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WORKING PAPER SERIES

Robots, AI, and Related Technologies: A Mapping of the New Knowledge Base

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Robots, AI, and Related Technologies:

A Mapping of the New Knowledge Base

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Abstract

Using the entire population of USPTO patent applications published between 2002 and 2019, and leveraging on both patent classification and semantic analysis, this paper aims to map the current knowledge base centred on robotics and AI technologies. These technologies will be investigated both as a whole and distinguishing core and related innovations, along a 4-level core-periphery architecture. Merging patent applications with the Orbis IP firm-level database will allow us to put forward a threefold analysis based on industry of activity, geographic location, and firm productivity. In a nutshell, results show that: (i) rather than representing a technological revolution, the new knowledge base is strictly linked to the previous technological paradigm; (ii) the new knowledge base is characterised by a considerable – but not impressively widespread – degree of pervasiveness; (iii) robotics and AI are strictly related, converging (particularly among the related technologies) and jointly shaping a new knowledge base that should be considered as a whole, rather than consisting of two separate GPTs; (iv) the U.S. technological leadership turns out to be confirmed.

JEL classification: O33.

Keywords: Robotics, Artificial Intelligence, General Purpose Technology, Technological Paradigm, Industry 4.0, Patents full-text.

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1. Introduction

Are robotics and Artificial Intelligence (AI) fostering a technological revolution, popularly known as fourth industrial revolution, that is Industry 4.0? This is probably the most interesting socio-economic question nowadays. With the purpose of addressing such a challenging question, the present paper investigates U.S. patent data to determine how and to what extent automation is really fostering a new technological paradigm and – partially in contrast – how much they are related to the previous ICT paradigm.

A second aim of this study is to assess the nature and pervasiveness of the new knowledge base using novel measures able to capture both *core* technologies (basically those clearly identified by proper patent codes) and *related* technologies (out of the inner core, but strictly linked to the new knowledge base).

A third purpose of this work is to investigate whether robotics and AI can be considered as parts of the same technological paradigm or instead as separated – albeit related – general purpose technologies (see the theoretical discussion in Section 2).

Accordingly, we will single out robotics and AI technologies, distinguishing core patents and related patents, along a 4-level core-periphery architecture. This mapping exercise will be based on the investigation of the entire population – covering both manufacturing and services – of USPTO (United States Patent and Trademark Office) patent applications published between 2002 and 2019. The strategy, aimed at identifying technological proximity, will leverage on both patent classification schemes and on the semantic analysis of patents full texts (see Montobbio et al., 2020; for alternative methodologies, see Kogler et al., 2013; Angue et al., 2014).

Then, we will map core and related patents into patenting firms. To this purpose, we will match USPTO applications with the Orbis IP firm-level database to single out the industry and geographical (by country) distribution of those firms leading the automation wave, both in general and distinguishing between core and related technologies. This should allow to identify leading industries and countries behind the establishment of the new knowledge base. Moreover, digging into the sectoral belonging and geographical position of the respective patenting firms, we will be able to assess whether (and how much) the current knowledge base differs from the previous ICT paradigm, its degree of sectoral pervasiveness, and the extent to which robotics and AI are related to one another and converging.

Finally, to provide a tentative picture of the possible economic impact of the new knowledge base on the performance of firms engaged in the provision of new technologies (both core and related ones), we will study the dynamics of labour productivity in patenting firms (Csáfordi et al., 2020). The idea here is that co-evolution of science, technology, and production might be associated – in the long-run – with a superior performance at the firm level (Pugliese et al., 2019). However, in the short-term, it is well-known that the implementation of a new knowledge base may be even counterproductive, in terms of productivity

performance, due to a mismatch between the emerging technologies and the current institutional and organisational framework – the so-called *Solow's paradox* (see Solow, 1987).

The paper is organised as follows. Section 2 summarises the extant literature, emphasising similarities and divergences between the general purpose technology approach and the techno-economic paradigm approach. Section 3 describes the data and methodology used in our analysis. Section 4 presents and discusses the main results. Finally, Section 5 wraps up and puts forward some conclusions related to the three research questions posed in this introduction.

2. General Purpose Technologies and Techno-Economic Paradigms

To single out more detailed research hypotheses able to disentangle the basic question posed by this paper (are robotics and AI fostering a fourth industrial revolution, the so-called Industry 4.0?), one should critically recall two strands of literature. The first one is rooted in mainstream economics and deals with the key concept of *general purpose technology* (GPT); the second one comes from the Neo-Schumpeterian/evolutionary approach and focusses on the change in the *techno-economic paradigm* (TEP).

According to Bresnahan and Trajtenberg (1995), Lipsey et al. (2005), and Jovanovic and Rousseau (2005), a GPT is a single technology – such as steam, electricity, internal combustion, and Information Technology (IT) – that underpins other technologies and multiply their value. Since it is “characteri[s]ed by the potential for pervasive use in a wide range of sectors” (Bresnahan and Trajtenberg, 1995, p. 84), technological and economic “pervasiveness” is therefore the first, distinctive property of any GPT.

According to the same authors, a second property of a GPT is its ability to bring about and foster “generalised productivity gains”. However, whereas the first property is uncontroversial, the second one is not equally obvious. For example, analysing the “Electrification era” from 1894 until 1930, and the IT era from 1971 onwards, Jovanovic and Rousseau (2005) observe that, in spite of exerting a protracted aggregate impact over a long period, both of these GPTs were associated to productivity slowdowns taking place at the start of their initial diffusion. In fact, in the case of electrification, David and Wright (1999) show that a marked acceleration of productivity growth in U.S. manufacturing occurred only after World War I, and was made possible by the adoption of the electric dynamo. By the same token, the very first effect of ICT implementation was a generalised decrease in productivity in the U.S. economy – the so-called Solow's paradox (Solow, 1987), *i.e.* a widespread difficulty to translate ICT investments into increases in productivity (see Ortega-Argilés, et al., 2014). The strong positive impact of GPTs on productivity is therefore not straightforward and may also vary not only over time, but also across economies and industries (Ristuccia and Solomou, 2014).

Turning our attention to the evolutionary tradition, according to Freeman (1990) and Dosi (1982) (see also Freeman, 2019; Dosi, 1988), interdependencies between different organisational and institutional elements characterise the emergence of a bundle of technologies, which all together may signal that a technological breakthrough has occurred and a new TEP (according to Freeman) or a new *technological paradigm* (according to Dosi) is in the making. The empirical implication of these assumptions is that, when two or more new major technologies come along at the same time, they initially bring about a “constellation” of changes, “the productivity effects of which have yet to be fully realised” (Freeman, 1990, p. 4).

