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Digital technologies, technological improvement rates, and innovations "Made in Switzerland"

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Abstract

Technologies evolve at different paces and their rate of improvement varies considerably. We demonstrate that the fastest technological progress currently occurs in the digital domain and empirically investigate the relationship between technologies' improvement rates and breakthrough innovations as measured by forward citations of patents. Our empirical estimates suggest that patents from the digital sphere, as well as those related to fast-improving technologies, are associated with a higher probability to produce breakthrough innovations. We then investigate Swiss core industries' specialization patterns toward these potential high-impact technologies and compare the state of cutting-edge innovation in Switzerland to other countries. Our findings imply that the Swiss innovation system is among the laggards regarding innovations in today's fastest improving digital technologies.

Keywords Technological change, Technological progress, Patents, Digitization

JEL Classification O30, O32, O33

1 Introduction

Today's rapid technological progress primarily concerns digital technologies, be it artificial intelligence (AI), cloud computing or customer relationship management. But it is by no means restricted to the computer and software industry. Rather, digital innovations are also widespread in the manufacturing sector, which primarily reflects that digital technologies can have general-purpose characteristics.[1] Such technologies are a crucial ingredient of economic growth (e.g., Helpman, 1998; Bresnahan & Trajtenberg, 1995), and their early adoption can yield long-lasting advantages for first-movers in their respective fields (e.g., Brynjolfsson et al., 2021; Tambe et al., 2020; Triulzi et al., 2020). Unsurprisingly, software-related patenting has surged dramatically over the last decades, whereas the bulk of the increase was heavily

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[1] See, for example, Bresnahan (2010) or Jovanovic and Rousseau (2005) for an overview of general-purpose technologies. With regard to digital technologies, Basu and Fernald (2007) discuss GPT characteristics of information and communication technologies (ICT) and Goldfarb et al. (2023) of artificial intelligence. Bessen and Hunt (2007) discuss the spread of digital technologies to the manufacturing sector. More specifically for manufacturing, Rajarajan et al. (2021), Porter and Heppelmann (2015), and Porter and Heppelmann (2014) investigate challenges of smart connected products and the Internet of things.

concentrated in a few tech-clusters (Chattergoon & Kerr, 2022).[2] With this respect, Bloom et al. (2021) find that clusters which were pioneers in inventing disruptive technologies over the last decades have higher wages and more high-skilled jobs many years after the technology first emerged, suggesting that early involvement in novel disruptive technologies may have long-lasting economic benefits.

Which set of technologies are potentially disruptive today and in the near future? And how are different countries—particularly Switzerland—positioned with respect to innovations in these technologies? These are the questions to which our paper contributes. Naturally, technologies from the digital domain are primary candidates to focus on, since digitization is transforming all aspects of economic activity (e.g., Brynjolfsson & McAfee, 2014). However, many other technologies also evolve at high speed and might become disruptive as well (e.g., battery technology). Furthermore, since some digital technologies have already emerged more than 40 years ago, they differ considerably from each other with respect to their rate of technological improvement. For example, digital control systems for loudspeakers is a rather mature digital technology with mostly incremental improvements. In contrast, improvements occur very rapidly in cloud computing (Singh et al., 2021). Accordingly, not every digital technology is necessarily related to disruptive changes today and it is challenging to distinguish disruptive technologies from others. As a workaround, researchers have often focused on particular technologies that have already been found to be disruptive. The most prominent example is the subject of artificial intelligence and its potential labor market implications.[3] A recent study by Singh et al. (2021) takes a different and more holistic approach: Instead of focusing on one or a few selected technologies, these authors introduce a framework which allows to estimate different technologies' improvement rates.[4] This enables us to distinguish very dynamic (and potentially disruptive) technologies from slower evolving ones. Our paper thus builds heavily on this framework to approach our above-stated research questions.

To do so, we first create a new dataset from different sources of information. More specifically, we combine patent data from the United States Patent and Trademark Office (USPTO) with information on whether a patent contains a digital technology from Inaba and Squicciarini (2017) and a novel indicator for technological improvement rates of 1757 distinct technologies that we obtain from Singh et al. (2021).[5] To the best of our knowledge, our paper is the first to connect these different sources of information. This allows us to accurately analyze the state of cutting-edge innovation in Switzerland and abroad.

A main advantage of our constructed dataset is that it enables us not only to evaluate the *quantity* of digital and non-digital innovations across countries and industries (i.e., their stock or share of digital and non-digital patents). It also allows us to approximate their technological *quality* (i.e., the technological improvement rate of a technology a patent is associated with). We show that this is relevant for two main reasons: First, the variation regarding the rate of technological improvement across digital technologies is rather large. Second, patents from the digital domain and such related to technologies with high improvement rates are associated with a higher probability to contain breakthrough innovations as measured by forward citations of patents.

To demonstrate the latter, we follow Kerr and Kerr (2018) and estimate a linear probability model in which the left-hand side contains a dummy variable indicating whether a patent contains a breakthrough innovation, as measured by forward citations. We provide empirical estimates and robustness tests showing that this pattern is also robust for different industries. This suggests that being innovative in digital and fast-improving technologies is important in various industries of the economy, including, for example, the pharmaceutical or machinery industry, toward which Switzerland's innovation system is relatively heavily specialized.

Yet, we show that Swiss innovations in most of the country's core industries are not particularly directed toward fast-improving digital technologies when compared to other countries. This is because the Swiss innovation system is generally only weakly engaged in digital technologies, and digital innovations in Switzerland are less likely to occur in the fastest improving digital technologies. In non-digital domains, Switzerland's position

[2] It should be mentioned that regulatory changes to the US intellectual property system also contributed to the increasing amount of software-related patenting in the USA (see, e.g., Graham & Vishnubhakat, 2013).

[3] Recent studies include, for example, Acemoglu et al. (2022), Goldfarb et al. (2023), or Tambe et al. (2020).

[4] A somewhat related concept has been presented recently by Pezzoni et al. (2022), who derive technological trajectories based on patent data for a broad set of new technologies from their emergence to their largest impact. Besides a different methodology in determining and characterizing technologies compared to Singh et al. (2021), Pezzoni et al. (2022) focus specifically on new technologies, which make up only a portion of all patented innovations. In contrast, Singh et al. (2021)'s proposed framework allows researchers to compare all technologies to each other on the basis of a single metric. This is particularly important when comparing digital to non-digital technologies, as the latter are often not new technologies.

[5] Our data features all USPTO patents filed by inventors from 9 major patenting countries—including Germany, the USA, China, and Switzerland—between 1990 and 2015.

is somewhat better, but it is also not among the leaders in rapidly evolving non-digital fields (except for innovations from the medical and pharmaceutical industries). Overall, Switzerland can thus be considered as a laggard in terms of innovations in today's fastest improving technologies. We argue that this could be a cause for concern, especially if adaption and catch-up become more difficult in the future, and if new technologies represent substitutes for more traditional ones.

Our paper is related to different strands of the literature that study technological changes and their interplay with competitiveness. From a technical point of view, our paper builds heavily on prior work regarding the emergence and speed of technological innovations (see, e.g., Singh et al., 2021; Triulzi et al., 2020; Magee et al., 2016).[6] Singh et al. (2021) provide us with our empirical measure for technologies' improvement rates, which is the basis for all empirical analyses in this paper. Our paper extends prior work in this area in two ways: First, we demonstrate a robust association between patented inventions' corresponding technological improvement rates and their probability to contain a breakthrough innovation as measured by forward citations. Second, we assess the extent to which countries' innovation systems are specialized with respect to fast-improving technologies, with a particular focus on Switzerland.

With this latter regard, our paper has a connection to several studies that focus on the state of innovation across industries in different countries. For example, Kelly et al. (2021) use patent texts to investigate long-run trends in innovation activities across different industries considering data back to 1840. Their results imply that innovation activities have been mainly dominated by the information technology industry in recent years. Another example is Confraria et al. (2021), who have a similar focus and investigate emerging technology patterns. One of their main findings is that European firms are not particularly well positioned in digital innovations such as software engineering and semiconductor devices. Furthermore, reports by the OECD (2019) or the European Commission (2017) provide extensive descriptive overviews of digital trends across countries, illustrating that firms from EU countries are typically lagging behind their peers from the USA and Japan in digital innovations.

With this respect, our paper also has a loose connection to several contributions that are focusing on the impact of early involvement in disruptive technologies on competitiveness. A major example is Bloom et al. (2021), who identify a set of 29 disruptive technologies from the last decades and show for the USA that regions who were pioneers in inventing these technologies have obtained long-lasting benefits in terms of wages and high-skilled employment. Tambe et al. (2020) focus on the firm level and demonstrate that digital capital accumulation predicts the productivity of firms in the USA in the near future.

Finally, our paper's main focus is on Switzerland, whereas existing studies focus mainly on counting the stock of digital patents in selected technological areas (Gramke & Glauser, 2017, in German language) industries (Rutzer & Weder, 2021, also in German language) or on the general scope of patent activities of the Swiss innovation system (Grampp et al., 2018, also in German language). These studies use patent data and compare the innovativeness of Switzerland in digital domains with other countries. Besides overall trends, the work of Gramke and Glauser (2017) also investigates in more detail the positioning of Switzerland in some important fields such as AI, the Internet of things, and robotics. The general conclusion of these three studies is that Switzerland is not among the top innovators in terms of the number of digital patents. Finally, also OECD (2019) focuses on Switzerland and highlights that the country's recent patent activities in ICT-related fields are below the OECD average. What we add to this literature is an analysis that additionally takes into account the specialization patterns of the Swiss innovation system with respect to its orientation toward faster or slower improving technologies.

The remainder of this paper is organized as follows. Section 2 focuses on the concept of technological improvement rates and describes data sources that allow us to investigate it. It then shows that digital technologies are among the most dynamic technologies and provide empirical estimates suggesting that patents from the digital domain and those related to fast-improving technologies are associated with a higher probability to produce breakthrough innovations. Section 3 examines patterns of the Swiss innovation system with respect to digital and fast-improving technologies, compares them with other countries, and discusses the findings. Section 4 concludes the paper.

2 Technological improvements and digital technologies

New and improved technologies are crucial ingredients for economic growth. After they first appear, inventors constantly add new functions, develop new methods and find new implementations that make a technology more valuable, efficient, and effective. As a result, technologies constantly evolve and improve. One well-known example for this is the famous Moore's law (named after Intel co-founder Gordon Moore), which states

[6] Recent summaries can be found, for example, in Singh et al. (2021) or Baumann et al. (2021).

that computer processing power doubles approximately every 18–24 months (Gustafson, 2011). Similar patterns can be observed for many other technological domains but their rate of improvement typically varies considerably: Some technologies evolve at a very fast pace, while others progress slowly (Magee et al., 2016). A natural question arising from this is which technologies are the fastest-improving ones. Previous research has mainly relied on case studies to evaluate progress across different technologies which makes comparisons rather difficult.[7] In turn, they offer some insight with regard to the technologies that evolve particularly fast. Herrmann et al. (2018) for health care, Ferràs-Hernández et al. (2017) for automotives, and Midttun and Piccini (2017) for the energy sector all argue that especially digital technologies are improving at remarkably fast pace across these very different sectors of the economy. But beyond such case studies, it remains challenging to investigate technical improvement rates for a wide range of detailed technologies in a standardized way. To approach this, Singh et al. (2021) provide a framework that allows to capture annual improvement rates of an extensive set of 1757 granular technologies. These technologies range from "Network management specifically client-server applications" to "IT based prepayment for services," "Automatic vehicle washing," or "Hitching assemblies for towing vehicles." Since these are very distinct technologies, their improvement rates also vary considerably.[8]Singh et al. (2021) build on an extensive previous literature to arrive at these improvement rate estimates. A key contribution in this regard is Magee et al. (2016) who calculate technical improvement rates for 28 fields based on different "real-world" metrics (e.g., based on the cost of watts per hour for batteries, of sequencing a genome, or of printing one mm3 per second). In a follow-up contribution, Triulzi et al. (2020) identify patents that belong to the 28 technologies whose annual improvement rates have been determined by Magee et al. (2016). They then use information from these patents to train an empirical model that is able to accurately predict the improvement rates of the technologies these patents are associated with. Eventually, Singh et al. (2021) use this trained model to extend and predict improvement rates for 1757 technologies. "Appendix A.1" provides methodological details regarding this framework.

The 1757 technologies Singh et al. (2021) focus on were constructed endogenously using the classification overlap method introduced by Benson and Magee (2013, 2015) and are assigned unique identifiers that can be associated with patents.[9] Hence, we can combine information from patent data (e.g., on the location where a patented invention was developed) with the improvement rate of the technologies a patent is associated with. This allows us to investigate the rate of technology improvement across countries and industries. Naturally, however, the focus on patents also means that we only capture patented inventions in our analysis. This is an important yet common limitation in the corresponding literature. For example, it is well established that not every invention is patentable (e.g., Griliches, 1998) and some important innovations may never be patented (e.g., Fontana et al., 2013). Furthermore, the propensity to patent and to cite other patents varies across industries (e.g., Lerner & Seru, 2022; Kuhn et al., 2020) and differences in patenting over time can be affected by legal changes—especially for ICT (Graham & Vishnubhakat, 2013). This limitation could be mitigated by utilizing alternative data sources that proxy innovative activity more reliably. However, finding such data has been extremely difficult, which is why patent data are generally thought of as an imperfect but relatively good measure of inventive activity (e.g., Acs et al., 2002). Other challenges of using patent data, such as differing propensities to patent across technology fields, can be more directly approached with appropriate techniques, which we describe in the following. In doing so, we also present the patent dataset we use for our study and explain how we combine different sources of information for out final dataset.

