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AI as a new emerging technological paradigm: evidence from global patenting

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Abstract

Artificial intelligence (AI) is emerging as a transformative innovation with the potential to drive significant economic growth and productivity gains. This study examines whether AI is initiating a technological revolution, signifying a new technological paradigm, using the perspective of evolutionary neo-Schumpeterian economics. Using a global dataset combining information on AI patenting activities and their applicants between 2000 and 2016, our analysis reveals that AI patenting has accelerated and substantially evolved in terms of its pervasiveness, with AI innovators shifting from the ICT core industries to non-ICT service industries over the investigated period. Moreover, there has been a decrease in concentration of innovation activities and a reshuffling in the innovative hierarchies, with innovative entries and young and smaller applicants driving this change. Finally, we find that AI technologies play a role in generating and accelerating further innovations (so revealing to be "enabling technologies", a distinctive feature of GPTs). All these features have characterised the emergence of major technological paradigms in the past and suggest that AI technologies may indeed generate a paradigmatic shift.

JEL classification: O31; O33

Keywords: Artificial Intelligence, Technological Paradigm, Structural Change, Patents

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Daniel Vertesy makes clear that the views and opinions expressed are only those of the authors and do not necessarily reflect those of the International Telecommunication Union or its member states, which cannot be held responsible for them.

1. Introduction

Artificial intelligence (AI) has been emerging as one of the most important innovations of recent decades, with the potential to fundamentally transform economic structures and societies at large (Brynjolfsson and McAfee 2011; Brynjolfsson and McAfee 2014; Agrawal et al. 2019). By featuring the properties of both a general-purpose technology (GPT) and a method of invention (Griliches 1957; Cockburn et al. 2019; Agrawal et al. 2024), it is increasingly expected to become a powerful driver of innovation, productivity gains and economic growth in the years and decades to come. Initial evidence is supporting the idea that machine learning and a constellation of related data science technologies share the features of a GPT (Cantner and Vannuccini 2021; Goldfarb et al. 2023), namely widespread application, scope for improvement, and complementarity with other technologies (Bresnahan and Trajtenberg 1995). By automating the generation of increasingly accurate predictions (Agrawal et al. 2019), AI may augment inventors and organisations at discovering new ideas (Jones 2022) while reducing risks and costs of innovation (Haefner et al. 2021), eventually counterbalancing the knowledge burden and enhancing the ability of finding new ideas (Jones 2009; Bloom et al. 2020; Antonelli et al. 2023). A growing number of evidence documents the growing contribution of AI for scientific discoveries (Bianchini et al. 2022; Wang et al. 2023), firms' innovation (Bouschery et al. 2023; Rammer et al. 2022; Verganti et al. 2020) and productivity gains (Czarnitzki et al. 2023; Damioli et al. 2021; Yang 2022).

While these studies clearly indicate the potential of AI technologies to positively affect long-term growth, it is an open question whether AI will have a comparable impact on welfare to those induced by the GPTs of the past, such the steam engine, electricity, the computer and the internet. Recent evidence suggests a "digitalisation paradox" whereby AI and related technologies may increase the complexity of performing R&D through new forms of routine (or "mundane") tasks that, as data preparation and robots maintenance, are central to AI (Ribeiro et al. 2023). More fundamentally, a major challenge is that AI can exacerbate the market dominance of large "superstar" companies, which has been reflected in declining business dynamism (Decker et al. 2017) and increasing market power in the United States (Covarrubias et al. 2020; De Loecker et al. 2020) and worldwide (De Loecker et al. 2021). De Loecker et al. (2021) document that technology-driven productivity gains have been offset by raising market power leading to a net welfare loss in the United States economy between 1980 and 2016. The larger capital intensity of AI as compared to other technologies (Besiroglu et al. 2024) generates concerns that AI diffusion may lead to further market concentration, thereby limiting the impact on economic growth. Finally, the impact of AI technologies on the labor market is an open issue, where complementary and substitution effects can heavily affect both the level and the composition of the workforce, in terms of the required skills and tasks (see, for instance, Montobbio et al. 2022; Quoc Phu and Duc Hong 2022; Damioli et al. 2024; for a survey: Montobbio et al. 2023).

In view of this debate, this study adopts the lens of the evolutionary/neo-Schumpeterian economics to investigate the extent to which AI is generating a technological revolution - i.e. the emergence of a new technological paradigm (Dosi 1982 and 1988; Freeman 1990; Freeman and Louçã 2001) - or, by contrast, whether AI is a continuation of the trajectory of the digital revolution, based on the ICT paradigm initiated half a century ago[1].

Evolutionary economists argue that technologies evolve by revolutions whereby new paradigms disrupt the trajectory of established ones. Simply put, a technological paradigm refers to a specific framework of technological knowledge (centred around a constellation of interdependent core technologies), problem-solving methods, and practices that dominate a particular field at a given time. A technological trajectory refers to the "normal" path of progress and development within a technological paradigm over time, representing the specific directions in which technology evolves, often characterized by incremental improvements and occasionally by radical (but not revolutionary and pervasive) innovations. As the paradigm matures, growth rates may slow until a new disruptive innovation wave initiates the next cycle. Central to this framework is the idea that sustained long-term economic growth is largely dependent on the emergence of new technological paradigms that disrupt old ones in a cyclical process of creative destruction driving major leaps in productivity.

Historical examples support the view that the cyclical process by which new paradigms replace outdated ones has driven sustained economic growth in the last two and half centuries. James Watt's substantial improvements to the steam engine in the 1760s and 1770s led to the gradual emergence of a new paradigm characterized by mechanized manufacturing that disrupted traditional agrarian economies in what is known as the first industrial revolution. Innovations such as electricity, the internal combustion engine, and chemical manufacturing towards the end of 19th century gradually led to the establishment of a new paradigm characterised by mass production in what is known as the "Fordist" mode of production. Started in the second half of the 20th century with the development of the first mainframes, a new paradigm known as the digital revolution gradually imposed showing significant accelerations since the 1980s with the advent of personal computers, the internet, smartphone, etc. (Information and Communication Technologies: ICTs; see Freeman et al. 1982; Freeman and Soete 1987).

Indeed, AI and related technologies are clearly embedded in the digital ICT paradigm, as their development and functionality fundamentally depend on digital technologies, information processing, and communication infrastructures. Using a sample of innovative European companies between 1995 and 2016, Igna and Venturini (2023) document of systematically larger probabilities of patenting in AI for companies that previously patented in ICT-related fields. This could explain the high concentration of AI patents (Dernis et al. 2019) and publications (Klinger and Stathoulopoulos, 2020, 2021) in few large firms with prior expertise in ICT.

However, while it is obvious that the emergence of AI technologies is deeply rooted in the ICT paradigm, an interesting (and challenging) research question is assessing whether a qualitative change in the accelerated AI dynamic evolution can be detected, even in the early stages of the diffusion of these new technologies. In other words, is AI gradually departing from being a constituent part of the ICT trajectory and possibly originating a new paradigm? This research

[1] According to Dosi (1982), these are the proposed definitions of technological paradigm and technological trajectory: the former is "…a pattern of solution of selected technological problems, based on selected principles derived from natural sciences and on selected material technologies"" (ibidem, p. 152), while the latter is "…the pattern of normal problem solving activity (i.e. of progress) on the ground of a technological paradigm. " (ibidem, p. 152). While a new paradigm changes the "state of the art" and occurs every 50/60 years, a technological trajectory is the normal technological path of problem solving characterized by cumulativeness and irreversibility.

question is at the core of the present contribution; to our knowledge, this is the first paper to directly address this topic.

In more detail, this paper exploits a global dataset combining information on AI patenting activities and their applicant entities in order to study the features of AI technologies during their emerging phase - namely between 2000 and 2016 - and to assess whether some dynamic patterns are detectable and whether evidence can be used to disentangle the core research question introduced above.

The rest of the paper is organised as follows. Section 2 outlines the conceptual framework, Section 3 describes the empirical setting, Section 4 discusses the results, and Section 5 concludes.