Whereas “pervasiveness” is a distinctive feature of the bundle of technologies that characterise any TEP, their introduction does not necessarily lead to productivity gains. Indeed, according to Freeman and co-authors, a new TEP is tested during the declining phase of the previous paradigm with no (or even negative) impact on productivity, while only the subsequent widespread diffusion of the established new TEP is fostering productivity gains and economic booming (see Freeman et al., 1982; Freeman and Soete, 1987). Moreover, for productivity gains to occur, closer interactions between and within firms, and various institutional, cultural, and territorial factors are necessary pre-conditions which may take time to be established (Perez, 1983, 1994; Dosi et al., 2020). In this framework, a “good match” between the new TEP and the institutional context – both at the micro and macro level – is a pre-condition for the complete development of the technological revolution and for the diffusion of its widespread impacts on productivity and economic growth. Operationalising this intuition, one might therefore argue that the empirical identification of a positive and statistically significant association between a measure of the emergence of a new TEP and a measure of productivity dynamics is a clue that the former is already established and will soon exert its impact on economic growth.

The main difference, if any, between the GPT and the TEP approach lies in the fact that the former emphasises the importance of a single technology, the latter of a bundle of technologies. Nevertheless, the underlying view of the relationship between new technologies and long-run economic growth is substantially the same. Just to emphasise three more common aspects besides pervasiveness and the association with marked discontinuity in the dynamics of productivity, both approaches: (i) focus on technological breakthroughs which have the potential to affect the entire economy; (ii) agree upon the idea that the emergence of new technologies creates long waves of economic growth (Rosenberg and Frischtak, 1984; Freeman and Louçã, 2001; Aghion and Howitt, 1998)¹; (iii) assess the importance of institutional changes occurring *vis-à-vis* the emergence of drastic/radical technological innovations. With regard to the last point, most of the papers collected in Helpman (1998) highlight the importance for the GPT approach of qualitative changes associated to the emergence of a new technology, while Gomulka (1990) states that the TEP approach identifies in a bundle of new technologies the trigger factor which endogenously gives rise to several qualitative changes at the economic, institutional, and social level.

1 See also Staccoli and Virgillito (2020) for a recent analysis of long waves in labour-saving automation technologies.

The extant recent empirical literature on GPTs and TEPs as frameworks to investigate the emergence of robotics and AI is rather limited. Use of text-mining techniques to retrieve keywords in the title or the abstract of AI patents led, among others, WIPO (2019) and Damioli et al. (2020) to acknowledge the role of AI as a GPT, not different from electricity, the Internet, and other major breakthroughs emerged during earlier technological phases. Applying network analysis to identify the co-occurrence of two robot technologies in patents registered with the USPTO and the Korean Intellectual Property Office (KIPO), Lee et al. (2016) find evidence of technological convergence in robotics, therefore corroborating the hypothesis of robotics itself as a GPT.

The above examples are consistent with the definition of Curran et al. (2010), who suggest that identification of convergence in industrial technologies entails that these display the features of a GPT. In fact, studying Information and Communication Technology (ICT) as a GPT, Curran and Lecker (2011) gather evidence of “convergence” as a distinctive feature of major technological revolutions.²

The available theories and empirical results about the emergence of GPTs and the formation of TEPs provide useful insights for answering the main questions posed in Section 1: are robotics and AI really sparking a fourth industrial revolution? Is this new knowledge base really pervasive, both from a technological and an economic point of view? Are robotics and AI GPTs independent of each other, or do they jointly represent the pillars of a new TEP?³

To answer the questions posed above, we will hereinafter map automation technologies, distinguishing *core* patents in robotics and AI and *related* patents, with differing degrees of closeness to the core. This mapping exercise will provide some clues to assess whether robotics and AI are revolutionary, whether they are pervasive, and how much they are related to one another (converging into the same TEP).

3. Data and methodology

Our analysis begins with the universe of patent applications (hereafter, simply patents) published by the USPTO between 1st January 2002 and 31st December 2019. This is the widest time horizon we can accomplish with full year data, given that applications before 15th March 2001 are not publicly available. The USPTO Bulk Data Storage System⁴ releases patents full-text data on a weekly basis as concatenated XML files, which for our target period amount to 6,018,243 distinct documents. Since the very same patent

2 The reader may think of the convergence of microelectronics, TLC, and software, as a specific feature of the ICT revolution (see Mowery and Rosenberg, 1998).

3 Paraphrasing David and Wright (1999), the question can be also asked as follows: Does robotics stand to AI as the electric dynamo stands to electrification? In fact, the dynamo represented for David and Wright (1999) an “enabling technology” in the sense of Bresnahan and Trajtenberg (1985, p. 84), namely a new device “opening up new opportunities rather than offering complete, final solutions.”

4 Available at <https://bulkdata.uspto.gov/>.

may be published multiple times at various stages of its lifespan under different *kind codes*, we remove all duplicates and only retain newest versions.

Given our initial dataset, which comprises 5,918,127 *unique* patents, we single out (Section 3.1) two subsets therein, one related to robotics technology, the other to artificial intelligence (AI). In identifying applicable patents, we adopt a mix of two criteria, in a fashion similar to Montobbio et al. (2020): the first criterion targets CPC (Cooperative Patent Classification) codes, assigned by patent examiners before publication, which are known to be relevant to the objective technological fields; the second criterion, instead, looks for the presence of certain keywords within patents full texts.

Rather than treating the membership of a patent to either subset (robotics or AI) as binary (i.e. either a patent belongs to a subset, or it does not), we leverage on the two aforementioned search criteria to devise a multi-level core-periphery architecture (Section 3.2) in which a patent is positioned depending on its fitness.

The selected patents are matched with the Orbis IP (BvD) database, from which detailed information about their corporate assignees can be extracted, when applicable (Section 3.3). In particular, we focus on their geographic location, sector of activity, and productivity.

Following the outlined methodological steps, Section 4 shall present, for each core-periphery level, the countries and industries which have contributed the most in terms of innovative effort, and the average productivity of corporate assignees, disaggregated by industry.

3.1. Robotics and AI patents

The first step of our methodological roadmap deals with the identification of robotics and AI patents. In doing so, we adopt a twofold approach, scouring patent full-texts for specific keywords and classification codes.

