Measuring artificial intelligence: a systematic assessment and implications for governance

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January 2, 2025

Governing artificial intelligence (AI) inventions is high on the political agenda, but it is not clear how to define and empirically measure it. We compare four approaches to identifying patented AI inventions that reflect different ways of understanding and defining AI. Using US patents from 1990-2019, we assess the extent to which each approach qualifies AI as a general purpose technology (GPT) and study patterns of concentration, both of which are policy-relevant criteria. The four approaches overlap in only 1.37% of patents and vary in size, accounting for shares ranging between 3-17% of all US patents in 2019. The smallest set of AI patents in our sample, identified by recent AI keywords, is the most GPT-like, with high levels of growth and generality. All four approaches show that AI inventions are concentrated at a few firms, confirming concerns about market competition. Our results suggest that policy implementation may not be straightforward and should consider more than one classification method, as identifying AI inventions ultimately depends on how AI is defined.

JEL Classifications: O31, O33, O34

Keywords: Artificial Intelligence, Governance, General Purpose Technology, Concentration, Patent, Classification

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1. Introduction

Artificial intelligence (AI) governance is high on the agenda of national and international policy, often reflecting the view that future AI could and should be shaped to mitigate risks and make it beneficial for all (Jelinek et al., 2021; Mazzucato et al., 2022; Schmitt, 2022). Governance requires a clear identification of AI technologies, but so far a consensual AI definition is lacking (Krafft et al., 2020). A wide audience is interested in understanding recent trends in AI development but the lack of clear identification strategies can hamper research to assess the impact of AI and the effectiveness of regulatory policy (Dafoe, 2018). Ambiguities in AI definitions and measurement may help understand some of the empirical ambiguities about AI impacts, for example, on labour markets, technological leadership, and patterns of growth and productivity (Cazzaniga et al., 2024; Brynjolfsson et al., 2021; Bresnahan, 2023; Alderucci et al., 2020; Babina et al., 2024). In this paper, we use patents as a quantitative and qualitative record of AI inventions. Comparing the differences across four different AI classification methods, we investigate how empirical conclusions about the characteristics and concentration of AI can be sensitive to the chosen method.

AI is often described as a general purpose technology (GPT) shaping the future technological and economic evolution, with wide-ranging impacts on production processes, labour markets, and technological and economic leadership at national and international levels (Agrawal et al., 2019; Cockburn et al., 2019; Brynjolfsson et al., 2021; Cockburn et al., 2018; Valdes and Rudyk, 2017; Webb, 2019; Alderucci et al., 2020). Testing these predictions requires a robust empirical measure of AI; yet, the ex-ante measurement of radical novelty is challenging (Schumpeter, 2005). AI is believed to be still at an early stage (Brynjolfsson et al., 2021), and its long-run effects have not yet manifested and can be affected by decisions undertaken today (Jacobides et al., 2021; Petit, 2017; Fanti et al., 2022).

It is not the aim of this paper to identify the best definition of AI – it is rather to investigate differences and agreements of different measurement methods, and their implications for AI policy and research. We do so by comparing four samples of AI patents, each reflecting a different way to understand AI, as outlined in the literature. The samples are identified by:

1. keywords focusing on recent trends in neural networks, robotics, and natural language processing (NLP);
2. scientific citations reflecting the academic origins of AI;
3. the World Intellectual Property Organization (WIPO) classification method, accounting for both the hardware and software dimensions of AI; and
4. the United States Patent and Trademark Office (USPTO) approach capturing the widespread use of AI in other inventions.

In the union of all samples, we identify 732k AI patents from 1990 to 2019. The individual samples vary greatly by scale: 54k patents are captured by the Keyword, 178k by the
Science, 159k by the WIPO, and 595k by the USPTO approach. Strikingly, all four methods agree on only 1.37% of AI patents, with pairwise overlaps of 10-20% or less throughout the entire period. Further, the four approaches reflect disparate time trends, with the Science and USPTO sample showing an AI slowdown in recent years, while Keyword and WIPO patents tell a story of accelerating growth since the 2000s.

We evaluate whether the four samples reflect the beliefs of AI being a GPT, by assessing three GPT characteristics established in the literature (Bresnahan and Trajtenberg, 1995; Hall and Trajtenberg, 2006; Petralia, 2020):

1. Growth: GPTs are engines of growth with continued technological improvements (Petralia, 2020). We measure this feature by the growth rates of each AI sample, and those sets of patents that rely on them, as indicated by citations.

2. Generality: GPTs can be used across a wide range of products and processes. We examine the technological diversity of patent citations. As GPTs often experience long delays before being widely taken up (Comin and Mestieri, 2018), we measure citation lags between AI and subsequent inventions (Hall and Trajtenberg, 2006).

3. Complementarity: GPTs complement technologies in many fields (Petralia, 2020), being reflected in a high technological diversity. We quantify the diversity of co-classifications of AI patents across technology groups.

Evaluating the “GPTness” of AI is relevant because it indicates the potential for continued growth in all areas of the economy with large social benefits in the long run (Lipsey et al., 2005). GPTs are characterised by public good features, which can be a justification for public support (Bresnahan and Trajtenberg, 1995).

Whether AI is a GPT or not can not be taken as empirically given: If AI inventions have little or no GPT characteristics, arguments claiming that AI needs public support would be undermined. However, an observed lack of GPTness could also be a matter of classification or barriers to the realisation of AI benefits, which do not necessarily arise by themselves: commercial actors may maximise the private rather than the social value of an invention, leading to a pre-mature lock-in to an inferior pathway of AI development (Klinger et al., 2020; Bresnahan, 2023). This consideration motivates an additional analysis of the agency dimension of AI patenting, identifying the key actors in its development, and evaluating the concentration of inventive activities.

Our results indicate that all methods classify AI as a GPT, yet the AI inventions identified by Keywords and the WIPO method show the highest level of GPTness. Inventive activities by firms appear least concentrated in technology areas identified by Keywords. Relying on GPTness and diversity in the market of AI development, one may conclude that AI as captured by Keywords bear the greatest potential for public benefits, compared to the other methods. This could guide policy, aimed at supporting AI inventions for the public good.

It should be noted that our patent-based approach only captures a small niche of the entire AI ecosystem (Jacobides et al., 2021) and we evaluated only a narrow set of criteria that may be relevant for AI policy. Attempts to empirically assess the impact
of AI and policy should therefore rely on a variety of methods to identify AI before drawing conclusions. Our systematic comparison can guide methodological choices in patent-based research by highlighting the implications and conceptual considerations in defining and measuring AI. Further, our results inform discussions on AI definitions by showing consensual features of AI and quantifying nuanced differences in the types of industries, technology fields, and key players involved in AI development.

This research is relevant for a wide audience, ranging from researchers (who reflect on AI definitions or use AI-classification as a tool in applied research) to policy makers (who rely on AI definitions in everyday policy making and on empirical insights on AI impact, which may be sensitive to AI-classification). A deeper reflection on AI definitions and their implementation may help clarify some of the empirical controversies about AI impacts on society.

The remainder of our paper is structured as follows: Section 2 introduces GPTs and AI in patent data; Section 3 describes the methods, followed by the results (Section 4). In Section 5, we discuss the findings, and Section 7 concludes.

2. Background

Here, we review (1) the arguments for AI being a GPT (Section 2.1), (2) the history of AI and its definitions (Section 2.2) and (3) patents as a data source (Section 2.3).

2.1. What is a GPT, and does it matter for AI?

Bresnahan and Trajtenberg (1995) introduce the concept of a GPT as a technology which pervades the economy and spurs inventions, both endogenously and through complementarities. Well-established GPTs, such as electricity and Information and Communication Technologies (ICTs), are widely considered as long-term drivers of societal value, growth and technological progress. Research on identifying GPTs in quantitative data focused three main characteristics: (1) growth originating from capacity for rapid intrinsic improvement, (2) generality given by the pervasiveness throughout the economy, and (3) complementarity arising from the ability to spawn spillover productivity across sectors (Bresnahan and Trajtenberg, 1995; Lipsey et al., 2005).

The first criterion refers to GPTs’ inherent capacity to rapidly improve. If the technology is sufficiently mature to be valuable for many uses, this should be reflected in high growth rates. The second criterion refers to GPTs’ ability to engender new methods of production or innovation. Due to their pervasiveness, GPTs inspire a wave of technological inventions as they embody new universal tools for production and research. Other impactful technologies, such as nuclear power and fMRI, lack the generality required to pervade a significant number of sectors (Agrawal et al., 2018; Brynjolfsson et al., 2019). The third criterion captures how GPTs spawn productivity spillovers across a range of industries through their ability to augment and complement extant products and processes. This often comes with creative destruction and technological discontinuities rendering established technologies and jobs obsolete (Lipsey et al., 2005).
Together, these criteria require longer or varying periods for GPTs to evolve, spread and unleash their full economic impact (Lipsey et al., 2005). Once the inventions have evolved and spread sufficiently, GPTs rely on supporting infrastructure and secondary inventions to restructure organisations and production processes throughout the economy (Bresnahan, 2023).

While much work framed AI as a GPT (e.g. Agrawal et al., 2018; Cockburn et al., 2018; Brynjolfsson et al., 2021; Cockburn et al., 2019; Valdes and Rudyk, 2017; Webb, 2019; Alderucci et al., 2020), others raised that the GPT concept may be a too simplistic framework for understanding AI. Recent work has raised potential issues with conceptualising AI as a GPT from a policy perspective (Jacobides et al., 2021), and the realisation of GTP benefits may not be taken for granted (Bresnahan, 2023). Bresnahan and Trajtenberg (1995) argue that GPTs could create market failures because they are useful everywhere (public good characteristics), and, therefore, be associated with welfare losses due to underinvestment. However, it is unclear whether AI represents a single GPT or is an amalgamation of many technologies that fulfil different functions, including data provision, prediction, classification, soft- and hardware, and edge applications (Jacobides et al., 2021).

Certain parts of AI ecosystems may be more essential than others, such as access to large-scale data and computing resources. Countries and companies show different specialisations in sub-areas of AI, but those that lack access to the critical components of AI run the risk of being cut off from realising the benefits of AI (Franco et al., 2023; Klinger et al., 2020; Cazzaniga et al., 2024; Jacobides et al., 2021; Bresnahan, 2023; Babina et al., 2024).

Therefore, if AI is understood as a system of technologies and resources with a potentially hierarchical dependency structure, the study of AI needs to be broadened to include key actors that shape technological evolution. The possible concentration of AI development at few key players (Klinger et al., 2020; Babina et al., 2024) has raised concerns about the power of Big Tech (Jacobides et al., 2021) and hubs (Klinger et al., 2020). The concentration raises doubts about the need for public funding of AI, which would be proclaimed by the GPT perspective (Jacobides et al., 2021; Bresnahan and Trajtenberg, 1995). In contrast, additional support could entrench existing asymmetries without further intervention from competition policy and market regulation (Petit, 2017; Hennemann, 2020).

In this paper, we analyse whether the GPT framing is consistent with the four different AI classification approaches. Our analysis is informative along three main dimensions: (1) timescale and history: different definitions of AI affect the timescale on which it is viewed and the perceived history of its development; (2) concentration and key actors: theoretical approaches differ in which key actors that are indentified to shape AI innovation and the implications for market power; (3) GPT characteristics: the choice of definition may suggests different guidelines for the direction of funding and investment in AI technologies, depending on the degree of GPT public goods characteristics that are found in the data. While being limited to patented AI inventions, which excludes various essential components of AI systems, such as data, human and physical capital resources (Jacobides et al., 2021; Franco et al., 2023), the examples above that our anal-
ysis investigates the methodological basis of empirical research on AI and its impact. The results of this research are of interest for a broader audience, by highlighting how empirical controversies may arise from such methodological choices.

2.2. AI history and different definitions

Broadly speaking, AI is concerned with systems and technologies associated with intelligence. As there is no consensus on a precise definition of AI, research evaluating AI as a GPT must make choices on AI definition and its scope.

The conceptual roots of AI stem back to Alan Turing around the 1950ies (Turing, 1950), and a series of research results and inventions in the following decades led to breakthroughs in the ability of computers to be useful in computational problem-solving. High expectations coupled with limited computing power and funding withdrawal saw a slowdown in AI development during both the late 1970s and again in the 1990s, forming periods referred to as “AI winters” (Stuart and Norvig, 2003).

Modern AI (at latest, since the mid-2000s) is to a large degree based on methods from machine learning (ML), typically computational approaches to detect and model patterns in various data sources (Mitchell et al., 2007). ML builds upon computer science, statistics, logic, probability, and optimisation. Furthermore, ML methods software is often paired with hardware sensors, actuators, and controls to create intelligent systems: Such a mix of ML software with computer hardware has been considered as one way to build AI systems.

Recent work contends that modern AI research is being rapidly privatised and narrowed towards deep learning (a particular form of ML) at the expense of other relatively unexplored domains, such as symbolic learning (Bianchini et al., 2020; Klinger et al., 2020; Jurowetzki et al., 2021; Whittaker, 2021). Moreover, a dependence appears to exist on relatively speaking narrow and deep digital transformation in firms (Bresnahan, 2023). It remains to be seen whether this narrowing will impact what definitions will be used to capture the full scope of future AI inventions. These may also include new sub-fields that are, at present, relatively unexplored.

Taken together, we can see both general longer-term trends and the recent concentration of inventions, often using a few specific technologies. The choice about the breadth of an AI definition is important research and policy, but making this choice is not trivial. We are already seeing attempts to make AI definitions more technology-neutral, for example in the work for the forthcoming EU legislation regulating AI, an AI system is defined as:

“a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments”

and the specific connection to ML is further emphasized in the text\(^1\) as

\(^1\)https://www.europarl.europa.eu/doceo/document/TA-9-2023-0236_EN.html
“AI systems often have machine learning capacities that allow them to adapt and perform new tasks autonomously. Machine learning refers to the computational process of optimizing the parameters of a model from data, which is a mathematical construct generating an output based on input data. Machine learning approaches include, for instance, supervised, unsupervised and reinforcement learning, using a variety of methods including deep learning with neural networks.

[...] Comparably simpler techniques such as knowledge-based approaches, Bayesian estimation or decision-trees may also lead to legal gaps that need to be addressed by this Regulation, in particular when they are used in combination with machine learning approaches in hybrid systems.

[...] AI systems can be used as stand-alone software system, integrated into a physical product (embedded), used to serve the functionality of a physical product without being integrated therein (non-embedded) or used as an AI component of a larger system. If this larger system would not function without the AI component in question, then the entire larger system should be considered as one single AI system under this Regulation.”

which suggests a challenge is to be sufficiently specific to draw clear system boundaries. Here, it is easy to see the room for different classification methods/identification strategies.

2.3. Patents as a data source

We use patent data to investigate overlap and differences in the characteristics between four AI definitions. Patents are detailed track records of inventions and require the disclosure of the technological knowledge embodied in the patented invention. Patent offices hold stocks of millions of patents assigned to different technological fields using hierarchical patent classification systems. One patent can be classified into a variety of technology fields, which describe the nature of the patented technology (Jaffe and De Rassenfosse, 2017). Patents have been previously been used to study AI inventions multiple times (Cockburn et al., 2018; WIPO, 2019b; USPTO, 2020; Verendel, 2023).

Patents are assigned to one or more codes from hierarchical patent classification systems, such as the Cooperative Patent Classification (CPC) system developed by the European and US patent offices. These codes help describe the qualitative nature of a patent, for example, whether it is related to specific computing techniques or hardware for data transmission, or related to functions in another sector of the economy.

Patent documents also indicate citations to other patents and academic articles help distinguish the patented invention from previous inventions. Inventors are also required to establish the novelty of their invention in relation to existing technology. These

\[\text{https://worldwide.espacenet.com/patent/cpc-browser}\]
citations are frequently used by innovation scholars as they reveal the cumulative dependencies between technologies, and may be interpreted as an indicator of the extent to which an invention builds on existing knowledge and technology (Jaffe and De Rassenfosse, 2017). Previous research that frames AI as a GPT has also used patent data (Cockburn et al., 2018); it should be noted that various alternatives have been used including industry-, firm-, and technology-level non-patent quantitative and qualitative data (e.g. Klinger et al., 2018; Bresnahan, 2023; Trajtenberg, 2018; Goldfarb et al., 2023).

Other studies have also used conceptual frameworks that denote the vulnerability and potential of occupations and economic sectors to AI, however such methodologies proffer only relative and speculative analysis of the impact of AI (Cazzaniga et al., 2024).

3. The four different AI classification approaches

In our analysis, we sample four sets of AI patents identified by distinct AI definitions applied to patent data, and compare the four sets by their GPTness and other characteristics. More specifically, for GPT characteristics we contrast the estimated growth, generality and complementarity of AI patents classified by (1) keywords, (2) science citations, (3) the WIPO, and the (4) USPTO method drawn from all USPTO patents granted during 1990-2019. For analysis of the concentration of inventive activity, we use metrics for concentration. The four different approaches are implemented as follows:

First, the Keyword method is replicated from Cockburn et al. (2018) and relies on text search terms (NLP, robotics, neural networks). This approach reflects short-term perspectives on AI and attributes its progress to themes that became dominant over the past decade.

Second, we use scientific citations to AI research including grey literature and conference proceedings (Marx and Fuegi, 2020) as AI identifier. This conceptualises AI technologies as an outcome of science and academic research (Arthur, 2009; Jee and Sohn, 2023). As discussed below, this approach is subject to limitations because citation practices differ across technological fields.

Third, the WIPO method focuses on the technical underpinnings of AI, including AI functions, techniques, ML, and various areas of applied computing. It combines a set of keywords with computer-specific technological classification codes (WIPO, 2019a).

Fourth, the method implemented by the USPTO relies on the broadest understanding of AI. This technique uses a trained ML classifier on patent text and citations to identify innovations related to knowledge processing, speech, hardware, evolutionary computation, NLP, ML, computer vision, planning and control (Giczy et al., 2021). This broad conceptualisation of AI is also reflected in the significant volume of AI patents identified through this method, including a large share of downstream AI applications.

For further background on these definitions and details on their implementation, we refer the reader to Appendices A-B.
4. Results

Here we compare the four AI samples by their general characteristics (4.1), GPT characteristics (4.2), and concentration (4.3).

4.1. General characteristics of AI

Table 1 shows, for each method, growth rates (panel A), inventor types (panel B), main industries (panel C), countries of origin (panel D), public support (panel E), and main technology classes (panel F).