2. Conceptual framework

Some previous studies might suggest that AI is a natural progression within the ICT paradigm rather than a distinct one, representing a gradual evolution of software capabilities that benefit from increased processing power, data storage and management capabilities, greater data availability, and algorithmic advancements, while not disruptively departing from it. Emerging evidence from patenting activity (Lee and Lee 2021, Santarelli et al. 2023) and plant-level management practices (Cetrulo and Nuvolari 2019) supports this "continuation" view. In contrast, some distinctive features of AI support the idea that AI may constitute the core technology underpinning the emergence of a new distinct paradigm, often labelled as the fourth industrial revolution (Schwab 2017). AI is fundamentally different from ICT technologies in that its core capability – making predictions (Agrawal et al. 2019) – differs from those of the computer – computing (Bresnahan 1999; Nordhaus 2007) – and the internet – i.e. managing information (Goldfarb and Tucker 2019). Obviously enough, these distinctive features of AI technologies are even more evident after the arrival of the generative AI algorithms, such as ChatGPT. Moreover, as already mentioned, AI has the features of both a GPT and method of invention, which imply large cross-sectoral and cross-functional application and large integration with research and development activities, suggesting that AI may establish a new set of technological actors, rules, practices, and potentials, just as observed in the past when new paradigms emerged. Pointing towards this direction, Igna and Venturini (2023) showed that differences are widening in the drivers of innovation in the fields of AI and ICT.

More in general, technological trajectories and paradigms (Dosi 1982 and 1988) focus on continuities and discontinuities in technological innovation. A paradigmatic change results from the interplay of scientific advances, economic factors, institutional conditions, and unresolvable problems along an earlier trajectory. Moreover, the broader concept of “techno-economic paradigm” (Perez 1983; Freeman and Perez 1988; Freeman 1994) is based on the realization that technological evolution is cyclical by nature, where extended periods of gradual accumulation are (rarely) punctuated by radical and disruptive changes. In this framework, the diffusion of radically new technologies with the emergence of a new technological paradigm brings about the need for fundamental socio-economic changes that should be widely spread across the society. This interaction initially implies a “mismatch” between the potentialities of the new technologies and the inadequacy of the current institutional setting; this mismatch often leads to a productivity slowdown (the so-called Solow’s paradox, Solow 1987), which can be solved only through a substantial upgrading of the societal and institutional framework ("match") (see Draka et al, 2007).

Freeman and Louca (2001) and Perez (2010) consider the age of ICTs as the latest techno-economic paradigm, based on a bundle or constellation of innovations (including microelectronics and the PC, software, telecommunication and internet); the organizational innovation embedded in the networking firm and the new institutions shaping the other pillars of a National System of Innovation (NSI): education, finance and policy (Nelson 1993).

Indeed, identifying the emergence of a new techno-economic paradigm in real-time is challenging, as clarity often comes in retrospect (Von Tunzelmann et al. 2008). Historically, the emergence of new paradigms has been characterised by turmoil, with technology and market shares widely distributed among many actors, frequent entry and exit of companies, and mismatching between radically new technological solutions to become standards and lagging institutional structures, as mentioned above.

Several aspects distinguish a new technological paradigm from path-dependent and cumulative changes along a technological trajectory (David 1985; Ruttan 1997).

Firstly, the emergence of a new technological paradigm is marked by a significant departure from the previous paradigm. New paradigms introduce a constellation of radically novel technologies that involve technological revolutions; in turn, these changes imply "unlearning" established patterns of technological solutions and embracing fundamentally new approaches. In contrast, incremental changes along a technological trajectory typically involve adding new technologies to improve, refine, or complement existing ones in a cumulative manner. This distinction highlights the disruptive nature of paradigmatic shifts compared to the incremental nature of trajectory evolution.

Secondly, a key feature of a paradigmatic shift is the fact that the core technologies of a new technological paradigm become increasingly pervasive, widespread and deeply integrated into various economic activities. These technologies exemplify the characteristics of GPTs, namely disruptive innovations that diffuse broadly across the economy and generate further innovations ("enabling technologies"), impacting multiple sectors and market structures. The pervasive nature of GPTs underscores their broad applicability and transformative potential, distinguishing them from more narrowly focused technological advancements within an ongoing technological trajectory.

Thirdly, the innovations spurring a new technological paradigm are often led by new companies, with young firms replacing incumbents with outdated capabilities (the Schumpeterian "creative destruction": Schumpeter 1912). Indeed, innovators in the core technologies of a new paradigm are often innovative startups and young firms, more adept at navigating the new paradigm. Therefore, the advent of a new technological paradigm is characterized by an increase in competition, lower market concentration rates, instability in the innovation ranking and the dominance of entrepreneurial industries ("Schumpeter Mark I": see Winter 1984; Malerba and Orsenigo 1996; Klepper 1997; Breschi et al. 2000). This "entrepreneurial regime" contrasts with a "routinized regime" ("Schumpeter Mark II"), where a relatively stable technological environment see innovations generated by established firms;

indeed, when a technological paradigm establishes into a consolidated technological trajectory, larger and mature incumbents tend to dominate the innovation scenario[2].

3. Data, sample and methods

To gain a comprehensive view on the changes in the innovative landscape of AI technologies from a global perspective, this study exploits a large-scale, world-wide, and micro-level database of 23,915 applicants holding at least one AI patent in the period 2000-2016.

Drawing upon the methodology firstly developed in Van Roy et al. (2020) and further refined in Damioli et al. (2024) for the selection of AI patents, our study employs a keyword-based search to identify AI-related patents by scanning titles and abstracts[3]. This method aligns with previous research in the field of AI and robotics (Keisner et al. 2015; De Prato et al. 2019; European Commission 2018; Cockburn et al. 2019; WIPO 2019; Bianchini et al. 2023; Calvino et al. 2023). Some of these scholars utilised keyword searches in combination with specific technological classes to isolate relevant patents (Keisner et al. 2015; Cockburn et al. 2019; WIPO 2019; Calvino et al. 2023). Our approach does not impose any limits on predefined technological classes due to AI technologies' pervasive nature; as a potential GPT, AI spans numerous scientific disciplines and technological fields (Bianchini et al. 2022; WIPO 2019; see also previous sections).

The data collection process relied on the Spring 2018 release of the PATSTAT worldwide patent database, maintained by the European Patent Office. This database was examined using text-mining tools to identify all DOCDB patent families featuring our AI-related keywords in their titles or abstracts. Employing the DOCDB simple family, which groups together patent applications that cover identical technical content, effectively reduces the risk of double counting by consolidating multiple filings of the same invention into a single count (detailed methodology described in Van Roy et al. 2020). Following the extraction of these patents, we retrieved from the Bureau van Dijk Electronic Publishing (BvD) ORBIS database essential accounting data on applicants that applied for AI patents. Using patent application numbers, we traced applicants in the ORBIS Intellectual Property database and retrieved their non-AI patent applications along with geographic and economic data from the ORBIS Companies database. The data collection process is visually summarised in Figure A1 in Appendix A.

A limitation of the resulting dataset is that, by integrating the PATSTAT database with the ORBIS Companies database for firm-level analysis, it inherits the different coverage of ORBIS across countries (see Bajgar et al. 2020; Hallak and Harasztosi 2019; Gal 2013; Kalemli-Özcan et al. 2024). In particular, as shown in Table A2 in Appendix A, it underrepresents applicants based in the United States (US)[4]. Nevertheless, a manual check of company names indicates that our sample includes all US AI leaders that could come to our mind. For instance, our

[2] A number of other features characterising the emergence of a new paradigm are not studied in this analysis, as they require information not available to the authors, and are left for future research. In particular, new paradigms are associated with radical product innovations that disrupt existing markets and create new ones, while cumulative changes along a trajectory involve the dominance of process innovation and incremental innovations that enhance the existing products.

[3] Our set of keywords, used in the mentioned previous studies, is detailed in Table A1 of Appendix A and reflects a comprehensive review of the existing related literature.

