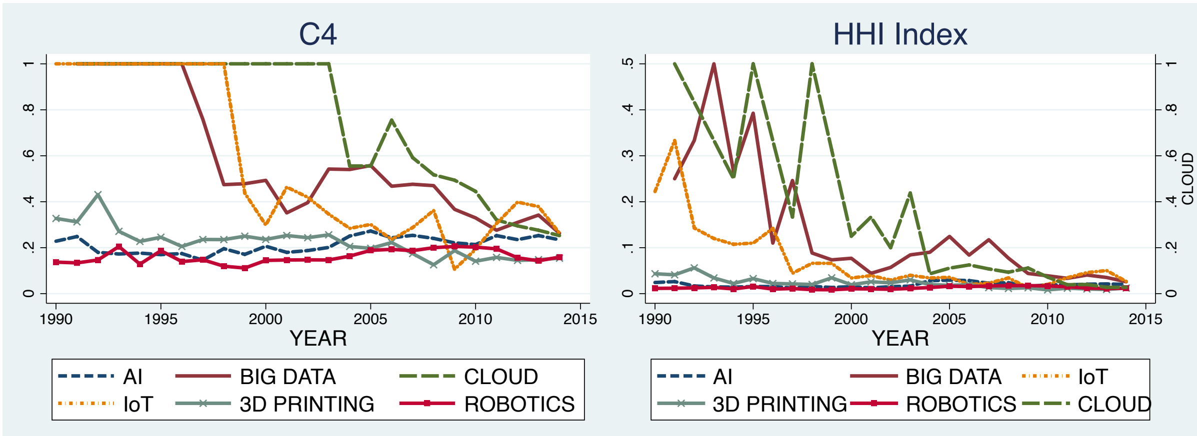


Figure 2 - Time evolution and growth rate



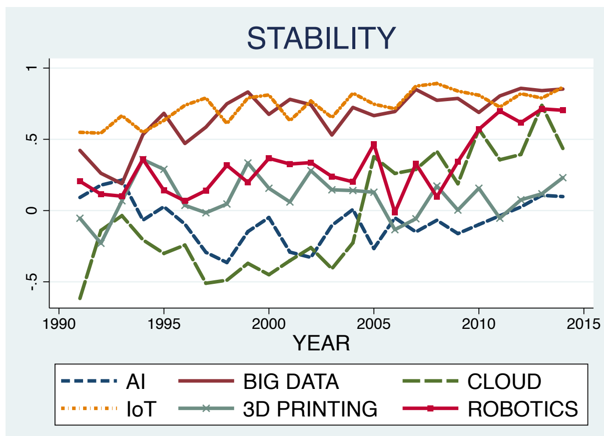
Source: Authors calculations

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



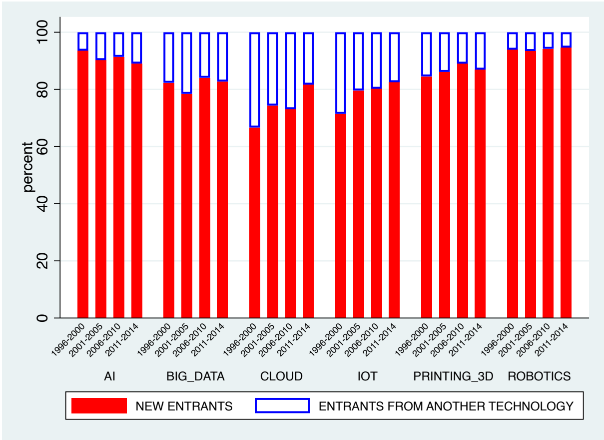
Source: Authors calculations

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 - Similarity of used industrial knowledge base by technology