For all methods, AI inventions have become increasingly diversified across industries and countries over the past three decades, suggesting that AI has become increasingly disseminated throughout the economy. Further, all methods show that AI inventions are disproportionately borne by commercial enterprises (panel B) and associated with the computer and machinery manufacturing industries (panel C). Despite classifying numbers of patents that differ on the order of magnitude, all approaches show the expected dominance of the US in AI patents. However, the use of US patents over-represents inventors from this country.

We find differences in the growth rates of the Science and the USPTO approaches suggesting that these two groups have not accelerated in the post-2000s as clearly as the other categorie.
Table 1: AI patents by four classification approaches

|                                | Keyword | Science | WIPO   | USPTO   |
|--------------------------------|---------|---------|--------|---------|
| **A. Growth**                  |         |         |        |         |
| Growth rate (1990-99)          | 0.98    | 6.69    | 2.38   | 3.87    |
| Growth rate (2000-09)          | 0.79    | 1.32    | 1.21   | 1.16    |
| Growth rate (2010-19)          | 3.77    | 0.91    | 3.02   | 1.07    |
| **B. Inventor type (patent assignee)** |         |         |        |         |
| % Commercial                   | 0.86    | 0.85    | 0.90   | 0.91    |
| % Individual                   | 0.06    | 0.03    | 0.05   | 0.05    |
| % University                   | 0.05    | 0.10    | 0.04   | 0.03    |
| % Other non-profit             | 0.03    | 0.04    | 0.02   | 0.02    |
| **C. Industry affiliation (patent assignee)** |         |         |        |         |
| % Pharmaceuticals (manufacturing) | 0.01  | 0.17    | 0.01   | 0.01    |
| % Computer (manufacturing)     | 0.68    | 0.76    | 0.79   | 0.84    |
| % Machinery & equipment (manufacturing) | 0.49  | 0.28    | 0.54   | 0.22    |
| % Other manufacturing          | 0.14    | 0.10    | 0.09   | 0.09    |
| % Computer programming (service) | 0.06  | 0.07    | 0.09   | 0.12    |
| **D. Country of origin (patent applicant)** |         |         |        |         |
| % USA                          | 0.62    | 0.75    | 0.65   | 0.72    |
| % Japan                        | 0.14    | 0.08    | 0.15   | 0.10    |
| % S. Korea                     | 0.04    | 0.02    | 0.03   | 0.02    |
| % Germany                      | 0.05    | 0.03    | 0.03   | 0.03    |
| % China                        | 0.01    | 0.01    | 0.02   | 0.01    |
| % Canada                       | 0.02    | 0.02    | 0.02   | 0.02    |
| **E. Public support**          |         |         |        |         |
| % Public support (1990-99)     | 0.31    | 0.39    | 0.29   | 0.21    |
| % Public support (2000-09)     | 0.34    | 0.48    | 0.31   | 0.23    |
| % Public support (2010-17)     | 0.33    | 0.52    | 0.28   | 0.22    |
| **F. CPC 1-digit codes**       |         |         |        |         |
| % Human necessities (A)        | 0.15    | 0.18    | 0.08   | 0.08    |
| % Performing operations (B)    | 0.31    | 0.05    | 0.11   | 0.04    |
| % Chemistry; Metallurgy (C)    | 0.03    | 0.16    | 0.01   | 0.01    |
| % Physics (G)                  | 0.66    | 0.75    | 0.95   | 0.79    |
| % Electricity (H)              | 0.25    | 0.26    | 0.27   | 0.33    |
| % General/Cross-sectional (Y)  | 0.05    | 0.04    | 0.03   | 0.04    |
| **Number of patents**          | 54,145  | 178,004 | 158,652 | 595,047 |

Notes: This table compares the scale and scope of AI invention identified by each definition, concerning inventor types (commercial, individual, non-profit, university), industry affiliation (based on NACE Rev. 2 classification), country of origin, reliance on public R&D support, and technological classification. Note that the data on public support ends in 2017.

Comparing how the inventions are classified by CPC 1-digit codes, all approaches score similarly by their relation to electricity (H). WIPO patents are most notably clustered in the ‘Physics’ category, while ‘Chemistry’ patents are most identified by the Science approach. Patents identified by the Keyword and Science approaches produce the most diverse range of AI patents. The high share (95%) of WIPO in ‘Physics’ is caused by the method: the WIPO method filters by design for patents classified into CPC-section ‘G - Physics’ (WIPO, 2019a).

Figure 1 shows the pace of AI invention. Represented as a share of all granted US
patents, the USPTO approach identifies roughly 16.6% of all US patents as AI in 2019 (see Figure D.10 in Appendix D.3.1). For all approaches, we find that this share increased over time from 1-2% in the 1990s to 3-17% in 2019.

Figure 1: AI Patents by Year (1990-2019)

Notes: The right panel shows the number of AI patents over time as identified by the four approaches. The left panel shows the evolution of the Jaccard similarities computed for each year in our dataset.

To quantify the overlap of the four samples (the degree to which they extract the same sets of patents or not), we compute the pairwise Jaccard similarities and their evolution over time, shown in Figure 1b. All pairs of AI samples show low overlaps, ranging at or well below 20%. The WIPO approach shows the highest agreement with the other groups, and the similarity of the WIPO-Keyword and the Science-USPTO pairs increased most strongly over time. Keywords demonstrate the lowest Jaccard similarity to the other classification approaches, which may be due to the small number of patents in this sample.

Overall, only 10,062 or 1.37% of all unique granted patents are uniformly identified as AI patents by all four methods, indicating that quantitative conclusions about the scale and reach of AI are sensitive to the chosen classification method. In the next section, we adopt a qualitative perspective, and discuss how these differences affect the extent to which AI qualifies as a GPT.

3The Jaccard similarity for two sets of patents is given by

\[
J(A, B) = \frac{|\text{patents in both } A \text{ and } B|}{|\text{patents in union of } A \text{ and } B|} = \frac{|A \cap B|}{|A \cup B|}
\]

with \( J(A, B) \in [0, 1] \) where \( J(A, B) = 0 \) if both sets do not overlap and \( J(A, B) = 1 \) if both sets are identical. In other terms, the overlap between the sets can range from 0% to 100%.
4.2. GPT characteristics of AI

We study the GPTness of AI by comparing the four AI samples by their growth, generality, and complementarity, summarised in Table 2 and discussed step by step throughout this section.

Table 2: Measure of GPT characteristics of AI

|                  | Keyword | Science | WIPO  | USPTO |
|------------------|---------|---------|-------|-------|
| **A. Growth**    |         |         |       |       |
| Avg. growth rate | 0.12    | 0.15    | 0.14  | 0.13  |
| **B. Generality**|         |         |       |       |
| Avg. generality index (1 digit) | 0.81   | 0.77    | 0.76  | 0.73  |
| Avg. generality index (3 digit) | 0.94   | 0.90    | 0.90  | 0.87  |
| Avg. generality index (4 digit) | 0.97   | 0.96    | 0.95  | 0.95  |
| **C. Complementarity** |       |         |       |       |
| Avg. number of CPC (1 digit) | 1.43   | 1.40    | 1.36  | 1.27  |
| Avg. number of CPC (3 digit) | 1.67   | 1.64    | 1.64  | 1.43  |
| Avg. number of CPC (4 digit) | 1.92   | 1.97    | 2.05  | 1.64  |

Notes: This table gives a comparison of the GPT-like characteristics of AI inventions classified by each distinct technique. Note that the generality index is defined as share of citations to patents in different CPC classes at different aggregation levels. Citations within the same class are excluded.

4.2.1. Growth

Panel A of Table 2 shows the average growth rate between two consecutive years, and Figure 2 shows how these rates evolved over time. We include lowess (local regression) smoother fits (Cleveland, 1979) in each plot to show the overall pattern.

We observe the following: First, each sample shows positive growth rates in most years, as anticipated for GPTs. Second, each AI definition demonstrates a dip in growth during the early 2000s before taking off again in recent years. Third, the smaller AI samples produced by the Keyword and WIPO methods show an accelerating growth rate in the last few years, in contrast to the USPTO and Science samples. Taken together, we see positive growth rates and differences in time trends between the approaches.

In the Appendix D.1 (Figures D.4), we study benchmarks that have been discussed in the literature as potential GPTs, such as nano- and climate technology, biochemistry or general computing. We find that the AI samples show higher growth rates compared to most other GPT-candidates, but performing a Wilcoxon signed rank test, we find that most of these differences are not significant (see D.2.1), although they are significantly higher than those of average patents. Across our AI samples, the differences between

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4 However, a comparison with benchmark groups shows that patenting decreased across many sectors during this period (see Figure D.4 in Appendix D.1.1).

5 Note that these tests rely on a very small number of observations and growth patterns of the four AI
the four classification methods are not significant, except for the USPTO approach, which shows significantly lower growth rates compared to the others.

Figure 2: Growth of Patents by Year

![Graphs of growth rates by year for different approaches: Keyword, Science, WIPO, and USPTO.](image)

Notes: The four AI approaches have different growth patterns over time. The averages for all are positive, but the Keyword and WIPO approaches both have increasing growth rates.

If AI was a GPT, it should be an enabler of follow-up inventions in non-AI sectors, as reflected in the growth of patent citations by non-AI patents. Figure 3 shows that the patents citing AI (excluding those that are themselves AI by the respective approach) have similar profiles over time. The size ranking is consistent with the counts and shares shown above (Figure 2). The positive downstream growth suggests that each approach generates a growing number of invention spillovers to non-AI sectors. Significance tests in D.9 indicate that the differences between the triple Keyword-Science-WIPO cannot be statistically distinguished, except for Keyword showing the slowest uptake in the 1990s and taking off thereafter. These three approaches score significantly higher than the USPTO sample. Figure 3b suggests that all four methods capture different portions of a larger group of similar technologies.

samples that fluctuate and differ across the three decades.
Figure 3: Patents Citing AI

Notes: Panel (a) shows the actual number of AI citing patents. Panel (b) shows growth rates plotted from 1995 and onwards.

4.2.2. Generality

We use two indicators to evaluate the generality of AI inventions; describing the extent to which AI inventions are cited in diverse technology fields. First, we assess the generality index (Trajtenberg et al., 1997; Hall and Trajtenberg, 2006), given by the inverse of the concentration of the 1-digit CPC-codes of AI-citing patents, similar to a Hirschmann-Herfindahl Index (HHI). Technical details and additional results are provided in A.2 and D.3.2.

\[ GI_i = 1 - \sum_j N_j \left( \frac{\#cites_{ij,t}}{\sum_{j=1}^{N_j} \#cites_{ij,t}} \right)^2 \]

where \#cites_{ij} is the number of citations to patents labeled as AI by method i from CPC class j, using CPC codes at the 1-digit, 3-digit, and 4-digit level; \#cites_{ij} excludes citations within the same class. \(N_j\) is the number of different CPC classes.

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6The formula of the generality index \(GI_i\) is given by
Figure 4: Generality Index at the 1-digit CPC-section level

(a) Generality index
(b) Z-score scaled generality

Notes: The z-scored value equals the level of the generality index minus its average across the four approaches divided by the standard deviation for each year.

Figure 4 shows the evolution of the generality index over time. The Keyword sample shows the highest level of generality, which is consistent over the three decades (Figure 4b). Hence, citations from other technology fields to Keyword AI patents are most equally distributed across different fields. The WIPO and Science samples score at similar levels, with a slightly higher generality score given to Science. The USPTO sample shows the lowest generality across all CPC levels, which may be surprising given the size of the sample. Towards the end of the time period, the decline in the generality of the Keyword and USPTO methods needs to be considered with caution, as the number of citations of recently granted patents is lower given the time needed for innovations to be cited.

Second, we assess generality by the mean annual average number of unique citing classes citing to an AI patent, accounting for the increase in annual patenting rates and avoiding an over-representation of the generality of patents in more recent years. Again, we compile this metric for different CPC digit levels.
The z-scored value equals the level of the generality index calculated at the 1-digit level minus its average across the four approaches divided by the standard deviation for each year.

At all levels of aggregation, the Keyword patents are the most general (Table 2 and Figure 5). At the 1-digit level, Science scores second, closely followed by WIPO. WIPO ranks higher at the 3- and 4-digit level. The USPTO patents demonstrate the lowest number of unique 1-, 3-, and 4-digit patent citations. Again, the decline in recent years can be explained by the time lags in receiving citations.

Significance tests (see D.2.2) confirm that the highest generality scores of the Keyword and the lowest of the USPTO method are statistically significant. The differences between the science and WIPO approaches are negligible at the 1-digit level. In D.3.2, we also report the number of unique citing technology classes for AI patents that are cited at least once (see Table D.39). Interpreting backward citations as an indicator of the value of a patent (Kogan et al., 2017), this measure focuses only on high-value patents. Again, the Keyword patents show the highest generality across all CPC digit levels. Science scores slightly higher than WIPO at the 1-digit level, and vice versa at the 3- and 4-digit level. The USPTO approach shows again the lowest generality.

As before, we benchmark our AI samples against all patents and other GPT candidates. Table D.2 shows that the generality index of all patents is higher than our AI samples, which is a natural feature, confirming the usefulness of the generality index in capturing the widespread use of patents. Among other groups, biochemistry/genetic engineering, nanotechnology, and climate inventions related patents have high generality scores. Figure D.5b shows that the time series pattern of the generality score is quite stable, except for some end-of-the-period fluctuations. For our second measure of generality, we find that AI patents show more generality than the entire patent universe at any level of CPC codes (Table D.3). Biochemistry/genetic engineering and climate-related patents show high patent-level generality. These numbers show that our generality measures are appropriate, at least for some known GPT candidates. Again, we provide additional results on the generality of AI-citing patents that are not AI themselves. These are qualitatively consistent, although the differences between the AI samples are smaller (see Appendix D.4).
Table 3: Average Citation Lags by Approach

| Period     | Keyword | Science | WIPO | USPTO |
|------------|---------|---------|------|-------|
| all periods| 10.16   | 8.90    | 9.63 | 9.80  |
| 1990-1999  | 14.17   | 13.26   | 13.77| 13.64 |
| 2000-2009  | 9.92    | 9.08    | 9.38 | 9.34  |
| 2010-2019  | 4.33    | 4.15    | 4.19 | 4.33  |

Notes: This table shows the average number of years taken until a patent in the sample is cited. The average number of years is lower in recent years, because the data ends in 2019 causing a truncation of the maximal time lag.

Patent citations to GPTs are said to occur with long lags (Hall and Trajtenberg, 2006), as organisational and complementary inventions are required during an early phase of “learning and destruction” before a GPT can spread through the economy (Crafts, 2021; Bresnahan, 2023). In Table 3, we show the average citation lags of our AI samples, given by the average number of years between the grant year of a patent and the patents citing the patent. Keyword patents again rank top, by showing the longest average lags.

Altogether, the AI sample identified by the Keywords shows consistently the highest level of generality across different metrics.

4.2.3. Complementarity

As a measure of complementarity, we examine the co-classification of AI by multiple CPC codes, attached to the patents. If AI complements a wide range of other technologies, AI patents would be co-classified across diverse technological fields.

Figure 6: Diversity of AI – Share of technology classes

![Graph showing percentage of technology classes](image)

(a) % of all 3-digit CPC

(b) % of all 4-digit CPC

Note: Panel (a) shows the percentage of 3-digit CPC codes and panel (b) shows the percentage of 4-digit CPC as a share of all codes in the respective category. Note that the total number of 3-digit and 4-digit CPC codes are 136 and 674, respectively according to the February 2022 version.

Figure 6 shows the percentage of 3- and 4-digit CPC classes associated with each set
of AI patents. USPTO patents span the most diverse pool of technology classes, with CPC classes ranging from 70-90% of all possible codes. This can be explained by the large number of AI patents in the USPTO approach, compared to the others (Table 1).

However, the smaller AI samples took off over time: starting around 2010, the share of codes associated with Keyword, Science, and WIPO patents rapidly increased. Significance tests show that the differences between the triple Keyword-Science-WIPO are statistically insignificant, but all score significantly lower than USPTO patents (Table D.29 and D.31).

Figure 7: Patent-level diversity - Average technology classes

To take account of the differences in sample sizes, we calculate the annual averages of the number of 1-, 3- and 4-digit CPC codes per patent, shown in Table 2, D.42 and D.3.2. An average WIPO patent is associated with 1.64 3-digit classes and 2.05 4-digit classes across all years. Keyword or Science patents are on average associated with slightly fewer classes, whereas the USPTO patents appear to be the least multidisciplinary by this metric. The highest score of the WIPO method at the 4-digit level and the weak diversity performance of the USPTO approach are statistically significant.

At the 1-digit level, Keyword and Science AI patents show similar values (1.39-1.40) and cannot be distinguished statistically. The other approaches rank significantly lower, with the USPTO approach showing the least complementarity. In Figure 7, we show the average number of co-classifications over time at the 3- and 4-digit level. All panels show a rising diversity towards the second half of the last decade, with the strongest increase for WIPO patents.

In D.1.1, we provide results for benchmark GPT candidates, confirming that our measures are performing equally well in capturing the increasing diversity of other GPTs suggested in the literature.7

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7Given the heterogeneity of CPC classes, it is difficult to evaluate the compare the different candidates by their diversity as our selection of benchmarks is entirely based on CPC codes at the 3- and 4-digit level. For example, it is almost a natural feature of the Y02-codes used to identify climate technology span a wide range of technologies.
Summing up, all AI samples show an increasing technological diversity. Accounting for differences in sample size, we find that the WIPO method captures the highest diversity at the more disaggregate level, while Science and Keyword AI patents are more diverse at the 1-digit section level. The high diversity of WIPO patents at more granular levels may be explained by the method’s design which focuses on patents classified into various definitions of the computing, performing operations and hardware components of AI (see Section B.4). In contrast, Keywords and Science patents are not constrained by the CPC classes included.