2.1 Dataset construction

We consider all granted USPTO patents for 9 important inventor countries obtained from the official USPTO patentsview database and leverage information from Patstat on DOCDB patent families to avoid double counting of patents containing the same invention.[10], [11] In particular, we only consider the first patent filed at the USPTO from

[7] See, e.g., Bloom et al. (2021), Sharifzadeh et al. (2019), Herrmann et al. (2018), Benson et al. (2018), Ferràs-Hernández et al. (2017), Midttun and Piccini (2017) for some recent contributions.

[8] A list of the ten fastest and ten slowest improving technologies of their framework can be found in Table 3 in "Appendix." The full list can be accessed at https://zenodo.org/record/4779832#.Yjstn-fMK38.

[9] The identifiers are constructed from the overlapping first three-digit UPC codes and first four-digit IPC codes of the most relevant patents that have been assigned to each technology. As shown in Benson and Magee (2015), such endogenously created technologies have a high relevance and a high differentiation with respect to knowledge and technical functionality, which has been further confirmed in Singh et al. (2021) who demonstrate that 97.2% of USPTO patents can be attributed to at least one of their endogenously created technologies.

[10] Besides Switzerland, we consider the eight most important inventor countries based on the total number of patents granted at the USPTO between 2010 and 2015 for our analyses. These are Canada, China, France, Germany, Japan, South Korea, the UK, and the USA.

[11] Patstat can be accessed at https://data.epo.org/expert-services/index.html. An introduction to the database is given in De Rassenfosse et al. (2014). A DOCDB patent family is composed of different patents containing the same technical invention, i.e., all having the same prior art (Webb et al., 2005).

all patents belonging to the same DOCDB patent family. We then attribute technology improvement rates from Singh et al. (2021) to these patents. To do so, we gather the patents' International Patent Classification (IPC) number(s) and their US Patent Classification System (UPC) number(s) which allow us to merge technology improvement rates to patents.[12] For USPTO patents UPC codes are only available until early 2015. Thus, the time span of our analysis is limited to patents filed till the year 2015, as we cannot add improvement rates to patents filed later. It is important to keep in mind that we thus assign the same rate of technological improvement to *every* patent belonging to a certain technology from Singh et al. (2021). Hence, a patent's improvement rate refers to its corresponding technology and not to a hypothetical improvement the patent makes to its corresponding technology.

Next, we use the 4-digit IPC number(s) to differentiate whether a patent is a digital patent or not. We build on Inaba and Squicciarini (2017) who determine for each 4-digit IPC number whether the class is a digital technology or not. Each patent is assigned to one or more IPC numbers. We define a patent as digital if it belongs to at least one 4-digit IPC number that has been classified as digital by Inaba and Squicciarini (2017).[13] This information enables us to distinguish whether a patent or a technology is a digital one. Further, we also map patents to NACE industries. To do so, we use the correspondence table from Patstat between 4-digit IPC numbers and NACE industries (see Looy et al., 2014). Each patent is assigned a probability of belonging to a certain NACE industry based on its four-digit IPC number(s), and we assign a patent to the industry with the highest probability.[14]

In a next step, we gather metadata stated on patents from our USPTO sample. We consider information on the year of a patent's filing, the year of its publication, and the country address(es) of its inventor(s). The latter are used to map patents to countries. If a patent has inventors from several countries, we assign the patent to each country for which an inventor address exists.[15] Furthermore, we extract the number of inventors, the number of claims of a patent, and the number of different countries involved in the research that led to the patent. Finally, we also approximate the importance of patents. To do so, we use information on patent citations and calculate the number of citations a patent receives from subsequent patents (so-called forward citations). Forward citations are a well-established measure in the literature following a simple underlying idea: Patents that protect very valuable innovations are receiving more citations from subsequent patents (see, e.g., Kogan et al., 2017; Hall et al., 2005). Thus, forward citations can be used as an approximation for an innovation's importance and patents can be ranked according to their number of forward citations. We consider for each patent the number of received forward citations within five years after publication. Following Kelly et al. (2021), Grampp et al. (2018) or Gramke and Glauser (2017), we define a patent as containing a breakthrough (or significant) innovation if it is among the 10% most cited patents within its corresponding World Intellectual Property Organization (WIPO) technology field and publication year.[16] The combined information from all these sources allows us to perform analyses across technologies, countries, and industries in the remainder of this paper.

2.2 Digital technologies, improvement rates, and breakthrough innovations

We first want to investigate improvement rate differences across technologies. Since case study evidence points to significant differences between the digital and non-digital domain, we start by focusing on improvement rate

[12] Note that we consider patents that can be attributed to multiple technologies (and thus multiple improvement rates) multiple times. An alternative would be to calculate the average among all assigned technology improvement rates. However, our chosen approach is much better suited for the purpose of our analysis which includes to focus on the spread of ***all*** technologies across countries and industries and not just a mean rate of improvement.

[13] Using such an approach defines innovations also as digital if they "only" combine digital methods or components with non-digital ones. An example might be parts of a magnetic resonance imaging device (non-digital electrical/medical engineering) that features a machine learning algorithm (digital patent) to detect tumors or some smart home applications combining both digital technologies and electrical/engineering technologies.

[14] When mapping patents to industries, one could also use fractional counts. We refrain from doing so because this would complicate our empirical analyses. However, to test the robustness of our choice we calculate the correlation between the average industry improvement rates across six industries using i) the highest probability mapping and ii) fractional counts. It is reassuring that the correlation is 0.999 across the NACE industries of our set of 9 countries and 0.992 for Swiss industries alone. The correlation decreases slightly to 0.987 (0.983 for Switzerland alone) when only digital patents are considered. The main reason for this high correlation is the large number of patents that are unambiguously mapped to one industry. For more details, see Fig. 6 in "Appendix" showing a cumulative density plot of mapping probabilities.

[15] The literature uses mainly two different methods to assign patents to countries based on inventor addresses (OECD, 2009). Besides the simple count used in our paper, patents can also be assigned to countries on a fractional base. In this case, the number of inventors belonging to a country is used as weight. Since we are primarily interested in the spread of technologies across all involved inventor countries, we choose the count-based method.

[16] The WIPO classifies each patent to one or more of 35 aggregated technology fields (for details, see Schmoch, 2008). By creating forward citation percentiles for each publication year and technology group, we take into account differing citation distributions between technology groups and over time (see, for example, Jaffe & De Rassenfosse, 2019). If a patent has been assigned to more than one WIPO technology field and is classified one time as within the 10% and another time not, we classify it as a breakthrough patent. Note that building on Patstat information also allows us to not only include citation information from USPTO patents, but also from patents registered at the EPO and WIPO.

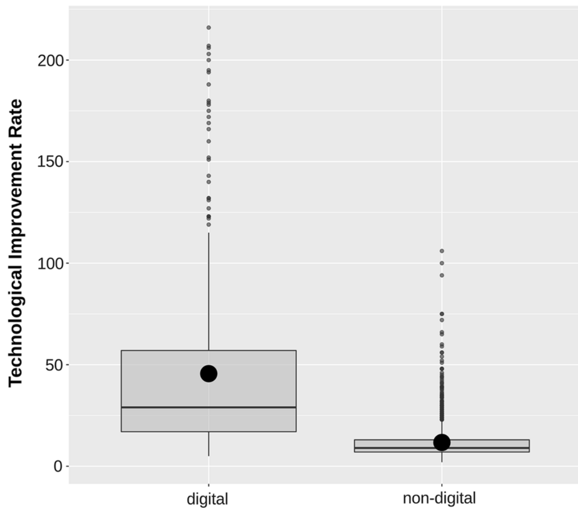

Fig. 1 Technological improvement rates of digital and non-digital technologies. *Notes*: The boxplot shows the distribution of improvement rates of 1753 different technologies from Singh et al. (2021). The split into the digital or non-digital group is based on the approach proposed by Inaba and Squicciarini (2017). The horizontal line shows the median, the big dot the mean, the upper limit of the box the 25th, and the lower limit the 75th percentile. The length of the whisker shows the data that are within 1.5 times the interquartile range. Outliers are marked by small dots

differentials between digital and non-digital technologies. To do so, we check for each of the 1757 technologies we obtained from Singh et al. (2021) if their corresponding IPC 4-digit number is labeled as digital by Inaba and Squicciarini (2017) and classify it accordingly. We can then visualize improvement rates for the two groups in Fig. 1.[17]

The average and median rate of technological improvement is clearly higher for digital technologies (45.6 and 29 vs. 11.7 and 9, respectively), and the fastest improving technologies are all to be found in the digital group. This clearly highlights how digital technologies are progressing at remarkable pace. At the same time, the variation is large within both groups—and substantially more pronounced for digital technologies. This indicates that there are substantial differences within the digital domain and some digital technologies are evolving much more dynamically than others. However, even though several digital technologies have modest improvement rates, the current frontier of technological improvement seems clearly directed toward digital technologies.

But does faster technological progress also mean that these technologies produce more breakthrough innovations compared to slower evolving ones? We can investigate this crucial question by analyzing whether patents from the digital domain and related to technologies with high improvement rates are likelier to contain a breakthrough innovation as measured with forward citations of patents. To do so, we follow a similar approach as Kerr and Kerr (2018) and estimate a linear probability model of the following functional form:

$$\begin{aligned} \mathrm{TP}_i = {} & \beta_1 D_i + \beta_2 k_i + \beta_3 D_i : k_i + \beta_4 \mathrm{inv}_i + \beta_5 \mathrm{num\_ctry}_i \\ & + \beta_6 \mathrm{claims}_i + \beta_7 \mathrm{bwd\_cits}_i + \mathrm{FE}_{j,t} + \varepsilon_i . \end{aligned} \tag{1}$$

TP_i is a dummy variable indicating whether patent i belongs to the breakthrough-patent group proxied by our previously explained measure that is based on the top 10% forward citations (FWD90). We estimate three specifications: In the first one, the right-hand side contains a dummy variable D_i stating whether patent i belongs to a digital technology or not. In the second, we consider the improvement rate of the technology of patent i, k_i. In the third one, we include the digital dummy and also add an interaction term between the digital dummy and the improvement rate, $D_i : k_i$. This allows us to analyze whether an association exists between the improvement rate and breakthroughs for the group of digital and non-digital technologies alike. Thus, β_1, β_2, and β_3 are our parameters of interest. Moreover, we include in all specifications several variables to control for different types of research and development (R&D) input that might impact the importance of the innovation. We use the number of inventors inv_i and the number of distinct inventor countries $\mathrm{num\_ctry}_i$ as proxies for the employed human capital. The variable claims_i contains the number of claims of a patent. Patent claims represent the intellectual property protection provided by a patent. They can thus be seen as an indicator for a patent's technological scope, which might affect the number of its received forward citations (Kerr & Kerr, 2018). In addition, we use the number of backward citations $\mathrm{bwd\_cits}_i$ to capture the amount of external knowledge which has been embodied in the patent. Each patent belongs to one industry and year. In order to take into account unobserved heterogeneity across industries and years, we also consider industry (j), year (t), and industry-year fixed

[17] There are 362 digital and 1391 non-digital technologies. Four of the 1757 technologies of Singh et al. (2021) are not part of our patent data and therefore not considered.

Table 1 Technological improvement rates and breakthrough innovations

Dependent variable	**FWD90**		
Model	**(1)**	**(2)**	**(3)**
Digital	1.859***		2.991***
	(0.427)		(0.691)
k		0.030***	
		(0.010)	
Non-digital: *k*			0.148***
			(0.022)
Digital: *k*			0.023***
			(0.004)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	4,259,239	4,259,239	4,259,239

All estimations include USPTO patents from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA of the filing years 1990–2015. If a patent has inventors from more than one of those countries, it will only take into account once. The first model specification shows an association between digital domains and breakthrough innovations across all industries. The second considers an association between technology improvement rates and breakthrough innovations, and the third do the same but distincts between digital and non-digital domains. In order to show associations in percentage points, we have multiplied the FWD90-dummy by 100. The industry fixed effects are at the level of the six industries included in the analysis, namely Computer/ICT, Machinery, Medical, Electrical, Chemical, and Pharma. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^{*} < 0.1; p^{**} < 0.05; p^{***} < 0.01$

effects summarized by the vector $FE_{j,t}$.[18] Finally, ϵ_i is the error term of the model and we cluster standard errors by industry j.