[4] Instead, our dataset fully takes into account AI patenting by Asian countries, with particular reference to the consolidated roles of Japan and South Korea and the emerging leading role of China.

inspection confirms the presence of companies such Amazon, Apple, Meta, Microsoft, Netflix, Nvidia, IBM, and Tesla.

A second limitation is that our data coverage is constrained to AI patenting activities from 2000 to 2016. Therefore, our data availability allows to investigate the dynamic patterns of AI technologies in their emerging phase (Van Roy et al. 2020).

The resulting sample encompasses 23,915 AI innovators, which we define as the entities that applied for at least one AI-related patent family between 2000 and 2016. AI innovators applied for slightly more than 100 thousand AI patent families and almost 6.5 million non-AI ones (Table 1). AI patenting strongly accelerated over time, driven by an even steeper growth of the number of AI innovators, with a corresponding decline in the number of AI families each AI innovator applied for on average. Non-AI patenting also grew but at a much more moderate pace, indicating an increase in the degree of specialization in AI patenting, which in turn can reflect a change in patenting behavior of early AI innovators as time goes by and/or a different patenting behavior of the applicants that started patenting in AI later in the period. These changes were stark. Comparing the 2000-2005 and the 2011-2016 sub-periods, AI innovators increased by 338%, AI patent families they applied for by 276%, non-AI ones by 15%, the ratio between AI and non-AI patent families by 227%, while the number of AI patent families every AI innovator applied for declined on average by 25%.

In the next section we analyse the dynamics of various indexes typically used to measure economic and technological dynamism, which we compared over time. Having in mind our main research question and the perspectives discussed at the end of the previous section, we focus on:

i) changes in industry composition of AI innovators, with a particular focus on the relative importance of ICT core industries in order to measure a potential departure from the ICT paradigm;
ii) changes in measures of the concentration of AI patenting - namely concentration ratios indicating the share of AI patent families applied for by the top *n* AI innovators - and Spearman rank correlations[5] of AI innovators (in order to assess the stability/instability of innovative hierarchies);
iii) changes in innovative entry rates, defined as the number of applicants patenting in AI for the first time over the total number of AI innovators in the same year, and in the characteristics of AI innovators, namely year of foundation (or most recent consolidation) and number of employees;
iv) changes in overall innovative activity as a consequence of patenting in AI, to assess the possible enabling role of AI technologies (a distinctive feature of GPTs).

[5] Spearman rank correlation, often denoted as Spearman's rho (ρ), is a non-parametric measure of the strength and direction of the association between two ranked variables. It is computed as $\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$, where d_i^2 indicates the difference between the ranks of each AI innovators in two consecutive years.

Table 1. Patent activity of AI innovators

Period	Applicants with 1+AI patent families		AI patent families		AI patent families per patenting entity	Non-AI patent families		Ratio AI/non-AI patent families
	Number	Yearly % change	Number	Yearly % change		Number	Yearly % change	
2000	804		2,372		3.0	343,771		0.007
2001	879	9.3	2,715	14.5	3.1	352,847	2.6	0.008
2002	871	-0.9	2,704	-0.4	3.1	347,394	-1.5	0.008
2003	901	3.4	2,777	2.7	3.1	349,223	0.5	0.008
2004	922	2.3	2,848	2.6	3.1	370,073	6.0	0.008
2005	1,056	14.5	3,220	13.1	3.0	382,250	3.3	0.008
2006	1,214	15.0	3,603	11.9	3.0	372,544	-2.5	0.010
2007	1,352	11.4	3,866	7.3	2.9	375,901	0.9	0.010
2008	1,625	20.2	4,515	16.8	2.8	385,425	2.5	0.012
2009	1,912	17.7	4,803	6.4	2.5	359,245	-6.8	0.013
2010	2,131	11.5	5,595	16.5	2.6	373,957	4.1	0.015
2011	2,560	20.1	6,668	19.2	2.6	390,467	4.4	0.017
2012	3,245	26.8	8,301	24.5	2.6	419,099	7.3	0.020
2013	3,535	8.9	9,038	8.9	2.6	420,946	0.4	0.021
2014	3,660	3.5	10,122	12.0	2.8	411,022	-2.4	0.025
2015	5,279	44.2	14,242	40.7	2.7	425,432	3.5	0.033
2016	5,531	4.8	14,205	-0.3	2.6	402,193	-5.5	0.035
Total 2000-2016	23,915		101,594		4.2	6,481,789		0.016
% change between 2000-2005 and 2011-2016	338.2		276.1		-24.6	15.1		226.9

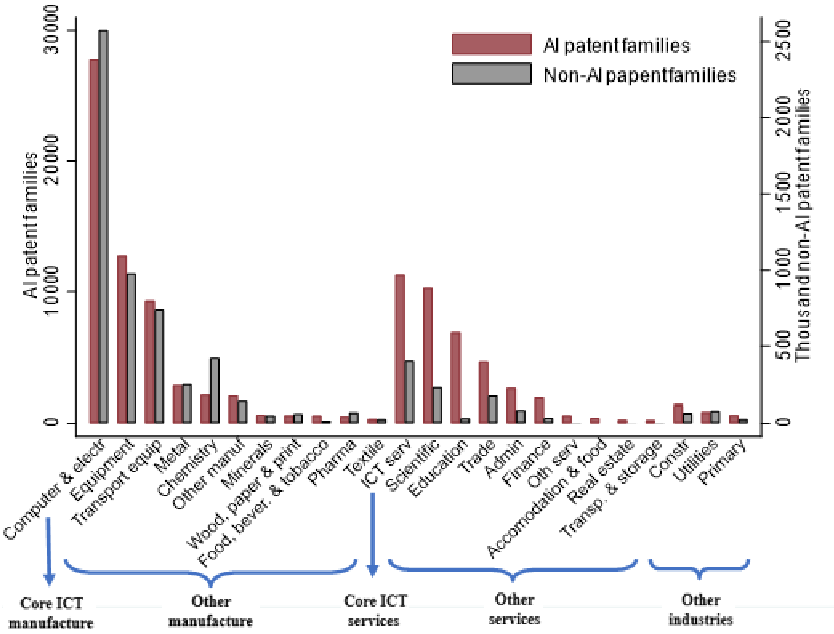
Notes: yearly non-AI patent families, as well as the resulting total 2000-2016 and % change between 2000-2005 and 2011-2016, include non-AI patent families of all 23,915 applicants making 1+ AI patent in the period, independently on aa applicant making or not AI patent families in the considered year.

4. Results

4.1 AI and the ICT paradigm

We use the main industry classification of applicants to examine the integration of AI patenting within ICT industries. From 2000 to 2016, about 38% of AI patent families were filed by entities in core ICT industries, with 27% in ICT manufacturing (computers, electronics, optical products, electrical equipment) and 11% in ICT services (publishing, audiovisual and broadcasting, telecommunications, IT, and other information services).[6] Other significant industries include machinery manufacturing (13%), transport equipment (9%), and scientific research and development (10%). AI patenting is also notably prevalent in service industries, accounting for 39% of total AI patents, compared to only 15% of non-AI patents filed by AI innovators in service industries.