4.3. Concentration in AI

Many policy-related discussions on AI center around the concerns about an increasing concentration in the market for AI technologies, undermining fair competition and equal participation in the benefits of AI (Petit, 2017; Babina et al., 2024; Mazzucato et al., 2022; Jelinek et al., 2021; Schmitt, 2022). We report on the empirical basis of these concerns for different conceptions of AI, as they are embodied in our four samples of AI patents. The Science approach captures the most non-commercial AI inventions by individuals, non-profit organisations and universities, with a notably higher concentration of patenting ascribed to the pharmaceutical industry, compared to machinery and manufacturing for both WIPO and Keyword. This may be explained by the high share of biotech-related patents in the Science sample, which are more often filed by academic inventors whose inventions originate from their research. Geographically (Panel E), the Keyword and WIPO patents include more AI patents of foreign inventors, especially from Japan. Chinese inventors are not present in the top-list, despite China’s vital role in AI development in recent years (Jacobides et al., 2021). This can be partially explained by the time period covered, as China’s position at the global frontier in high-quality patenting only became apparent during the preceding decade. However, this omission may also be caused by a potential bias of relying only on US patents in this study.\(^8\)

Moreover, each of the four classification methods draws a different picture of the reliance of AI inventions on public R&D support (Table see 1 Panel F). In the USPTO sample, only one-fifth of AI patents received public support, while in the Science sample this jumps to half in the last decade. This resonates with the inventor types (Table 1 Panel C): AI as classified by the USPTO appears to be mostly commercially driven, while academic AI inventions take a higher share in the Science sample, as public R&D support is often channelled through academic research institutions.

In Table 4, we show the top-ten firms ranked by their share in AI inventions for each of our AI samples. Consistently, we find that AI inventions are dominated by a few key technology and communication companies. We also uncover a broad consistency among the firms, with IBM, Microsoft, and Google occupying the top ranks.

To analyse the full distribution beyond the top-ten firms, we calculate the concentration ratio (CR) and HHI, shown in Table 5. The four-firm (eight-firm) CR is given by the share of patents filed by the top-four (top-eight) firms inventing AI, and the HHI is

\(^8\)A discussion of the implications of this bias can be found in Section 6.
### Table 4: Top AI-producing firms

|                      | Keyword | Science | WIPO   | USPTO  |
|----------------------|---------|---------|--------|--------|
| Company name         | %       | Company name | %       | Company name | %       | Company name | %       |
| IBM Corp             | 0.05    | IBM Corp | 0.07   | IBM Corp  | 0.07    | IBM Corp  | 0.09    |
| Microsoft            | 0.02    | Microsoft | 0.06   | Microsoft | 0.04    | Microsoft | 0.04    |
| Samsung              | 0.02    | Google  | 0.03   | Google    | 0.02    | Google    | 0.02    |
| Fanuc Corp           | 0.02    | Apple   | 0.02   | Canon     | 0.02    | Intel     | 0.02    |
| Google               | 0.02    | Sony    | 0.01   | Samsung   | 0.02    | Samsung   | 0.01    |
| Siemens              | 0.02    | Siemens | 0.01   | Sony      | 0.02    | Hewlett Packard | 0.01 |
| Honda Motor          | 0.01    | Hewlett Packard | 0.01 | Intel     | 0.01    | AT&T      | 0.01    |
| Amazon               | 0.01    | Intel   | 0.01   | Amazon    | 0.01    | Sony      | 0.01    |
| Intel                | 0.01    | AT&T    | 0.01   | Siemens   | 0.01    | Amazon    | 0.01    |
| Sony                 | 0.01    | Canon   | 0.01   | Fujitsu   | 0.01    | Canon     | 0.01    |

Notes: This table reports the top-ten AI producing firms for each AI definition. IBM, Microsoft, and Google are among the top-five AI patenting firms across all four groups. The column share reports the share of commercial patents accounted by a firm within each AI definition. For example, IBM accounts for 4-7% of all AI patents produced by commercial firms.

Given by the sum of squares of the share of AI patents produced by each firm. Consistently, across measures of concentration, AI inventions identified by Keywords are the least concentrated with the lowest HHI and CRs.

Contrary to concerns raised in the literature (Petit, 2017), we do not observe that AI inventions have become more concentrated in fewer firms over the past three decades. We observe minor fluctuations, but cannot observe any clear trend for any of the four AI samples. Note that our data only reflects trends in the distribution of patented AI inventions across firms. Worries about rising concentration have also been raised about concentration in final goods markets, when the productivity gains of AI are unequally distributed (Babina et al., 2024), and in the control over critical assets such as data, computational resources, and platforms (Jacobides et al., 2021; Franco et al., 2023).
Table 5: Concentration of Firms innovating in AI

|                      | Keyword | Science | WIPO | USPTO |
|----------------------|---------|---------|------|-------|
| **A. Concentration Ratio (CR)** |         |         |      |       |
| Four-firm CR         | 0.117   | 0.174   | 0.162| 0.177 |
| Eight-firm CR        | 0.175   | 0.219   | 0.221| 0.228 |
| **B. Herfindahl–Hirschman Index (HHI)** |         |         |      |       |
| HHI (overall)        | 0.007   | 0.012   | 0.011| 0.014 |
| HHI (1990-1999)      | 0.008   | 0.012   | 0.013| 0.014 |
| HHI (2000-2009)      | 0.006   | 0.013   | 0.015| 0.016 |
| HHI (2010-2019)      | 0.009   | 0.013   | 0.011| 0.014 |

Notes: This table shows the measures of concentration of AI-producing commercial firms. The concentration ratio (CR) measures the market share of top-four (or top-eight) firms. The Herfindahl–Hirschman Index (HHI) is calculated as the sum of squares of shares of patent produced by each firm within each of the four AI definition patent samples.

5. Discussion

Defining AI is a challenging task, as with every novel technology that has not yet unleashed its full impact and scope (Krafft et al., 2020; Schumpeter, 2005), which can be shaped by the socio-technical and regulatory environment (Geels, 2005). Shaping AI has gained increasing attention in current discussions on AI governance, aimed at mitigating risks and maximising benefits for all (Mazzucato et al., 2022; Bresnahan, 2023). However, AI policy requires a clear identification of the area of AI where action may be required (Krafft et al., 2020).

Our analysis of the GPTness and concentration contributes insights relevant for two dimensions of AI policy: (1) policy could prioritise AI inventions that are most beneficial to broader society with the greatest public benefits (Mazzucato et al., 2022; Bresnahan, 2023), which may be indicated by high levels of GPTness (Lipsey et al., 2005). (2) AI policy could aim to avoid risks of power concentration when the core resources to develop and use AI are unequally distributed. Preventing concentration also reduces the risk that AI development pathways are prematurely narrowed in those areas that promise the greatest short-term private benefits, whilst other areas (Klinger et al., 2020; Jacobides et al., 2021; Bresnahan, 2023) that would be beneficial for a more diverse range of actors remain underdeveloped.

5.1. AI as a General Purpose Technology

We studied four different approaches to identifying AI patents. We find that all methods show some qualitative consistency: all classification techniques show low levels of AI inventions during the 1990s (also known as “AI winter”) followed by a rise since the 2000s (Stuart and Norvig, 2003; Klinger et al., 2020); all confirm that AI can be viewed
as a GPT; all associate AI with similar industries and core technology fields; and all show patterns of concentration among similar groups of key firms. Several characteristics are consistent, which may inform innovation scholars and regulators who are searching for a robust definition of AI, as a basis for impact evaluation and regulatory action (Krafft et al., 2020).

Table 6: Summary of Findings

| Characteristic | Keyword | USPTO | WIPO | Science | Metric | Based on |
|---------------|---------|-------|------|---------|--------|----------|
| Growth        | 🟪      | 🟧    | 🟩   | 🟪      | Growth rate | Counts   |
| Generality    | 🟪      | 🟧    | 🟩   | 🟪      | Generality index | Citations |
| Complementarity| 🟨      | 🟧    | 🟩   | 🟨      | Avg. # tech. classes | CPC codes |

This brief summary of our results shows which patent group generates the strongest average estimate of each GPT characteristic over the last 10 years. Red (yellow) colour indicates the strongest (weakest) performance.

Quantitatively, our four classification methods show some disagreement: AI as captured by Keywords and WIPO took off over the past decade, while the other two suggest a relative innovation slowdown. Both identify patents that are most GPT-like, and capture more from machinery and equipment manufacturing, which is also reflected in the key firms being identified as leading inventors of AI. The Keyword method captures only a very narrow set of inventions (54k), but these patents show the highest levels of GPTness (see Table 6) – and also lowest levels of concentration in inventive activity.

Framing AI as a GPT using our patent-based metrics is consistent with historical GPTs in patent data, like computer & communication and electrical engineering & Electronics (Petralia, 2020). The author illustrated the GPTs’ absolute levels of growth, generality and complementarity, and how they dwarf other innovation clusters at the time (Petralia, 2020). In contrast, non-GPT innovations such as mechanics are similarly distinguishable in patent data by their moderate long-term growth rates and lower, quickly plateauing levels of co-classification. In Section D, we show how other technologies do not meet our three analytical criteria and may not be considered as GTPs, including wire-less communications, biochemistry/genetic engineering and nanotechnology.

5.2. Concentration in AI patenting

Concentration and GPTness interact, as GPTs have public good characteristics, with high innovation spillovers and lagged private returns for diverse actors, making the short-term profit maximisation based on these technologies more unlikely (Bresnahan and Trajtenberg, 1995). This may be reflected in lower levels of the concentration of AI inventions that are most GPT-like. In our results, the low concentration in AI as captured by Keywords resonates with its high ranking by GPTness (Section 4.2), supporting the claim that AI inventions as captured by Keywords are most GPT-like. The Keyword method identifies many patents centred around ML, which was also by Goldfarb et al. (2023) identified as a technology with a high GPT potential.
The realisation of GPT benefits for all does not necessarily come by itself: commercial actors may maximise the private instead of the social value of an invention, leading to a pre-mature lock-in in an inferior pathway of AI development (Klinger et al., 2020; Mazzucato et al., 2022; Bresnahan, 2023). Our identification of core inventions and technological areas, where AI exhibits strongest GPTness and lowest levels of concentration, as identified by Keywords, may be indicative of promising areas of AI where public support can be eventually justified. However, any such decision should rely on methodologically pluralist insights, as every method including ours has limitations (see Section 6).

Due to their high levels of GPTness, the technologies captured by Keywords seem to be well-suited candidates for receiving support. However, when it comes to innovation bottlenecks and policies to help overcome them, they may not be found at the invention level, as captured by patents, but rather at the diffusion level when it comes to business transformation and AI adoption (Bresnahan, 2023). This resonates with preventing excessive concentration, as the barriers to adopt and benefit from AI systems are unequally distributed across firms (Babina et al., 2024).

Our analysis has consistently demonstrated, across all methods, that concentration in AI inventions did not increase over the past three decades. This may suggest that barriers to entry to the market of AI innovation did not recently become higher, and contrasts with other research raising this to be a major concern (Tambe et al., 2020; Agrawal et al., 2019; Mazzucato et al., 2022). This may be due to the nature of digital inventions, which are associated with a relatively low capital intensity and high levels of modularity (Bresnahan, 2023). The modularisation of the AI ecosystem facilitates the entry of novel players (Jacobides et al., 2021; Bresnahan, 2023) as it allows computational resources and basic hardware to be externally sourced at affordable prices. However, our restriction to the level of AI patents does not allow us to deduce trends in vertical integration across all levels of AI systems, control over network resources, or emerging patterns of polarised AI-induced productivity growth, which are relevant areas of competition policy (Petit, 2017; Ducuing, 2020; Franco et al., 2023; Rikap, 2024).

5.3. Research guidance on measuring AI patents

Our systematic comparison of the four classification methods has implications for patent-based research (Fujii and Managi, 2018) as we show that empirical results may differ across methods. For example, the USPTO and Science methods suggest a slowdown in AI inventions in recent years, which is not found when using Keywords or WIPO. This may lead to different conclusions and candidate explanations, for example, whether the decline or rise can be attributed to a narrowing and corporatisation of AI research (Klinger et al., 2020; Jee and Sohn, 2023). We also find minor differences in the top-ranking of firms being among the leaders in AI, and their nationalities. This is relevant when investigating the performance of national innovation systems, given the influence of these systems on the emergent pathway of AI specialisation (Rikap, 2024; Jacobides et al., 2021). For example, the Science method qualifies Apple as a top-ten inventor of AI, but it excludes Samsung, which is among the top-five for all other methods. Such
differences can have material impacts, as investors and banks base their funding decisions and loan conditions on prospective economic performance indicators, which may include patents in emergent technologies such as AI.

Our comparison may guide patent-based AI research on the choice of method, which may be dependent on the intended research goals. Our results suggest that the impact of AI as a GPT can be best studied by relying on the Keyword or WIPO methods. Other methods may be more appropriate for studying the wide-spread diffusion of AI, which seem to be well captured in the USPTO sample, or the role of science in developing AI technology, as encoded in Science citations.

Measuring AI remains a challenge, but our comparison can inform discussions on AI definitions by showing consensual features of AI and quantifying nuanced differences in the types of industries, technology fields, and key players being involved in its development. Other methodologies, including those which use conceptual indicators of how vulnerable potential sectors are to AI, can provide only conjectural analysis (Cazzaniga et al., 2024). Often, definitions of technologies are determined ex-post, after research, development, and diffusion have been accomplished (Schumpeter, 2005). Here, we quantify the consensus and differences in the nuances of AI that is developed by commercial inventors filing patents. We can only speculate, but the consensus can be indicative of the type of AI that is most likely to be pursued further.

The simple Keyword approach generating a narrow set of key patents appears desirable for researchers aiming to catch emerging GPTs. Small patent groups may indicate a clearer distinction from other patents (Kovács et al., 2021). There is also a greater potential for future growth, compared to the USPTO approach that suggests that 16.6% of all US patents today are already based on AI.

During our analysis, we also discovered that the Keyword method reproduced from Cockburn et al. (2018) may be further simplified. We found that the majority of patents can be identified using a narrower set of four terms (ML, neural network, robot, pattern recognition), rather than the original list of over forty words. However, we cannot rule out that the high levels of GPTness of the Keyword method reflect only a short-term trend of the uptake of ML in commercially valuable AI inventions, as captured by patents, while the full scope of AI remains unleashed (Klinger et al., 2020).

6. Limitations

Patent data comes with various well-documented limitations and biases that may have an impact on the interpretation of our measures of AI, GPTs, and their implications for AI policy.

First, patents are used heterogeneously across industries, firms, and technologies, and some inventions cannot be protected by patents. Other means of IP protection such as trade secrets, trademarks, copyrights, and lead time may dominate in particular sectors, causing a bias (Granstrand, 2009; Jee et al., 2024; Verendel, 2023; Hötte and Jee, 2022). Further, the number of co-classifications, and patent and science citations differs across technology fields (Jaffe and De Rassenfosse, 2017; Hötte et al., 2021), which may affect
our measures of GPTness.

Second, patents measure technical inventions, but not diffusion and the emergence of AI-related services (Goldfarb et al., 2023). Data and various other relevant parts of AI ecosystems (Jacobides et al., 2021) are not captured, as there are no patents in these areas. Diffusion may be reflected in changing production technology and input requirements of firms (Bresnahan, 2023). However, our results are consistent with Goldfarb et al. (2023) who use data on skill requirements in jobs and confirm that ML is likely to be a GPT.

Third, we are restricted to patents filed at the USPTO. While US patents can serve as a good proxy of the global technological frontier, this may not be universally true for AI. AI specialisation strategies are heterogeneous across countries, including China and the EU (Fujii and Managi, 2018; Jacobides et al., 2021; Rikap, 2024). Foreign, and especially Chinese, inventors are not excluded from filing patents in the US, but they may face barriers and/or have reduced incentives compared to filing domestic patents. Also, examination practices at patent offices in different jurisdictions are heterogeneous, which can affect patent citations or co-classifications (Jaffe and De Rassenfosse, 2017).

Fourth, the performance of the different approaches to capture the GPTness of AI may be specific for the time period (1990-2019), while the future of AI may be influenced by the decisions made today (Bresnahan, 2023; Goldfarb et al., 2023). Human-selected inputs like keywords, technology codes, or definitions of AI-science may also be chosen differently in the future (Schumpeter, 2005). The high GPTness of the Keyword and WIPO approaches could reflect the recent popularity of a narrow set of technology buzzwords (especially ML), but our results may differ when applied to other time periods in the future. This limitation can be related to the discussion on “AI narrowing” Klinger et al., 2020, suggesting that AI research became significantly less diverse in recent time, concentrated in a small group of private firms and focused on a narrow set of ML techniques.

Our analysis is restricted to GPTness and concentration as evaluation criteria relevant for AI policy, while being silent about other objectives such as safety, societal impact, and privacy (Roche et al., 2023; Krafft et al., 2020). Attempts to empirically assess the impact of policy on the evolution of AI should rely on a variety of methods for identifying AI and evaluation criteria, that are aligned with the goals set by policy.

Ultimately, our results suggest that the extent to which AI can be seen as a GPT, as well as its future scale and scope, is sensitive to the chosen classification method. This underscores the importance of balancing multiple classification techniques when considering how political and economic measures could affect AI’s projected future impact.

7. Conclusions

We performed a systematic analysis of four separate approaches to identifying patented AI inventions that are distinct and only partially overlapping. We demonstrated that quantitative and qualitative assessments of AI are sensitive to the classification method. We also investigated patterns of concentration in AI innovations. Our results indicate
qualitative overlaps in various dimensions, which are strong compared to benchmark
technologies. This suggests the existence of a common understanding of AI, yet the
devil is in the details.

Our analysis provides guidance to policy makers and innovation scholars on how to
identify patented AI inventions. For example, researchers interested in studying the
GPT-like characteristics of AI, a simple keyword-based approach produces a narrowly
defined set of patented technologies that demonstrate the canonical GPT features of
intrinsic growth, wide usefulness, and complementarity.

Altogether, our results (1) provide robust support for conceptualising AI (or more
narrowly ML) as having GPT characteristics, (2) illustrate the utility of tracking AI
inventions using patent data, and (3) underscore the need to use multiple AI classifica-
tion techniques to counteract the dependence of conclusions on methodological choices,
especially when it comes to market concentration.
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A. Measuring GPTs

Currently, there exists a number of alternative metrics to capture GPT characteristics. Given the lack of consensus, many believe GPTs should be better identified as sophisticated networks of technologies sharing “underlying principles and mutual dependencies” (Petralia, 2020).

Historically, patent growth rates have been used to capture the endogenous elaboration of technologies similar to GPTs (Moser and Nicholas, 2004; Jovanovic and Rousseau, 2005; Petralia, 2020). Petralia (2020) uses patent growth rates, co-classifications, and a text-mining algorithm to successfully reproduce the canonical GPTs contained within the broad USPTO categories of electricity and computer communication. However, the author finds great heterogeneity within these pools of patents, which contain both dynamic and stagnant inventions. Moreover, the author notes that the identification of more diffuse and diverse GPTs, such as AI, may require “bottom-up” classification approaches using lower levels of aggregation that can scan multiple technological classes for common principles.