Table 1 presents the estimation results for the time window 1990–2015. In column (1), we take only the digital dummy, control variables, and fixed effects into account. As the positive coefficient shows, patents from digital technologies are associated with more breakthrough innovations as measured with forward citations of patents: All else equal, our estimates imply that a digital patent has a 1.86 percentage points increased likelihood of being a breakthrough innovation.[19] Next, we focus on the technology improvement rate. Column (2) shows a positive association for the improvement rate k with our breakthrough indicator, implying that patents from faster-improving technologies have an increased likelihood of containing a breakthrough innovation. In particular, according to our estimate, a patent belonging to a technology with a ten percentage points higher improvement rate has, ceteris paribus, a 0.3 percentage points higher likelihood of containing a breakthrough innovation.[20] In column (3), we analyze whether this positive association from column (2) can be observed for both the digital and non-digital group. The results show a positive association for both groups, but it is much stronger for the non-digital domain. While this might come as a surprise at first sight, it can be well explained. First, improvement rates of digital technologies are much more widely dispersed. Second, they have a higher average improvement rate. This implies a high multicollinearity between the digital dummy and the interaction term $digital : k$, which is also visible by the increased coefficient of the digital dummy in column (3) compared to its counterpart in column (1). In Tables 7, 8, and 9 of "Appendix," we show that the pattern from Table 1 remains very robust when considering different subgroups of years, different time thresholds for forward citations to indicate breakthrough innovations, and some alternative measures for breakthrough innovations, respectively.[21]

Taken together, these results show that patents belonging to the digital domain or a technology with faster progress are associated with a higher likelihood of containing a breakthrough invention as measured by forward citations. This supports our initial hypothesis that the current frontier of technological improvement seems clearly directed toward fast-improving digital technologies. But does this pattern also hold for different industries? To evaluate this, we now focus on six different industries, which are of particular importance for the Swiss innovation system.[22]

[18] For the econometric estimations, we do not assign patents to countries. Otherwise a patent resulting from an international R&D activity would be added multiple times if the inventors are located in more than one of the countries considered.

[19] Note we have multiplied the indicator dummy TP_i by 100 to show associations in percentage points.

[20] This association might appear low initially. But considering that technological improvement rates range from 2 to 216 percent, we note that the probability of a patent associated with the latter improvement rate to contain a breakthrough innovation is 6.42 percentage points higher compared to the former.

[21] In addition, in Table 15 of "Appendix" we indicate that the association between technology improvement rate and breakthrough innovations is significantly different for the digital and non-digital domains.

[22] We focus on the six Swiss industries that have filed the most patents in recent years and are therefore of great importance for Switzerland as an innovation hub. These are the Chemical, Computer/ICT, Electrical, Machinery, Medical, and Pharma industry, as listed in Table 6. The respective NACE codes and total number of patents are shown in Table 4 in "Appendix." A allocation according to different countries and industries is again shown in "Appendix" in Table 5. The Nomenclature générale des Activités économiques dans les Communautés Européennes (NACE) Rev. 2 system of the EU is identical to the Swiss NOGA 2008 system up to the fourth level. For more information, see https://www.bfs.admin.ch/bfs/en/home/statistics/industry-services/nomenclatures/noga.assetdetail.344513.html.

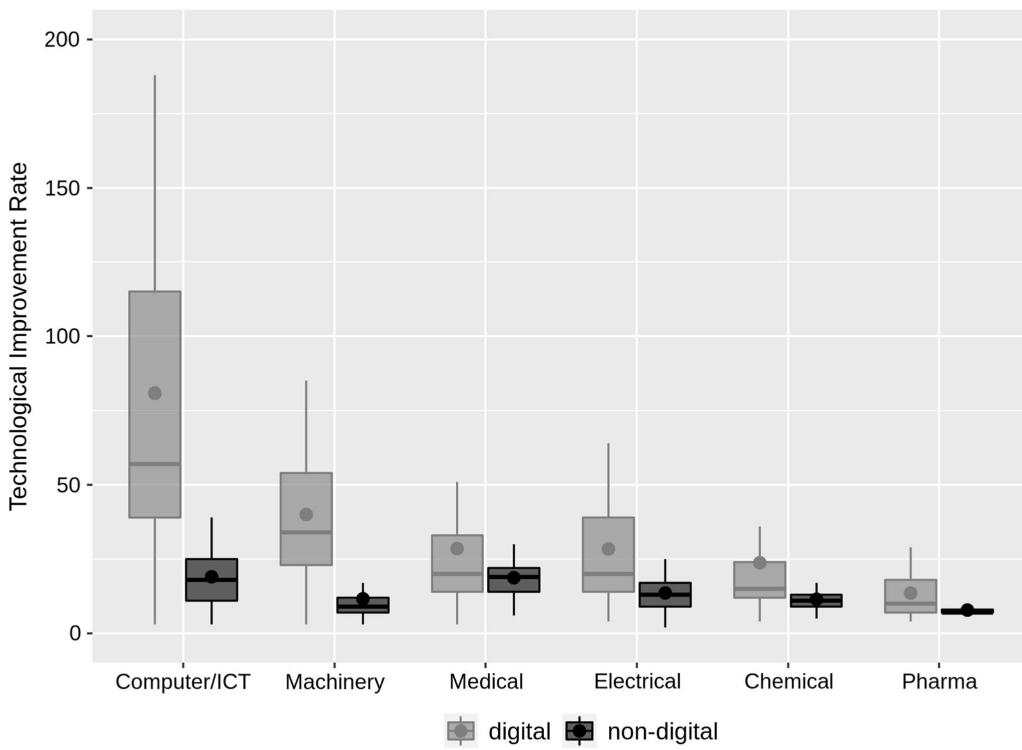

Fig. 2 Technological improvement rates of digital and non-digital technologies across industries. *Notes:* 1757 different improvement rates from Singh et al. (2021) are assigned to USPTO patents of the filing years 2010–2015. This results in a total of 283'431 USPTO patents. Patents are then split into the digital or non-digital group based on the approach proposed by Inaba and Squicciarini (2017) and assigned to industries according to De Rassenfosse et al. (2014). The horizontal line shows the median, the big dot the mean, the upper limit of the box the 25th, and the lower limit the 75th percentile. The length of the whisker shows the data that are within 1.5 times the interquartile range. Compared to Fig. 1, we do not show outliers to increase clarity

As a starting point, Fig. 2 depicts descriptive statistics for the technological improvement rate across industries based on patents from 2010 to 2015.[23] The same overarching pattern as shown before in Fig. 1 for technologies also holds for these six industries: The digital group's average rate of technological improvement is higher in all industries. Apart from that, there are interesting patterns across industries. First of all, the average technological improvement rate is relatively similar across industries for the non-digital group, ranging from 7.8 in the pharmaceutical industry to 19.0 in the computer/ICT industry. Substantial differences only emerge when focusing on the digital group, whose level differs considerably. For example, digital technologies in the machinery industry have a substantially higher average improvement rate of 39.7 compared to the pharmaceutical or chemical industry, with 13.5 and 23.9, respectively. In other words, companies in machinery are much more intensively incorporating fast-improving digital technologies into their R&D activities. Could this mean that digital technologies are simply less important in the pharmaceutical or chemical industry, for example? If this were the case, fast-improving digital innovations should not be more valuable than non-digital ones in these industries. Again, this can be evaluated using patent data. As before, we estimate the following simple linear model to investigate this question empirically:

$$\begin{aligned}\mathrm{TP}_i = {} & \beta_{1j} D_i : \mathrm{IND}_j + \beta_{2j} k_i : \mathrm{IND}_j + \beta_{3j} D_i : k_i : \mathrm{IND}_j \\ & + \cdots \quad + \beta_4 \mathrm{inv}_i + \beta_5 \mathrm{num\_ctry}_i + \beta_6 \mathrm{claims}_i \\ & + \beta_7 \mathrm{bwd\_cits}_i + \mathrm{FE}_{j,t} + \varepsilon_i .\end{aligned} \tag{2}$$

In comparison with model (1), we now additionally consider industry-interaction terms denoted by $\ldots : \mathrm{IND}_j$,

[23] As mentioned before, the time span is limited till the year 2015, because improvement rates can only be added to USPTO patents up to this year. Considering a 5-year window allows us to make an as up-to-date assessment as possible, and at the same time, to consider a sufficient number of patents. Since it takes on average 23.3 months (USPTO, 2021) for a patent to be granted (and for some even longer), this selection has the additional advantage that most patent applications filed during the 2010–2015 time period have either been rejected or granted and are not still pending. Our data for this analysis therefore contains a nearly complete picture of all granted applications of this period.

where j marks the industry to which patent i belongs to. Again, we estimate three specifications. In the first one, we include the interaction term D_i : IND_j, which allows us to analyze whether digital domains are associated with more breakthrough innovations as measured with forward citations of patents than non-digital ones at the industry level. In the second specification, we use the second interaction term k_i : IND_j. This gives indications on whether the positive association between improvement rates and breakthroughs also hold for different industries. In the last specification, we consider the interaction terms D_i : IND_j and D_i : k_i : IND_j. This enables us to investigate for different industries whether the associations are evident for digital and non-digital technologies alike. Hence, the parameter vectors β_{1j}, β_{2j}, and β_{3j} are of interest to us. The control variables and fixed effects are similar to model (1) and used in each specification. Again, we cluster standard errors at the industry level.

Table 2 shows the results. As one can see from column (1), the positive association between digital technologies and our indicator for breakthrough innovations holds for all investigated industries. The same is true for faster-improving technologies (column 2). Thus, the previous results across all industries were not solely driven by some industries but show up for all considered industries. Moreover, there exist substantial differences between the industries. In particular, the positive associations linked to a higher improvement rate are particularly strong in the electrical and medical industry, and rather low in the machinery and, especially, in the computer/ICT industry. It is now interesting to analyze whether the associations are more driven by innovations in the digital or non-digital domain. First of all, the first rows of column (3) show that patents from the digital domain are associated with an increased likelihood of containing a breakthrough innovation as measured with forward citations of patents in all six industries. At the same time, this digital level effect is accompanied by a reduced association between improvement rates and breakthrough innovations when compared to non-digital domains: All else equal, faster-improving technologies are more strongly associated with breakthroughs in the non-digital domain compared to the digital one. This even goes so far that there is no longer an association between the improvement rate and our breakthrough indicator for the digital domain in the chemical and medical industry.[24] Still, in these industries, the digital domain as such is associated with more breakthroughs as measured with forward citations of patents, albeit for these industries it seems not to matter whether these are faster or slower progressing digital technologies. At the same time, however, a positive association between technology improvement rates and our indicator of breakthrough innovations shows up for the non-digital domain for all investigated industries. In addition, in Tables 10, 11, 13, and 14 of "Appendix," we show that the pattern from Table 2 remains robust when different subsets of years, different time thresholds for forward citations to indicate breakthrough innovations, and some alternative measures of breakthrough innovation are considered, respectively. This heterogeneity in the association between digital and non-digital domains at the industry level shows that it is important to consider both dimensions (i.e., distinction between digital and non-digital domains and differences in the improvement rates of technologies).[25]

The results of these regressions can thus be summarized as follows: Patents of the digital domain are associated with a higher probability of containing a breakthrough innovation as measured with forward citations. At the same time, this is true for technologies with higher improvement rates. When differentiating between digital and non-digital technologies at the industry level, the latter association is still evident for the non-digital domain. For the digital domain, in turn, it only remains valid for some industries. However, for all industries, digital innovations per se are associated with a higher incidence of breakthrough innovations. These results suggest that companies which are relatively strongly specialized in digital and rapidly improving technologies should also see a higher number of breakthrough innovations. Consequently, this finding should also translate to the level of industries and countries: If a country's innovation system produces more inventions in digital and rapidly improving technologies, it should benefit from a higher number of breakthroughs. And since early involvement in innovations in disruptive fields has been found to strongly affect long-term prosperity (e.g., Bloom et al., 2021), our empirical results suggest that innovation systems that are involved in bringing forward the fastest improving technologies may benefit from substantial benefits in the future.

3 The state of digital innovation in Switzerland and abroad

Against the background of our empirical results, we next analyze the specialization patterns of Swiss industries toward digital and fast-improving technologies in comparison with other important countries. We start by

[24] In Table 12 of "Appendix," we show that there exists a high positive correlation between digital technology domains and improvement rates for all observed industries.

[25] Table 15 in "Appendix" explicitly shows this heterogeneity by considering a model with all three interaction terms $\beta_{1j}D_i : \text{IND}_j + \beta_{2j}k_i : \text{IND}_j + \beta_{3j}k_i : D_i : \text{IND}_j$ simultaneously, with β_{3j} as the parameter vector of interest.