Figure 1. AI and non-AI patent families by industry of applicant AI innovator, 2000-2016



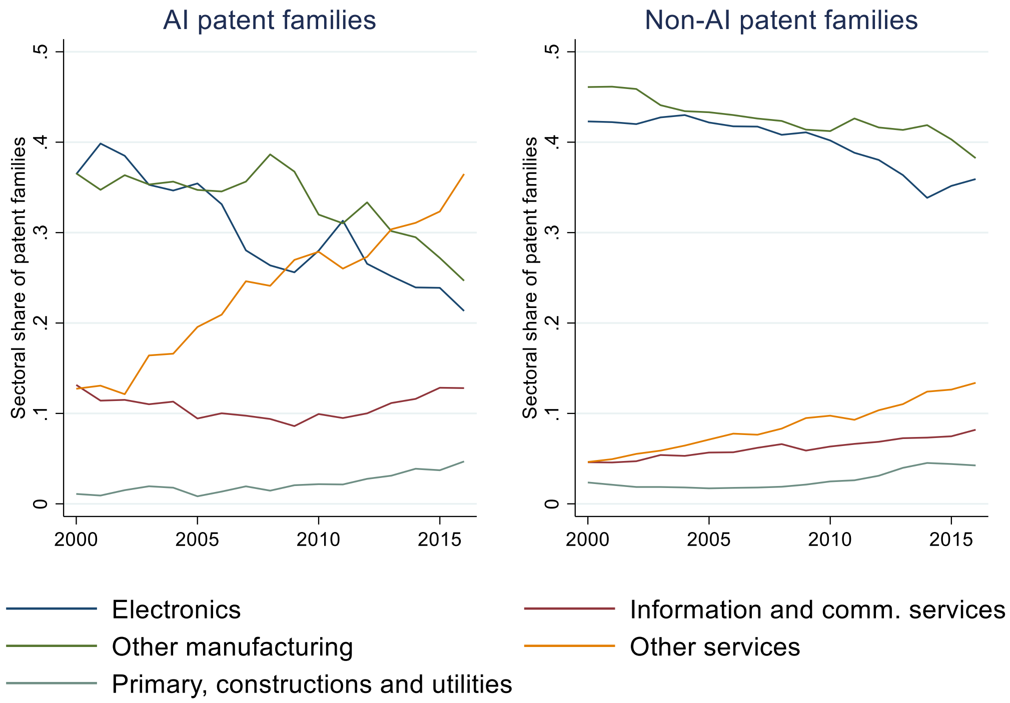
Notes: Table A3 in Appendix A1 provides the concordance between industry classes used in this graph and NACE Rev 2.0 2-digit classes.

However, Figures 2 and 3 reveal significant changes in the industry composition of AI innovators over time, which are not apparent in the static snapshot provided by Figure 1. AI patents filed by companies in core ICT industries decreased from around 50% in the early 2000s to about 35% by the mid-2010s. This decline is entirely due to a drop in AI patents from ICT manufacturing companies, which fell from over 35% in the early 2000s to below 25% by the mid-2010s. Meanwhile, the fraction of AI patents in core ICT services remained stable at around 11%. Moreover, there was a significant increase in AI patents from applicants in non-core ICT service industries, rising from about 12% in the early 2000s to 36% in 2016, when

[6] See Table A3 in the Appendix for the concordance between industry classes used in Figure 1, 2 and 3, and NACE Rev 2.0 2-digit classes.

nearly half (49%) of AI patents were from service industries. Non-AI patent families showed similar trends but with more subtle changes.

Figure 2. AI and non-AI patent families shares by broad industry class of applicant AI innovator

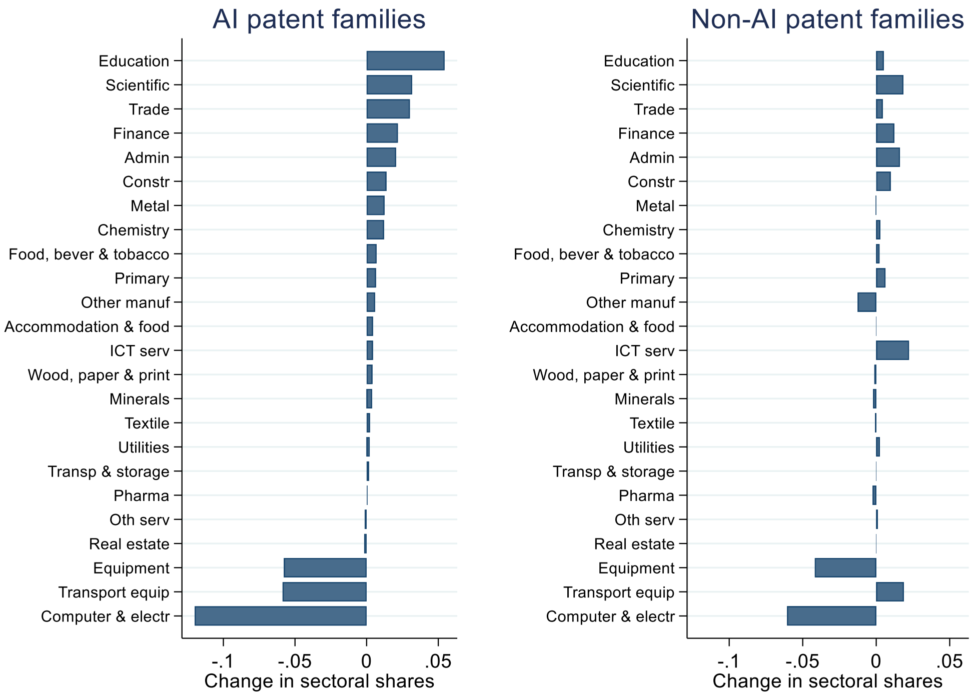


Notes: AI innovators are 23,915 applicants who applied for at least 1 AI patent in the period. Table A3 in Appendix A1 provides the concordance between broad industry classes used in this graph and NACE Rev 2.0 2-digit classes.

To gain a more detailed understanding of these changes, Figure 3 compares shares of AI innovators between the 2000-2005 and 2011-2016 periods for more granular industry classes. Significant increases were observed in the education industry (from 3% to 8%), reflecting the growing role of universities and other scientific institutions in AI innovation; in R&D and professional services (from 7% to 11%), highlighting increased AI usage in research and development activities; and in trade industries (from 3% to 6%), indicating the rising importance of AI in e-commerce. Conversely, the largest decrease was in ICT core manufacturing (from 35% to 25%), followed by transport equipment manufacturing (from 13% to 7%) and machinery manufacturing ("equipment" from 16% to 11%).

Overall, the sectoral composition of AI innovators has shifted from being heavily rooted in the ICT paradigm in the early 2000s to becoming increasingly prevalent across non-ICT service industries by the mid-2010s, so revealing an increasing rate of pervasiveness.

Figure 3. Change in industry shares of AI and non-AI patent families of AI innovators between 2000-2005 and 2011-2016



Notes: AI innovators are 23,915 applicants who applied for at least 1 AI patent in the period. Table A3 in Appendix A1 provides the concordance between industry classes used in this graph and NACE Rev 2.0 2-digit classes.

4.2 Concentration of AI innovation

This subsection analyses the evolution of the concentration of AI patenting among AI innovators. Patent distributions are typically highly skewed, with a few applicants accounting for a large share of total patents. In the case of AI, the top 50 (10) innovators, representing 0.2% (0.04%) of total AI innovators, filed 29% (12%) of total AI patent families in the sample.

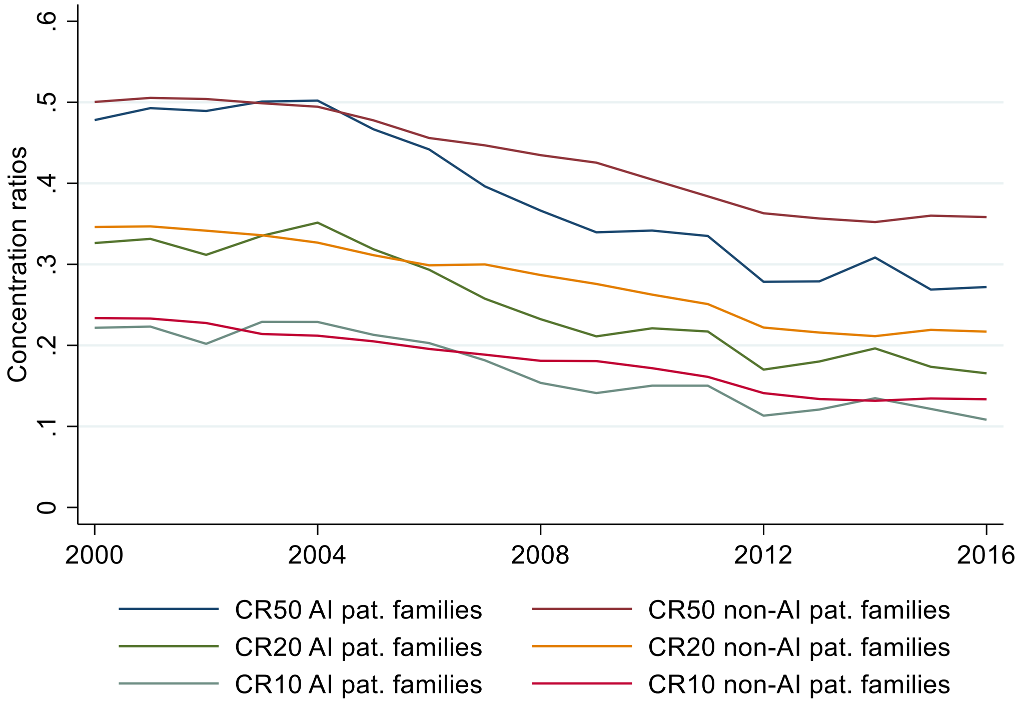
Figure 4 illustrates the evolution of concentration ratios, measuring the share of patent families accounted for by top AI innovators each year[7], both in AI and non-AI fields. While concentration ratios for non-AI patenting activities are also reported, it is important to note that their interpretation differs. Computed on a sample of AI innovators, non-AI concentration ratios do not indicate overall concentration in non-AI patenting activities but are conditional on having patented in AI.