Hall and Trajtenberg (2006) attempt to capture GPTs by measuring the patent growth rates and unbiased generality measures for the most-cited US patents and the patents which cite them. The authors also find great heterogeneity between patents, which underscores the need for multiple metrics to satisfactorily capture GPTs.

In the next section, we motivate our selection of patent measures for GPT characteristics and connect each with empirical facts about AI’s dissemination and the three canonical GPT features.

A.1. Growth

For more than a decade, AI methods have become more powerful and complex as a result of new technical methods, increased data availability, and improved hardware. Consequently, AI invention has shifted away from specific application-based methods to more generalised learning-orientated systems (Cockburn et al., 2019). With this refinement, the performance of many sub-fields of AI, such as image and text recognition, have seen remarkable improvements in performance (Brynjolfsson et al., 2021). This is reflected in the exponential growth of patenting activity referencing terms such as ML and deep learning (see Appendix, Figure C.2).

Based on these observations, we measure improvements in AI via the growth rates of each group of patents and changes to their share of all patents, from 1990 to 2020 (Hall and Trajtenberg, 2006; Petralia, 2020). We also look at the growth of the patents that cite such technologies: the “GPT hypothesis” in previous work has been that inventions that build on GPT-like technologies should spawn more new inventions (Hall and Trajtenberg, 2006).

Let $N_{i,t}$ denote the number of patents in a group $i \in \{\text{keyword, science, WIPO, USPTO}\}$ at time $t$, indexed by year. We compute the growth rate as
\[ \frac{N_{i,t} - N_{i,t-1}}{N_{i,t-1}}. \]  

(A.0)

**A.2. Generality**

AI has already begun to pervade a myriad of industries as it expands beyond computer science into such diverse fields as structural biology, transport, and imaging (Cockburn et al., 2019). In the early 1990s, AI methods remained largely confined to computer science. However, over the past decade, the majority of patents referencing these technologies have appeared in secondary domains (Cockburn et al., 2019). Based on the work of Trajtenberg et al. (1997), we capture this stylised fact through the ‘generality’ of patents, measuring the dissemination of AI across different technology fields.

To do so, we build on patent citation data and assume that a forward citation link entails information about the use of a patent in a subsequent invention (Jaffe and De Rassenfosse, 2017). To operationalise wide usefulness, we rely on a modified version of the generality metric by Trajtenberg et al. (1997) and Hall and Trajtenberg (2006) given by

\[ 1 - \sum_{j} \left( \frac{\#cites_{ij,t}}{\sum_{j=1}^{N_{j}} \#cites_{ij,t}} \right)^{2} \]  

(A.0)

where \( \#cites_{ij} \) is the sum of citations to patents labelled as AI by classification approach \( i \) from technology class \( j \), whereby we use the CPC 1-digit level as class. The number of citations \( \#cites_{ij} \) excludes citations within the same class: \( N_{j} \) is the number of different CPC classes. Our approach differs to that of Trajtenberg et al. (1997) as we apply the method to each group of AI patents belonging to a variety of CPC sections. For the main analysis, we focus on 1-digit CPC sections, as these are more technologically distant than 3-digit or 4-digit classes and subclasses, whose results we also report.

Our generality measure is calculated for the entire group of patents in \( i \) with \( N_{i} \) unique patents. To address concerns that this metric may be affected by differences between group sizes, we additionally calculate patent-level metrics given by the average number of citing classes, i.e.

\[ \frac{1}{N_{i,t}} \sum_{p=1}^{N_{i,t}} \sum_{j=1}^{N_{d}} \mathbb{1}(\#cites_{p,j,t} \geq 0) \]  

(A.0)

where \( \mathbb{1}(\#cites_{p,j,t} \geq 0) = 1 \) if patent \( p \) in \( i \) is cited by at least one patent in technology class \( j \) out of the total number of classes \( N_{d} \) at level with \( d \subset \{1, 3, 4\} \) s in the code. \( N_{i} \) is the number of patents in approach \( i \). Again, we exclude within-class citations and present results at both the 1-digit CPC section level (\( d = 1 \)) and higher orders of disaggregation (\( d = 3 \) or \( d = 4 \)).
A.3. Complementarity

Thirdly, GPTs augment existing products and processes in a range of novel contexts to generate productive complementarities throughout the economy (Bresnahan and Trajtenberg, 1995; Petralia, 2020). AI technologies have been shown to complement and rely on secondary inventions, related to areas such as cloud computing and big data, which increase access to larger and more affordable data-sets (Brynjolfsson et al., 2019). Furthermore, because diverse AI systems share similar underlying structures and can share information, advances in one application of ML, such as machine vision, can spur inventions in other fields, such as autonomous vehicles.

Following the approach of Petralia (2020), we measure the extent to which AI patents enhance and supplement other inventions through the diversity of their technology class co-occurrences. For our analysis, we calculate the share of 3- and 4-digit CPC codes \( d = 3, 4 \) assigned to the patents in each group of AI patents. Specifically, we calculate the following *diversity measure* over time is

\[
\frac{\#CPC_{s_i,d,t}}{N_d}
\]

where \( i \) denotes each of the four patent classification approaches, \( d \) is the classification level and \( t \) is year. \( N_d \) refers to the number of CPC codes found in use for a particular group of patents, where the codes include \( d \) digits. Note that there are 136 and 674 CPC codes, respectively at the 3- and 4-digit level (according to the February 2022 version of CPC codes).

As the above measure could be biased by patent volume, we also calculate the average number of distinct 1-, 3-, and 4-digit CPC codes per patent per year. The *diversity per patent* over time is

\[
\frac{1}{N_{i,t}} \sum_p \#CPC_{s_p,i,d,t}
\]

where \( d \) represent the technology class represented by 1-, 3-, or 4-digit CPC codes. The time series graphs for the latter measures depict how an average patent’s complementarity across technology sections evolves over time.

B. Measuring AI

In our analysis, we compare four methodologically and conceptually distinct approaches to identifying AI inventions in patents based on (1) keyword search, (2) science citations, (3) the WIPO, and the (4) USPTO method. Here, we introduce these classification approaches in detail.
B.1. Data source

We apply our methods to all patents granted by the USPTO from 1990-2019. For the analysis, we create four groups of AI patents for each classification method and complement each with supplementary information.

From PATSTAT (Spring 2021 edition, EPO (2021)) we sourced patent grant dates and from the USPTO we downloaded the Master classification file (April 2021 version) which contains CPC classifications of patents.\(^9\) We added further data on patent-to-patent citations and patent titles from GooglePats obtained in an earlier project (Hötte et al., 2021). For our analysis, we supplemented the citation data with citation year and the technology classes of both the citing and cited patent. In doing so, we obtained networks which represent citations from technology fields at different levels of aggregation to our four sets of AI patents. We also made use of the Reliance on Science database (Marx and Fuegi, 2020) for citation data between patents and science.

B.2. Keyword search

Our first classification technique is a straight-forward approach based on keyword search, in which researchers use their discretion to develop a set of terms that reflect the very recent developments in AI. In this paper, we use the set of keywords provided in the appendix of Cockburn et al., 2018.\(^10\) The keywords used in this paper focus on three sub-fields of AI: symbolic systems, learning algorithms, and robotics (see Table C.1 for the full list of keywords). According to the authors, the symbolic systems represent “complex concepts through logical manipulation of symbolic representations” and include “natural language processing” and “pattern recognition.” Learning algorithms include core analytic techniques such as neural networks, deep learning, and ML. The last category, robotics, is related to automation or applications of AI (e.g. computer vision and sensory networks).

We search for these keywords in patent titles, abstracts, claims, and descriptions using USPTO data. We match the resulting list with patents granted by the USPTO between 1990 and 2019. The main advantage of the keyword approach is its simplicity and ease of implementation. Moreover, carefully chosen keywords can capture recent changes in the AI field. However, the success of this approach depends on the judgement and familiarity of the researcher to the field of AI. Missing important keywords could lead to under-representation of a sub-field. Our approach yields 67,187 patents.

\(^9\)https://bulkdata.uspto.gov/data/patent/classification/cpc/

\(^10\)While we use the keywords from Cockburn et al., 2018, we do not fully replicate their approach. They use two subsets of patents: (1) patents classified by the USPC code 706 (Artificial Intelligence) and 901 (Robots); and (2) patents identified by searching titles for the selected keywords. Here we use patents identified by keyword search only, but we extend our search to match keywords also from abstract, claims, and description. We do not use the USPC classification codes since the WIPO method takes a more comprehensive approach combining keywords with IPC or CPC classifications. Also, with our extensive keyword search, we miss only a few patents which are in the first group (i.e., USPC 706 and 901) but not in the second group of Cockburn et al., 2018.
B.3. Science citations

This classification approach harnesses the scientific basis of patents. In particular, we classify a patent as an AI patent if it makes at least one citation to a scientific paper in the scientific field of “Computer Science; Artificial Intelligence” (short, AI paper) as categorised by the Web of Science (WoS). Scientific citations are added to patent documents for multiple reasons such as describing the technological content of the invention or distinguishing the legal claim from other publicly available knowledge (see Narin et al., 1995; Meyer, 2000; Tijssen, 2001; Ahmadpoor and Jones, 2017; Marx and Fuegi, 2019). A citation link to an AI paper indicates that the patent is technologically related to AI because it builds on scientific advancements in this field. A limitation of this approach is that it only identifies AI patents within the subset of patents that make citations to science.

For this method, we use data from the Reliance on Science (RoS) database (Marx and Fuegi, 2019; Marx and Fuegi, 2020; Marx and Fuegi, 2021) which comprises a mapping from patents to scientific articles indexed in Microsoft Academic Graph (MAG) (Sinha et al., 2015). Scientific articles are tagged by the WoS fields indicating the field of science into which an article is grouped.\footnote{Note that this assignment was made at the paper level using a probabilistic mapping which is different from the journal-based categorisation of Clarivate Analytics (Web of Science).}

The citation links in the RoS database cover citations made by both the patent applicant and examiner, as well as citations indicated at both the front page and body of the patent document. Marx and Fuegi (2019) identified citations through a sequential probabilistic text recognition technique. Each citation link is tagged with a confidence score indicating the reliability of the matching approach. In the RoS data, roughly one third (34\%) of all US patents granted in 2019 can be attributed with at least one citation to science.

In our study, we identified AI papers by their WoS categories and extracted all patents with at least one citation link to an AI paper. We kept only citation links with a reliability score greater than three, which corresponds to a precision rate of 99.5\% and a recall of 93\%. This approach yields 178,004 AI patents.

B.4. World Intellectual Property Organisation (WIPO) Method

The WIPO methodology for classifying AI patents was published in 2019 and validated by a team of patent experts (WIPO, 2019a; WIPO, 2019b). The aim behind the methodology is to capture three aspects of AI invention: (1) core AI techniques (deep learning, other learning methods, various type of logic, clustering, etc.); (2) functional applications of AI that can be used to simulate human-like cognitive capacities (such as vision, language, or decision-making); and (3) end-user application fields (such as automation in business, health, or military).

This methodology is based on both a keyword search of patent texts and the use of patent classification codes (CPC and IPC). In this technique, some patents are classified
based on only a subset of the technological codes, or keywords, whilst others are identified by a combination of both.

The list of keywords used in this approach covers core AI methods as well as computing and mathematical concepts used in such technologies. These keywords are matched to the text in the patent titles, abstracts, and claims.

This approach identifies 158,652 patents.

B.5. United States Patent and Trademark Office (USPTO) Classification

The USPTO approach uses a supervised ML classifier to identify AI patents (see Giczy et al., 2021). This ML model is trained to classify eight components of AI technologies, namely: machine learning, evolutionary computation, natural language processing, speech, vision, knowledge processing, planning/control, and AI hardware. The ML model is trained on the abstracts and claims of a seed (positive set) and an anti-seed (negative set). The seeds are chosen carefully for each respective component by taking an intersection of CPC, IPC, and USPC codes, as well as Derwent’s World Patents Index™. The seeds are expanded based on patent families, CPC codes, and citations to identify all patents linked to the seed set. The anti-seed set is selected randomly from all remaining patents. For training, each text is pre-processed and embedded via the Word2Vec algorithm. The ML models also encode backward and forward citations in a citation vector. The predictions from the ML model are further validated using a small subset of patents that are manually examined.

Published in August 2021, the resulting dataset contains 13.2 million USPTO patents and pre-grant publications issued or published between 1976 and 2020. For consistency with our other approaches, we only consider patents granted between 1990 and 2019 and exclude pre-grant publications. The remaining data yields 595,047 patents.
C. Keywords in detail

C.1. Words used in the Keyword approach

| Symbols                                | Learning                          | Robotics                     |
|----------------------------------------|-----------------------------------|------------------------------|
| natural language processing            | machine learning                  | computer vision              |
| image grammars                         | neural networks                   | robot                        |
| pattern recognition                    | reinforcement learning            | robots                       |
| image matching                         | logic theorist                    | robot systems                |
| symbolic reasoning                     | bayesian belief networks          | robotics                     |
| symbolic error analysis                | unsupervised learning             | robotic                      |
| pattern analysis                       | deep learning                     | collaborative systems        |
| symbol processing                      | knowledge representation and      | humanoid robotics            |
|                                        | reasoning                          |                              |
| physical symbol system                 | crowdsourcing and human            | sensor network               |
|                                        | computation                        |                              |
| natural languages                      | neuromorphic computing            | sensor networks              |
| pattern analysis                       | decision making                   | sensor data fusion           |
| image alignment                        | machine intelligence              | systems and control theory   |
| optimal search                         | neural network                    | layered control systems      |
| symbolic reasoning                     |                                   |                              |
| symbolic error analysis                |                                   |                              |

C.2. AI keywords in patent texts

We split all the patent texts into three time periods (1990-1999, 2000-2009, 2010-2019) and search through the texts for keywords. Then, in each period (and for each category) we count the unique number of matching documents and what percentages of the AI patents match according to this keyword. Figures C.1, C.2, and C.3 below illustrate both counts and shares.
Figure C.1: Symbolic keywords: in full texts

| Keyword                              | 1990-1999 | 2000-2009 | 2010-2019 |
|--------------------------------------|-----------|-----------|-----------|
| pattern recognition                  | 3920      | 8458      | 24841     |
| pattern analysis                     | 583       | 1816      | 5830      |
| natural language processing          | 195       | 924       | 8856      |
| image alignment                      | 195       | 543       | 2045      |
| image matching                       | 192       | 617       | 3409      |
| natural languages                    | 151       | 283       | 1087      |
| symbol processing                    | 38        | 179       | 430       |
| optimal search                       | 38        | 168       | 399       |
| symbolic reasoning                   | 17        | 9         | 47        |
| image grammars                       | 2         | 7         | 5         |
| symbolic error analysis              | 0         | 0         | 0         |
| physical symbol system               | 0         | 0         | 0         |

| Keyword                              | 1990-1999 | 2000-2009 | 2010-2019 |
|--------------------------------------|-----------|-----------|-----------|
| pattern recognition                  | 74        | 65        | 53        |
| pattern analysis                     | 11        | 14        | 12        |
| natural language processing          | 3.7       | 7.1       | 19        |
| image alignment                      | 3.7       | 4.2       | 4.4       |
| image matching                       | 3.6       | 4.7       | 7.3       |
| natural languages                    | 2.8       | 2.2       | 2.3       |
| symbol processing                    | 0.71      | 1.4       | 0.92      |
| optimal search                       | 0.71      | 1.3       | 0.85      |
| symbolic reasoning                   | 0.32      | 0.07      | 0.1       |
| image grammars                       | 0.04      | 0.05      | 0.01      |
| symbolic error analysis              | 0         | 0         | 0         |
| physical symbol system               | 0         | 0         | 0         |

AI keywords: Full text counts

AI keywords: Full text percentages per time period
Figure C.2: Learning keywords: in full Texts

| AI keywords: Full text counts          | 1990-1999 | 2000-2009 | 2010-2019 |
|---------------------------------------|-----------|-----------|-----------|
| neural network                        | 3244      | 6358      | 21309     |
| neural networks                       | 2335      | 4946      | 19307     |
| decision making                       | 917       | 3157      | 10915     |
| machine intelligence                  | 345       | 1195      | 4108      |
| machine learning                      | 193       | 1558      | 32531     |
| unsupervised learning                 | 97        | 344       | 3059      |
| knowledge representation and reasoning| 49        | 26        | 192       |
| reinforcement learning                 | 27        | 130       | 1777      |
| bayesian belief networks               | 1         | 216       | 1384      |
| deep learning                         | 0         | 5         | 3221      |
| neuromorphic computing                 | 0         | 0         | 147       |
| logic theorist                         | 0         | 0         | 0         |
| crowdsourcing and human computation    | 0         | 0         | 0         |

| AI keywords: Full text percentages per time period | 1990-1999 | 2000-2009 | 2010-2019 |
|---------------------------------------------------|-----------|-----------|-----------|
| neural network                                    | 45        | 35        | 22        |
| neural networks                                   | 32        | 28        | 20        |
| decision making                                   | 13        | 18        | 11        |
| machine intelligence                              | 4.8       | 6.7       | 4.2       |
| machine learning                                  | 2.7       | 8.7       | 33        |
| unsupervised learning                             | 1.4       | 1.9       | 3.1       |
| knowledge representation and reasoning            | 0.68      | 0.14      | 0.2       |
| reinforcement learning                            | 0.37      | 0.72      | 1.8       |
| bayesian belief networks                           | 0.01      | 1.2       | 1.4       |
| deep learning                                     | 0         | 0.03      | 3.3       |
| neuromorphic computing                             | 0         | 0         | 0.15      |
| logic theorist                                     | 0         | 0         | 0         |
| crowdsourcing and human computation                | 0         | 0         | 0         |
Figure C.3: Robotics keywords: in full Texts

| Keyword                           | 1990-1999 | 2000-2009 | 2010-2019 |
|----------------------------------|-----------|-----------|-----------|
| robot                            | 2361      | 8743      | 87581     |
| computer vision                  | 723       | 14467     |           |
| sensor network                   | 147       | 806       | 204       |
| sensor data fusion               | 34        | 44        | 246       |
| collaborative systems            | 17        | 44        | 204       |
| systems and control theory       | 2         | 0         | 18        |
| humanoid robotics                | 0         | 1         | 46        |
| layered control systems          | 0         | 0         | 3         |
| robots                           | 0         | 0         | 0         |
| robot systems                    | 0         | 0         | 0         |
| robotics                         | 0         | 0         | 0         |
| robotic                          | 0         | 0         | 0         |
| sensor networks                  | 0         | 0         | 0         |

| Keyword                           | 1990-1999 | 2000-2009 | 2010-2019 |
|----------------------------------|-----------|-----------|-----------|
| robot                            | 95        | 91        | 79        |
| computer vision                  | 4.2       | 6.7       | 13        |
| sensor network                   | 0.85      | 2.3       | 7.8       |
| sensor data fusion               | 0.2       | 0.18      | 0.22      |
| collaborative systems            | 0.1       | 0.13      | 0.18      |
| systems and control theory       | 0.01      | 0         | 0.02      |
| humanoid robotics                | 0         | 0         | 0.04      |
| robots                           | 0         | 0         | 0         |
| robot systems                    | 0         | 0         | 0         |
| robotics                         | 0         | 0         | 0         |
| robotic                          | 0         | 0         | 0         |
| sensor networks                  | 0         | 0         | 0         |
| layered control systems          | 0         | 0         | 0         |
D. Additional results

D.1. Comparison to benchmarks

The following figures reproduce time series of growth rates, counts, and shares for additional groups of patents. The benchmarks were identified in previous discussions of GPT technologies in the literature (nanotechnology, biochemistry, green technologies, computing). Climate patents were also included as a group of technologies where one can expect wide diversity, as climate inventions can be expected to cover many sectors of the economy.