Table 2 Technological improvement rates and breakthrough innovations across industries

Dependent variable	FWD90		
Model	**(1)**	**(2)**	**(3)**
Digital: Chemical	5.736*** (0.459)		8.035*** (0.704)
Digital: Computer/ICT	1.843*** (0.279)		2.062*** (0.232)
Digital: Electrical	4.806*** (0.198)		6.985*** (0.391)
Digital: Machinery	0.866*** (0.295)		1.260*** (0.254)
Digital: Medical	3.596*** (0.413)		7.333*** (0.690)
Digital: Pharma	1.536*** (0.343)		1.501*** (0.432)
k:Chemical		0.117*** (0.026)	
k:Computer/ICT		0.021*** (0.006)	
k:Electrical		0.256*** (0.015)	
k:Machinery		0.054*** (0.009)	
k:Medical		0.167*** (0.031)	
k:Pharma		0.096*** (0.035)	
Non-digital: *k*:Chemical			0.191*** (0.021)
Digital: *k*:Chemical			− 0.005 (0.020)
Non-digital: *k*:Computer/ICT			0.086*** (0.017)
Digital: *k*:Computer/ICT			0.020*** (0.007)
Non-digital: *k*:Electrical			0.415*** (0.030)
Digital: *k*:Electrical			0.124*** (0.016)
Non-digital: *k*:Machinery			0.167*** (0.016)
Digital: *k*:Machinery			0.039*** (0.014)
Non-digital: *k*:Medical			0.227*** (0.044)
Digital: *k*:Medical			0.020 (0.023)
Non-digital: *k*:Pharma			0.087** (0.040)
Digital: *k*:Pharma			0.059* (0.034)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	3,243,802	3,243,802	3,243,802

All estimations include USPTO patents from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA of the filing years 1990–2015. If a patent has inventors from more than one of those countries, it will only take into account once. The first model specification shows associations between digital domains and breakthrough innovations for different selected industries. The second considers associations between technology improvement rates and breakthrough innovations, and the third do the same but distincts between digital and non-digital domains. In order to show associations in percentage points, we have multiplied the FWD90-dummy by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^* < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

examining the shares of Swiss industries' digital patents and compare them to those of other countries.[26] Figure 3 shows that Switzerland's share of digital patents in an industry in relation to all patents of that industry is rather low across all industries, whereas the distance to the first

[26] We focus on the same six industries as before and again take into account all patents filed by inventors from 9 inventor countries at the USPTO between 2010 and 2015. It is important to note here that all country comparisons in this paper are based on the residence of patent inventors (see Sect. 2). Hence, our descriptive analyses make an assessment about the specialization of a country's overall innovation system and not about the competitiveness of its firms (which can perform parts of their research abroad). For example, Fig. 3 suggests that innovations developed in Switzerland are much less directed toward digital technologies compared to other countries.

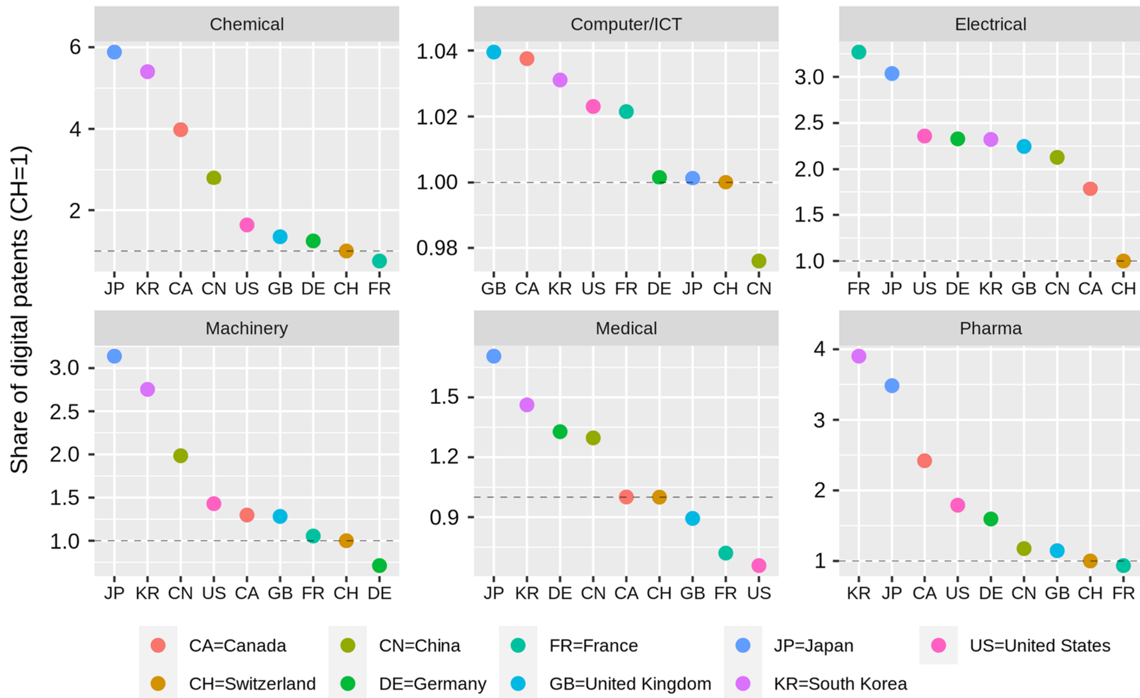

Fig. 3 Share of digital patents of different industries and countries. *Notes*: Calculations based on the definition for digital IPC classes from Inaba and Squicciarini (2017) that were matched to USPTO patents between 2010 and 2015. The figure shows the number of digital patents of industry *j* of country *c* relative to the total number of patents of industry *j* of country *c*, normalized by the value of the respective Swiss industry: $\frac{(\text{num\_digital\_pat}_{j,c}/\text{num\_pat}_{j,c})}{(\text{num\_digital\_pat}_{j,c=\text{CH}}/\text{num\_}pat_{j,c=\text{CH}})}$

ranked country is particularly large for the chemical and pharmaceutical industries.[27]

It is noteworthy that Switzerland's innovation system is relatively heavily specialized in exactly these two industries compared to most other countries (a further one being the medical industry, see Table 6 in "Appendix"): Over the time window of our study, the pharmaceutical industry represented 22% of Swiss patenting, and the chemical industry accounted for another 10%. Yet, the amount of digital patenting in these two core Swiss industries is about three to six times lower compared to the leading countries, Japan and South Korea. Another industry with substantial weight for Switzerland is the machinery industry (14% of Swiss patents). But again, digital patenting is much lower compared to the leading countries. Similar and consistent to the findings of, e.g., Gramke and Glauser (2017) and Grampp et al. (2018), Fig. 3 thus clearly demonstrates that Switzerland's innovation system is not particularly directed toward the digital domain—and that this holds for all investigated industries. This could be a problem since, as we have previously shown, such innovations are associated with a higher probability of breakthrough innovations.

However, in addition to simply examining digital patenting shares, we can now also focus on the improvement rates of the technologies Swiss digital patents are associated with. This provides an indication about whether the relatively small number of Swiss digital patents is nevertheless specialized toward fast evolving technologies. Figure 4 provides the respective graphical evidence. Similar to before, the figure again suggests that Switzerland lags

[27] The figure shows the share of digital patents of an industry of a country in relation to all patents of that industry and country, normalized by the corresponding Swiss share. This measure is often used to investigate technology specializations of a country, where a value greater (lower) than one means that the respective other country has relatively more (less) digital patents in an industry than (in our case) Switzerland. By using the share of digital patents, this measure also takes differences in the size of industries between countries into account, as long as the share of digital patents does not systematically depend on the size of an industry. This, however, seems not to be the case for our sample. First, we have calculated the correlation between the share of digital patents of a country's industry and its average number of employees (i.e., proxy for size) between 2010 and 2015. For the number of employees, we used data from the OECD-STAN database. Unfortunately, we could not calculate the number of employees for Medical Technology and Computer/ICT, as these are composed of different NOGA sub-industries. Moreover, figures for China are not included in the STAN database. For the remaining subsample of eight countries and four industries, there is virtually no correlation (although we are aware of the fact of the really small sample of only eight observations for each industry): Chemical 0.00878, Electrical 0.0634, Machinery 0.00609, and Pharma − 0.0216. Second, as shown in Fig. 7 of "Appendix," the ranking of the countries remains quite stable if the absolute number of digital patents in relation to the employment of an industry and country is considered. In particular, Switzerland is also at the lower end of the rankings in all industries.

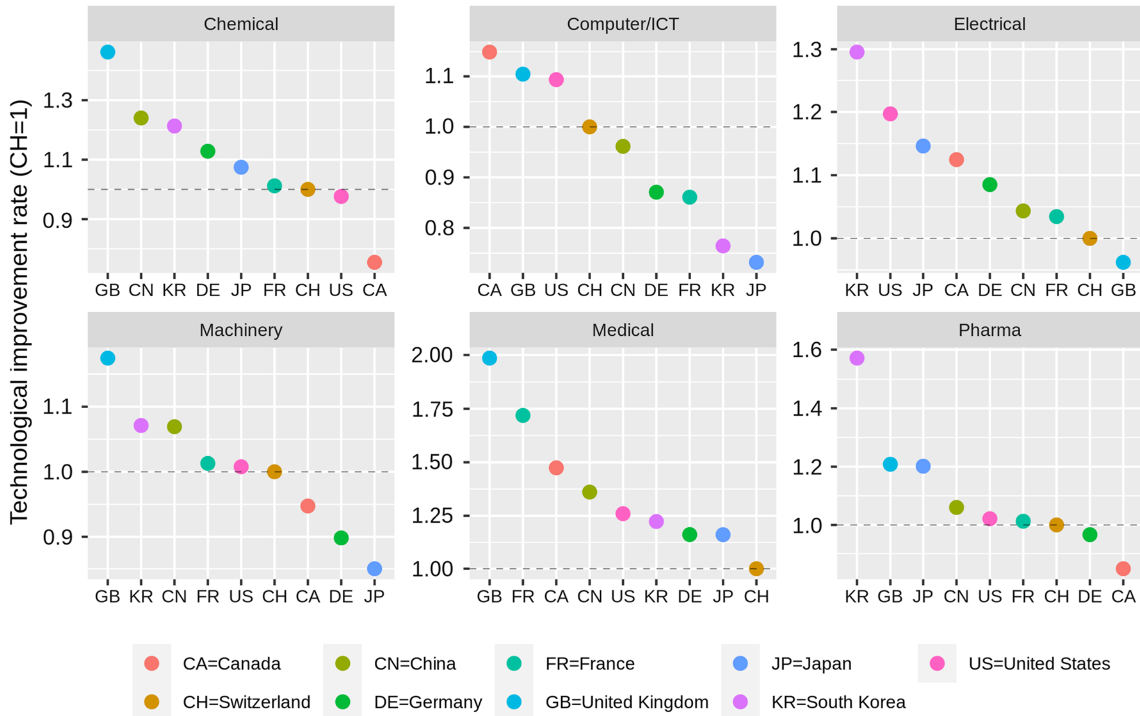

Fig. 4 Average technological improvement rates for digital patents of different industries and countries. *Notes*: Calculations based on improvement rates of 1757 technologies taken from Singh et al. (2021) and the definition for digital IPC classes from Inaba and Squicciarini (2017) that were both matched to USPTO patents between 2010 and 2015. The average technological improvement rate is normalized according to the value of Switzerland

behind the leading countries. Swiss digital innovations generally occur in digital technologies with rather low improvement rates, and Switzerland's backlog against other countries is most pronounced for the medical industry. For this industry, the average improvement rate is only about half of that of the UK. Furthermore, Switzerland lags the top-ranked country by around 60% in the pharmaceutical industry, by around 30% in the electrical industry, and by around 15% in the machinery and computer/ICT industries.[28] For these latter four industries, our regression estimates have shown significant relationships of digital patents' improvement rates with their breakthrough potential. Thus, Switzerland's lack of specialization toward the fastest improving digital technologies might indicate a further threat to its future potential to produce breakthroughs in these industries.

That said, fast-improving technologies naturally exist outside the digital sphere as well, and the Swiss innovation system might be better positioned in the non-digital domain. Figure 9 in "Appendix" illustrates that Swiss innovations related to non-digital technologies have similar improvement rates in the medical and pharmaceutical industry compared to other countries. But for the chemical, computer/ICT, electrical, and machinery industries, Switzerland is again positioned among the laggards, whereas the backlog is particularly substantial in the electrical and machinery industries. Hence, there is also a backlog for Switzerland compared to other countries in non-digital technologies. But the Swiss innovation system seems to be much closer to the forefront of cutting-edge innovation outside the digital domain. Nevertheless, overall, the relatively weak performance of the Swiss innovation system in digital technologies dominates. Figure 10 in "Appendix" illustrates this by showing average technological improvement rates for all patents no matter if they are digital or not. Switzerland again lags the leading countries' average improvement rates substantially in almost all industries. In the machinery industry, Swiss innovations are associated with an

[28] Figure 4 in "Appendix" additionally shows the average improvement rates of digital patents for different industries, whose improvement rates are above a country's 70th, 80th, and 90th percentile. When considering only these subsets of patents belonging to the technologies with the respective highest improvement rates, the backlog of Switzerland becomes stronger for the chemical, electrical, medical, and pharmaceutical industry. It is less pronounced for the computer/ICT industry and, interestingly, disappears for the machinery industry. Besides this additional information, this robustness check also underpins our findings that Switzerland's digital innovations occur mainly in technologies with rather low improvement rates compared to other countries.

around 80% lower improvement rate compared to South Korea, which leads the ranking. In the electrical industry, Switzerland is around 25% behind the highest improvement rate of Japan, and in the pharmaceutical industry it is lagging South Korea by close to 20%.[29]

Taken together, the descriptive evidence thus highlights a relatively weak engagement of Switzerland's innovation system with digital technologies. Furthermore, digital innovations in Switzerland are less likely to occur in the fastest improving digital technologies compared to the leading countries. Together, these two patterns are the drivers for Switzerland's rather low overall specialization toward technologies with high improvement rates, which suggests that the country's innovation system tends to be a laggard regarding the most dynamically evolving technologies.