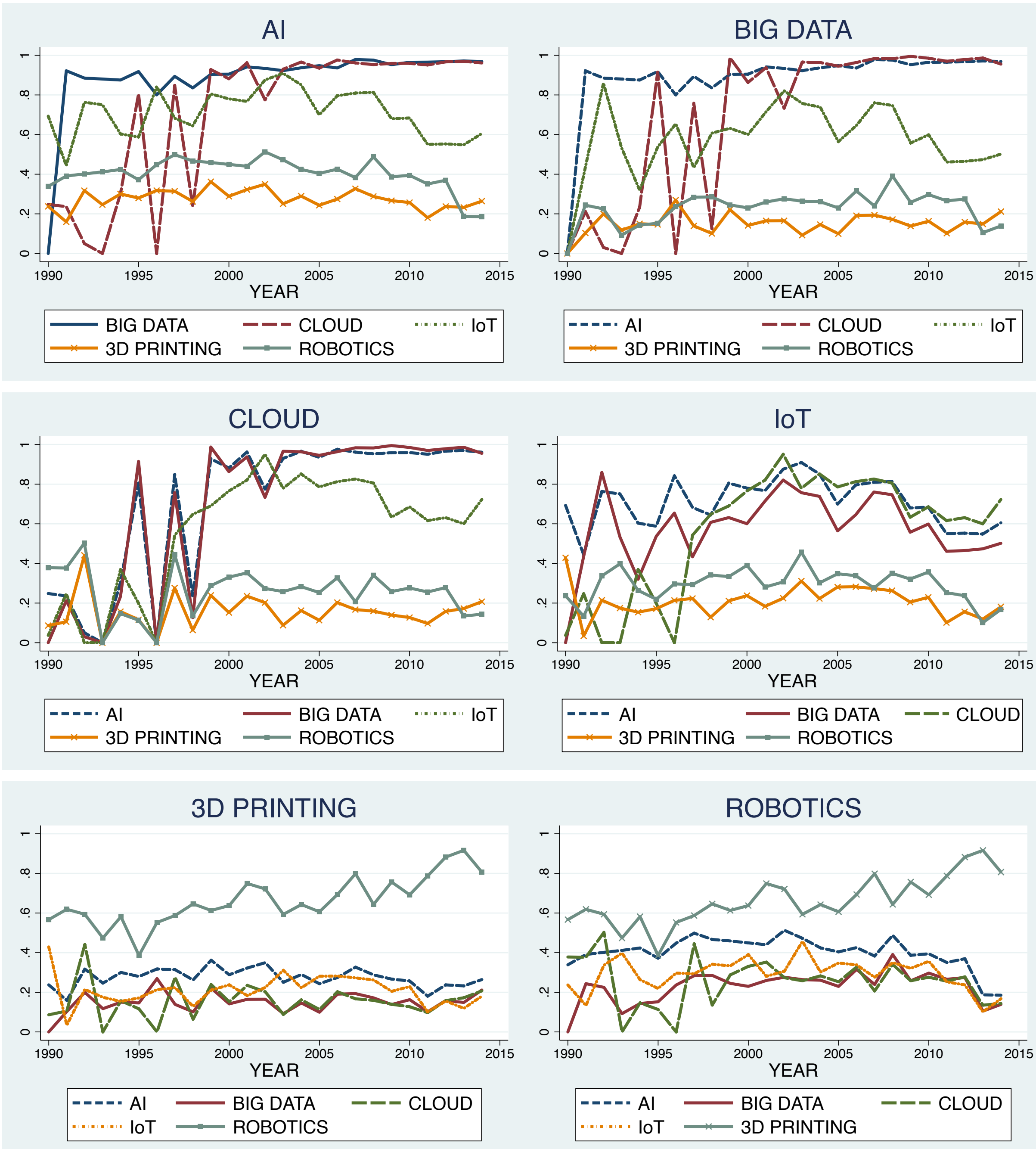

AI
BIG DATA
CLOUD
IoT
3D PRINTING
ROBOTICS
YEAR
1990
1995
2000
2005
2010
2015
0
.2
.4
.6
.8
1
BIG DATA, CLOUD, IoT, 3D PRINTING, ROBOTICS
AI, CLOUD, IoT, 3D PRINTING, ROBOTICS
AI, BIG DATA, IoT, 3D PRINTING, ROBOTICS
AI, BIG DATA, CLOUD, 3D PRINTING, ROBOTICS
AI, BIG DATA, CLOUD, IoT, ROBOTICS
AI, BIG DATA, CLOUD, IoT, 3D PRINTING