Patent classification codes, assigned by patent examiners before publication, provide an in-depth mapping scheme based on the technical features of patents' content. The Cooperative Patent Classification (CPC) system, adopted by the USPTO since 1st January 2013, has a deeply nested hierarchical structure and accounts for more than 260,000 categories. Official concordance tables⁵ mapping former USPC (United States Patent Classification) classes 901 ("Robots") and 706 ("Data processing: artificial intelligence"), widely used in similar studies covering older patents, to newer CPC codes, provide the targets of our first search criterion. In particular, USPC classes 901 and 706 can be traced to, respectively, 124 and 244 unique full-digit CPC codes. In addition to these latter, junction *groups* Y10S901 (for robotics) and Y10S706 (for AI) and their *subgroups*, which target "Technical subjects covered by former USPC" (cf. class Y10), are also included in the search step. A patent is deemed associated to robotics or to AI technology if it has been assigned at least one of the codes in either the underlying concordance table or in the mentioned junction

⁵ Available at <https://www.uspto.gov/web/patents/classification/cpc/html/us901tocpc.html> and <https://www.uspto.gov/web/patents/classification/cpc/html/us706tocpc.html>.

group⁶. Among our initial universe of 5,918,127 patents, there exist 22,931 robotics and 295,688 AI patents, selected according to their displayed CPC codes, of which 2,179 overlap as both robotics and AI. In the remainder of this paper, we shall refer to robotics and AI patents selected according to this criterion as “CPC robotics” and “CPC AI” patents, respectively.

While classification codes are useful for singling out inventions according to the technical content of underlying patents, they prove quite limited in scope since they are unable to encompass complementary artefacts and technologies which are tightly related, yet do not belong, to the target search field. If a patent is not classified as, say, AI, but mentions, possibly repeatedly, some keywords which are intimately and unambiguously relevant to AI, it is plausible that the patent is somehow related to the latter field.

Our second criterion relies on keyword search to capture additional patents which are related to the ones found in the previous step. Following Montobbio et al. (2020), robotics patents are required to mention the word “robot” (or any of its derivatives, such as ‘robots’, ‘robotic’, ‘robotics’ etc.), possibly multiple times, somewhere across their title, abstract, description, or claims sections. Even though this criterion may sound overly simplistic, the word “robot” is remarkably specific and unambiguous: broadly speaking, it is very hard to conceive a sentence embedding that word which at the same time is entirely unrelated to the field of robotics, especially within the context of a patent office. In a similar fashion, to locate AI patents we look for any of the 48 keywords listed in Van Roy et al. (2020, Table 2) excluding “robotics”, which we report in Table 1 for convenience.

Among our initial universe of 5,918,127 patents, there exist 201,278 robotics and 370,317 AI patents, selected according to relevant keyword search, of which 43,519 overlap as both robotics and AI. In the remainder of this paper, we shall refer to robotics and AI patents selected according to this criterion as “KW robotics” and “KW AI” patents, respectively. It holds that 15,858 CPC robotics patents are also KW robotics patents, and 79,997 CPC AI patents are also KW AI patents. We assume that a matched CPC code is stronger, or more reliable, on average, than a matched keyword, in associating a patent to a certain technological field. Following this assumption, we remove patents from the KW robotics and KW AI subsets which have been already selected as CPC robotics or CPC AI, respectively. Before moving forward, it is useful to recap the various magnitudes involved, reported in Table 2.

Contrary to Montobbio et al. (2020), we do not impose ex-ante a minimum number (greater than one) of occurrences of keywords or CPC codes for a patent to be deemed robotics- or AI-related. These numbers however will play a crucial role in forming the basis of the core-periphery architecture outlined in the next section.

⁶ Since applications published before the introduction of the CPC scheme (1st January 2013) can not display the assigned CPC codes, we use the CPC Master Classification File (MCF) for U.S. Patent Applications, also retrievable from the USPTO Bulk Data Storage System, which attributes relevant CPC codes to older applications.

Keywords		
Artificial intelligence	Evolutionary computation	Predictive modeling
Artificial intelligent	Face recognition	Probabilistic modeling
Artificial reality	Facial recognition	Random forest
Augmented realities	Gesture recognition	Reinforcement learning
Augmented reality	Holographic display	Self-drive
Automatic classification	Humanoid robot	Sentiment analysis
Autonomous car	Internet of things	Smart glasses
Autonomous vehicle	Knowledge representation	Speech recognition
Bayesian modeling	Machine intelligence	Statistical learning
Big data	Machine learn	Supervised learning
Computational neuroscience	Machine to machine	Transfer learning
Computer vision	Mixed reality	Unmanned aerial vehicle
Data mining	Natural language processing	Unmanned aircraft system
Data science	Neural Network	Unsupervised learning
Decision tree	Neuro-Linguistic programming	Virtual reality
Deep learn	Object detection	Voice recognition

Table 1: AI keywords. Source: Van Roy et al. (2020).

	Robotics	AI	Overlap	Unique
CPC	22,931	295,688	2,179	316,440
KW	185,420	290,320	31,516	444,224
Total	208,351	586,008	52,323	742,036

Table 2: Relevant magnitudes of the robotics and AI subsets, and their overlap.

3.2. Core-periphery architecture

The given definition of a robotics or AI patent in the previous section is intentionally broad and comprehensive. At this stage, we leverage on the matching score therein to construct a 4-level core-periphery architecture aimed at capturing the degree of technological relatedness to the objective fields. We argue that, the more CPC codes in our target list a patent is assigned, or the more often a patent mentions our target keyword(s), the more likely that the patent constitutes a core technological advancement in either the field of robotics or AI. Conversely, the weaker the matching in our search criteria, the more likely that the patent is less intimately related to the said technological fields.

	Robotics	AI
CP 1	11,409	138,626
CP 2	47,628	145,736
CP 3	35,488	134,527
CP 4	113,826	167,119
Total	208,351	586,008

Table 3: Relevant magnitudes of the robotics and AI core-periphery levels.

Given the four subsets of patents selected in the previous section, CPC robotics, CPC AI, KW robotics, and KW AI, we consider their distributions according to the following measures: for each CPC patent, we compute the ratio between the number of matched CPC codes (from the concordance tables mentioned in the previous section) and the overall number of CPC codes assigned by patent examiners; regarding KW patents, we count the number of times any target keyword is mentioned in each patent.⁷ We then construct the 4 core-periphery (CP) levels, in increasing order of distance from the core, by splitting the various distributions in quartiles and making the following attributions, for either robotics and AI patents:

- CP1. 3rd and 4th quartiles of CPC patents;
- CP2. 2nd quartile of CPC patents and 4th quartile of KW patents;
- CP3. 1st quartile of CPC patents and 3rd quartile of KW patents;
- CP4. 1st and 2nd quartiles of KW patents.

In this way, we allow for an overlap of CPC and KW patents in the middle CP levels, while we maintain the idea that CPC patents are on average closer to the core than KW patents. Table 3 summarises the number of patents in each CP level for both robotics and AI patents.

While the aforementioned choice of attribution may seem arbitrary, it is possible to show, once firm level data is extracted in the next section, that the obtained CP levels exhibit a satisfactory degree of mutual consistency (see the Appendix and Table 11).