D.1.1. Growth

Figure D.4: Growth Rates of Benchmark Patents by Year

![Graphs showing growth rates for different groups of patents over the years.]

(a) All  (b) G06  (c) H04W
(d) C12  (e) B82  (f) Y02

Note: “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.
D.1.2. Generality

Table D.2: Average Generality Index (1990-2019): Benchmark Categories

|        | All | G06 | H04W | C12 | B82 | Y02 |
|--------|-----|-----|------|-----|-----|-----|
| 1 digit| 0.82| 0.62| 0.62 | 0.74| 0.79| 0.85|
| 3 digit| 0.95| 0.82| 0.82 | 0.85| 0.92| 0.95|
| 4 digit| 0.82| 0.62| 0.62 | 0.74| 0.79| 0.85|

Notes: The generality index is defined as share of citations to patents in different CPC classes at different aggregation levels (see A.2). Citations within the same class are excluded. “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.

Figure D.5: Generality Index at the 1-digit CPC-section Level

(a) AI citing patents  
(b) Benchmark

Table D.3: Average CPC Classes Making Citations: Benchmark Categories

|        | All | G06 | H04W | C12 | B82 | Y02 |
|--------|-----|-----|------|-----|-----|-----|
| 1 digit| 1.27| 1.00| 0.68 | 1.46| 2.36| 1.99|
| 3 digit| 2.48| 1.99| 1.19 | 2.52| 4.39| 3.32|
| 4 digit| 3.97| 3.31| 2.80 | 4.18| 6.42| 5.10|

Notes: The table shows number of different CPC classes making a citation to an average patent of the respective group. Citations within the same class are excluded. “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.
Figure D.6: Average Number of CPC Classes Citing AI

(a) AI citing patents

(b) Benchmark

Note: “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.

Table D.4: Average Number of Citing CPC Classes – Cited Patents

|          | All | G06 | H04W | C12 | B82 | Y02 |
|----------|-----|-----|------|-----|-----|-----|
| 1 digit  | 2.39| 2.03| 2.00 | 2.78| 3.35| 3.29|
| 3 digit  | 4.28| 3.78| 3.35 | 4.60| 6.22| 5.48|
| 4 digit  | 6.44| 5.96| 5.63 | 7.47| 9.08| 8.42|

Notes: The table reports numbers of different CPC classes making a citation to an average patent of the respective group that receives at least one citation. Citations within the same class are excluded. “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.

Figure D.7: Average Number of CPC Classes Citing AI: Subset of Cited Patents

(a) AI citing patents

(b) Benchmark

Note: “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.

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Table D.5: Average Citation Lags by Patents in Benchmark Categories

| Period    | All   | G06   | H04W  | C12   | B82   | Y02   |
|-----------|-------|-------|-------|-------|-------|-------|
| 1990-1999 | 13.57 | 12.78 | 12.47 | 14.58 | 12.14 | 13.49 |
| 2000-2009 | 9.19  | 9.00  | 8.75  | 10.15 | 8.58  | 8.92  |
| 2010-2019 | 4.29  | 4.19  | 3.83  | 4.29  | 4.33  | 4.08  |

Notes: This table shows the average number of years it takes until a patent in the sample is cited. The average number of years is lower during the more recent decade as the maximal time lag is truncated since our data ends in 2019. “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.

D.1.3. Complementarity

Figure D.8: Share of technology classes: diversity of benchmark categories

(a) % of all 3-digit CPC
(b) % of all 4-digit CPC

Note: Panel (a) shows the percentage of 3-digit CPC codes and panel (b) shows the percentage of 4-digit CPC as a share of all codes in the respective category. Note that the total number of 3-digit and 4-digit CPC codes are 136 and 674, respectively. “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.

Table D.6: Yearly Average Number of 3- and 4-digits CPC Codes per Patent

|          | All | G06 | H04W | C12 | B82 | Y02 |
|----------|-----|-----|------|-----|-----|-----|
| 1 digit  | 1.36| 1.36| 1.32 | 1.80| 2.48| 2.47|
| 3 digit  | 1.54| 1.62| 1.43 | 2.32| 3.03| 2.85|
| 4 digit  | 1.80| 1.81| 2.26 | 2.93| 3.50| 3.39|

Notes: The table shows the average of annual average number of technology classes by 1-, 3- or 4-digit CPC per patent. “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate invention-related patents, respectively.
Figure D.9: Average Technology Classes: Patent-Level Diversity of Benchmark Categories

(a) Average Number of 1-digit CPC

(b) Average Number of 3-digit CPC

(c) Average Number of 4-digit CPC

Note: “All” refers to all patents, G06, H04W, B82, C12, and Y02 refers to computing, wireless communications, biochemistry/genetic engineering, nanotechnology, and climate-related patents, respectively.
D.2. Significance tests

Here, we provide the results of a series of pair-wise Wilcoxon signed rank tests showing whether the differences between the means reported in Table 2, D.40, D.41, D.39, D.42 are significant.

D.2.1. Growth

Table D.7: Growth Rates

| period   | pair | Keyword | Science | WIPO | USPTO | All  | G06   | H04W  | C12  | B82  |
|----------|------|---------|---------|------|-------|------|-------|-------|------|------|
| 1990-2019| Science | 1.00   | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-2019| WIPO  | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-2019| USPTO | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-2019| All   | 0.02    | 0.00    | 0.00 | 0.00  | 1.00 | 1.00  | 1.00  | 1.00 | 0.00 |
| 1990-2019| G06   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 0.86  | 0.04 | 1.00 |
| 1990-2019| H04W  | 0.27    | 0.62    | 0.74 | 0.17  | 0.00 | 0.00  | 0.04  | 0.04 | 0.04 |
| 1990-2019| C12   | 1.00    | 0.08    | 0.40 | 0.76  | 1.00 | 0.75  | 0.01  | 0.01 | 0.01 |
| 1990-2019| B82   | 1.00    | 0.29    | 1.00 | 0.69  | 1.00 | 0.86  | 0.04  | 1.00 | 1.00 |
| 1990-2019| Y02   | 1.00    | 0.60    | 0.32 | 0.67  | 0.03 | 0.86  | 0.00  | 1.00 | 1.00 |
| 1990-1999| Science | 0.18   |         |      |       |      |       |       |      |      |
| 1990-1999| WIPO  | 1.00    | 0.85    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-1999| USPTO | 0.62    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-1999| All   | 1.00    | 0.45    | 1.00 | 1.00  | 1.00 | 0.45  | 0.45  | 0.45 | 0.45 |
| 1990-1999| G06   | 0.32    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-1999| H04W  | 0.45    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-1999| C12   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-1999| B82   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 1990-1999| Y02   | 1.00    | 0.32    | 1.00 | 0.32  | 1.00 | 0.32  | 1.00  | 0.32 | 1.00 |
| 2000-2009| Science | 1.00   |         |      |       |      |       |       |      |      |
| 2000-2009| WIPO  | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| USPTO | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| All   | 1.00    | 0.43    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| G06   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| H04W  | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| C12   | 1.00    | 0.43    | 1.00 | 0.78  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| B82   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2000-2009| Y02   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2010-2019| Science | 0.55   |         |      |       |      |       |       |      |      |
| 2010-2019| WIPO  | 1.00    | 0.71    | 1.00 | 0.85  | 1.00 | 0.85  | 1.00  | 0.85 | 1.00 |
| 2010-2019| USPTO | 1.00    | 1.00    | 0.85 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2010-2019| All   | 0.09    | 0.71    | 0.09 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2010-2019| G06   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2010-2019| H04W  | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2010-2019| C12   | 0.55    | 1.00    | 0.30 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |
| 2010-2019| B82   | 0.09    | 0.09    | 0.09 | 0.09  | 0.09 | 0.09  | 0.09  | 0.09 | 0.09 |
| 2010-2019| Y02   | 1.00    | 1.00    | 1.00 | 1.00  | 1.00 | 1.00  | 1.00  | 1.00 | 1.00 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
### Table D.8: Summary Statistics for Growth Rates

| Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | BS2 | Y02 |
|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 0.12 | 0.15 | 0.14 | 0.13 | 0.05 | 0.13 | 0.21 | 0.08 | 0.08 |
| Median 1990-2019 | 0.00 | 0.12 | 0.12 | 0.09 | 0.03 | 0.08 | 0.17 | 0.05 | 0.08 |
| St.dev. 1990-2019 | 0.15 | 0.17 | 0.16 | 0.16 | 0.10 | 0.15 | 0.20 | 0.15 | 0.16 |
| Mean 1990-1999 | 0.09 | 0.26 | 0.16 | 0.20 | 0.06 | 0.19 | 0.32 | 0.18 | 0.17 |
| Median 1990-1999 | 0.03 | 0.27 | 0.09 | 0.12 | 0.03 | 0.16 | 0.30 | 0.13 | 0.09 |
| St.dev. 1990-1999 | 0.14 | 0.17 | 0.17 | 0.19 | 0.10 | 0.18 | 0.23 | 0.17 | 0.14 |
| Mean 2000-2009 | 0.05 | 0.10 | 0.09 | 0.09 | 0.01 | 0.08 | 0.12 | -0.01 | 0.09 |
| Median 2000-2009 | 0.03 | 0.06 | 0.07 | 0.09 | 0.01 | 0.07 | 0.07 | -0.06 | 0.09 |
| St.dev. 2000-2009 | 0.08 | 0.12 | 0.19 | 0.15 | 0.09 | 0.15 | 0.21 | 0.14 | 0.13 |
| Mean 2010-2019 | 0.21 | 0.11 | 0.18 | 0.12 | 0.08 | 0.12 | 0.19 | 0.09 | -0.02 |
| Median 2010-2019 | 0.17 | 0.07 | 0.16 | 0.08 | 0.07 | 0.09 | 0.19 | 0.06 | -0.03 |
| St.dev. 2010-2019 | 0.16 | 0.13 | 0.09 | 0.15 | 0.10 | 0.12 | 0.09 | 0.16 | 0.12 |

### Table D.9: Growth Rates (Citing AI)

| period | pair | Keyword | Science | WIPO | USPTO | G06 | H04W | C12 | BS2 | Y02 |
|--------|------|---------|---------|------|-------|-----|------|-----|-----|-----|
| 1990-1999 | Science | 1.00 |
| 1990-1999 | WIPO | 1.00 | 1.00 |
| 1990-1999 | USPTO | 0.02 | 0.00 | 0.01 |
| 1990-1999 | G06 | 0.14 | 0.00 | 0.00 | 1.00 |
| 1990-1999 | H04W | 0.91 | 0.89 | 1.00 | 0.01 | 0.00 |
| 1990-1999 | C12 | 0.89 | 0.62 | 0.96 | 1.00 | 1.00 | 0.10 |
| 1990-1999 | BS2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 1990-1999 | Y02 | 0.07 | 0.12 | 0.96 | 1.00 | 1.00 | 0.05 | 1.00 | 1.00 |
| 1990-1999 | Y02 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

Notes: Table excludes those patents that themselves are AI by the respective classification approach. Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.10: Summary Statistics for Growth Rates (Citing AI)

| Period       | Keyword | Science | WIPO | USPTO | G06 | H04W | C12 | B82 | Y02 |
|--------------|---------|---------|------|-------|-----|------|-----|-----|-----|
| Mean 1990-2019 | 0.95   | 0.75   | 1.74 | 0.53  | 0.96 | 1.29 | 0.70 | 1.67 | 0.70 |
| Median 1990-2019 | 0.14   | 0.13   | 0.12 | 0.09  | 0.11 | 0.19 | 0.08 | 0.12 | 0.10 |
| St.dev. 1990-2019 | 4.80   | 2.56   | 8.61 | 1.71  | 4.08 | 5.34 | 2.58 | 7.77 | 2.65 |
| Mean 1990-1999   | 2.81   | 2.15   | 5.38 | 1.52  | 4.91 | 3.89 | 2.09 | 5.14 | 2.07 |
| Median 1990-1999 | 0.57   | 0.58   | 0.68 | 0.54  | 0.44 | 0.73 | 0.43 | 0.39 | 0.40 |
| St.dev. 1990-1999 | 6.69   | 4.43   | 14.24| 2.93  | 7.21 | 9.43 | 4.50 | 13.83| 4.63 |
| Mean 2000-2009   | 0.14   | 0.13   | 0.13 | 0.10  | 0.11 | 0.17 | 0.11 | 0.16 | 0.10 |
| Median 2000-2009 | 0.12   | 0.10   | 0.12 | 0.09  | 0.09 | 0.12 | 0.04 | 0.13 | 0.09 |
| St.dev. 2000-2009 | 0.17   | 0.16   | 0.16 | 0.13  | 0.13 | 0.19 | 0.22 | 0.17 | 0.15 |
| Mean 2010-2019   | 0.10   | 0.09   | 0.09 | 0.06  | 0.05 | 0.09 | 0.07 | 0.07 | 0.07 |
| Median 2010-2019 | 0.07   | 0.07   | 0.08 | 0.05  | 0.05 | 0.09 | 0.06 | 0.06 | 0.07 |
| St.dev. 2010-2019 | 0.13   | 0.13   | 0.14 | 0.10  | 0.10 | 0.13 | 0.15 | 0.13 | 0.10 |

Notes: Table excludes those patents that themselves are AI by the respective classification approach.

D.2.2. Generality

Table D.11: Generality Index at 1-Digit Level.

| Period       | 1-digit Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|--------------|-----------------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-2019    | 0.00            | 0.00   | 0.00 | 0.00  | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| 1990-1999    | 0.09            | 1.00   | 0.09 | 0.09  | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2000-2009    | 0.09            | 0.09   | 0.09 | 0.09  | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2010-2019    | 0.09            | 0.09   | 0.09 | 0.09  | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.12: Summary Statistics for Generality Index at 1-Digit Level.

| Period          | Keyword | Mean 1990-2019 | Median 1990-2019 | St.dev. 1990-2019 |
|-----------------|---------|----------------|------------------|-------------------|
|                 |         | 0.81           | 0.81             | 0.02              |
|                 |         | 0.77           | 0.77             | 0.02              |
|                 |         | 0.76           | 0.76             | 0.03              |
|                 |         | 0.73           | 0.73             | 0.03              |
|                 |         | 0.83           | 0.83             | 0.02              |
|                 |         | 0.7           | 0.7              | 0.02              |
|                 |         | 0.68           | 0.68             | 0.02              |
|                 |         | 0.78           | 0.78             | 0.01              |
|                 |         | 0.82           | 0.82             | 0.01              |
|                 |         | 0.81           | 0.81             | 0.01              |
|                 | Science | 0.81           | 0.81             | 0.02              |
|                 | WIPO    | 0.77           | 0.77             | 0.02              |
|                 | USPTO   | 0.76           | 0.76             | 0.03              |
|                 | All     | 0.73           | 0.73             | 0.03              |
|                 | G06     | 0.83           | 0.83             | 0.02              |
|                 | H04W    | 0.7           | 0.7              | 0.02              |
|                 | C12     | 0.68           | 0.68             | 0.01              |
|                 | B82     | 0.79           | 0.79             | 0.01              |
|                 | Y02     | 0.82           | 0.82             | 0.01              |

Table D.13: Generality Index at 3-Digit Level

| Period   | 3-digit Keyword | Mean 1990-2019 | Median 1990-2019 | St.dev. 1990-2019 |
|----------|-----------------|----------------|------------------|-------------------|
| 1990-2019| Science         | 0.00           | 0.00             | 0.00              |
|          | WIPO            | 0.00           | 0.74             | 0.00              |
|          | USPTO           | 0.00           | 0.00             | 0.00              |
|          | All             | 0.00           | 0.00             | 0.00              |
|          | G06             | 0.00           | 0.00             | 0.00              |
|          | H04W            | 0.00           | 0.00             | 0.00              |
|          | C12             | 0.00           | 0.00             | 0.00              |
|          | B82             | 0.00           | 0.00             | 0.00              |
|          | Y02             | 0.00           | 0.00             | 0.00              |
| 1990-1999| Science         | 0.00           | 0.09             | 0.09              |
|          | WIPO            | 0.00           | 0.39             | 0.39              |
|          | USPTO           | 0.00           | 0.29             | 0.29              |
|          | All             | 0.00           | 0.09             | 0.09              |
|          | G06             | 0.00           | 0.09             | 0.09              |
|          | H04W            | 0.00           | 0.09             | 0.09              |
|          | C12             | 0.00           | 0.09             | 0.09              |
|          | B82             | 0.00           | 0.09             | 0.09              |
|          | Y02             | 0.00           | 0.09             | 0.09              |
| 2000-2009| Science         | 0.00           | 0.00             | 0.00              |
|          | WIPO            | 0.00           | 1.00             | 1.00              |
|          | USPTO           | 0.00           | 0.09             | 0.09              |
|          | All             | 0.00           | 0.09             | 0.09              |
|          | G06             | 0.00           | 0.09             | 0.09              |
|          | H04W            | 0.00           | 0.09             | 0.09              |
|          | C12             | 0.00           | 0.09             | 0.09              |
|          | B82             | 0.00           | 0.09             | 0.09              |
|          | Y02             | 0.00           | 0.09             | 0.09              |
| 2010-2019| Science         | 0.00           | 0.00             | 0.00              |
|          | WIPO            | 0.00           | 1.00             | 1.00              |
|          | USPTO           | 0.00           | 0.09             | 0.09              |
|          | All             | 0.00           | 0.09             | 0.09              |
|          | G06             | 0.00           | 0.09             | 0.09              |
|          | H04W            | 0.00           | 0.21             | 0.21              |
|          | C12             | 0.00           | 0.09             | 0.09              |
|          | B82             | 0.74           | 0.67             | 0.67              |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.14: Summary Statistics for Generality Index at 3-Digit Level

| Period     | 4-digit | Keyword | Science | WIPO | USPTO | All  | G06 | H04W | C12 | B82 | Y02 |
|------------|---------|---------|---------|------|-------|------|-----|------|-----|-----|-----|
| Mean 1990-2019 | 0.94 | 0.9 | 0.9 | 0.87 | 0.95 | 0.86 | 0.87 | 0.88 | 0.93 | 0.94 |
| Median 1990-2019 | 0.94 | 0.9 | 0.9 | 0.87 | 0.95 | 0.86 | 0.86 | 0.88 | 0.93 | 0.94 |
| St.dev. 1990-2019 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.0 |
| Mean 1990-1999 | 0.94 | 0.91 | 0.91 | 0.89 | 0.96 | 0.87 | 0.88 | 0.88 | 0.93 | 0.94 |
| Median 1990-1999 | 0.94 | 0.91 | 0.92 | 0.9 | 0.96 | 0.88 | 0.88 | 0.93 | 0.94 | 0.94 |
| St.dev. 1990-1999 | 0 | 0.01 | 0.01 | 0.02 | 0 | 0.01 | 0.01 | 0 | 0 | 0 |
| Mean 2000-2009 | 0.94 | 0.89 | 0.89 | 0.86 | 0.85 | 0.85 | 0.86 | 0.88 | 0.88 | 0.94 |
| Median 2000-2009 | 0.94 | 0.89 | 0.89 | 0.86 | 0.85 | 0.85 | 0.88 | 0.88 | 0.93 | 0.94 |
| St.dev. 2000-2009 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mean 2010-2019 | 0.93 | 0.89 | 0.9 | 0.86 | 0.84 | 0.86 | 0.87 | 0.88 | 0.92 | 0.94 |
| Median 2010-2019 | 0.94 | 0.89 | 0.9 | 0.86 | 0.86 | 0.86 | 0.88 | 0.88 | 0.93 | 0.94 |
| St.dev. 2010-2019 | 0.02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.