Figure 7 - Similarity of using industrial knowledge base by technology

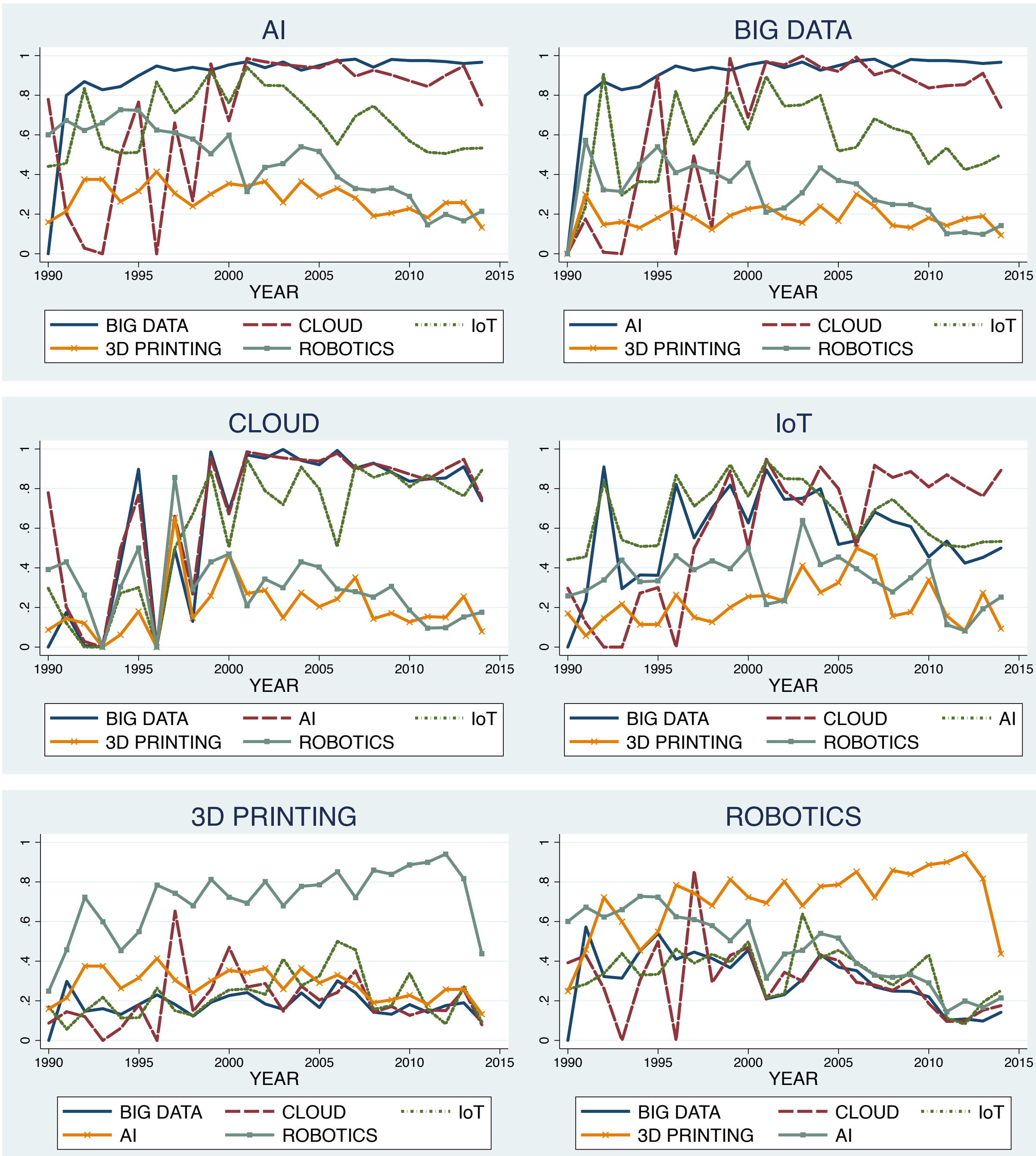


Figure 8 - Distribution of cited patents between enabling technologies


Citations made by AI patents to:
Citations made by Big Data patents to:
Citations made by Cloud patents to:
Citations made by IoT patents to:
Citations made by 3D Printing patents to:
Citations made by Robotics patents to:
percent
YEAR
0
.2
.4
.6
.8
1
1990
1993
1996
1999
2002
2005
2008
2011
2014
ROBOTICS
3D PRINTING
CLOUD
IoT
BIG DATA
AI