3.3. Firm-level data

With the aim of extracting firm-level data about last known corporate assignees, we match patents in our selected subsets with the Orbis IP (BvD) database through the relevant publication numbers. Out of 742,036 unique patents, 615,182 (approximately 83%) are matched to at least one firm, of which 175,949 are robotics patents, 483,098 are AI patents, and 43,865 are both robotics and AI patents. In total, 62,972 firms hold at

⁷ Since the selection of KW AI patents depends on a multiplicity of keywords, we are implicitly assuming a constant and unitary rate of substitution between an additional occurrence of a keyword already mentioned, and the occurrence of a previously unmentioned keyword.

least one of our selected patents, of which 23,772 hold at least one robotics patent, 50,221 hold at least one AI patent, and 11,021 hold both robotics and AI patents.

Our variables of interest include the country where each firm is incorporated, its sector of activity, denoted by a 3-digit NAICS 2017⁸ (North American Industry Classification System) code, and its productivity, defined as average sales per employee over the period 2015–2019 inclusive.⁹ While value added per employee would constitute a superior measure of firm productivity, availability of added value data on Orbis IP is very scant and would force us to neglect about 80% of matched firms. We therefore resort to approximating firm productivity as sales per employee with the purpose of retaining the maximum amount of available information.

Given the core-periphery architecture outlined in the previous section, we shall evaluate, for robotics and AI patents at each CP level, the overall contribution of each country and each industrial sector to the innovative effort behind patented technologies therein. Moreover, we shall present and compare the average productivity of the relevant sectors in each CP level. All these measures are weighted proportionally to the number of patents held by each corporate assignee at the various CP levels. These findings are presented and discussed in the next section.

4. Results

While in the previous section we have proposed and discussed our core-periphery taxonomy and the way in which we have associated patents with their holding firms, the aim of this section is threefold. First, we will map the patents taking into account their sectoral belonging on the one hand, and their nationality on the other hand (Sections 4.1 and 4.2). Second, we will investigate the degree of similarity between robotics and AI technologies, to assess whether they can be considered as components of the same paradigm or rather as separate GPTs (Section 4.3). Third, we will present and discuss the productivity performance of the companies involved in robotics and AI technologies (Section 4.4).

4.1. Industries

Table 4 assigns all our robotics patents to the sectors which the holder company belongs to. The sectors are identified by their NAICS 3-digit codes and are ranked according to the first column, reporting their overall prevalence. The following columns report the sectoral incidence within the four core-periphery categories.

Not surprisingly, “machinery manufacturing” (corresponding to NAICS code 333, which comprises “establishments primarily engaged in manufacturing industrial and commercial machinery”) is playing a

⁸ See the specification at <https://www.census.gov/eos/www/naics/>.

⁹ In case some of the yearly data are missing, we compute the average using only available data.

NAICS	Title	Overall	CP 1	CP 2	CP 3	CP 4
334	Computer and Electronic Product Manufacturing	21.64%	23.82%	20.53%	17.92%	22.99%
333	Machinery Manufacturing	14.28%	30.18%	18.92%	15.51%	10.38%
541	Professional, Scientific, and Technical Services	13.64%	9.09%	12.45%	13.74%	14.57%
325	Chemical Manufacturing	7.78%	0.78%	6.28%	9.18%	8.68%
336	Transportation Equipment Manufacturing	6.14%	8.83%	7.25%	6.51%	5.3%
522	Credit Intermediation and Related Activities	4.04%	1.4%	3.58%	3.85%	4.56%
339	Miscellaneous Manufacturing	3.81%	1.11%	4.43%	4.57%	3.62%
611	Educational Services	3.61%	2.03%	3.4%	3.62%	3.85%
335	Electrical Equipment, Appliance, and Component Manufacturing	3.12%	8.26%	3.98%	2.79%	2.33%
551	Management of Companies and Enterprises	2.31%	1.62%	2.14%	2.44%	2.42%
561	Administrative and Support Services	2.09%	1.43%	2.19%	1.88%	2.18%
423	Merchant Wholesalers, Durable Goods	2.05%	1.96%	2.08%	2.32%	1.97%
511	Publishing Industries (except Internet)	1.75%	0.88%	1.18%	1.3%	2.2%
332	Fabricated Metal Product Manufacturing	1.07%	1.35%	0.99%	1.16%	1.05%
921	Executive, Legislative, and Other General Government Support	1.07%	0.55%	0.83%	1.06%	1.22%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.0%	0.3%	0.53%	1.74%	1.04%
326	Plastics and Rubber Products Manufacturing	0.89%	0.32%	0.63%	0.79%	1.08%
621	Ambulatory Health Care Services	0.75%	0.14%	0.5%	0.7%	0.93%
424	Merchant Wholesalers, Nondurable Goods	0.73%	0.19%	0.6%	0.82%	0.81%
517	Telecommunications	0.56%	0.22%	0.49%	0.44%	0.66%

Table 4: Sectoral relevance to robotics patents for each core-periphery level.

leading role in robotics patenting, with more than 30% of the patents in the core category belonging to this industry. Interestingly enough, its role is declining when we move to the periphery, dropping to about 19% in CP2, about 15.5% in CP3, and about 10.4% in CP4. As a result, on the whole ranking – including both core and related technologies – “machinery manufacturing” (333) is ranked second, with an overall weight equal to 14.28%.

Indeed, in the overall ranking, “computer and electronic product manufacturing” (corresponding to NAICS code 334, which comprises “establishments primarily engaged in manufacturing computers, computer peripheral equipment, communications equipment, and similar electronic products, as well as components for such products”) is leading, with a percentage equal to 21,64%; however, this sector turns out to be less important than “machinery manufacturing” in the very core (about 24% of CP1 patents), while its weight maintains relevance in the remaining three categories (ranging from 18% to 23%).

Putting together these first results, it is obvious that machinery manufacturing and computer and electronic product manufacturing account for more than 50% of core robotics patenting, with machinery manufacturing appearing central in the very core, and computer and electronic product manufacturing more or less equally distributed from the technological core to the related but more peripheral technologies. While not surprising, this outcome highlights, on the one hand, the key role of manufacturing in robotics patenting and, on the other hand, the crucial link between robotics and computer and electronic manufacturing (that is an intrinsic strong relationship between the previous technological paradigm and the new knowledge base – see Section 2).

The third sector accounting for a relevant portion of robotics patenting is “professional, scientific and technical services” (corresponding to NAICS code 541, which comprises “establishments primarily engaged in activities in which human capital is the major input”). This sector accounts for 13.64% of the entire patent population and ranges from about 9% in CP1 to about 14.5% in CP4. High-tech services are therefore rather active in robotic patenting, and their role monotonically increases when we move to the technological periphery.