Table D.15: Generality Index at 4-Digit Level

| Period     | 4-digit | Keyword | Science | WIPO | USPTO | All  | G06 | H04W | C12 | B82 | Y02 |
|------------|---------|---------|---------|------|-------|------|-----|------|-----|-----|-----|
| 1990-1999  | 0.00    | 0.00    | 0.00    | 0.00 | 0.00  | 0.00 | 0.00| 0.00 | 0.00| 0.00| 0.00 |
| 1990-2009  | 0.09    | 0.09    | 0.09    | 0.09 | 0.09  | 0.09 | 0.09| 0.09 | 0.09| 0.09| 0.09 |
| 2000-2009  | 0.09    | 0.09    | 0.09    | 0.09 | 0.09  | 0.09 | 0.09| 0.09 | 0.09| 0.09| 0.09 |
| 2010-2019  | 0.63    | 0.33    | 0.33    | 0.33 | 0.33  | 0.33 | 0.33| 0.33 | 0.33| 0.33| 0.33 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.16: Summary Statistics for Generality Index at 4-Digit Level.

|                  | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|------------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| **Mean 1990-2019** | 0.97    | 0.96    | 0.95 | 0.95  | 0.98| 0.94| 0.94 | 0.95| 0.97| 0.98|
| **Median 1990-2019** | 0.97    | 0.96    | 0.95 | 0.94  | 0.98| 0.94 | 0.94 | 0.95| 0.97| 0.99|
| **St.dev. 1990-2019** | 0.01   | 0      | 0.01 | 0.01  | 0.01| 0.01 | 0.01 | 0.01| 0    | 0   |
| **Mean 1990-1999** | 0.97    | 0.96    | 0.96 | 0.96  | 0.98| 0.94| 0.94 | 0.95| 0.97| 0.99|
| **Median 1990-1999** | 0.98    | 0.96    | 0.96 | 0.96  | 0.99| 0.94| 0.94 | 0.95| 0.97| 0.99|
| **St.dev. 1990-1999** | 0      | 0.01   | 0.01 | 0.01  | 0   | 0.01| 0.01 | 0   | 0   | 0   |
| **Mean 2000-2009** | 0.97    | 0.95    | 0.95 | 0.95  | 0.98| 0.94| 0.94 | 0.95| 0.97| 0.98|
| **Median 2000-2009** | 0.97    | 0.95    | 0.95 | 0.95  | 0.98| 0.94| 0.94 | 0.95| 0.97| 0.98|
| **St.dev. 2000-2009** | 0      | 0      | 0    | 0     | 0   | 0   | 0    | 0   | 0   | 0   |
| **Mean 2010-2019** | 0.97    | 0.96    | 0.95 | 0.95  | 0.98| 0.94| 0.94 | 0.95| 0.97| 0.98|
| **Median 2010-2019** | 0.97    | 0.96    | 0.96 | 0.95  | 0.98| 0.94| 0.94 | 0.95| 0.97| 0.98|
| **St.dev. 2010-2019** | 0      | 0.01   | 0.01 | 0.01  | 0   | 0.01| 0.01 | 0   | 0   | 0   |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.

Table D.17: Average Number of Citing Classes (All) at 1-Digit Level

| Period      | 1-digit Keyword | 1-digit Science | 1-digit WIPO | 1-digit USPTO | 1-digit All | 1-digit G06 | 1-digit H04W | 1-digit C12 | 1-digit B82 | 1-digit Y02 |
|-------------|-----------------|-----------------|--------------|---------------|-------------|-------------|--------------|-------------|-------------|-------------|
| **1990-2019** | 0.00            | 0.00            | 0.00         | 0.00          | 0.00        | 0.00        | 0.00         | 0.00        | 0.00        | 0.00        |
| **1990-1999** | 0.00            | 0.00            | 0.00         | 0.00          | 0.00        | 0.00        | 0.00         | 0.00        | 0.00        | 0.00        |
| **2000-2009** | 0.00            | 0.00            | 0.00         | 0.00          | 0.00        | 0.00        | 0.00         | 0.00        | 0.00        | 0.00        |
| **2010-2019** | 0.00            | 0.00            | 0.00         | 0.00          | 0.00        | 0.00        | 0.00         | 0.00        | 0.00        | 0.00        |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
### Table D.18: Summary Statistics for Average Number of Citing Classes (All) at 1-Digit Level

| Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 2.98 | 2.53 | 2.57 | 2.38 | 2.14 | 2.17 | 2.14 | 2.15 | 3.08 | 2.77 |
| Median 1990-2019 | 3.38 | 2.85 | 3.03 | 2.72 | 2.45 | 2.51 | 2.43 | 2.26 | 3.79 | 3.3 |
| St.dev. 1990-2019 | 1.24 | 1.1 | 1.15 | 1.17 | 1.06 | 1.03 | 1.06 | 1.08 | 1.5 | 1.24 |
| Mean 1990-1999 | 4.04 | 3.58 | 3.59 | 3.5 | 3.16 | 3.17 | 3.11 | 3.26 | 3.26 | 3.81 |
| Median 1990-1999 | 4.03 | 3.57 | 3.61 | 3.52 | 3.17 | 3.11 | 3.11 | 3.26 | 3.29 | 3.81 |
| St.dev. 1990-1999 | 0.12 | 0.09 | 0.08 | 0.08 | 0.04 | 0.04 | 0.15 | 0.1 | 0.09 | 0.07 |
| Mean 2000-2009 | 3.41 | 2.82 | 2.94 | 2.88 | 2.33 | 2.49 | 2.36 | 2.28 | 3.73 | 3.24 |
| Median 2000-2009 | 3.38 | 2.85 | 3.03 | 2.72 | 2.45 | 2.51 | 2.43 | 2.26 | 3.79 | 3.3 |
| St.dev. 2000-2009 | 0.52 | 0.42 | 0.55 | 0.54 | 0.44 | 0.46 | 0.36 | 0.43 | 0.6 | 0.38 |
| Mean 2010-2019 | 1.48 | 1.2 | 1.17 | 0.94 | 0.84 | 0.9 | 0.85 | 0.88 | 1.2 | 1.25 |
| Median 2010-2019 | 1.61 | 1.31 | 1.27 | 0.99 | 0.85 | 0.97 | 0.88 | 0.95 | 1.18 | 1.27 |
| St.dev. 2010-2019 | 0.86 | 0.65 | 0.64 | 0.57 | 0.58 | 0.55 | 0.54 | 0.58 | 0.89 | 0.89 |

### Table D.19: Average Number of Citing Classes (All) at 3-Digit Level

| Period | 3-digit Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|--------|-----------------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-2019 | Science | 0.00 | | | | | | | | |
| 1990-2019 | WIPO | 0.00 | 0.00 | | | | | | | |
| 1990-2019 | USPTO | 0.00 | 0.01 | 0.00 | | | | | | |
| 1990-2019 | All | 0.00 | 0.00 | 0.00 | 0.00 | | | | | |
| 1990-2019 | G06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | | | |
| 1990-2019 | H04W | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | | |
| 1990-2019 | C12 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | | |
| 1990-2019 | B82 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| 1990-2019 | Y02 | 0.00 | 0.02 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 1990-1999 | Science | 0.09 | | | | | | | | |
| 1990-1999 | WIPO | 0.09 | 0.96 | | | | | | | |
| 1990-1999 | USPTO | 0.09 | 1.00 | 0.25 | | | | | | |
| 1990-1999 | All | 0.09 | 0.09 | 0.09 | 0.09 | | | | | |
| 1990-1999 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | | | | |
| 1990-1999 | H04W | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.59 | | |
| 1990-1999 | C12 | 0.09 | 0.09 | 0.09 | 0.09 | 0.25 | 0.09 | 0.09 | | |
| 1990-1999 | B82 | 1.00 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 1990-1999 | Y02 | 0.09 | 1.00 | 1.00 | 1.00 | 0.09 | 0.09 | 0.10 | 0.09 | 0.09 |
| 2000-2009 | Science | 0.09 | | | | | | | | |
| 2000-2009 | WIPO | 0.09 | 0.09 | | | | | | | |
| 2000-2009 | USPTO | 0.09 | 0.25 | 0.09 | | | | | | |
| 2000-2009 | All | 0.09 | 0.09 | 0.09 | 0.09 | | | | | |
| 2000-2009 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | | | |
| 2000-2009 | H04W | 0.09 | 0.09 | 0.09 | 0.09 | 0.64 | 0.09 | | | |
| 2000-2009 | C12 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 2000-2009 | B82 | 0.15 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 2000-2009 | Y02 | 0.09 | 0.09 | 0.64 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2010-2019 | Science | 0.17 | | | | | | | | |
| 2010-2019 | WIPO | 0.10 | 1.00 | | | | | | | |
| 2010-2019 | USPTO | 0.09 | 0.09 | 0.09 | | | | | | |
| 2010-2019 | All | 0.09 | 0.09 | 0.09 | 0.09 | | | | | |
| 2010-2019 | G06 | 0.09 | 0.09 | 0.09 | 0.10 | 0.17 | | | | |
| 2010-2019 | H04W | 0.10 | 0.09 | 0.09 | 0.10 | 1.00 | 0.10 | | | |
| 2010-2019 | C12 | 0.09 | 0.09 | 0.09 | 0.10 | 1.00 | 0.10 | 1.00 | | |
| 2010-2019 | B82 | 0.09 | 1.00 | 1.00 | 0.58 | 0.11 | 0.49 | 0.38 | 0.10 | |
| 2010-2019 | Y02 | 0.09 | 1.00 | 1.00 | 0.38 | 0.09 | 0.38 | 0.17 | 0.09 | 0.41 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
### Table D.20: Summary Statistics for Average Number of Citing Classes (All) at 3-Digit Level

| Period       | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|--------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 6       | 4.82   | 5.07 | 4.57  | 3.59| 4   | 3.92 | 3.56| 5.88| 5.12|
| Median 1990-2019 | 6.73   | 5.31   | 5.92 | 4.95  | 4   | 4.41| 4.11 | 3.64| 7.29| 6.06|
| St.dev. 1990-2019 | 2.9    | 2.47   | 2.62 | 2.67  | 1.95| 2.22| 2.4  | 2   | 3.23| 2.59|
| Mean 1990-1999 | 8.65   | 7.37   | 7.56 | 7.36  | 5.4 | 6.24| 6.65 | 5.75| 8.54| 7.49|
| Median 1990-1999 | 8.58   | 7.27   | 7.54 | 7.44  | 5.57| 6.27| 6.78 | 5.74| 8.64| 7.57|
| St.dev. 1990-1999 | 0.4    | 0.44   | 0.26 | 0.24  | 0.1 | 0.14| 0.68 | 0.29| 0.39| 0.23|
| Mean 2000-2009 | 6.88   | 6.22   | 5.78 | 4.97  | 4.01| 4.44| 3.96 | 3.69| 7.29| 5.94|
| Median 2000-2009 | 6.73   | 5.31   | 5.92 | 4.95  | 4   | 4.41| 4.11 | 3.64| 7.29| 6.06|
| St.dev. 2000-2009 | 1.4    | 1.05   | 1.47 | 1.42  | 0.91| 1.19| 0.9  | 0.86| 1.74| 0.99|
| Mean 2010-2019 | 2.36   | 1.86   | 1.88 | 1.38  | 1.21| 1.32| 1.16 | 1.24| 1.82| 1.91|
| Median 2010-2019 | 2.6    | 1.96   | 2.01 | 1.41  | 1.19| 1.39| 1.18 | 1.3  | 1.69| 1.83|
| St.dev. 2010-2019 | 1.54   | 1.07   | 1.1  | 0.88  | 0.87| 0.83| 0.76 | 0.85| 1.44| 1.44|

### Table D.21: Average Number of Citing Classes (All) at 4-Digit Level

| Period       | 4-digit Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|--------------|-----------------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-2019    | Science         | 0.00    |      |       |     |     |      |     |     |     |
|              | WIPO            | 0.00    | 0.00 |       |     |     |      |     |     |     |
|              | USPTO           | 0.00    | 0.10 | 0.00  |     |     |      |     |     |     |
|              | All             | 0.00    | 0.00 | 0.00  | 0.00|     |      |     |     |     |
|              | G06             | 0.00    | 0.00 | 0.00  | 0.00|     |      |     |     |     |
|              | H04W            | 0.00    | 0.88 | 0.07  | 0.88| 0.00| 0.00  |     |     |     |
|              | C12             | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00|     |
|              | B82             | 0.21    | 0.05 | 0.42  | 0.00| 0.00| 0.00  | 0.03| 0.00| 0.00|
|              | Y02             | 0.00    | 0.88 | 0.01  | 0.44| 0.00| 0.00  | 0.03| 0.00| 0.02|
| 1990-1999    | Science         | 0.17    |      |       |     |     |      |     |     |     |
|              | WIPO            | 0.09    | 1.00 |       |     |     |      |     |     |     |
|              | USPTO           | 0.09    | 1.00 | 1.00  |     |     |      |     |     |     |
|              | All             | 0.09    | 0.09 | 0.09  | 0.09|     |      |     |     |     |
|              | G06             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  |     |     |     |
|              | H04W            | 1.00    | 0.17 | 1.00  | 0.45| 0.09| 0.09  |     |     |     |
|              | C12             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 1.00| 0.09|     |
|              | B82             | 1.00    | 0.71 | 1.00  | 0.38| 0.09| 0.09  | 1.00| 0.09|     |
|              | Y02             | 0.09    | 1.00 | 0.09  | 0.38| 0.09| 0.09  | 0.29| 0.09| 0.09|
| 2000-2009    | Science         | 0.09    |      |       |     |     |      |     |     |     |
|              | WIPO            | 0.09    | 0.09 |       |     |     |      |     |     |     |
|              | USPTO           | 0.09    | 0.64 | 0.09  |     |     |      |     |     |     |
|              | All             | 0.09    | 0.09 | 0.09  | 0.09|     |      |     |     |     |
|              | G06             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  |     |     |     |
|              | H04W            | 0.09    | 0.09 | 0.09  | 0.53| 0.09| 0.09  |     |     |     |
|              | C12             | 0.09    | 0.09 | 0.09  | 0.64| 0.09| 0.09  | 0.09| 0.09|     |
|              | B82             | 0.92    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09|     |
|              | Y02             | 0.09    | 0.09 | 0.64  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 2010-2019    | Science         | 0.16    |      |       |     |     |      |     |     |     |
|              | WIPO            | 0.09    | 0.19 |       |     |     |      |     |     |     |
|              | USPTO           | 0.09    | 0.09 | 0.09  |     |     |      |     |     |     |
|              | All             | 0.09    | 0.09 | 0.09  | 0.09|     |      |     |     |     |
|              | G06             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  |     |     |     |
|              | H04W            | 0.09    | 0.09 | 0.09  | 1.00| 0.09| 0.30  |     |     |     |
|              | C12             | 0.09    | 0.09 | 0.09  | 0.11| 0.74| 0.09  |     |     |     |
|              | B82             | 0.09    | 0.19 | 0.11  | 1.00| 0.16| 1.00  | 1.00| 0.19|     |
|              | Y02             | 0.09    | 1.00 | 1.00  | 0.33| 0.09| 0.33  | 0.30| 0.09| 0.09|

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.22: Summary Statistics for Average Number of Citing Classes (All) at 4-Digit Level

| Period          | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|-----------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019  | 9.26    | 7.82    | 8.42 | 7.5   | 5.26| 6.15| 7.62 | 5.72| 8.81| 7.87|
| Median 1990-2019| 10.62   | 8.63    | 9.9  | 8.04  | 5.84| 6.74| 7.93 | 5.66| 10.77| 9.37|
| St.dev. 1990-1999| 4.55    | 4.13    | 4.47 | 4.55  | 2.93| 3.51| 4.85 | 3.38| 5.16| 4.12|

| Period          | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|-----------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 2000-2009  | 10.78   | 8.48    | 9.72 | 8.15  | 5.87| 6.85| 7.64 | 5.78| 10.84| 9.21|
| Median 2000-2009| 10.62   | 8.63    | 9.9  | 8.04  | 5.84| 6.74| 7.93 | 5.66| 10.77| 9.37|
| St.dev. 2000-2009| 2.28    | 1.85    | 2.69 | 2.56  | 1.43| 1.99| 1.91 | 1.48| 3.07| 1.71|

| Period          | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|-----------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 2010-2019  | 3.68    | 2.88    | 2.98 | 2.09  | 1.7 | 1.93| 2.06 | 1.86| 2.39| 2.76|
| Median 2010-2019| 3.81    | 3.17    | 3.17 | 2.12  | 1.67| 2.04| 2.07 | 1.92| 2.18| 2.56|
| St.dev. 2010-2019| 2.4     | 1.7     | 1.88 | 1.37  | 1.24| 1.23| 1.39 | 1.5  | 1.93| 2.14|

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.