The concentration of AI and non-AI patent families applied for by AI innovators clearly declined during the period considered (Figure 4). For instance, the fraction of patents (both AI and non-AI) filed by the top 50 most prolific innovators decreased from about 50% in the early 2000s to below 30% for AI patents and about 35% for non-AI patents by the mid-2010s. Similar declines in concentration are observed when considering the top 20 and top 10 innovators,

[7] Notice that yearly concentration ratios are by construction larger than the corresponding ones computed on the whole period.

though the gap between concentration ratios in AI and non-AI narrows when focusing on a smaller number of top innovators.

Figure 4. Concentration ratios of AI and non-AI patent families among AI innovators



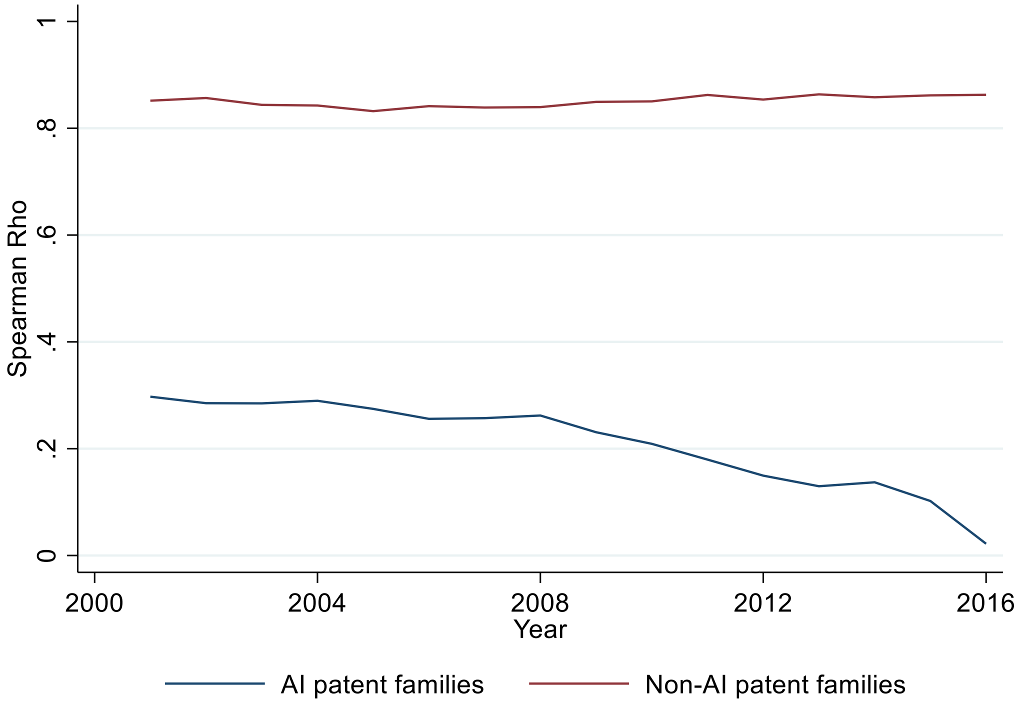
Notes: AI innovators are 23,915 applicants who applied for at least 1 AI patent in the period. Concentration ratios (CR) indicate the share of AI patent families applied for by the 50th, 20th and 10th top AI innovators in each year.

Next, we examine changes across the entire distribution of AI innovators. Figure 5 plots the Spearman rank correlation over time for AI and non-AI patent families. The correlation for applicant rankings based on AI patent families shows a consistent decline from about 0.3 in 2000 to less than 0.1 in 2016. In contrast, the correlation for non-AI patent families remains relatively stable around 0.85. This indicates a much higher consistency in the ranking of AI innovators based on non-AI patents and a decreasing consistency based on AI patent families, revealing a dynamic reshuffle in the AI innovation hierarchy[8].

Overall, these findings indicate a strong dynamism among top AI innovators over time. Moreover, the smaller concentration ratios for AI compared to non-AI patents towards the end of the observation period and the increasing gap between AI and non-AI Spearman correlations suggest that applicants that started patenting in AI later in the period played an important role in the observed dynamics. The next subsection focuses on this issue.

[8] If we narrow the analysis to the top 50 innovators, yearly AI Spearman correlations are always below the non-AI ones and also decreasing over time (see Figure A2 in Appendix A). This is a further confirmation of a marked dynamism in AI patenting hierarchy over the examined period.

Figure 5. Spearman rank correlations of AI innovators in AI and non-AI patenting



Notes: AI innovators are 23,915 applicants who applied for at least 1 AI patent in the period. Spearman rank correlation, or Spearman's rho, is a non-parametric measure of the strength and direction of the association between two ranked variables. The values indicate the correlation between the rank of companies in the focal year with respect to the previous year.

4.3 AI innovators

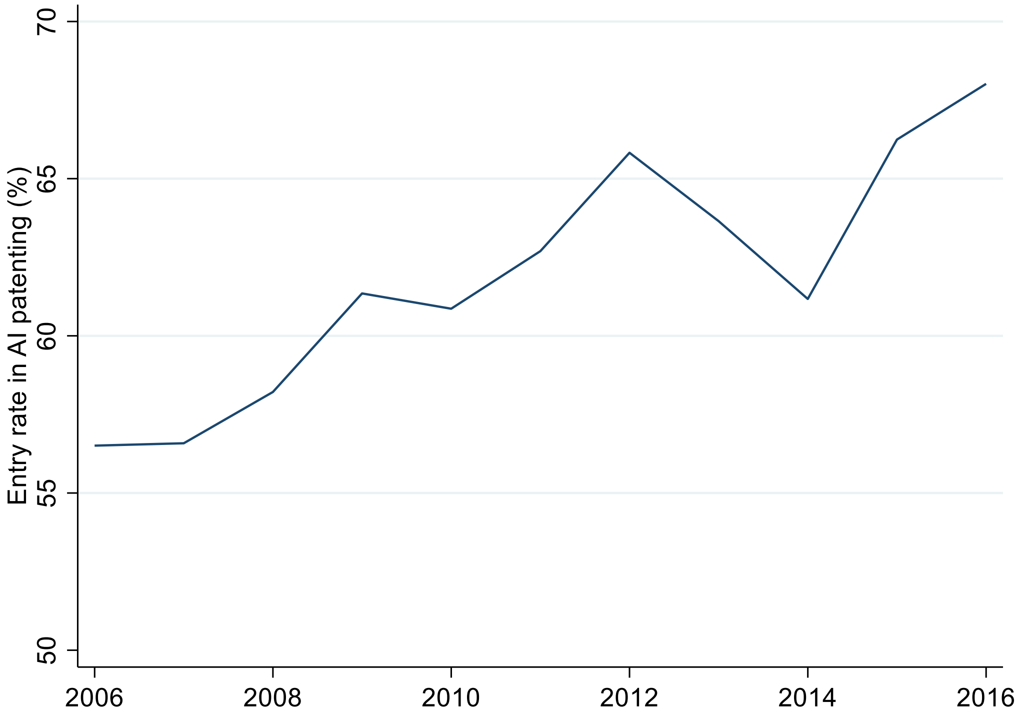
In the previous subsections, we have highlighted significant changes in the sectoral composition of AI innovators and a reshuffling of their relative importance. Here, we investigate one possible determinant of these changes: the inflow of new AI innovators.