A smaller – albeit still relevant – role in the core technologies (CP1) is played by “transportation equipment manufacturing” (336, starting from about 9% in the very core and monotonically declining to about 5% in CP4) and by electrical devices (335), also decreasing from the core (about 8%) to the periphery (about 2%). In contrast, some industries are definitely under-represented in the core, but are quite important in the related technologies; this is the case of “chemical manufacturing” (325) which holds less than 1% of patents in the core category and increases up to about 9% in CP3 and CP4, and of both “miscellaneous manufacturing” (339) and “credit intermediation” (522) which hold about 1% of patents in the core category and increases up to about 4% in the more peripheral categories.

Other industries, which deserve to be mentioned for their (relatively minor) role in the core, are “educational services” (611, about 2% in CP1), with a more relevant role in the related technologies; “merchant wholesalers, durable goods” (423, about 2% in CP1, with a similar role in the periphery); “management of companies and enterprises” (551, about 1.5% in CP1, with an increasing role in the related technologies) and “administrative and support services” (561, about 1.5% in CP1, with a slightly increasing role in the periphery).

NAICS	Title	Overall	CP 1	CP 2	CP 3	CP 4
334	Computer and Electronic Product Manufacturing	25.66%	21.9%	24.55%	25.75%	29.3%
541	Professional, Scientific, and Technical Services	19.01%	23.18%	19.05%	17.94%	16.76%
511	Publishing Industries (except Internet)	7.33%	7.61%	8.4%	6.61%	6.8%
522	Credit Intermediation and Related Activities	5.99%	5.99%	5.66%	5.8%	6.42%
336	Transportation Equipment Manufacturing	5.53%	3.77%	6.07%	7.05%	5.19%
333	Machinery Manufacturing	4.27%	4.1%	4.76%	4.16%	4.08%
561	Administrative and Support Services	2.99%	3.23%	2.96%	2.99%	2.84%
517	Telecommunications	2.74%	2.27%	2.53%	2.58%	3.39%
335	Electrical Equipment, Appliance, and Component Manufacturing	2.36%	2.25%	2.79%	2.42%	2.02%
423	Merchant Wholesalers, Durable Goods	2.3%	2.13%	2.26%	2.28%	2.46%
551	Management of Companies and Enterprises	2.21%	2.94%	2.09%	2.13%	1.83%
611	Educational Services	2.02%	1.81%	1.82%	2.15%	2.24%
339	Miscellaneous Manufacturing	1.75%	0.93%	1.56%	2.5%	1.92%
325	Chemical Manufacturing	1.36%	0.89%	1.09%	1.58%	1.76%
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	1.35%	2.06%	1.27%	1.13%	1.09%
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	1.29%	1.14%	1.06%	1.2%	1.69%
519	Other Information Services	1.28%	1.49%	1.57%	1.25%	0.89%
518	Data Processing, Hosting, and Related Services	0.91%	1.42%	1.05%	0.75%	0.56%
921	Executive, Legislative, and Other General Government Support	0.88%	1.1%	0.86%	0.83%	0.75%
424	Merchant Wholesalers, Nondurable Goods	0.49%	0.69%	0.4%	0.43%	0.45%

Table 5: Sectoral relevance to AI patents for each core-periphery level.

On the whole, robotics patenting appears to be characterised by a clear leadership of machinery, electrical and computer manufacturing (and to a lesser extend high-tech services and transportation), particularly within core technologies.

However, robotics also shows an appreciable degree of pervasiveness: particularly when we move to related technologies, other additional industries are rather active both within manufacturing (chemicals, miscellaneous) and services (professional, scientific, technical, credit and educational services).

Turning our attention to AI technologies, Table 5 reports the sectoral ranking in a similar fashion to the previous Table 4.

In AI technologies the leadership is shared between “professional, scientific and technical services”¹⁰ (541) and “computer and electronic product manufacturing” (334), with the former leading in the core (about 23% in CP1) and declining when we move to the related technologies, and the latter slightly behind in the core (about 22%) but monotonically increasing moving to the periphery up to about 29%. As a result, the overall ranking is led by computer and electronic manufacturing with an incidence of about 25.5%.

Therefore, the leadership in AI technologies (where the design and production of algorithms require a joint contribution of hardware and software components) appears equally spread between manufacturing and services, and this marks a relevant difference in comparison with robotics, more centred on manufacturing. On the other hand, computer and electronic manufacturing turns out to be a key sector in both technological maps; this outcome is important since it highlights both a high degree of connectivity between robotics and AI technologies and a strong relationship between the new knowledge base and the former technological paradigm (see the research questions posed in Section 1).

A further corroboration of the key role of services in AI technologies comes from the important roles played by “publishing industries” (corresponding to NAICS code 511, which comprises “establishments primarily engaged in publishing newspapers, periodicals, books, databases, software and other works”) and “credit intermediation” (corresponding to NAICS code 522, which comprises “establishments that (1) lend funds raised from depositors; (2) lend funds raised from credit market borrowing; or (3) facilitate the lending of funds or issuance of credit”), which both score between 6% and 7% in the overall ranking and in the four core-periphery categories.

Other industries worth to be mentioned are “transportation equipment manufacturing” (336), “machinery manufacturing” (333, relatively marginal with regard to AI technologies, while being a clear leader in robotics, see above), “administrative and support services” (561), “telecommunications” (517, a new entry in our sectoral mapping), electrical devices (335), “merchant wholesalers, durable goods” (423), “management of companies and enterprises” (551), and “educational services” (611). All these sectors show an incidence ranging from 2% to 6% with no strikingly significant change moving from the core to the periphery.

Indeed, with the notable exception of the two leading sectors (with high-tech services more important within the core, and computer and electronic manufacturing playing a larger role in the related technologies),

¹⁰ This result is expected, since code 541 includes software.

Country	Overall	CP 1	CP 2	CP 3	CP 4
United States	54.94%	30.88%	52.65%	57.55%	57.47%
Japan	16.22%	36.04%	19.38%	15.66%	13.13%
European Union *	14.22%	14.42%	13.22%	14.08%	14.64%
South Korea	5.61%	6.6%	5.09%	3.27%	6.44%
Germany	5.14%	7.18%	5.29%	5.2%	4.86%
Netherlands	1.86%	1.06%	1.48%	1.46%	2.21%
United Kingdom	1.86%	1.52%	1.55%	2.01%	1.97%
Switzerland	1.73%	2.17%	1.85%	1.7%	1.65%
China	1.5%	3.27%	1.76%	1.79%	1.12%
Taiwan	1.3%	3.33%	1.64%	1.2%	1.0%
Canada	1.26%	1.04%	1.25%	1.46%	1.23%
France	1.1%	1.13%	1.02%	1.0%	1.16%
Israel	0.89%	0.44%	0.83%	0.9%	0.95%
Sweden	0.77%	1.11%	0.79%	0.8%	0.71%
Finland	0.65%	0.26%	0.21%	0.33%	0.96%
Italy	0.59%	0.88%	0.78%	0.63%	0.48%
Australia	0.59%	0.22%	0.66%	0.61%	0.6%
Ireland	0.59%	0.08%	0.6%	1.05%	0.5%
Denmark	0.45%	0.19%	0.46%	0.52%	0.45%
Singapore	0.43%	0.4%	0.4%	0.34%	0.48%
Belgium	0.41%	0.04%	0.21%	0.3%	0.55%

* sum of EU member states as of 31st December 2019

Table 6: Country relevance to robotics patents for each core-periphery level.

the AI mapping appears more balanced than robotics, with a similar incidence of the different sectors across the four core-periphery categories.