Table D.23: Average Number of Citing Classes (Cited) at 1-Digit Level

| Period          | 1-digit | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|-----------------|---------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-1999       | Science | 0.00    | WIPO    | 0.00 | 0.26  |
| 1990-1999       | USPTO   | 0.00    | 0.00    | 0.00 |
| 1990-1999       | All     | 0.00    | 0.00    | 0.00 | 0.42  |
| 1990-1999       | G06     | 0.00    | 0.00    | 0.00 | 0.00  |
| 1990-1999       | H04W    | 0.00    | 0.00    | 0.00 | 0.00  |
| 1990-1999       | C12     | 0.00    | 0.42    | 0.32 | 0.01  |
| 1990-1999       | B82     | 0.00    | 0.00    | 0.00 | 0.00  |
| 1990-1999       | Y02     | 0.42    | 0.00    | 0.00 | 0.00  |

| Period          | 1-digit | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|-----------------|---------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 2000-2009       | Science | 0.00    | WIPO    | 0.00 | 0.09  |
| 2000-2009       | USPTO   | 0.09    | 0.34    | 0.29 |
| 2000-2009       | All     | 0.09    | 0.09    | 0.09 | 0.09  |
| 2000-2009       | G06     | 0.09    | 0.09    | 0.09 | 0.09  |
| 2000-2009       | H04W    | 0.09    | 0.09    | 0.09 | 0.09  |
| 2000-2009       | C12     | 0.09    | 0.26    | 0.32 | 0.97  |
| 2000-2009       | B82     | 0.09    | 0.09    | 0.09 | 0.09  |
| 2000-2009       | Y02     | 0.09    | 0.09    | 0.09 | 0.09  |

| Period          | 1-digit | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|-----------------|---------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 2010-2019       | Science | 0.09    | WIPO    | 0.09 | 0.09  |
| 2010-2019       | USPTO   | 0.09    | 0.09    | 0.09 |
| 2010-2019       | All     | 0.09    | 0.09    | 0.55 | 0.09  |
| 2010-2019       | G06     | 0.09    | 0.09    | 0.09 | 0.53  |
| 2010-2019       | H04W    | 0.09    | 0.09    | 0.22 | 0.53  |
| 2010-2019       | C12     | 0.56    | 0.09    | 0.09 | 0.09  |
| 2010-2019       | B82     | 0.09    | 0.09    | 0.09 | 0.09  |
| 2010-2019       | Y02     | 0.09    | 0.09    | 0.09 | 0.09  |
Table D.24: Summary Statistics for Average Number of Citing Classes (Cited) at 1-Digit Level

| Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 3.44 | 2.99 | 2.96 | 2.83 | 2.81 | 2.67 | 2.53 | 3.05 | 3.74 |
| Median 1990-2019 | 3.67 | 3.17 | 3.19 | 2.96 | 2.92 | 2.79 | 2.54 | 3.07 | 4.05 |
| St.dev. 1990-2019 | 0.78 | 0.67 | 0.71 | 0.74 | 0.58 | 0.6 | 0.5 | 0.76 | 0.56 |
| Mean 1990-1999 | 4.14 | 3.66 | 3.66 | 3.63 | 3.44 | 3.24 | 3.28 | 3.6 | 4.4 |
| Median 1990-1999 | 4.12 | 3.66 | 3.65 | 3.44 | 3.03 | 0.14 | 0.08 | 0.09 | 0.07 |
| St.dev. 1990-1999 | 0.1 | 0.07 | 0.06 | 0.07 | 0.03 | 0.14 | 0.08 | 0.09 | 0.07 |
| Mean 2000-2009 | 3.08 | 3.14 | 3.12 | 2.94 | 2.91 | 2.78 | 2.49 | 3.09 | 4.04 |
| Median 2000-2009 | 3.07 | 3.17 | 3.19 | 2.96 | 2.92 | 2.79 | 2.54 | 3.07 | 4.05 |
| St.dev. 2000-2009 | 0.41 | 0.35 | 0.45 | 0.42 | 0.35 | 0.27 | 0.2 | 0.39 | 0.26 |
| Mean 2010-2019 | 2.5 | 2.16 | 2.11 | 1.95 | 2.08 | 1.97 | 1.86 | 2.48 | 2.78 |
| Median 2010-2019 | 2.56 | 2.16 | 2.12 | 1.94 | 2.06 | 1.97 | 1.83 | 2.52 | 2.73 |
| St.dev. 2010-2019 | 0.43 | 0.22 | 0.19 | 0.18 | 0.22 | 0.15 | 0.12 | 0.25 | 0.33 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.

Table D.25: Average Number of Citing Classes (Cited) at 3-Digit Level

| Period | 3-digit Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 |
|--------|----------------|--------|------|-------|-----|-----|------|-----|-----|
| 1990-1999 | Science | 0.09 | | | | | | | |
| 1990-1999 | WIPO | 0.09 | 1.00 | | | | | | |
| 1990-1999 | USPTO | 0.09 | 1.00 | 1.00 | | | | | |
| 1990-1999 | All | 0.09 | 0.09 | 0.09 | 0.09 | | | | |
| 1990-1999 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | | | |
| 1990-1999 | H04W | 0.09 | 0.09 | 0.09 | 0.09 | 0.15 | 1.00 | | |
| 1990-1999 | C12 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.84 | 0.95 | | |
| 1990-1999 | B82 | 1.00 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 1990-1999 | Y02 | 0.09 | 1.00 | 1.00 | 1.00 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2000-2009 | Science | 0.09 | | | | | | | |
| 2000-2009 | WIPO | 0.09 | 0.32 | | | | | | |
| 2000-2009 | USPTO | 0.09 | 0.10 | 0.09 | | | | | |
| 2000-2009 | All | 0.09 | 0.09 | 0.09 | 0.09 | | | | |
| 2000-2009 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 0.34 | | | |
| 2000-2009 | H04W | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 2000-2009 | C12 | 0.09 | 0.09 | 0.09 | 0.09 | 0.77 | 0.77 | 0.09 | | |
| 2000-2009 | B82 | 0.10 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 2000-2009 | Y02 | 0.09 | 0.09 | 0.34 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | | |
| 2010-2019 | Science | 0.15 | | | | | | | |
| 2010-2019 | WIPO | 0.11 | 1.00 | | | | | | |
| 2010-2019 | USPTO | 0.09 | 0.09 | 0.09 | 0.09 | | | | |
| 2010-2019 | All | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | |
| 2010-2019 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 1.00 | 0.15 | | | |
| 2010-2019 | H04W | 0.15 | 0.11 | 0.15 | 0.79 | 0.52 | 0.74 | | | |
| 2010-2019 | C12 | 0.15 | 0.18 | 0.15 | 0.09 | 0.09 | 0.09 | 0.11 | | |
| 2010-2019 | B82 | 1.00 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | | |
| 2010-2019 | Y02 | 1.00 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 1.00 | |
### Table D.26: Summary Statistics for Average Number of Citing Classes (Cited) at 3-Digit Level

| Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 6.76 | 6.54 | 5.71 | 5.27 | 4.57 | 4.76 | 4.47 | 4.9 | 6.85 | 6.1 |
| Median 1990-2019 | 7.3 | 5.91 | 6.23 | 5.37 | 4.78 | 4.89 | 4.29 | 4.96 | 7.79 | 6.56 |
| St.dev. 1990-2019 | 2.25 | 1.89 | 2 | 2.14 | 1.37 | 1.65 | 1.83 | 1.28 | 2.27 | 1.67 |
| Mean 1990-1999 | 8.86 | 7.55 | 7.69 | 7.6 | 6.01 | 6.51 | 6.69 | 6.29 | 8.67 | 7.76 |
| Median 1990-1999 | 8.82 | 7.43 | 7.67 | 7.65 | 6.04 | 6.52 | 6.81 | 6.24 | 8.76 | 7.82 |
| St.dev. 1990-1999 | 0.36 | 0.39 | 0.35 | 0.23 | 0.09 | 0.14 | 0.67 | 0.26 | 0.4 | 0.23 |

### Table D.27: Average Number of Citing Classes (Cited) at 4-Digit Level

| Period     | 4-digit | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|------------|---------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-1999  | Science | 0.00    |         |      |       |     |     |      |     |     |     |
| 1990-1999  | WIPO    | 0.00    | 0.00    |      |       |     |     |      |     |     |     |
| 1990-1999  | USPTO   | 0.00    | 0.04    | 0.00 |       |     |     |      |     |     |     |
| 1990-1999  | All     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00|      |     |     |     |
| 1990-1999  | G06     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  |      |     |     |
| 1990-1999  | H04W    | 0.00    | 0.37    | 0.06 | 0.90  | 0.00| 0.00| 0.00  | 0.00 |     |     |
| 1990-1999  | C12     | 0.00    | 0.00    | 0.00 | 0.07  | 0.00| 0.00| 0.00  | 0.01 | 0.19|     |
| 1990-1999  | B82     | 0.35    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00 | 0.00|     |
| 1990-1999  | Y02     | 0.00    | 0.00    | 0.83 | 0.04  | 0.00| 0.00| 0.00  | 0.16 | 0.00| 0.03|

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.28: Summary Statistics for Average Number of Citing Classes (Cited) at 4-Digit Level

| Period   | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | BS2 | Y02 |
|----------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 10.4     | 8.94    | 9.43 | 8.56  | 6.66 | 7.26| 8.56 | 7.75 | 10.12 | 9.29 |
| Median 1990-2019 | 11.53    | 9.61    | 10.42| 8.72  | 6.96 | 7.49| 8.29 | 7.7  | 11.51 | 10.14 |
| St.dev. 1990-2019 | 3.62     | 3.28    | 3.53 | 3.79  | 2.15 | 2.71| 3.89 | 2.38 | 3.93  | 2.87 |
| Mean 1990-1999 | 13.64    | 12.4    | 12.79| 12.66 | 8.89 | 10.1| 13.25| 10.42| 13.4  | 12.07 |
| Median 1990-1999 | 13.76    | 12.2    | 12.82| 12.78 | 8.94 | 10.09| 13.52| 10.41| 13.53 | 12.26 |
| St.dev. 1990-1999 | 0.54     | 0.61    | 0.42 | 0.28  | 0.21 | 0.17| 1.31 | 0.55 | 0.91  | 0.51 |

D.2.3. Complementarity

Table D.29: Share of CPC Classes at 3-Digit Level

| Period   | 3-digit | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | BS2 | Y02 |
|----------|---------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-2019 | Science | 0.29    |         |      |       |     |     |      |     |     |     |
| 1990-2019 | WIPO    | 0.15    | 0.29    |      |       |     |     |      |     |     |     |
| 1990-2019 | USPTO   | 0.00    | 0.00    | 0.00 |       |     |     |      |     |     |     |
| 1990-2019 | All     | 0.00    | 0.00    | 0.00 | 0.00  |     |     |      |     |     |     |
| 1990-2019 | G06     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00|     |      |     |     |     |
| 1990-2019 | H04W    | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00|      |     |     |     |
| 1990-2019 | C12     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  |     |     |     |
| 1990-2019 | B82     | 0.00    | 0.00    | 0.01 | 0.00  | 0.00| 0.00| 0.00  | 0.29 |     |     |
| 1990-2019 | Y02     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00 | 0.00 | 0.00|
| 2000-2009 | Science | 1.00    |         |      |       |     |     |      |     |     |     |
| 2000-2009 | WIPO    | 1.00    | 0.77    |      |       |     |     |      |     |     |     |
| 2000-2009 | USPTO   | 0.18    | 0.09    | 0.18 |       |     |     |      |     |     |     |
| 2000-2009 | All     | 0.18    | 0.18    | 0.18 | 0.18  |     |     |      |     |     |     |
| 2000-2009 | G06     | 0.18    | 0.18    | 0.18 | 0.18  | 0.18|     |      |     |     |     |
| 2000-2009 | H04W    | 0.18    | 0.09    | 0.09 | 0.18  | 0.18| 0.09|      |     |     |     |
| 2000-2009 | C12     | 0.09    | 0.09    | 0.12 | 0.09  | 0.18| 0.09| 0.09  | 0.09 |     |     |
| 2000-2009 | B82     | 0.63    | 0.63    | 1.00 | 0.09  | 0.18| 0.18| 0.18  | 0.18 | 0.18 | 0.18|
| 2000-2009 | Y02     | 0.18    | 0.09    | 0.09 | 0.18  | 0.18| 0.18| 0.18  | 0.09 | 0.09 | 0.18|
| 2010-2019 | Science | 0.88    |         |      |       |     |     |      |     |     |     |
| 2010-2019 | WIPO    | 0.09    | 0.13    |      |       |     |     |      |     |     |     |
| 2010-2019 | USPTO   | 0.13    | 0.09    | 0.09 |       |     |     |      |     |     |     |
| 2010-2019 | All     | 0.13    | 0.09    | 0.09 | 0.13  |     |     |      |     |     |     |
| 2010-2019 | G06     | 0.13    | 0.13    | 0.13 | 0.88  | 0.09|     |      |     |     |     |
| 2010-2019 | H04W    | 0.09    | 0.09    | 0.09 | 0.13  | 0.13| 0.09|      |     |     |     |
| 2010-2019 | C12     | 0.09    | 0.09    | 0.13 | 0.09  | 0.13| 0.13| 0.13  | 0.09 |     |     |
| 2010-2019 | B82     | 0.09    | 0.09    | 0.88 | 0.09  | 0.13| 0.13| 0.13  | 0.13 | 0.13 | 0.88|
| 2010-2019 | Y02     | 0.09    | 0.09    | 0.09 | 0.13  | 0.13| 0.13| 0.13  | 0.13 | 0.13 | 0.13|

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
### Table D.30: Summary Statistics for Share of CPC Classes at 3-Digit Level

|                     | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|---------------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019      | 0.61    | 0.6     | 0.59 | 0.82  | 0.93| 0.7 | 0.3  | 0.51| 0.54| 0.87|
| Median 1990-2019    | 0.6     | 0.59    | 0.57 | 0.83  | 0.93| 0.71| 0.28 | 0.49| 0.57| 0.88|
| St.dev. 1990-2019   | 0.15    | 0.16    | 0.12 | 0.06  | 0   | 0.13| 0.17 | 0.12| 0.14| 0.03|
| Mean 1990-1999      | 0.47    | 0.43    | 0.48 | 0.76  | 0.93| 0.56| 0.13 | 0.4  | 0.37| 0.85|
| Median 1990-1999    | 0.45    | 0.43    | 0.51 | 0.75  | 0.93| 0.56| 0.12 | 0.4  | 0.36| 0.85|
| St.dev. 1990-1999   | 0.08    | 0.1     | 0.07 | 0.05  | 0   | 0.06| 0.03 | 0.06| 0.06| 0.02|
| Mean 2000-2009      | 0.59    | 0.59    | 0.58 | 0.82  | 0.93| 0.7 | 0.27 | 0.38 | 0.57| 0.87|
| Median 2000-2009    | 0.6     | 0.58    | 0.57 | 0.83  | 0.93| 0.71| 0.28 | 0.49 | 0.57| 0.88|
| St.dev. 2000-2009   | 0.04    | 0.03    | 0.04 | 0.02  | 0   | 0.04| 0.05 | 0.04| 0.05| 0.02|
| Mean 2010-2019      | 0.78    | 0.77    | 0.71 | 0.87  | 0.93| 0.85| 0.49 | 0.64| 0.68| 0.9 |
| Median 2010-2019    | 0.79    | 0.77    | 0.69 | 0.86  | 0.93| 0.85| 0.46 | 0.69| 0.67| 0.91|
| St.dev. 2010-2019   | 0.08    | 0.06    | 0.08 | 0.03  | 0   | 0.04| 0.11 | 0.09| 0.04| 0.02|

### Table D.31: Share of CPC Classes at 4-Digit Level

| Period  | 4-digit Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 |
|---------|-----------------|---------|------|-------|-----|-----|------|-----|-----|
| 1990-1999 | Science | 0.83 |      |       |     |     |      |     |     |
| 1990-1999 | WIPO | 0.83 | 0.33 |       |     |     |      |     |     |
| 1990-1999 | USPTO | 0.00 | 0.00 | 0.00 |     |     |      |     |     |
| 1990-1999 | All | 0.00 | 0.00 | 0.00 | 0.00 |     |      |     |     |
| 1990-1999 | G06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |      |     |     |
| 1990-1999 | H04W | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |     |     |
| 1990-1999 | C12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |     |
| 1990-1999 | B82 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.31|
| 1990-1999 | Y02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2000-2009 | Science | 0.77 |       |       |     |     |      |     |     |
| 2000-2009 | WIPO | 0.48 | 0.42 |       |     |     |      |     |     |
| 2000-2009 | USPTO | 0.09 | 0.09 | 0.09 |     |     |      |     |     |
| 2000-2009 | All | 0.09 | 0.09 | 0.09 | 0.09 |     |      |     |     |
| 2000-2009 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |     |     |     |
| 2000-2009 | H04W | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |     |
| 2000-2009 | C12 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2000-2009 | B82 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2000-2009 | Y02 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2010-2019 | Science | 0.48 |       |       |     |     |      |     |     |
| 2010-2019 | WIPO | 0.09 | 0.22 |       |     |     |      |     |     |
| 2010-2019 | USPTO | 0.09 | 0.09 | 0.09 |     |     |      |     |     |
| 2010-2019 | All | 0.09 | 0.09 | 0.09 | 0.09 |     |      |     |     |
| 2010-2019 | G06 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |     |     |     |
| 2010-2019 | H04W | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.22|
| 2010-2019 | C12 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.25 |
| 2010-2019 | B82 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| 2010-2019 | Y02 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
### Table D.32: Summary Statistics for the Share of CPC Classes at 4-Digit Level

| Keyword | 1990-2019 | 1990-1999 | 2000-2009 | 2010-2019 |
|---------|-----------|-----------|-----------|-----------|
| Mean    | 0.37      | 0.24      | 0.33      | 0.54      |
| Median  | 0.33      | 0.23      | 0.33      | 0.56      |
| St.dev. | 0.14      | 0.06      | 0.02      | 0.09      |