Figure 9 - Distribution of citing patents between enabling technologies

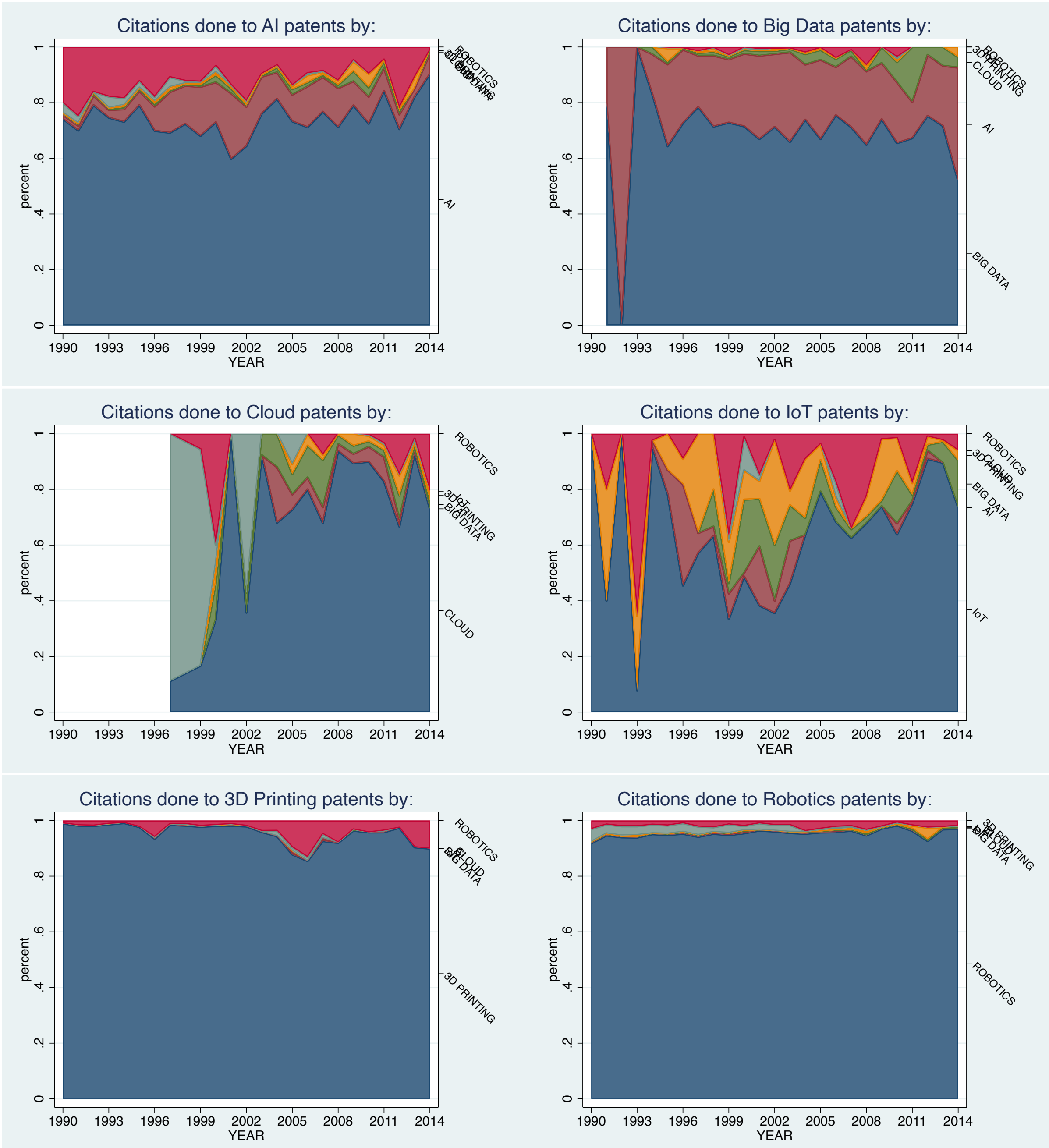
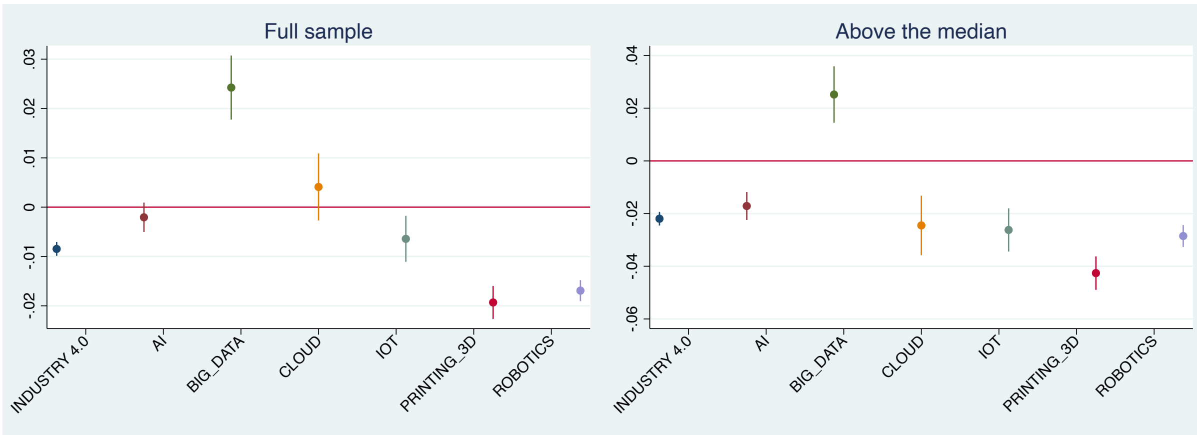