Out of the first 12 industries ranked in the robotics and AI charts, 10 overlap, while two manufacturing sectors (chemical and miscellaneous) only appear in robotics, and two service sectors (publishing industries and telecommunications) only appear in the AI top 12.

On the whole, AI technologies seem to be characterised by: a joint (and probably complementary) leadership of high-tech services (including software) and computer and electronic manufacturing; relatively minor sectoral discontinuities between core and related technologies (in contrast with robotics); and a considerable degree of pervasiveness with many manufacturing and service sectors actively involved. In the vast majority of industries, this pervasive impact overlaps with the one triggered by robotics technologies (see above).

4.2. Countries

In this section we investigate which countries are emerging as leaders in the robotics and AI technologies and so which are the nations at the forefront of the new knowledge base. Table 6 reports the country ranking in relation to robotics technologies; notice that European Union countries are included both as an aggregate and as single nations.

The U.S. definitely lead the ranking, accounting for more than 50% of total robotics patenting; with the notable exception of the core technologies (where Japan ranks first), the U.S. advantage is remarkably confirmed in CP2, CP3, and CP4. As was the case in the “ICT era”, the U.S. appear strongly dominant both in the core and related robotics technologies, while Japan seems to share a leading position only in the core technologies where computer and machinery manufacturing play a key role (see Table 4). The European Union, as a whole, jointly accounts for about 14% of robotics patenting, with no significant differences moving from core to related technologies.

South Korea and Germany are both playing a certain role in the core (CP1) as well as in the related technologies, with incidences which range around 5-6%. Another bunch of countries are represented with an overall weight larger than 1%, namely The Netherlands, U.K., Switzerland, China, Taiwan, Canada and France. On the whole, robotics patenting appears geographically very concentrated.

Turning our attention to the AI technologies, consider Table 7.

As far as AI technologies are concerned, the U.S. dominant position is even more striking: 2/3 of AI patents are held by U.S. companies, and this is true on the whole, for the core, and for the peripheral categories. Japan again ranks second, with an incidence around 10% across the different categories. The E.U. ranks third, accounting for about 9.5% of AI patenting, with no significant differences across the core-periphery categories.

As was the case with robotics (see Table 6), South Korea and Germany rank third and fourth, respectively, with a stronger presence of Germany in the core and of South Korea in CP2, CP3, and particularly in CP4. China, U.K., Canada, The Netherlands and Taiwan follow with percentages ranging from 1% to 2%.

In a nutshell, AI patenting appears even more geographically concentrated than robotics patenting, with the U.S. dominating the scene, a collateral – but still important – role of Japan and South Korea, while Germany and China follow behind.

Putting together the evidence from Table 6 and Table 7, we can conclude that the U.S. have a clear advantage in both robotics and AI technologies, accounting for 55%–65% of patenting activity in the new knowledge base; moreover, while this leadership is shared with Japan in the robotics core technologies, it is absolutely dominant in all the other examined categories. Although this outcome may be partially biased by

Country	Overall	CP 1	CP 2	CP 3	CP 4
United States	66.4%	68.75%	63.89%	66.18%	66.93%
Japan	10.05%	9.47%	12.28%	10.72%	8.09%
European Union *	9.52%	10.04%	9.14%	9.18%	9.73%
South Korea	4.92%	2.82%	4.9%	4.98%	6.45%
Germany	2.84%	3.93%	2.69%	2.53%	2.41%
China	2.12%	1.53%	2.85%	1.87%	2.16%
United Kingdom	1.46%	1.43%	1.35%	1.52%	1.53%
Canada	1.4%	1.56%	1.36%	1.35%	1.35%
Netherlands	1.32%	1.24%	1.35%	1.29%	1.37%
Taiwan	1.24%	1.4%	1.32%	1.26%	1.02%
Israel	0.89%	0.61%	0.96%	1.07%	0.88%
France	0.87%	0.9%	0.82%	0.81%	0.95%
Switzerland	0.81%	0.79%	0.69%	0.83%	0.9%
Finland	0.7%	0.53%	0.66%	0.56%	0.96%
Ireland	0.66%	0.84%	0.66%	0.59%	0.58%
Sweden	0.62%	0.4%	0.57%	0.76%	0.73%
Singapore	0.61%	0.47%	0.6%	0.66%	0.69%
Australia	0.49%	0.69%	0.48%	0.39%	0.44%
India	0.35%	0.63%	0.37%	0.26%	0.2%
Cayman Islands	0.31%	0.32%	0.28%	0.42%	0.25%
Hong Kong	0.24%	0.21%	0.27%	0.21%	0.27%

* sum of EU member states as of 31st December 2019

Table 7: Country relevance to AI patents for each core-periphery level.

the dataset used in this study (USPTO), it is however obvious that the new knowledge base is mainly forged in the U.S., with Japan, the E.U. and – to a lesser extent – South Korea playing a collateral role. For the time being, the rest of the world – including China – lags behind.

4.3. Similarities and differences between robotics and AI technologies

The degree of similarity between robotics and AI technologies in the patterns discussed in Sections 4.1 and 4.2 should be investigated in greater detail. This will help to answer the research questions put forward in Sections 1 and 2 concerning the possible revolutionary nature of these technologies, and whether they can be considered separate GPTs or as components of the same technological constellation, which in turn can be seen as the trigger factor of a new paradigm.

	Cosine similarity	Spearman correlation
Overall	89.61%	88.61%
CP 1	65.80%	63.25%
CP 2	83.94%	82.37%
CP 3	85.76%	84.27%
CP 4	93.25%	92.68%

Table 8: Cosine similarity and Spearman rank correlations between robotics and AI core-periphery levels.

As far as sectoral belonging is concerned, we already noticed that robotics patenting is more centred on manufacturing (particularly machineries and computers), while AI technologies are more focussed on services (particularly professional, scientific and technical services). Moreover, both robotics and AI share a key role played by computer and electronic product manufacturing.