We begin by examining AI innovative entry rates, defined as the fraction of AI innovators that patented for the first time. To ensure we identify truly new innovators, we use a six-year buffer to observe the patenting activities of AI innovators, calculating entry rates starting from 2006. Despite some oscillations, AI entry rates have generally increased throughout the period, rising from just above 55% in the mid-2000s to almost 70% in the mid-2010s (Figure 6). This indicates that the majority of AI innovators each year are applicants filing a patent in AI for the first time.

While the number of applicants applying for an AI patent for the first time grew continuously, Figure 7 shows that the average age of these entities at the time of their first AI patent steadily declined, from 19 years in 2006 to 12 years in 2016. Additionally, as shown in Figure A3 in Appendix A, for a subsample of AI innovators with valid employment information, the median number of employees at the time of their first AI patent also declined, nearly halving from about 150 in the late 2000s to about 80 in the mid-2010s.

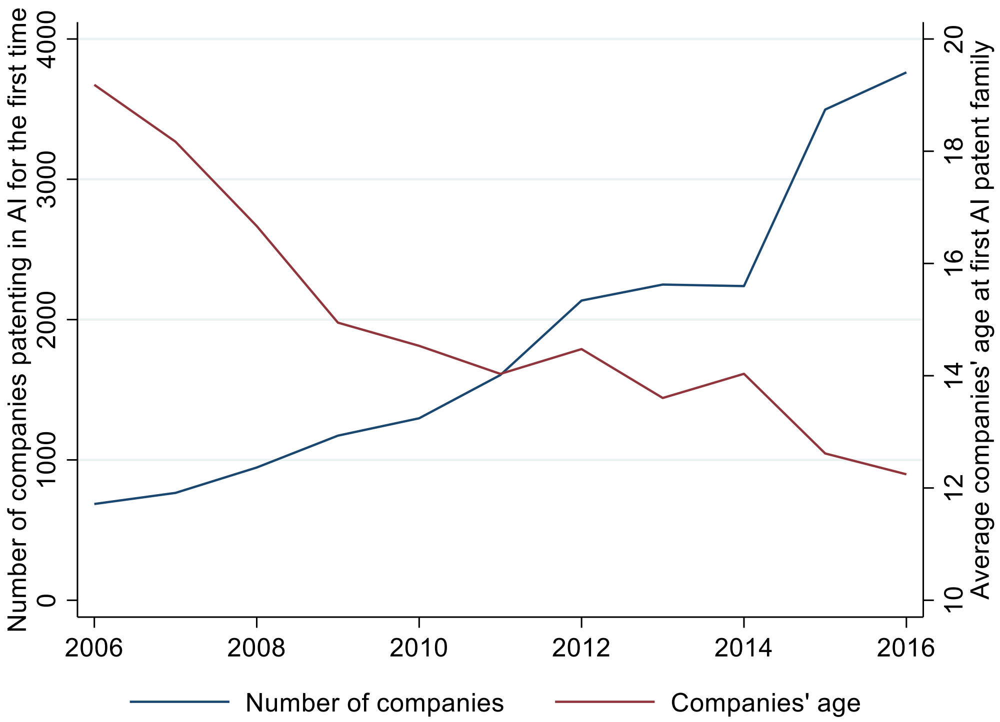
Taken together, these evidences reveal the emergence of an entrepreneurial regime (Schumpeter Mark I, see Section 2), at least with regard to innovation activities.

Figure 6. Entry rates of AI innovators



Notes: AI innovators are 21,675 applicants who applied for at least 1 AI patent in the period. Entry rates are defined as the percentage of applicants patenting in AI for the first time at time t over all applicants that patented in AI at time t.

Figure 7. Number and age of AI innovators at year of first AI patent family

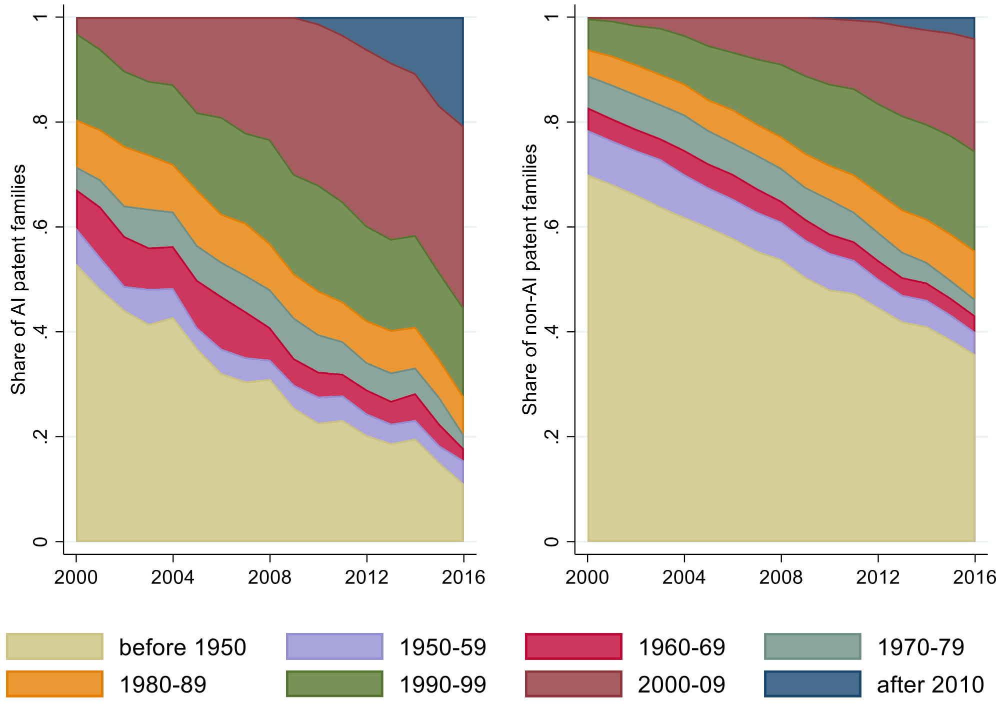


Notes: AI innovators are 20,356 applicants who applied for the first AI patent in the period. Age is defined based on the year of foundation or consolidation of the applicant.

The increasing number of younger and smaller applicants applying for AI patents does not necessarily mean that these entities account for a growing share of AI patent families. Figure 8 illustrates the evolution of the shares of AI and non-AI patent families by the year of foundation or consolidation of applicants. In 2000, entities established before 1950 applied for more than half of all AI patent families, while those founded between 1950 and 2000 accounted for 44% of AI patents. Over time, the share held by these groups decreased significantly, with the steepest decline observed among applicants established before 1950. By 2016, their share dropped to 11%, whereas those established between 1950 and 2000 recorded a smaller reduction, still holding 33% of AI patents. Meanwhile, younger applicants established from 2000 onwards steadily increased their share of AI patent families, reaching 55% in 2016. Similar trends are observed for non-AI patent families, but they are much less pronounced. In 2016, applicants established before 1950 still accounted for 35% of non-AI patents, and those established after 2000 for just 25%.

Overall, this evidence indicates that a growing number of AI innovators were young and small applicants specializing in AI patenting, significantly contributing to AI patenting throughout the period.

Figure 8. Share of AI patent families by year of foundation or consolidation of AI innovators



Notes: AI innovators are 23,915 applicants who applied for at least 1 AI patent in the period.