3.1 Discussion of results

The question is whether Switzerland should be concerned about these observed patterns. Since theoretical models typically suggest that technology diffusion is associated with the existence of first-moving innovators, early adopters, and laggards that catch up later, there is an argument that Swiss companies may simply focus on adoption instead of innovation in digital technologies.[30] However, since digital technologies may have special characteristics, being an adopter rather than an innovator can have various consequences.[31] To consider potential effects on longer-term economic competitiveness, it is therefore crucial to assess whether Switzerland's current backlog is a cause for concern.

On the one hand, R&D activities in digital and fast-improving technologies are typically associated with local spillovers, higher wages, and substantial value creation in the future.[32] Local R&D activities might also foster the technology adoption by local firms, which has been shown to depend on the existing overall knowledge stock regarding a new technology (e.g., Battisti et al., 2009). Moreover, in the majority of cases, digital and non-digital innovations are likely to be increasingly mingled together to create new products and services. If digital components become increasingly important in a wide range of products an ever greater share of the generated surplus might go to digital innovations.[33]

Another negative implication could arise if innovations compete (directly) with each other, i.e., are substitutes. In this case, faster-improving technologies might replace or lower the demand for products that are based on slower improving ones, since the former have usually new (and superior) features or perform much better (Hoisl et al., 2015). As a result, countries and their core industries might be at risk of being disrupted and leapfrogged if they focus on less rapidly advancing technologies.[34] With this regard, Switzerland's particularly pronounced digital backlog in some of its core industries (pharmaceuticals, chemicals, as well as the medical and machinery industry) could be critical.[35]

Hence, there are several factors that may lead to a situation where Switzerland might be confronted with challenges and miss out on long-term benefits if its innovation system is relatively weakly embracing novel digital technologies. Our empirical results support this view suggesting that fast-improving digital technologies are associated with a higher likelihood of breakthrough innovations as measured with forward citations of patents. It might therefore be beneficial to try to shift the Swiss innovation system toward technologies that could be associated with higher value creation in the future (see, e.g., Redding, 1999 for a theoretical rationale).

[29] Figure 11 in "Appendix" additionally shows the average improvement rates of all patents for different industries, whose improvement rates are above a country's 70th, 80th, and 90th percentile. As for the digital domain (see Footnote 28), the backlog of Switzerland becomes more pronounced for the chemical, electrical, medical, and pharmaceutical industry when focusing only on the patents that are part of the respective percentiles. In addition, the gap persists in these subsamples for the computer/ICT industry and the machinery industry, but is of lower magnitude.

[30] See, for example, Stokey (2021), Comin and Hobijn (2010), Hall (2004), Geroski (2000).

[31] Some distinctive characteristics of digital technologies are, for example, supply-side economics of scale due to high fixed costs and low marginal costs, demand-side economies of scale arising from increased consumer benefits with larger numbers of users, and general-purpose properties resulting from digital technologies' usefulness across very different industries (Brynjolfsson et al., 2021; Brynjolfsson & McAfee, 2014). Due to these characteristics of many ICT systems, it is, for example, particularly important in the area of ICT to distinguish between innovation and production on the one hand and adoption and usage on the other. For example, enterprise resource planning platforms, such as those from ORACLE or SAP, are used by companies in a wide variety of industries, but are developed only by just a few (IT) companies, implying big market power.

[32] See, for example, Bloom et al. (2021), Baldwin (2018), Hoisl et al. (2015), Hall et al. (2007).

[33] In the manufacturing sector, for example, this could happen if networks and ecosystems of smart and connected products become widespread (Porter & Heppelmann, 2015). In this case, it may no longer be innovations in the physical area that receive the largest share of the corresponding value added, but digital innovations, or more specifically, the provider of the networks and platforms as such (Bamberger & Lobel, 2017; Porter & Heppelmann, 2014).

[34] See, e.g., Confraria et al. (2021) or (Lee & Malerba, 2017) for a recent contribution, or Brezis et al. (1993) for an older seminal work.

[35] It should be noted, however, that our analysis does not allow us to evaluate whether or not different technologies compete with each other. Thus, our study cannot directly assess whether Swiss industries are at risk of being disrupted. Yet, due to the general-purpose nature of some digital technologies, it is very likely that at least some technologies in these industries will compete with older technologies or change from non-competitive to competitive technologies in the (near) future.

On the other hand, researchers have shown that laggards may catch-up to first-movers by exploiting positive spillovers, skipping some stages of the development process, or by following completely different, yet more efficient, technological paths (see, e.g., Au & Kauffman, 2001; Lee & Lim, 2001; Hoppe, 2000). In principle, economic theory even provides an argument that it may be beneficial for a country to refrain from changing its specialization at all, because countries are likely to generate the highest welfare when they specialize on the basis of their comparative advantages. Following this logic, our results would then simply imply that the Swiss innovation system has (at least until recently) its comparative advantage in more traditional, not-so-fast-improving fields. And an ongoing orientation toward these technological areas may well have advantages. For example, it might be easier to maintain a high competitiveness (e.g., by protecting some selected products with patents), because these areas do not require innovations that go beyond relatively slow and steady improvements.

In addition, due to specific characteristics of digital technologies (see Footnote 31), only a few so-called tech-clusters and superstar companies are likely to benefit greatly, while everyone else tends not to (Chattergoon & Kerr, 2022; Tambe et al., 2020; Triulzi et al., 2020). Since Switzerland is currently not one of the leading innovators in these areas, it could be advantageous to continue to stay out of such a tech-race and instead source ICT from the respective technology leaders. By doing so, Switzerland's lacking orientation toward digital innovations might be less serious as Swiss companies could simply relocate selected R&D activities to other countries or entirely source the required digital components from foreign firms (see, e.g., Harhoff et al., 2014; Griffith et al., 2006). Doing so might mitigate Swiss companies' risk of being leapfrogged and could thus sustain their international competitiveness.[36]

Overall, potential implications of Switzerland's backlog in digital innovations are thus ambiguous. However, we would consider it more concerning if the following conditions are met: First, we would expect more negative implications if the fraction of Swiss companies' products that is or will be competing with digital alternatives is large. Second, if it becomes apparent that digital parts of products will increasingly receive a larger share of the value creation. And third, if technological catch-up becomes more difficult over time, for example, due to a particular "technological regime" (Lee & Lim, 2001) that is associated with digital technologies (e.g., network effects).

[36] Since we are interested in the effects on Switzerland as a business location, the ownership structure and thus the question of whether the innovations originate from different companies or not only play a subordinate role which we will not further discuss here.

4 Conclusion

Technologies evolve heterogeneously and differ substantially with regard to their rate of technological improvement. In this paper, we have combined different sources of information to study these differences in detail. Our empirical findings suggest that primarily digital technologies improve at very fast pace, and patents from the digital domain and those related to the fastest improving technologies are more strongly associated with breakthrough innovations as measured with forward citations across industries. We then compare countries' specialization patterns with regard to the digital domain and investigate their orientation toward fast-improving technologies. We find that Swiss innovations are neither particularly focused on the digital domain, nor toward the fastest improving digital technologies. In the non-digital domain, the Swiss innovation system's backlog to the leading countries is (much) less pronounced, but it is also not among the forerunners in rapidly evolving fields except for the medical and pharmaceutical industries. However, overall, the relatively weak engagement in the digital domain dominates and Switzerland seems to be among the laggards with respect to innovations in today's fastest improving technologies.

Against this background, the question arises whether this could be of concern for Switzerland. As we have discussed, this might be especially the case if catch-up becomes more difficult, and if new technologies compete with older ones and thus represent substitutes. However, instead of being pure substitutes, it is likely that digital and non-digital innovations are increasingly merged together to create new products, services, and even entirely new ecosystems of connected smart products. A corresponding strategy for Switzerland in this scenario could be to focus on its core innovative strengths in the more tangible areas and to increasingly adapt digital innovations from abroad. However, this is not without risk, since digital innovations in particular are likely to be accompanied by high value creation, which Switzerland and its core manufacturing industries would then be missing out.

Overall, a crucial, yet open, question for the Swiss innovation system is thus how rapidly and smoothly it can adapt itself to fast-improving technologies. If catch-up is rather fast, the above-mentioned concerns would become less threatening for Switzerland as a research location. Therefore, we consider it a very interesting avenue for future research to evaluate the Swiss innovation system's rate of adaption toward differently evolving technologies. Another very interesting and challenging analysis would be to reveal underlying determinants that lead to the observed differences in countries' innovation systems.

5 Computational details

Most computations were performed at sciCORE scientific computing center at the University of Basel (http://scicore.unibas.ch). Data processing and visualizations were conducted in R (Version 4.1.3). We have mainly relied on the package collection tidyverse (Wickham et al., 2019) and estimated regressions using the package fixest (Bergé, 2018).

A Appendix

A.1 Technical appendix: estimating technological improvement rates

The paper builds on prior work by Singh et al. (2021) who estimate technological improvement rates based on information encoded in patents. Their approach is motivated by an observation from Triulzi (2015), who notes that companies with more "central" patents in the semiconductor industry were able to catch up faster to technological leaders. Triulzi et al. (2020) show that this observation does not only apply to companies in the field of semiconductors, but that the "centrality" of a whole technology field within the patent universe is indicative of its improvement dynamics. Building on these insights, Singh et al. (2021) estimate improvement rates for 1757 different technologies. In the following, we briefly outline how Singh et al. (2021) define and calculate the "centrality of patents" and how they use it to estimate technology improvement rates. This requires several steps. In a first step, Singh et al. (2021) calculated for each patent i the total number of so-called incoming paths of its backward citations:

$$\text{incoming paths}_i = L_{\text{BWD}_i} + \sum_{b \in \text{reachable}_{\text{BWD}_i}} L_{\text{BWD}_b}, \tag{3}$$

where L_{BWD_i} is the number of direct backward citations patent i has made (i.e., all patents that are cited by patent i) and the second term on the right-hand side the number of backward citations of all patents that can be reached from patent i by traveling backward within the patent citation network (see Fig. 5 for an illustration). In addition, Singh et al. (2021) also calculated the total number of so-called outgoing paths of patent i along its forward citations up to three years after filing:

$$\text{outgoing paths}_{i,t+3} = L_{\text{FWD}_{i,t+3}} + \sum_{b \in \text{reachable}_{\text{FWD}_{i,t+3}}} L_{\text{FWD}_b}, \tag{4}$$

where $L_{\text{FWD}_{i,t+3}}$ is the direct number of forward citations patent i has received until three years after the patent has been granted. And the second term on the right is the number of forward citations of all patents that can be reached from patent i by traveling the patent citation network forward to three years after the patent has been granted (see again Fig. 5 for an illustration). In a next step, they use these two measures to calculate a patent's "Search Path Node Pair" (*SPNP*) index. The SPNP index is calculated by multiplying Eqs. (3) and (4) with each other:

$$\text{SPNP}_{i,t+3} = (\text{incoming paths}_i + 1) * (\text{outgoing paths}_{i,t+3} + 1).$$

In order to avoid multiplications with zero, a constant of value one is added to each term.[37] The SPNP index depends on the filing year of patent i, its technology, and the number of citations it mentioned and received. Thus, in order to separate the centrality of a patent from all of these factors, Singh et al. (2021) calculate for each patent i the expected SPNP that includes all dependencies except the one they are interested in—namely, whether the patents that patent i cites and is cited by represent key nodes in the patent citation network. To achieve this, they calculate for each patent i 1000 different hypothetical $\text{SPNP}_{i,t+3}$ values by randomly swapping the patents along the incoming and outgoing paths while taking into account various constraints. First, they randomly swap patents from the same USPC class as patent i with patents from the same class and filing year as the ones swapped. Second, they randomly swap patents from a different USPC class than patent i with patents from the pool of all other patents having the same filing year as the swapped ones. Due to this randomization, "each patent preserve the same number of citations made and received, the same age profile of its citations made and received and the same share of citations made that go to patents classified in the same class" (Singh et al., 2021, p. 11). The only difference between the 1000 hypothetical worlds is that the cited and citing patents of patent i have different numbers of forward and backward citations.

[37] The calculations of Singh et al. (2021) differ slightly from those from Triulzi et al. (2020). Instead of the SPNP of the focal patent i, Triulzi et al. (2020) use the average SPNP of all backward citations of patent i.