Putting together these various pieces of evidence, we may assess that both the investigated key technologies are strongly linked with the former technological paradigm, triggered and shaped by the computer revolution. In this respect, the question whether robotics and AI technologies are really fostering a technological revolution or just a radical revival of the extant paradigm remains open. Moreover, robotics appears characterised by a manufacturing core, while AI technologies seem much more balanced between manufacturing and services. From this point of view, AI can be considered more widespread and pervasive than robotics. On the other hand, if we move from the core technologies to the periphery, robotics shows a better capacity to engage non-core sectors, while AI rankings are very similar¹¹.

However, both technologies display a considerable overall level of pervasiveness with a dozen of 3-digit sectors each showing to hold more than 2% of total patenting. Once again —within the first 12 sectors (accounting for more than 80% of the entire patenting activity in both technological fields) – in robotics, manufacturing sectors are more represented than services (56.8% vs. 27.7% of all patents), while the opposite is true for AI technologies (37.8% vs. 44.6% of all patents).

As already noticed, out of the first 12 industries ranked in the robotics and AI rankings, 10 are in common (and the remaining 4 are however within the top 20 sectors in both the rankings; see Table 4 and Table 5). In more detail, Table 8 reports two distinct proximity measures, namely cosine similarity and Spearman rank correlation, between the sectoral distributions of the different core-periphery categories for robotics and AI (see the Appendix for a formal definition).

¹¹ As can be seen in Table 11 reported in the Appendix, all the obtained cross-level similarity coefficients are systematically lower for robotics technologies, corroborating their more pervasive nature.

Indeed, the correlation coefficients between robotics and AI sectoral rankings are close to 90% for all patents, and monotonically increase from around 65% to about 93% if we move from the core (CP1) to the periphery (CP4).

If we jointly consider all these pieces of evidence, the emerging scenario might be summarised as follows:

- Robotics and AI are both strongly related and still dependent on computer technologies;
- Both technologies show a considerable level of pervasiveness; however, only 12 industries account for more than 80% of total patents both in robotics and AI;
- Although robotics is more concentrated in manufacturing, the two technologies appear rather similar in terms of sectoral penetration, particularly when we move from the core to the more peripheral technologies; this can be considered as an evidence supporting the convergence of the two key technologies of the current automation wave.

As far as geographical belonging is concerned, we have already underlined the dominant role of the U.S. in both the robotics and AI technologies. This is consistent with the leading U.S. role in the ICT paradigm and with the revealed strong relationships between robotics, AI, and computer technologies (see above). Since the three technological families are strictly interlinked, the U.S. seem to be favoured by their historical leadership in the past decades and by the intrinsic synergies they can exploit.

Japan, the E.U. and some other Asian countries (particularly South Korea and China) lag behind, with Japan playing a key role in robotics manufacturing.

In summary, whether robotics and AI technologies will prove to be revolutionary or incremental in comparison with the ICT, in both cases the dominant role of the U.S. will be confirmed for the decades ahead.

4.4. Productivity

In this section, we will discuss some preliminary evidence about the productivity performance exhibited by companies filing for patent protection in robotics and AI technologies (see Section 3.3 for details about the computation of average productivity levels).

Limiting our analysis to the leading sectors in both technologies and comparing the Table 9 and Table 10, we can detect the following pieces of evidence:

- Computer manufacturing companies show similar levels of productivity performance in the two technological fields (with AI leading), and in both cases productivity increases moving from the core to the periphery.

NAICS	Title	Overall	CP 1	CP 2	CP 3	CP 4
334	Computer and Electronic Product Manufacturing	380	358	348	384	397
333	Machinery Manufacturing	469	480	462	470	469
541	Professional, Scientific, and Technical Services	287	424	301	330	254
325	Chemical Manufacturing	552	444	529	693	509
336	Transportation Equipment Manufacturing	521	556	547	523	497
522	Credit Intermediation and Related Activities	385	412	406	403	372
339	Miscellaneous Manufacturing	310	334	262	299	333
611	Educational Services	207	220	219	199	204
335	Electrical Equipment, Appliance, and Component Manufacturing	282	293	281	276	280
551	Management of Companies and Enterprises	345	270	338	334	361
561	Administrative and Support Services	207	191	203	227	204
423	Merchant Wholesalers, Durable Goods	400	381	396	415	399
511	Publishing Industries (except Internet)	538	374	566	593	530
332	Fabricated Metal Product Manufacturing	297	310	301	311	289
921	Executive, Legislative, and Other General Government Support	139	131	133	139	144
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	378	116	554	371	352
326	Plastics and Rubber Products Manufacturing	227	252	252	242	220
621	Ambulatory Health Care Services	167	126	178	182	162
424	Merchant Wholesalers, Nondurable Goods	355	481	379	324	354
517	Telecommunications	292	527	281	162	312

Table 9: Average sectoral productivity (in thousand USD) of robotics patents holders for each core-periphery level.

- Machinery manufacturing firms exhibit a better performance in the robotics technologies, and in both cases they show a decreasing trend moving from CP1 to CP4.
- High-tech services display a higher average productivity in robotics (particularly in CP1); in robotics productivity decreases moving to the periphery, while the reverse is true in the AI technological field.
- In transportation manufacturing, productivity is higher in robotics and declines moving from CP1 to CP4, while the opposite is true in AI technologies.

NAICS	Title	Overall	CP 1	CP 2	CP 3	CP 4
334	Computer and Electronic Product Manufacturing	403	356	391	427	425
541	Professional, Scientific, and Technical Services	235	223	236	235	248
511	Publishing Industries (except Internet)	647	664	626	649	653
522	Credit Intermediation and Related Activities	430	427	422	444	427
336	Transportation Equipment Manufacturing	482	446	494	498	479
333	Machinery Manufacturing	348	361	360	358	319
561	Administrative and Support Services	188	197	205	190	167
517	Telecommunications	428	304	432	450	477
335	Electrical Equipment, Appliance, and Component Manufacturing	275	278	276	270	277
423	Merchant Wholesalers, Durable Goods	404	440	404	414	378
551	Management of Companies and Enterprises	410	441	424	377	383
611	Educational Services	192	174	182	204	200
339	Miscellaneous Manufacturing	261	248	254	263	269
325	Chemical Manufacturing	592	652	633	575	557
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	377	359	397	349	404
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	476	441	470	467	508
519	Other Information Services	450	466	463	452	401
518	Data Processing, Hosting, and Related Services	282	297	310	262	237
921	Executive, Legislative, and Other General Government Support	136	140	135	138	130
424	Merchant Wholesalers, Nondurable Goods	408	424	415	416	375

Table 10: Average sectoral productivity (in thousand USD) of AI patents holders for each core-periphery level.

On the whole, computer companies appear to have similar productivity performance in both technology fields, with a comparative advantage by firms operating in the related technologies, rather than in the core ones.

The other two manufacturing industries playing a relevant role in both technological fields are machinery and transportation. In those two sectors, companies are getting more in terms of productivity within robotics, and machinery firms are particularly productive in the core categories of both fields.