4.4 AI as an enabling technology

This subsection investigates the possible role of AI as an enabling technology for overall innovative activity, a characteristic feature of a GPT.

Table 2 illustrates the change in non-AI patenting activity between the three years before and after the first AI patent family application by each AI innovator. The analysis focuses on a subsample of 10,624 AI innovators who recorded their first AI patent between 2003 and 2013, ensuring the availability of three-year windows at the beginning and end of this period, in order to be able to compute the two three-year changes. On average, each AI innovator filed 24.4 non-AI patent families in the three years preceding their first AI patent and 43.6 in the three years following it. This absolute change corresponds to a 78.7% average increase in the number of non-AI patent families within the three years following the AI application.

While our dataset does not allow for a proper counterfactual design to precisely identify the additional impact of starting to patent in AI on the subsequent non-AI patenting activity, this growth rate contrasts sharply with an average three-year increase of just 5.9% in the overall non-AI patenting activity within our full sample during the 2003-2013 period (see also the general trend reported in Table 1). This comparison suggests a significant role for AI as an enabling technology for overall innovative activity.

Table 2 further highlights that this enabling role of AI becomes more pronounced as AI innovators engage more extensively in non-AI patenting activity prior to their first AI patent. Of the approximately 200,000 additional non-AI patent families filed by AI innovators in the three years following their first AI patent family, 79.8% were filed by those in the top decile of the distribution for non-AI patent families in the preceding three years. This finding underscores the necessity of a substantial level of a preexisting absorptive capacity (Cohen and Levinthal 1990) for AI to significantly boost overall innovation.

Table 2. Change in non-AI patents in the 3 years following the first AI patent, 2003-2013

	All applicants	Applicant distribution of the number of non-AI pat. families in 3 years prior to first AI patent family			
		Bottom 75 percentiles	Between 75th and 90th percentiles	Between 90th and 99th percentiles	Top 1st percentile
Number of applicants	10,624	7,914	1,636	967	107
Per-applicant non-AI pat. families in 3 years prior to first AI pat. family	24.4	0.0	7.0	138.0	1070.5
Per-applicant absolute change in non-AI pat. families in 3 years after first AI pat. family with respect to prior 3 years	19.2	0.5	23.0	133.5	311.5
Total absolute change in non-AI pat. families in 3 years after first AI pat. family compared to prior 3 years	203,799	3,714	37,635	129,115	33,335
% of total absolute change	100.0	1.8	18.5	63.4	16.4

Notes: computed on the 10,624 applicants applying their first AI patent between 2003 and 2013.

5. Conclusions

Artificial intelligence (AI) is emerging as a transformative innovation with the potential to drive significant economic growth and productivity gains, akin to a GPT. This study examines whether AI is ushering in a technological revolution, signifying the emergence of a new technological paradigm, as defined in the evolutionary tradition. Indeed, evolutionary economists argue that technologies evolve through revolutions in which new paradigms disrupt the trajectory of established ones, with a technological paradigm representing a dominant framework of core technologies, methods, and practices within a field at a given time (see Sections 1 and 2).

Our analysis has started recognizing that AI technologies are embedded in the digital ICT paradigm, relying heavily on digital technologies, information processing, and communication infrastructures. However, while some argue that AI is a natural progression within the ICT paradigm, others believe it may represent a new distinct paradigm, given its unique characteristics as a GPT and method of invention (enabling technology).

In order to disentangle this research question, this study has investigated developments in AI-related innovations from 2000 to 2016. Our research purpose has been to assess whether the advent of AI signalled a departure from the ICT paradigm, showed dynamic patterns in innovative concentration rates and hierarchies, and fostered the emergence of new players in AI innovation, as these features characterised the emergence of new paradigms in the past.

Using a global dataset on AI patenting activities and their applicants, the analysis reveals that AI patenting has not only accelerated but also substantially evolved in nature. The sectoral composition of AI innovators has shifted from being heavily rooted in the ICT industries in the early 2000s to becoming increasingly prevalent across non-ICT service industries by the mid-2010s. Additional findings indicate decreasing concentration rates in innovation and substantial reshuffling in innovative hierarchies. These shifts appear to be driven by increasing innovative entry rates and by the increasing important role of young and smaller applicants specializing in AI patenting. Finally, we find some evidence supporting the role of AI patenting in enhancing innovation in general, suggesting a possible enabling role of AI technologies (a distinctive feature of GPTs).

Overall, this evidence points to an increasing pervasiveness and diffusion of AI innovation and to the emergence of an “entrepreneurial regime” in AI innovation. Indeed, these patterns indicate a "shakeout" effect, where AI technologies, initially dominated by ICT incumbents, spread to involve other industries and younger and smaller applicants. All these features have characterised the emergence of major technological paradigms in the past and suggest that AI technologies may indeed generate a paradigmatic shift.

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Appendix A: Additional figures and tables