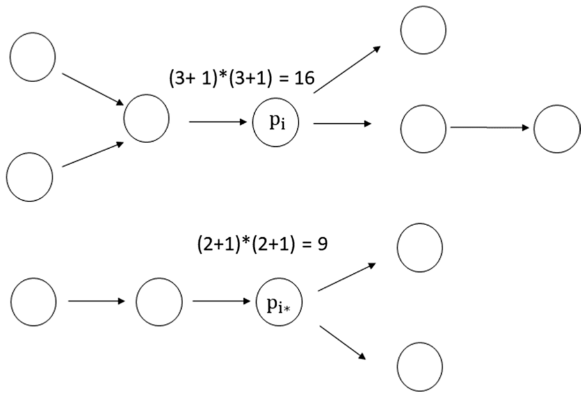

Fig. 5 Illustration of the SPNP index and randomization process. *Notes*: Assume patent p_i is the actual observed one in the citation network. It has received one direct backward citation, two indirect backward citations along the incoming paths and two direct forward citations and one indirect forward citation along the outgoing paths. Together with the added constants of one, this results in a SPNP of sixteen. In contrast, patent p_{i*} has randomly created backward and forward paths. By construction, it has the same number of backward and forward citations as patent p_i. But in the example the randomly assigned backward cited patent only cites one patent and the randomly assigned forward cited patents were not cited at all. This results in a lower SPNP of nine

To give an example, consider Fig. 5, where p_i is the actual observed patent in the citation network. Assume that it has received one direct backward citation and two indirect backward citations along the incoming paths. In addition, it received two direct forward citations and one indirect forward citation along the outgoing paths. In contrast, the backward and forward paths of patent p_i* have been artificially generated. By assumption of the randomization process, it has the same number of backward and forward citations as patent p_i. However, its randomly assigned backward and forward cited patents have fewer citations, resulting in a lower SPNP score of nine instead of sixteen.

In order to obtain the expected SPNP value of patent i, Singh et al. (2021) take the average over the 1000 hypothetical worlds. Using the resulting expected value and the corresponding standard deviation, they calculate the z-value of the SPNP for patent i as

$$z_i = \frac{\mathrm{SPNP}_{i,t+3} - E(\mathrm{SPNP}_{i,t+3})}{\sigma_{\mathrm{SPNP}_{i,t+3}}}.$$

Since the number of possible input paths increase over time, the z-values increase also as an artifact of the randomization process. To account for this, they normalize the z-values by using the rank quantile to which the z-value of patent i belongs according to its filing year and use this as the patent's centrality value. In the next step, Singh et al. (2021) take the average among the centrality values of all patents assigned to a technology and use it in an OLS-regression to estimate a relationship between the observed technology improvement rates (based on "real-world" metrics) for 30 technologies (which are the same as in Triulzi et al. 2020) and the average of the centrality of the associated patents. Finally, Singh et al. (2021) use this estimated relationship to predict the technology improvement rates for 1757 endogenously determined technologies, for which patent data exist but no "real-world" metrics on technology progress are available. In doing so, they take the mean of the centrality values of all patents belonging to a technology, put it into the estimated relationship, and eventually obtain an estimate for each of the 1757 endogenously determined technologies.

A.2 Additional graphs

See Figs. 6, 7, 8, 9, 10, 11.

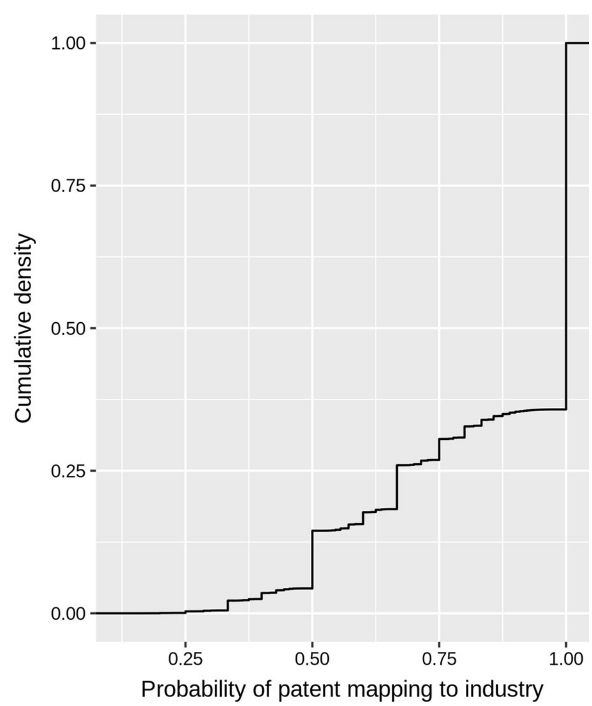

Fig. 6 Cumulative density of the patent-industry mapping probabilities. *Notes*: The graph shows the distribution of probabilities used to map patents to the Chemical, Computer/ICT, Electrical, Machinery, Medical, and Pharma industry. The data contain all patents used for our descriptive analysis. Specifically, it contains the filing years 2010–2015, the countries Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA

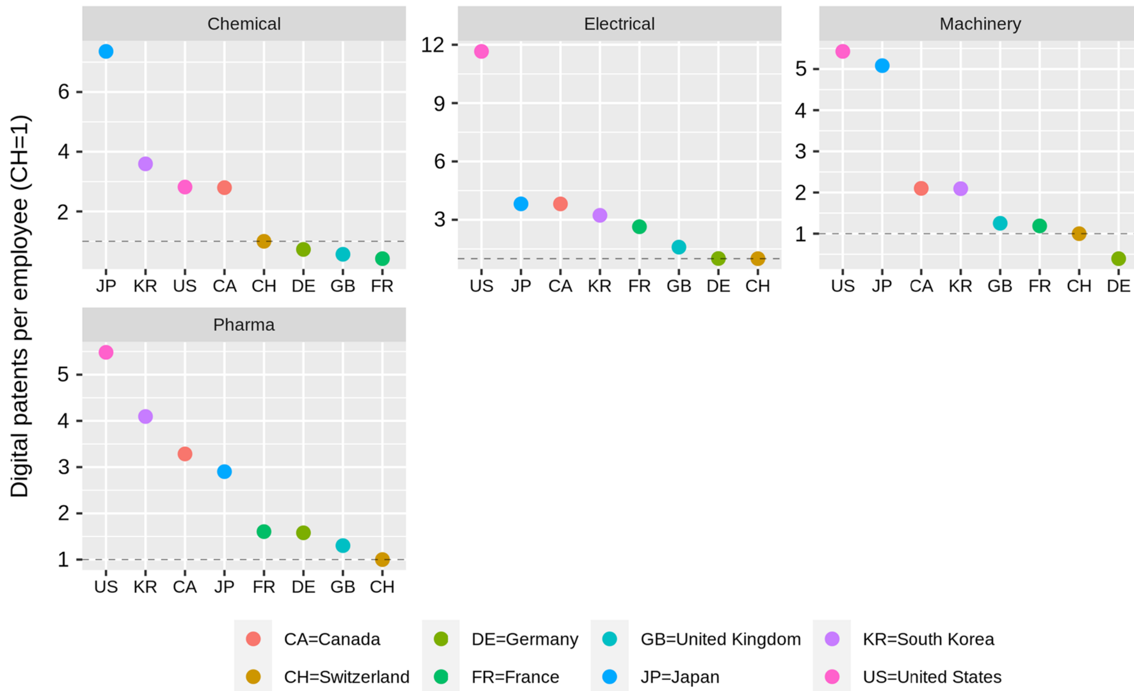

Fig. 7 Digital patents per employee across industries and countries. *Notes*: The y-axis shows digital patents of the years 2010–2015 relative to the average number of employees between 2010 and 2015 per industry and country normalized by the value of Switzerland. For the number of employees, we used data from the OECD-STAN database. Unfortunately, we could not calculate the number of employees for Medical Technology and Computer/ICT, as these are composed of different NOGA sub-industries. Moreover, values for China are not included in the STAN database

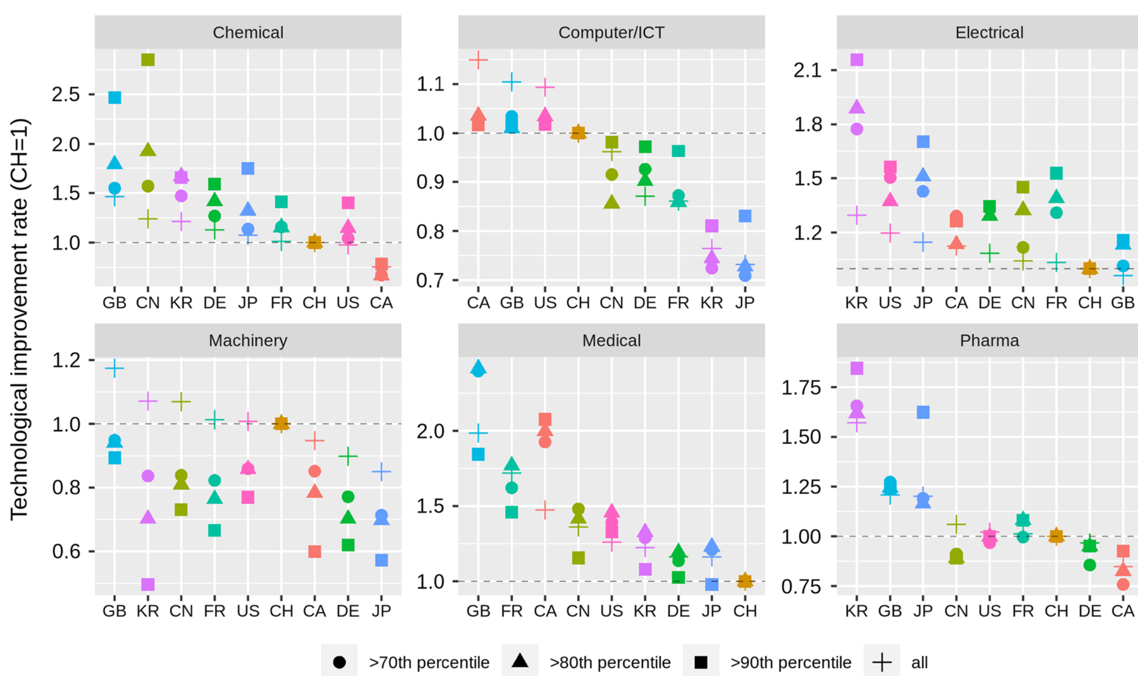

Fig. 8 Average technological improvement rates for digital patents across industries and countries for different percentile subsets. *Notes*: Calculations based on improvement rates of 1757 technologies taken from Singh et al. (2021) and the definition for digital IPC classes from Inaba and Squicciarini (2017) that were both matched to USPTO patents between 2010 and 2015. The average technological improvement rate is normalized according to the value of Switzerland. The plot shows average improvement rates for patents whose improvement rate is above the xth percentile of a given country. For comparison, the dots labelled as *all* show the averages across all patents as used in the main text

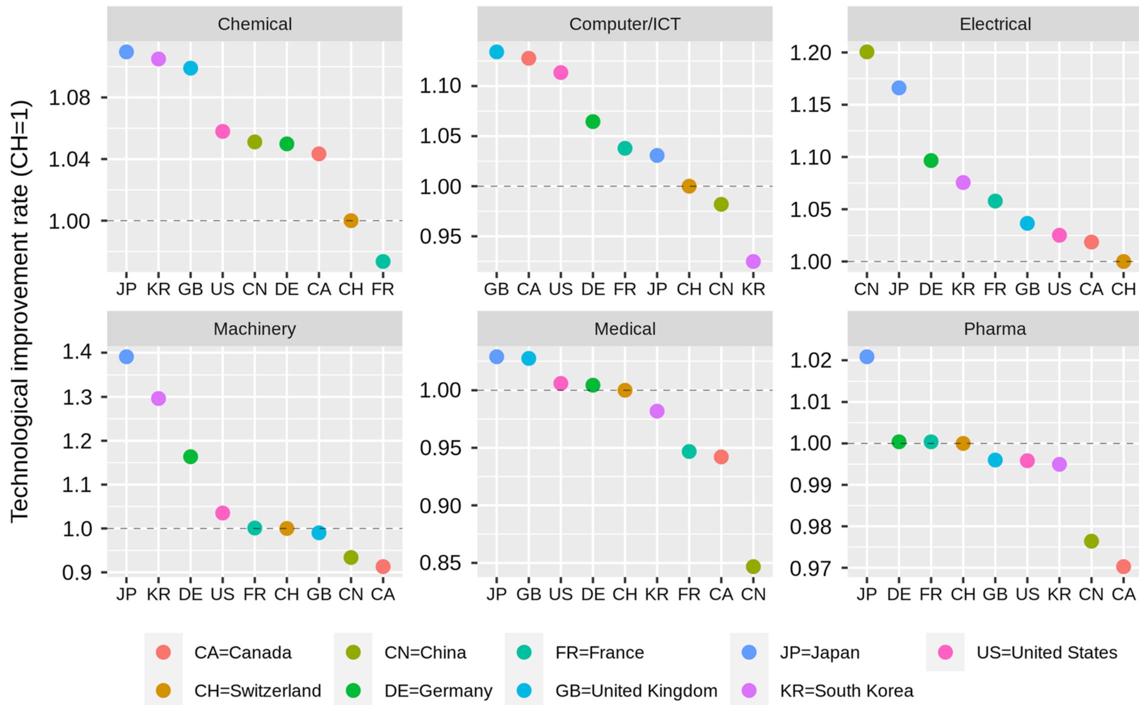

Fig. 9 Average technological improvement rates for non-digital patents across industries and countries. *Notes*: Calculations based on improvement rates of 1757 technologies taken from Singh et al. (2021) and the definition for digital IPC classes from Inaba and Squicciarini (2017) that were both matched to USPTO patents between 2010 and 2015. The average technological improvement rate is normalized according to the value of Switzerland