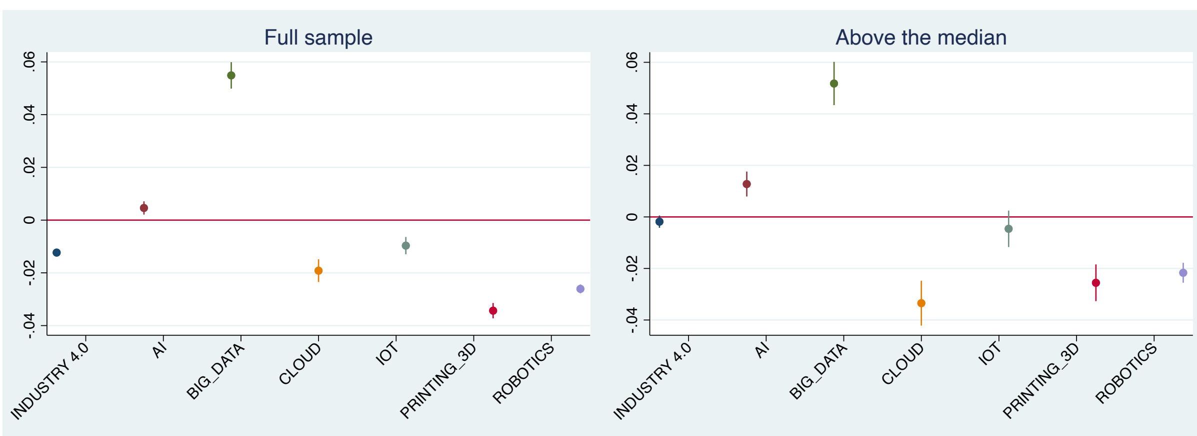
Figure 10 – Regression results for the split sample analysis on each technology