Professional, scientific and technical services are also more productive in robotics (particularly in the core), while within AI their productivity increases moving to the periphery.

With the exception of computer companies, in the other three leading sectors robotics firms are more productive than their AI counterparts, with outstanding performances in the robotics CP1 category. Taking into account that robotics technologies are less young than AI ones, this seems to suggest that leading companies should not be afraid of being on the technological frontier. Conversely, operating in the AI technologies appears more risky in terms of productivity performance (Solow's paradox), and this emerges particularly true within the CP1 category, at least for high-tech services and transportation. Finally, computer manufacturing firms (which accompany the new technologies well rooted in the previous paradigm – see previous subsections) are better performing in the related technologies where it is more likely to extract value from technological scale and scope economies.

5. Conclusions

The outcomes and the analyses put forward in the previous sections can be summarised in providing some answers to the three key questions laid down in the introduction (cf. Section 1).

First of all, can robotics and AI be considered the drivers of a proper technological revolution (what is popularly named as Industry 4.0)? The results discussed in Section 4 cast some doubts about the radicalism of the new knowledge base. Indeed, both computer manufacturing and software services still play a key role in supporting the diffusion of robotics and AI, and this holds true for the core knowledge and the related technologies as well (although hardware appears to be more crucial in the core for robotics, while this role is played by software in AI). This is a clear evidence that the new knowledge base is strictly linked to (and somehow dependent on) the previous technological paradigm. While the emergence of the “ICT paradigm” as a successor of the previous “Fordist/mass-production paradigm” was rightly seen as a revolution, nowadays the discontinuity seems to be less pronounced, and the new knowledge base appears to be more as a deepening of the current technological trajectory rather than a radical shift in paradigm. Consistently, the U.S. leadership is confirmed and incontestable.

A second purpose of this work was to assess the nature and pervasiveness of the new knowledge base. As discussed in Section 4 regarding both robotics and AI, twelve industries account for more than 80% of the entire patenting activity (with manufacturing sectors playing a leading role in robotics and services emerging as more crucial in AI). This means that the new knowledge base is characterised by a considerable (but not impressively widespread) degree of pervasiveness, at least for the time being.

Our third purpose of this work was to investigate whether robotics and AI can be considered as parts of the same “technological paradigm” or instead as separate – albeit related – “general purpose technologies”. As discussed in Section 4, ten out of the twelve leading sectors in robotics and AI patenting are in common

to the two technologies. Moreover, from a geographical point of view, the main actors are the same and ordered with the same ranking. These pieces of evidence support a view that considers robotics and AI strictly related, converging (particularly among the related technologies) and jointly shaping, if not a new paradigm (see above), a new knowledge base, which should be considered as a whole and not as consisting of two separate GPTs. Although robotics is more centred on manufacturing while AI finds its roots in high-tech services, the two technologies resemble an interconnected knowledge constellation, which can be legitimately named “automation”.

A further question that we raised in the Introduction was whether the new knowledge base involves productivity-enhancing innovation. This is a difficult question, and Section 4.4 aimed at providing just some preliminary descriptive evidence. On average, a better productivity performance is detectable more in robotics than in AI, and more in the related technologies than within the core ones. These outcomes seem to be consistent with the Solow’s paradox: newer technologies (AI) and innovation in the inner technological cores might be characterised by inferior productivity outcomes, at least at the dawn of a new knowledge base.

This study is of course affected by the limitation of being based on American patents: while the U.S. market is essential for companies aiming to play some role in the robotics and AI technologies, the USPTO database may still be biased against European and Asian actors, and therefore underestimate their role in the emergence of the new knowledge base.

Further research should extend the analysis to European and Asian patent offices, and investigate in more detail the relationship between the new knowledge base, productivity performance, and economic growth.

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Appendix

In this technical appendix we formally define the two proximity measures, namely cosine similarity and Spearman rank correlation, used in the construction of Table 8 and discussed in Section 4.3. As extensions to the underlying core-periphery levels are straightforward, we only explain their development in the overall case.

Once a group of patents are matched to their corporate assignee(s) (cf. Section 3.3), it is possible to build a rank of their corresponding sectoral industries, sorted by frequency of occurrence. Provided that there exist 99 NAICS codes at the 3-digit level, the ranking can be expressed as a vector in the 99-dimensional vector space of natural numbers. Given two such vectors $X, Y \in \mathbb{N}^{99}$ corresponding to, say, the whole sets of robotics and AI patents, respectively (or any of their core-periphery subsets), it is possible to define their cosine similarity as the cosine of the angle between them, which is also equal to the inner product of the same vectors normalised to unit length. Formally,

$$\text{cosine}(X, Y) := \frac{X \cdot Y}{\|X\| \|Y\|} = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2} \sqrt{\sum_i y_i^2}},$$

where x_i and y_i denote the components of vectors X and Y , respectively, and $\|\cdot\|$ denotes the Euclidean norm. Since rank vectors are non-negative, values of their cosine similarity are bound to the unit interval $[0, 1]$.

In a similar fashion, it is possible to define the Spearman rank correlation as the usual Pearson correlation coefficient between the rank vectors X and Y . Formally,

$$r_s := \rho_{XY} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}.$$

Once these similarity measures are defined, it is possible to check whether the core-periphery architecture devised in Section 3.2 displays a satisfactory degree of inner consistency. Ideally, given the defined hierarchy, adjacent levels should bear more mutual similarity than non-adjacent ones. Accordingly, level CP1 should be closer to level CP2 than to level CP3, and closer to level CP3 than to level CP4, and level CP2 should be closer to CP3 than to CP4. Table 11 reports the cross-level proximity measures, both in terms of cosine similarity and Spearman correlation, for both robotics and AI patents, corroborating our core-periphery structure by validating the aforementioned requirement.

Robotics	Cosine similarity				Spearman correlation			
	CP 1	CP 2	CP 3	CP 4	CP 1	CP 2	CP 3	CP 4
CP 1	●	94.54%	88.67%	82.37%	●	94.31%	88.01%	81.11%
CP 2	*	●	98.66%	95.38%	*	●	98.54%	94.9%
CP 3	*	*	●	97.16%	*	*	●	96.83%
CP 4	*	*	*	●	*	*	*	●

AI	Cosine similarity				Spearman correlation			
	CP 1	CP 2	CP 3	CP 4	CP 1	CP 2	CP 3	CP 4
CP 1	●	98.59%	97.45%	95.86%	●	98.45%	97.21%	95.51%
CP 2	*	●	99.61%	98.73%	*	●	99.57%	98.63%
CP 3	*	*	●	99.37%	*	*	●	99.33%
CP 4	*	*	*	●	*	*	*	●

Table 11: Cross-level cosine similarity and Spearman rank correlation within the core-periphery architecture for both robotics and AI patents.