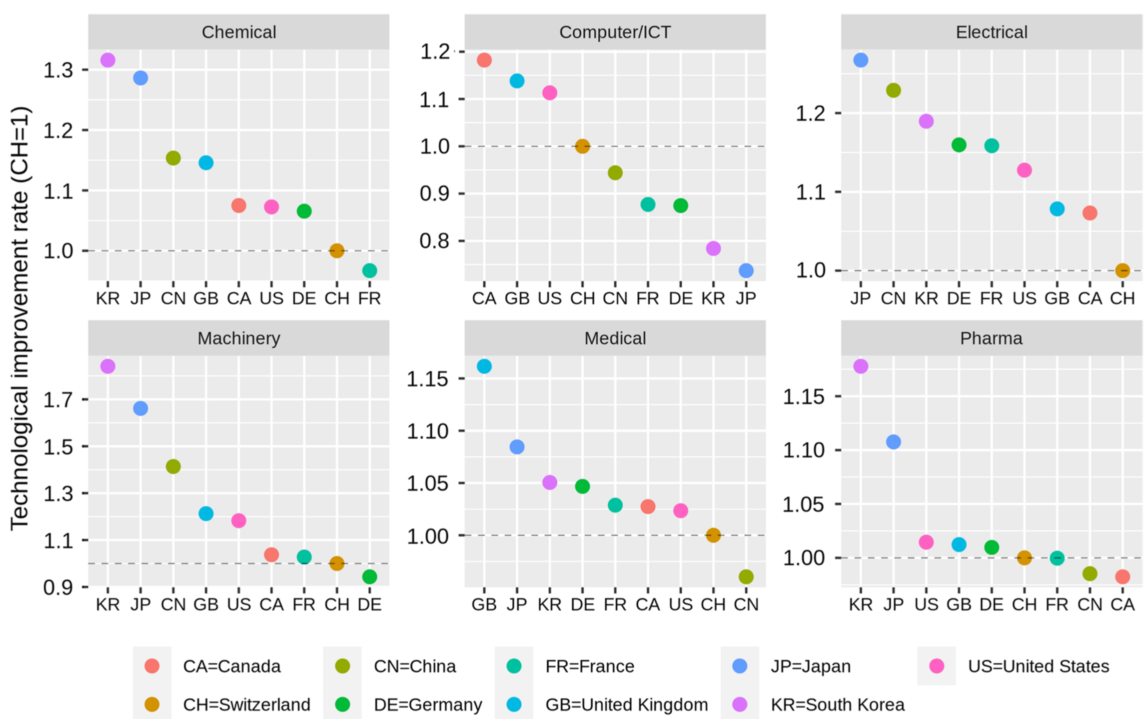

Fig. 10 Average technological improvement rates of all patents of different industries and countries. *Notes*: Calculations based on improvement rates of 1757 technologies taken from Singh et al. (2021) that were matched to USPTO patents between 2010 and 2015. The average technological improvement rate is normalized according to the value of Switzerland

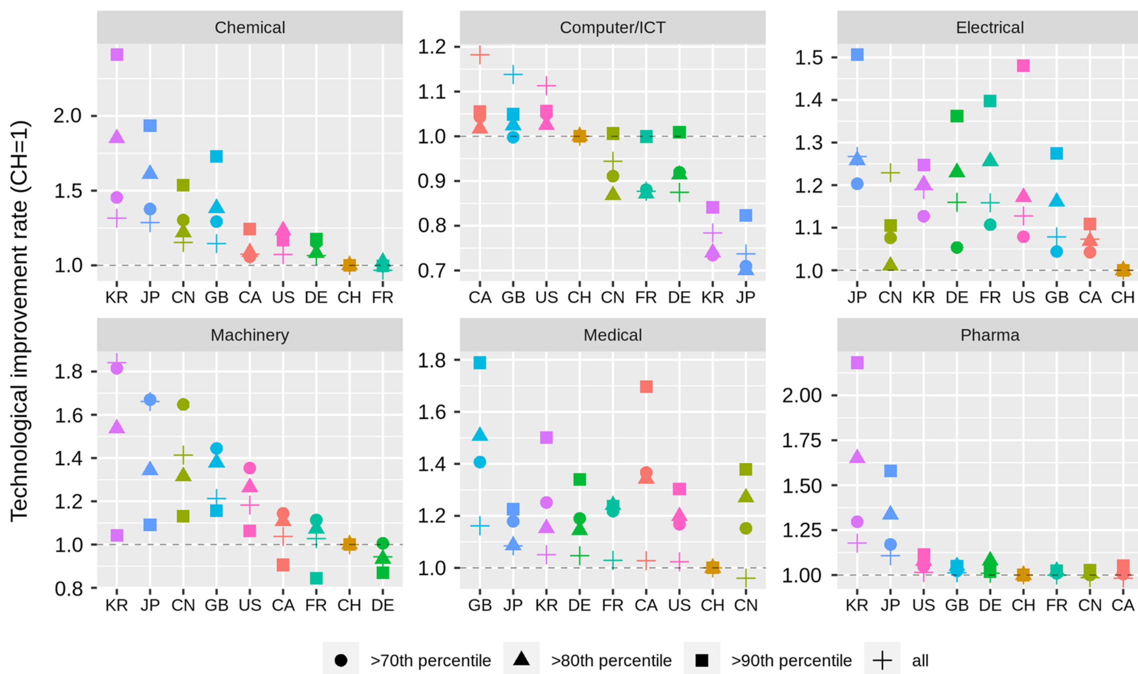

Fig. 11 Average technological improvement rates of all patents of different industries for different percentile subsets. *Notes*: Calculations based on improvement rates of 1757 technologies taken from Singh et al. (2021) that were matched to USPTO patents between 2010 and 2015. The average technological improvement rate is normalized according to the value of Switzerland. The plot shows average improvement rates for patents whose improvement rate is above the xth percentile of a given country. For comparison, the dots labeled as *all* show the averages across all patents as used in the main text

A.3 Additional tables

See Tables 3, 4, 5, 6 and 7.

In Table 8, we use different time thresholds for forward citations to indicate breakthrough innovations. While we take into account different citation practices between different technology areas by classifying breakthroughs per WIPO technology field and publication year, our threshold of five years could imply a systematic bias toward digital patents. As our results show, digital innovations have higher technology improvement rates and are therefore likely to spread and be adapted more quickly. This could imply that within a WIPO technology field digital patents are more often cited than other patents in the first years after publication. Using a time horizon of five years, breakthroughs in the non-digital area in particular could therefore be missed. To check this, we also consider seven- and ten-year thresholds of forward citations as criteria for breakthrough innovations. As the results of Table 8 show, digital patents are still associated with a higher probability of containing a breakthrough innovation when using seven- and ten-year forward citation thresholds. Also, the size of the coefficient remains very robust. This suggests that the results are not driven by the possibility that non-digital patents require a longer time horizon to be cited.

In Table 9, we use an alternative measure to indicate breakthrough innovations based on the similarity and dissimilarity of patent texts as popularized by Kelly et al. (2021) and Arts et al. (2021).[38] In particular, Kelly et al. (2021) calculate the importance of a patent by dividing the five-year forward by the five-year backward similarity of patent texts and propose that a higher value is a good indicator of breakthrough innovations. This is because a higher value can either emerge because of a lower backward similarity, which is the case if, ceteris paribus, the patent text differs stronger from past patents, indicating that the invention is somehow of a completely new type. Or it can be due to a higher forward similarity, which means the patent text is, ceteris paribus, more similar to future patents. As argued by Kelly et al. (2021), this

[38] The corresponding data are available at https://zenodo.org/record/3515985#.Yjsskk2ZO38.

Table 3 Improvement rates of the 10 top and bottom ranked technologies

Technology Code (UPC-IPC)	Predicted *k* (technological improvement rate)	Technology Description	Digital domain
719-G06F	216	Dynamic information exchange and support systems integrating multiple channels	Yes
709-G06F	207	Network management specifically client-server applications	Yes
709-G06Q	206	Network messaging system including advertisement	Yes
709-H04L	203	Network address and access management	Yes
726-H04L	200	Securing Enterprise Networks by system architecture (including security policies), user authentication, on the enterprise network, VPNs and defense mechanisms against DDoS attacks	Yes
726-G06F	195	Enterprise networks access management by individual users	Yes
725-H04N	194	Content delivery in video distribution systems	Yes
713-H04L	188	Data Encryption systems, including hybrid software/hardware systems and protocols for encryption, security associated with access and other security issues	Yes
380-H04N	180	methods and apparatus for mixing encrypted digital data with unencrypted digital data	Yes
707-G06F	179	Data management (including databases and novel data structures) for enabling and automating ecommerce activities	Yes
280-B62H	3	Supports for two wheeled vehicle and locks	No
280-B60S	3	Vehicle stabilization and miscellaneous operations	No
280-B60D	3	Hitching assemblies for towing vehicles	No
252-C10M	3	Lubricants	No
24-A45F	3	Clips, hooks, straps, ties, etc., for holding household items	No
227-B25C	3	Fastener driving apparatus—Power-assisted nail guns, staplers, etc.	No
223-A41D	3	Physical manipulation of clothes, particularly hangers	No
211-A47L	3	Racks and Trays for household items	No
16-B25G	3	Handles	No
84-G10D	3	Stringed, wind-based, percussion musical instruments	No

The information of columns 1–3 is directly taken from Singh et al. (2021, p. 19–20). Column 4 is derived using information from Inaba and Squicciarini (2017)

Table 4 Industry names and NACE codes

Industry	NACE code rev. 2 (NOGA 08)	Number of patents	Number of patents-UPC-IPC combinations
Chemical	20	190,568	375,203
Computer/ICT	26.1, 26.11, 26.12, 26.2, 26.30, 62	825,259	1,373,899
Electrical	27	164,648	218,703
Machinery	28	497,150	697,244
Medical	26.6, 32.5	121,302	185,216
Pharma	21	145,763	422,139

The NACE codes considered are based on a manual selection guided by Eurostat (2008). The number of patents relates to granted USPTO patents from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA granted between 1990 and 2015. Patents are assigned to industries based on the probabilistic matching described in De Rassenfosse et al. (2014). In doing so, each patent has been assigned to the industry with the highest matching probability. In addition, a patent is assigned to a Singh et al. (2021) technology based on its three-digit UPC and four-digit IPC code. If a patent belongs to more than one UPC-IPC code, it is assigned to each of it. The total number of distinguished patent-UPC-IPC combinations is shown in the last column

Table 5 Number of patent UPC-IPC code combinations per country and industry

Inventor Country	Chemical	Computer/ICT	Electrical	Machinery	Medical	Pharma
Canada	7859	35,574	5705	20,173	3788	16,238
China	3532	27,776	5115	5607	688	5129
France	19,242	30,573	6805	18,985	4758	25,623
Germany	53,486	59,280	17,412	66,577	12,971	41,315
Japan	85,961	357,049	53,442	187,692	16,287	49,001
South Korea	9086	100,521	12,386	21,478	1420	7053
Switzerland	8201	7256	2294	9642	3121	12,360
UK	14,450	35,434	4304	19,431	5191	28,742
USA	194,429	764,742	115,567	364,249	142,314	278,710

Patents are assigned to industries based on the probabilistic matching described in De Rassenfosse et al. (2014). In doing so, each patent has been assigned to the industry with the highest matching probability. Moreover, each patent has been assigned to the mentioned country if at least one inventor resided there (as mentioned in the inventor addresses of the patent texts). In addition, a patent is assigned to a Singh et al. (2021) technology based on its three-digit UPC and four-digit IPC code. If a patent belongs to more than one UPC-IPC code, it is assigned to each of it. Considering all these points leads to the shown total number of distinguished patent-UPC-IPC combinations per country and industry of the filing years 1990–2015

Table 6 Distribution of countries' patents across industries

Country	Chemical	Computer/ICT	Electrical	Machinery	Medical	Pharma	Others
Canada	0.05	0.40	0.05	0.15	0.02	0.07	0.26
China	0.05	0.54	0.10	0.10	0.01	0.06	0.14
France	0.10	0.32	0.04	0.13	0.02	0.15	0.24
Germany	0.12	0.24	0.06	0.18	0.04	0.10	0.26
Japan	0.07	0.43	0.06	0.19	0.02	0.03	0.20
South Korea	0.06	0.59	0.08	0.10	0.01	0.03	0.13
Switzerland	0.10	0.20	0.05	0.14	0.06	0.22	0.23
UK	0.07	0.40	0.04	0.15	0.03	0.13	0.18
USA	0.06	0.38	0.05	0.14	0.05	0.08	0.24

Patents are assigned to industries using the probabilities calculated as proposed by De Rassenfosse et al. (2014), where we make a unique match based on the highest probability. In order to assign patents to countries, we assign the patent to each country for which an inventor address exists. The numbers show the countries' share of USPTO patents for different industries of the filing years 2010–2015

should be the case for a patent with a strong influence on future inventions. They use a list of significant inventions such as stem cells, Google's PageRank algorithm, and gene transfer in order to substantiate their claim. As they show, patents codifying significant inventions also have a high importance score. Following Kelly et al. (2021), Grampp et al. (2018), Gramke and Glauser (2017), we thus define a patent as containing a breakthrough or significant innovation if it is among the 10% having the highest importance score within its WIPO technology field and publication year. This indicator then provides an alternative measure for identifying breakthrough patents and allows us to examine the robustness of our regression results. In addition, we also use different thresholds (75th percentile and 99th percentile) to identify breakthrough innovations. As Table 9 shows, the results remain robust (Table 10).