### Table D.33: Average Diversity at 1-Digit Level

| Period       | 1-digit | Keyword | Science | WIPO   | USPTO | All   | G06 | H04W | C12 | B82 | Y02 |
|--------------|---------|---------|---------|--------|-------|-------|-----|------|-----|-----|-----|
| 1990-2019    | Science | 1.00    | 0.37    | 0.36   | 0.6   | 0.96  | 0.49 | 0.17 | 0.27 | 0.29 | 0.74 |
| 1990-2019    | WIPO    | 0.40    | 0.02    | 0.00   | 0.25  | 0.6   | 0.49 | 0.01 | 0.15 | 0.13 | 0.08 |
| 1990-2019    | USPTO   | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  | 0.00 |
| 1990-2019    | All     | 0.00    | 0.02    | 1.00   | 0.00  | 1.00  |
| 1990-2019    | G06     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-2019    | H04W    | 0.00    | 0.01    | 0.03   | 0.00  | 0.00  |
| 1990-2019    | C12     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-2019    | B82     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-2019    | Y02     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | Science | 1.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | WIPO    | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | USPTO   | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | All     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | G06     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | H04W    | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | C12     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | B82     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 1990-1999    | Y02     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | Science | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | WIPO    | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | USPTO   | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | All     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | G06     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | H04W    | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | C12     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | B82     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2000-2009    | Y02     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | Science | 1.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | WIPO    | 1.00    | 1.00    | 1.00   | 1.00  |
| 2010-2019    | USPTO   | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | All     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | G06     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | H04W    | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | C12     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | B82     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |
| 2010-2019    | Y02     | 0.00    | 0.00    | 0.00   | 0.00  | 0.00  |

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
Table D.34: Summary Statistics for Average Diversity at 1-Digit Level

|                | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|----------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| Mean 1990-2019 | 1.39    | 1.4     | 1.36 | 1.27  | 1.36| 1.32| 1.8  | 2.48| 2.47|      |
| Median 1990-2019| 1.36    | 1.42    | 1.33 | 1.24  | 1.33| 1.32| 1.29 | 1.78| 2.48| 2.46 |
| St.dev. 1990-2019| 0.09   | 0.1     | 0.12 | 0.08  | 0.08| 0.11| 0.08 | 0.15| 0.11| 0.05 |
| Mean 1990-1999  | 1.35    | 1.3     | 1.27 | 1.24  | 1.31| 1.29| 1.33 | 1.64| 2.39| 2.43 |
| Median 1990-1999| 1.35    | 1.28    | 1.27 | 1.24  | 1.32| 1.29| 1.29 | 1.65| 2.37| 2.43 |
| St.dev. 1990-1999| 0.03   | 0.08    | 0.02 | 0.01  | 0.02| 0.01| 0.08 | 0.08| 0.08| 0.03 |
| Mean 2000-2009  | 1.35    | 1.43    | 1.33 | 1.24  | 1.33| 1.32| 1.26 | 1.79| 2.48| 2.46 |
| Median 2000-2009| 1.36    | 1.43    | 1.33 | 1.24  | 1.33| 1.32| 1.26 | 1.78| 2.48| 2.45 |
| St.dev. 2000-2009| 0.02   | 0.02    | 0.03 | 0.01  | 0.01| 0.01| 0.02 | 0.04| 0.03| 0.01 |
| Mean 2010-2019  | 1.47    | 1.47    | 1.48 | 1.35  | 1.45| 1.47| 1.37 | 1.97| 2.58| 2.52 |
| Median 2010-2019| 1.48    | 1.47    | 1.47 | 1.35  | 1.44| 1.48| 1.36 | 1.99| 2.55| 2.51 |
| St.dev. 2010-2019| 0.11   | 0.08    | 0.14 | 0.11  | 0.09| 0.12| 0.09 | 0.08| 0.1  | 0.06 |

Table D.35: Average Diversity at 3-Digit Level

| Period   | 3-digit | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|----------|---------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| 1990-2019| Science | 0.65    | 0.87    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| WIPO    | 0.38    | 0.87    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| USPTO   | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| All     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| G06     | 0.79    | 0.79    | 0.46 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| H04W    | 0.00    | 0.00    | 0.00 | 0.79  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| C12     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| B82     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-2019| Y02     | 0.00    | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00  | 0.00| 0.00| 0.00|
| 1990-1999| Science | 1.00    | 1.00    | 0.09 | 1.00  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 1990-1999| WIPO    | 0.09    | 1.00    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 1990-1999| USPTO   | 0.09    | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 1990-1999| G06     | 1.00    | 1.00    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 1990-1999| H04W    | 0.09    | 1.00    | 0.49 | 1.00  | 1.00| 1.00| 1.00  | 0.09| 0.09| 0.09|
| 1990-1999| C12     | 0.09    | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 1990-1999| B82     | 0.09    | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|
| 1990-1999| Y02     | 0.09    | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09  | 0.09| 0.09| 0.09|

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
### Table D.36: Summary Statistics for Average Diversity at 3-Digit Level

|                | Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|----------------|---------|---------|------|-------|-----|-----|------|-----|-----|-----|
| **Mean 1990-2019** | 1.61    | 1.64    | 1.64 | 1.43  | 1.62| 1.43| 2.32 | 3.03| 2.85|
| **Median 1990-2019** | 1.55    | 1.65    | 1.58 | 1.39  | 1.48| 1.56| 1.39 | 2.35| 2.99|
| **St.dev. 1990-2019** | 0.15    | 0.14    | 0.21 | 0.12  | 0.12| 0.15| 0.11 | 0.16| 0.19|
| **Mean 1990-1999** | 1.55    | 1.51    | 1.5  | 1.39  | 1.48| 1.57| 1.43 | 2.16| 2.88|
| **Median 1990-1999** | 1.56    | 1.48    | 1.48 | 1.4  | 1.48| 1.57| 1.4  | 2.16| 2.86|
| **St.dev. 1990-1999** | 0.04    | 0.1     | 0.04 | 0.02  | 0.03| 0.04| 0.09 | 0.15| 0.09|
| **Mean 2000-2009** | 1.54    | 1.69    | 1.58 | 1.36  | 1.48| 1.54| 1.35 | 2.36| 3.01|
| **Median 2000-2009** | 1.54    | 1.68    | 1.59 | 1.36  | 1.48| 1.54| 1.35 | 2.36| 3.01|
| **St.dev. 2000-2009** | 0.02    | 0.05    | 0.05 | 0.02  | 0.01| 0.02| 0.03 | 0.04| 0.07|
| **Mean 2010-2019** | 1.74    | 1.73    | 1.85 | 1.53  | 1.67| 1.75| 1.49 | 2.46| 3.2 |
| **Median 2010-2019** | 1.73    | 1.71    | 1.82 | 1.52  | 1.65| 1.74| 1.46 | 2.48| 3.15|
| **St.dev. 2010-2019** | 0.2     | 0.14    | 0.26 | 0.17  | 0.15| 0.21| 0.14 | 0.08| 0.22|

### Table D.37: Average Diversity at 4-Digit Level

| Period        | 4-digit Keyword | Science | WIPO | USPTO | All | G06 | H04W | C12 | B82 | Y02 |
|---------------|-----------------|---------|------|-------|-----|-----|------|-----|-----|-----|
| **1990-2019** | Science         | 0.01    |      |       |     |     |      |     |     |     |
|               | WIPO            | 0.00    | 0.10 |       |     |     |      |     |     |     |
|               | USPTO           | 0.00    | 0.00 | 0.00  |     |     |      |     |     |     |
|               | All             | 0.00    | 0.00 | 0.00  | 0.00|     |      |     |     |     |
|               | G06             | 0.00    | 0.00 | 0.00  | 0.00| 0.52|      |     |     |     |
|               | H04W            | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00 |     |     |     |
|               | C12             | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00 | 0.00|     |     |
|               | B82             | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00 | 0.00| 0.00|     |
|               | Y02             | 0.00    | 0.00 | 0.00  | 0.00| 0.00| 0.00 | 0.00| 0.00| 0.00|
| **1990-1999** | Science         | 1.00    |      |       |     |     |      |     |     |     |
|               | WIPO            | 1.00    | 1.00 |       |     |     |      |     |     |     |
|               | USPTO           | 0.09    | 0.09 | 0.09  |     |     |      |     |     |     |
|               | All             | 0.09    | 1.00 | 0.09  | 0.09|     |      |     |     |     |
|               | G06             | 0.09    | 1.00 | 0.09  | 0.09| 1.00|      |     |     |     |
|               | H04W            | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09|     |     |
|               | C12             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09|     |
|               | B82             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09| 0.09|
|               | Y02             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09| 0.09|
| **2000-2009** | Science         | 0.09    |      |       |     |     |      |     |     |     |
|               | WIPO            | 0.09    | 0.26 |       |     |     |      |     |     |     |
|               | USPTO           | 0.09    | 0.09 | 0.09  |     |     |      |     |     |     |
|               | All             | 0.09    | 0.09 | 0.09  | 0.09|     |      |     |     |     |
|               | G06             | 0.09    | 0.09 | 0.09  | 0.09| 0.28|      |     |     |     |
|               | H04W            | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09|     |     |
|               | C12             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09|     |
|               | B82             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09| 0.09|
|               | Y02             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09| 0.09|
| **2010-2019** | Science         | 0.25    |      |       |     |     |      |     |     |     |
|               | WIPO            | 0.09    | 0.09 |       |     |     |      |     |     |     |
|               | USPTO           | 0.09    | 0.09 | 0.09  |     |     |      |     |     |     |
|               | All             | 0.09    | 0.09 | 0.09  | 0.09|     |      |     |     |     |
|               | G06             | 0.09    | 0.09 | 0.09  | 0.09| 0.64|      |     |     |     |
|               | H04W            | 0.09    | 0.09 | 0.70  | 0.09| 0.09| 0.09 | 0.09|     |     |
|               | C12             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09|     |
|               | B82             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09| 0.09|
|               | Y02             | 0.09    | 0.09 | 0.09  | 0.09| 0.09| 0.09 | 0.09| 0.09| 0.15|

Notes: Entries show the p-value of a two-sided paired Wilcoxon signed rank test for the hypothesis that the compared pair ranks equal.
|                | Keyword  | Science | WIPO | USPTO | All  | G06  | H04W | Cl2  | B82  | Y02  |
|----------------|----------|---------|------|-------|------|------|------|------|------|------|
| Mean 1990-2019| 1.88     | 1.97    | 2.05 | 1.64  | 1.8  | 1.81 | 2.26 | 2.93 | 3.5  | 3.39 |
| Median 1990-2019| 1.77    | 1.97    | 1.96 | 1.56  | 1.71 | 1.71 | 2.2  | 2.89 | 3.41 | 3.36 |
| St.dev. 1990-2019| 0.26   | 0.25    | 0.38 | 0.21  | 0.21 | 0.25 | 0.21 | 0.3  | 0.27 | 0.23 |
| Mean 1990-1999| 1.77     | 1.73    | 1.76 | 1.55  | 1.68 | 1.69 | 2.16 | 2.64 | 3.31 | 3.2  |
| Median 1990-1999| 1.77    | 1.67    | 1.75 | 1.56  | 1.68 | 1.71 | 2.14 | 2.65 | 3.3  | 3.21 |
| St.dev. 1990-1999| 0.05   | 0.13    | 0.04 | 0.03  | 0.04 | 0.04 | 0.07 | 0.2  | 0.14 | 0.1  |
| Mean 2000-2009| 1.75     | 2       | 1.95 | 1.53  | 1.7  | 1.69 | 2.16 | 2.9  | 3.46 | 3.35 |
| Median 2000-2009| 1.75    | 1.99    | 1.98 | 1.54  | 1.7  | 1.69 | 2.17 | 2.89 | 3.44 | 3.36 |
| St.dev. 2000-2009| 0.03   | 0.06    | 0.09 | 0.02  | 0.01 | 0.03 | 0.09 | 0.07 | 0.1  | 0.05 |
| Mean 2010-2019| 2.12     | 2.19    | 2.43 | 1.83  | 2.01 | 2.05 | 2.45 | 3.24 | 3.72 | 3.63 |
| Median 2010-2019| 2.09    | 2.16    | 2.39 | 1.82  | 2   | 2.02 | 2.4  | 3.31 | 3.66 | 3.58 |
| St.dev. 2010-2019| 0.35   | 0.26    | 0.44 | 0.28  | 0.24 | 0.32 | 0.26 | 0.2  | 0.33 | 0.22 |

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D.3. Additional results

D.3.1. Volume and time trends

Figure D.10: AI patents by year (1990-2019)

(a) Share of AI patents

Notes: This figure shows the evolution of AI patents over time as identified by the four different approaches, as a share of all US patents granted in the same year.

D.3.2. Generality

Table D.39: Average number of citing CPCs (1990-2019): cited patents

| Keyword | Science | WIPO  | USPTO |
|---------|---------|-------|-------|
| 1 digit | 2.71    | 2.42  | 2.41  | 2.26  |
| 3 digit | 5.99    | 5.00  | 5.23  | 4.74  |
| 4 digit | 9.92    | 8.54  | 9.05  | 8.21  |

Notes: This table shows the numbers of different CPC classes making a citation to an average patent of the respective group, conditional on the patent being cited at least once. Citations within the same class are excluded.

Table D.40: Average Generality Index (1990-2019)

| Keyword | Science | WIPO  | USPTO |
|---------|---------|-------|-------|
| 1 digit | 0.76    | 0.73  | 0.72  | 0.68  |
| 3 digit | 0.91    | 0.87  | 0.87  | 0.84  |
| 4 digit | 0.96    | 0.95  | 0.94  | 0.93  |

Notes: The generality index is defined as share of citations to patents in different CPC classes at different aggregation levels (see A.2). Citations within the same class are excluded.
Table D.41: Average Number of Citing CPCs (1990-2019)

| Keyword | Science | WIPO | USPTO |
|---------|---------|------|-------|
| 1 digit | 2.15    | 1.83 | 1.82  | 1.68  |
| 3 digit | 5.18    | 4.14 | 4.39  | 3.91  |
| 4 digit | 8.90    | 7.41 | 8.04  | 7.13  |

Notes: This table shows the numbers of different CPC classes making a citation to an average patent of the respective group. Citations within the same class are excluded.

Figure D.11: Average Number of Classes Citing AI

(a) Subset of cited patents
(b) Subset of cited patents (z-score scaled)

Notes: The z-scored value equals the level of the generality index minus its average across the four approaches divided by the standard deviation for each year.

D.3.3. Complementarity

Table D.42: Average Number of 1-, 3- and 4-digit CPCs per Patent

| Keyword | Science | WIPO | USPTO |
|---------|---------|------|-------|
| 1 digit | 1.39    | 1.40 | 1.36  | 1.27  |
| 3 digit | 1.61    | 1.64 | 1.64  | 1.43  |
| 4 digit | 1.88    | 1.97 | 2.05  | 1.64  |

Note: The table shows the average of annual average number of technology classes by 1-, 3- or 4-digit CPC per patent.
D.4. Generality of AI descendants

In this section, we report additional results for the wide-ranging usefulness of technological descendants of AI, i.e. those patents that cite an AI patent but are not AI themselves. This serves as an additional indicator of the widespread of AI in a range of different products and processes. The results confirm the persistence of the ranking, indicating the highest generality of keyword patents across different indicators.

Table D.43: Average Generality Index: AI Descendants

| Citing Keyword | Citing Science | Citing WIPO | Citing USPTO |
|----------------|----------------|-------------|--------------|
| 1 digit        | 0.74           | 0.73        | 0.72         | 0.72         |
| 3 digit        | 0.89           | 0.87        | 0.87         | 0.88         |
| 4 digit        | 0.96           | 0.95        | 0.95         | 0.95         |

Notes: Generality is measured as \( G = 1 - \sum (s^2) \) with \( s \) as share of citations to patents in different CPC classes at different aggregation levels. Citations within the same class are excluded.

Table D.44: Average Number of Citing CPCs: AI Descendants

| Citing Keyword | Citing Science | Citing WIPO | Citing USPTO |
|----------------|----------------|-------------|--------------|
| 1 digit        | 1.32           | 1.15        | 1.23         | 1.16         |
| 3 digit        | 2.75           | 2.27        | 2.57         | 2.33         |
| 4 digit        | 4.82           | 3.99        | 4.57         | 4.06         |

Notes: This table shows the number of different CPC classes making a citation to an average patent of the respective group. Citations within the same class are excluded.
Table D.45: Average Number of Citing CPCs (Cited): AI Descendants

|        | Citing Keyword | Citing Science | Citing WIPO | Citing USPTO |
|--------|----------------|----------------|-------------|--------------|
| 1 digit| 2.35           | 2.17           | 2.24        | 2.17         |
| 3 digit| 4.60           | 4.04           | 4.39        | 4.10         |
| 4 digit| 7.51           | 6.60           | 7.29        | 6.63         |

Notes: The table shows the numbers of different CPC classes making a citation to an average patent of the respective group that receives at least one citation. Citations within the same class are excluded.

Table D.46: Average Citation Lags by Group of AI Citing Patents

| Period   | Citing Keyword | Citing Science | Citing WIPO | Citing USPTO |
|----------|----------------|----------------|-------------|--------------|
| 1990-1999| 12.79          | 12.59          | 12.66       | 12.47        |
| 2000-2009| 8.95           | 9.03           | 9.01        | 8.84         |
| 2010-2019| 4.30           | 4.29           | 4.22        | 4.28         |

Notes: This table shows the average number of years it takes until a patent in the sample is cited. The average number of years is lower during the more recent decade as the maximal time lag is truncated since our data ends in 2019. Note that the group of AI citing includes all patents that cite AI but are not identified as AI by the respective approach.