(a) Dependent variable: Generality



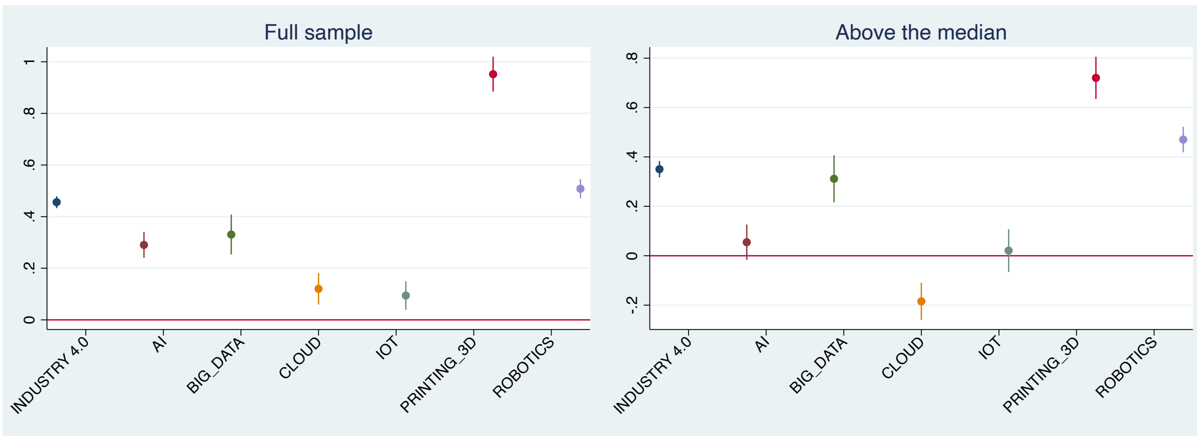
Legend: The estimation for the Industry 4.0 correspond to the results displayed in Table 7 column 3 (left side) and 6 (right side). The other presented estimates are derived from the same specification models run on the six technology subsample. The 95% confidence intervals are also reported

(b) Dependent variable: Originality



Legend: The estimation for the Industry 4.0 correspond to the results displayed in Table 7 column 3 (left side) and 6 (right side). The other presented estimates are derived from the same specification models run on the six technology subsample. The 95% confidence intervals are also reported

(c) Dependent variable: Average Longevity



Legend: The estimation for the Industry 4.0 correspond to the results displayed in Table 7 column 3 (left side) and 6 (right side). The other presented estimates are derived from the same specification models run on the six technology subsample. The 95% confidence intervals are also reported

APPENDIX A

Table A1 – Descriptive statistics of the set of patents related to Industry 4.0 and the control patent

PATENTS RELATED TO INDUSTRY 4.0						
Variable	Obs	Mean	Median	SD	Min	Max
ORIGINALITY	54109	0.0891	0.055	0.115	0	1
GENERALITY	54109	0.0869	0.0449	0.138	0	1
AVERAGE_LONGEVITY	54109	4.49	3.5	4.38	0	26.5
MAX_LONGEVITY	54109	6.85	5	7.14	0	29
FORW_CIT_5Y	54109	4.56	2	13.5	0	401
NUM_CLASS	54109	4.8	4	4.45	1	80
CONTROL PATENTS						
Variable	Obs	Mean	Median	SD	Min	Max
ORIGINALITY	269543	0.107	0.07	0.127	0	1
GENERALITY	269543	0.0999	0.0496	0.158	0	1
AVERAGE_LONGEVITY	269543	4	3	4.3	0	28
MAX_LONGEVITY	269543	6.08	4	6.99	0	29
FORW_CIT_5Y	269543	2.86	1	7.38	0	340
NUM_CLASS	269543	3.91	3	3.18	1	113

Table A2 – List of variables and sources

Variable	Description	Source
GENERALITY	1-HHI_p where HHI_p is the Hirschman-Herfindahl Index of the shares of the IPC classes (8-digit) of the citing patents (forward citations) in the first 5 years after the granting.	Our calculations using the EPO-PATSTAT Database (Autumn 2019)
ORIGINALITY	1-HHI_p where HHI_p is the Hirschman-Herfindahl Index of the shares of the IPC classes (8-digit) of the cited patents (backward citations).	

AV_LONGEVITY_Y	Average number of years between the filing of the patent and the latest forward citation
MAX_LONGEVITY_Y	Maximum number of years between the filing of the patent and the latest forward citation
FORW_CIT_5Y	Number of citations received by the patents in the 5 year after the patent grant
NUM_CLASS	Number of distinct 4-digit IPC class listed in the patents