Figure A1. Data matching procedure

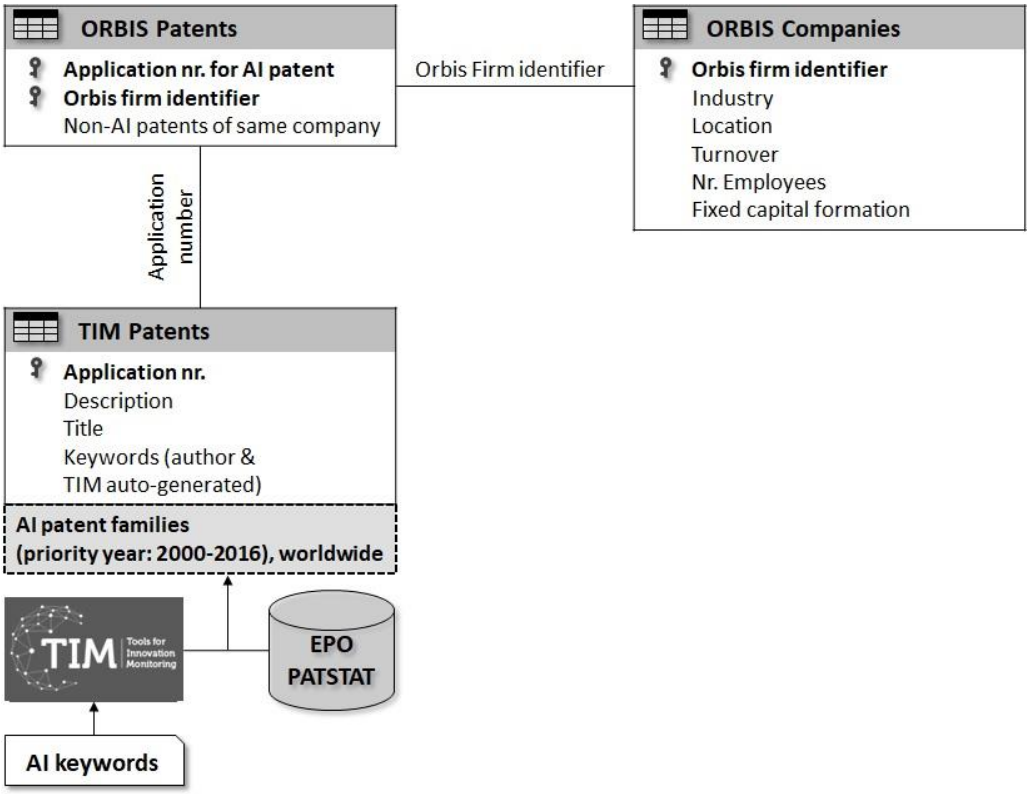
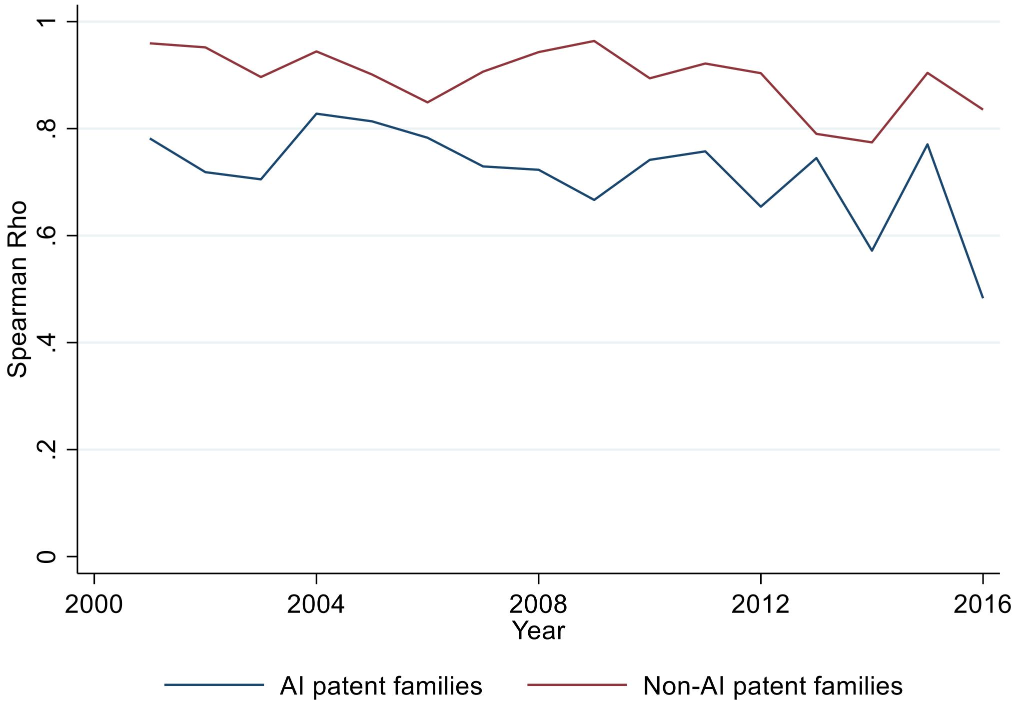
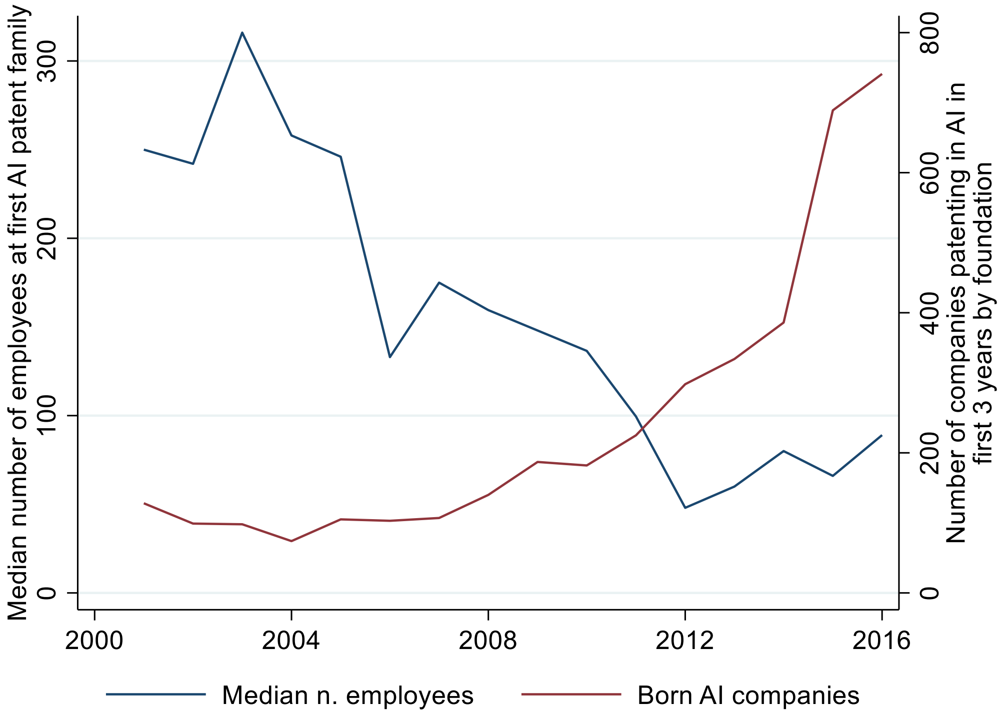


Figure A2. Spearman rank correlations of the top 50 innovators in AI and non-AI patenting



Notes: Spearman rank correlation, or Spearman's rho, is a non-parametric measure of the strength and direction of the association between two ranked variables. The values indicate the correlation between the rank of companies in the focal year with respect to the previous year.

Figure A3. Size of AI innovators at year of first AI patent family and number of ‘born AI patent



Notes: AI innovators are 11,512 applicantss who applied for the first AI patent in the period and non-missing employment. Employment at first year of AI patenting is valid for 50% of applicants, imputed using the closer valid value in time for the remaining 50%.

Table A1. List of keywords related to Artificial Intelligence

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

Table A2. AI patent families by country of applicant, 2000-2016

Country of AI innovator	% of AI patent families	% of non-AI patent families
China	37.1	13.4
Europe*	7.7	10.9
Japan	23.1	56.4
South Korea	16.6	5.2
United States	11.1	9.6
Other countries	4.4	4.5

Notes: Europe includes the European Union, Iceland, Lichtenstein, Norway, Switzerland, and the United Kingdom.

Table A3. Industrial classes used in the analysis

NACE Rev. 2 classes	2-digits codes	Detailed industry classes (Figures 1 and 3)	Broad industry classes (Figure 2)
Agriculture, forestry and fishing	01 to 03	Primary	Primary, utilities and construction
Mining and quarrying	05 to 09		
Manufacture of food products, beverages and tobacco products	10 to 12	Food, bever & tobacco	Other manufacture
Manufacture of textiles, apparel, leather and related products	13 to 15	Textile	
Manufacture of wood and paper products, and printing	16 to 18	Wood, paper & print	
Manufacture of coke, and refined petroleum products	19	Chemistry	
Manufacture of chemicals and chemical products	20		
Manufacture of rubber and plastics products	22		
Manufacture of pharmaceuticals, medicinal chemical and botanical products	21	Pharma	
Manufacture of other non-metallic mineral products	23	Minerals	
Manufacture of basic metals and fabricated metal products, except machinery and equipment	24 and 25	Metal	
Manufacture of computer, electronic and optical products	26	Computer & electr	Core ICT manufacture
Manufacture of electrical equipment	27		
Manufacture of machinery and equipment not elsewhere classified	28	Machinery	Other manufacture
Manufacture of transport equipment	29 + 30	Transport equip	
Other manufacturing, and repair and installation of machinery and equipment 31 to 33	31 to 33	Other manuf	
Electricity, gas, steam and air-conditioning supply 35	35	Utilities	

NACE Rev. 2 classes	2-digits codes	Detailed industry classes (Figures 1 and 3)	Broad industry classes (Figure 2)
Water supply, sewerage, waste management and remediation	36 to 39		Primary, utilities and construction
Construction	41 to 43	Constr	
Wholesale and retail trade, repair of motor vehicles and motorcycles 45 to 47	45 to 47	Trade	Other services
Transportation and storage	49 to 53	Transp & storage	
Accommodation and food service activities	55 and 56	Accommodation & food	
Publishing, audiovisual and broadcasting activities	58 to 60	ICT serv	Core ICT services
Telecommunications	61		
IT and other information services	62 and 63		
Financial and insurance activities	64 to 66	Finance	Other services
Real estate activities	68	Real estate	
Legal, accounting, management, architecture, engineering, technical testing and analysis activities	69 to 71	Scientific	
Scientific research and development	72		
Other professional, scientific and technical activities	73 to 75		
Administrative and support service activities	77 to 82	Admin	
Public administration and defence, compulsory social security	84	Oth serv	
Education	85	Education	
Human health services 86	86	Oth serv	
Residential care and social work activities	87 and 88		
Arts, entertainment and recreation	90 to 93		
Other services	94 to 96		
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	97 + 98		
Activities of extra-territorial organisations and bodies	99		