In Table 11, we use different time thresholds for forward citations to indicate breakthrough innovations across different industries. See text in Table 8 of Appendix for a brief rationale for this table. As the results of the table show, digital patents are still associated with a

Table 7 Technological improvement rates and breakthrough innovations: time period estimates

Dependent variable	FWD90		
Model	**1990–1999**	**2000–2009**	**2010–2015**
Digital	2.587***	2.705***	2.343**
	(0.958)	(0.656)	(0.924)
Non-digital: k	0.223***	0.102***	0.092***
	(0.038)	(0.018)	(0.024)
Digital: k	0.075***	0.009***	0.020***
	(0.008)	(0.003)	(0.003)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	1,651,734	2,108,654	498,851

All estimations include USPTO patents from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA. If a patent has inventors from more than one of those countries, it will only be included once. The first model specification considers only USPTO patents filed between 1990 and 1999, the second patents filed between 2000 and 2009, and the third patents filed between 2010 and 2015. In order to show associations in percentage points, we have multiplied the FWD90-dummy by 100. The industry fixed effects are at the level of the six industries included in the analysis, namely Computer/ICT, Machinery, Medical, Electrical, Chemical, and Pharma. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^* < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 8 Technological improvement rates and breakthrough innovations: different time spans of forward citations

Dependent variables	FWD90_5	FWD90_7	FWD90_10
Model	**(1)**	**(2)**	**(3)**
Variables			
Digital	1.863***	1.868***	1.770***
	(0.428)	(0.592)	(0.607)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	3,714,719	3,714,719	3,714,719

All estimations include USPTO patents of the filing years 1990–2010 if at least one inventor has been from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, or the USA. To better compare the results with the specification in the main text, the first specification (1) indicates a breakthrough innovation if the number of a patent's five-year forward citations is among the top 10% per publication year and WIPO technology field. The estimation results differ slightly from those in the main text, as we only include patents up to 2010, in order to be able to use longer forward citation spans in the other two specifications. The second specification (2) indicates a breakthrough innovation if the number of a patent's seven years forward citations is among the top 10% and the third (3) specification if the number of a patent's 10-year forward citations is among the top 10%. In order to show associations in percentage points, we have multiplied the FWD/IMP-dummies by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The industry fixed effects are at the level of the six industries included in the analysis, namely Computer/ICT, Machinery, Medical, Electrical, Chemical, and Pharma. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^* < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 9 Technological improvement rates and breakthrough innovations: different breakthrough measures

Dependent variables	**FWD75**	**FWD90**	**FWD99**	**IMP75**	**IMP90**	**IMP99**
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Digital	3.792***	2.991***	0.7378***	7.832**	5.470***	0.8458***
	(0.9897)	(0.6914)	(0.1424)	(3.359)	(1.787)	(0.2454)
Non-digital: k	0.2260***	0.1480***	0.0247***	0.4444***	0.2831***	0.0331***
	(0.0330)	(0.0221)	(0.0034)	(0.1177)	(0.0644)	(0.0081)
Digital: k	0.0387***	0.0228***	0.0035***	0.1482***	0.0755***	0.0095***
	(0.0050)	(0.0043)	(0.0012)	(0.0114)	(0.0094)	(0.0027)
Control variables						
inv	✓	✓	✓	✓	✓	✓
num_ctry	✓	✓	✓	✓	✓	✓
Claims	✓	✓	✓	✓	✓	✓
bwd_cits	✓	✓	✓	✓	✓	✓
Fixed effects						
Industry	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Year-Industry	✓	✓	✓	✓	✓	✓

All estimations include USPTO patents of the filing years 1990–2015 if at least one inventor has been from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, or the USA. Similar to the main text, the first three specifications (1)–(3) use the number of forward citations as an indication of breakthrough innovations. The first model specification indicates a breakthrough innovation if the number of a patent's five-year forward citations is among the top 25%, the second specification is similar to the used specifications in the main text, and the third specification if the number of a patent's five-year forward citations is among the top one percent. The other three specifications (4)–(6) consider an importance measure based on patent text similarity as proposed by Kelly et al. (2021). For details, see the accompanying text. In particular, the specification of column (4) indicates a breakthrough innovation if the patent's importance measure is among the top 25%, the specification of column (5) if it is among the top 10%, and the one of column (6) if it is among the top one percent. In order to show associations in percentage points, we have multiplied the FWD/IMP-dummies by 100. The industry fixed effects are at the level of the six industries included in the analysis, namely Computer/ICT, Machinery, Medical, Electrical, Chemical, and Pharma. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^* < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 10 Technological improvement rates and breakthrough innovations: time period estimates across industries

Dependent variables	**FWD90**		
Model	**(1990-1999)**	**(2000–2009)**	**(2010–2015)**
Variables			
Digital: Chemical	11.285*** (1.290)	6.997*** (0.674)	3.064*** (0.697)
Digital: Computer/ICT	2.008*** (0.314)	0.449 (0.281)	0.883*** (0.398)
Digital: Electrical	5.783*** (0.515)	6.959*** (0.577)	8.658*** (1.546)
Digital: Machinery	1.162*** (0.525)	0.938*** (0.194)	0.137 (0.701)
Digital: Medical	9.532*** (1.357)	5.714*** (0.717)	3.327*** (1.363)
Digital: Pharma	1.977*** (0.691)	0.062 (0.673)	1.938 (1.329)
Non-digital: *k*:Chemical	0.221*** (0.024)	0.124*** (0.028)	0.250*** (0.025)
Digital: *k*:Chemical	− 0.004 (0.038)	− 0.005 (0.015)	0.012 (0.033)
Non-digital: *k*:Computer/ICT	0.184*** (0.019)	− 0.001 (0.020)	0.001 (0.043)
Digital: *k*:Computer/ICT	0.071*** (0.003)	0.008 (0.008)	0.019*** (0.004)
Non-digital: *k*:Electrical	0.384*** (0.062)	0.415*** (0.032)	0.445*** (0.035)
Digital: *k*:Electrical	0.178*** (0.025)	0.109*** (0.027)	0.079*** (0.043)
Non-digital: *k*:Machinery	0.236*** (0.021)	0.131*** (0.012)	0.069*** (0.007)
Digital: *k*:Machinery	0.091*** (0.022)	0.017 (0.012)	0.015 (0.019)
Non-digital: *k*:Medical	0.393*** (0.032)	0.087*** (0.046)	0.024 (0.038)
Digital: *k*:Medical	0.067 (0.049)	0.013 (0.030)	0.045*** (0.027)
Non-digital: *k*:Pharma	0.195*** (0.038)	− 0.050 (0.062)	0.020 (0.098)
Digital: *k*:Pharma	0.158*** (0.059)	0.027 (0.052)	-0.008 (0.026)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	1,207,095	1,651,118	385,589

All estimations include USPTO patents from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA of the filing years 1990–2015. If a patent has inventors from more than one of those countries, it will only be included once. The first model specification considers only USPTO patents filed between 1990 and 1999, the second patents filed between 2000 and 2009, and the third patents filed between 2010 and 2015. In order to show associations in percentage points, we have multiplied the FWD90-dummy by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^* < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

higher probability of containing a breakthrough innovation for seven- and ten-year forward citation thresholds across all considered industries. Interestingly, the strength of the association is actually increasing for the two important Swiss industries: Pharmaceuticals and Medical-Tech (Tables 12, 13, 14, 15, 16).

Table 11 Technological improvement rates and breakthrough innovations across industries: different time spans of forward citations

Dependent variables	FWD90_5	FWD90_7	FWD90_10
Model	**(1)**	**(2)**	**(3)**
Digital: Chemical	6.367*** (0.469)	5.839*** (0.436)	5.359*** (0.376)
Digital: Computer/ICT	1.807*** (0.305)	1.458*** (0.216)	1.186*** (0.213)
Digital: Electrical	4.960*** (0.206)	5.695*** (0.238)	5.637*** (0.263)
Digital: Machinery	0.909*** (0.312)	0.673*** (0.213)	0.586*** (0.210)
Digital: Medical	3.666*** (0.476)	6.852*** (0.455)	7.357*** (0.401)
Digital: Pharma	1.416*** (0.431)	4.395*** (0.330)	4.615*** (0.230)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	2,825,155	2,825,155	2,825,155

All estimations include USPTO patents of the filing years 1990–2010 if at least one inventor has been from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, or the USA. To better compare the results with the specification in the main text, the first specification (1) indicates a breakthrough innovation if the number of a patent's five-year forward citations is among the top 10% of its publication year and WIPO technology field. The estimation results differ slightly from those in the main text, as we only include patents up to 2010, in order to be able to use longer forward citation spans in the other two specifications. The second specification (2) indicates a breakthrough innovation if the number of a patent's seven-year forward citations is among the top 10% and the third specification (3) if the number of a patent's 10-year forward citations is among the top 10%. In order to show associations in percentage points, we have multiplied the FWD/IMP-dummies by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^{*} < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 12 The digital domain and technological improvement rates: time period estimates across industries

Dependent variable	Technology improvement rate *k*			
Model	**1990–2015**	**1990–1999**	**2000–2009**	**2010–2015**
Variables				
Digital:Chemical	9.910***	10.786***	11.554***	12.434***
	(0.561)	(0.721)	(0.400)	(0.574)
Digital:Computer/ICT	56.664***	42.961***	63.412***	60.083***
	(2.077)	(4.720)	(0.446)	(1.221)
Digital:Electrical	12.368***	9.883***	14.058***	13.984***
	(0.534)	(0.670)	(0.351)	(0.246)
Digital:Machinery	26.689***	23.335***	29.885***	28.240***
	(0.828)	(0.925)	(0.219)	(0.424)
Digital:Medical	5.219***	1.899***	7.777***	8.795***
	(0.800)	(0.375)	(0.295)	(1.053)
Digital:Pharma	4.216***	3.582***	4.677***	5.607***
	(0.183)	(0.123)	(0.162)	(0.553)
Fixed effects				
Industry	✓	✓	✓	✓
Year	✓	✓	✓	✓
Year-Industry	✓	✓	✓	✓
Observations	3,243,802	1,207,095	1,651,118	385,589

All estimations include USPTO patents of the indicated filing years if at least one inventor has been from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, or the USA. In order to show associations in percentage points, we have multiplied the FWD90-dummy by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^{*} < 0.1$; $p^{**} < 0.05$;$p^{***} < 0.01$

Table 13 Technological improvement rates and breakthrough innovations: breakthrough measures across industries (part I)

Dependent variables	**FWD75**	**FWD90**	**FWD99**
Model	**(1)**	**(2)**	**(3)**
Variables			
Digital:Chemical	12.053*** (0.931)	8.035*** (0.704)	1.630*** (0.346)
Digital:Computer/ICT	2.363*** (0.338)	2.062*** (0.232)	0.292*** (0.066)
Digital:Electrical	8.078*** (0.712)	6.985*** (0.391)	1.607*** (0.102)
Digital:Machinery	1.717*** (0.496)	1.260*** (0.254)	0.243*** (0.053)
Digital:Medical	10.772*** (0.765)	7.333*** (0.690)	1.675*** (0.335)
Digital:Pharma	3.141*** (0.502)	1.501*** (0.432)	0.330*** (0.140)
Non-digital: *k*:Chemical	0.348*** (0.030)	0.191*** (0.021)	0.015*** (0.005)
Digital: *k*:Chemical	0.008 (0.017)	− 0.005 (0.020)	− 0.010** (0.004)
Non-digital: *k*:Computer/ICT	0.148*** (0.028)	0.086*** (0.017)	0.007* (0.004)
Digital: *k*:Computer/ICT	0.035** (0.016)	0.020*** (0.007)	0.003** (0.001)
Non-digital: *k*:Electrical	0.651*** (0.040)	0.415*** (0.030)	0.063*** (0.006)
Digital: *k*:Electrical	0.220*** (0.027)	0.124*** (0.016)	0.028*** (0.009)
Non-digital: *k*:Machinery	0.241*** (0.022)	0.167*** (0.016)	0.029*** (0.004)
Digital: *k*:Machinery	0.044* (0.024)	0.039*** (0.014)	0.010*** (0.004)
Non-digital: *k*:Medical	0.398*** (0.095)	0.227*** (0.044)	0.024** (0.011)
Digital: *k*:Medical	0.003 (0.047)	0.020 (0.023)	0.007 (0.012)
Non-digital: *k*:Pharma	0.172*** (0.052)	0.087** (0.040)	0.012 (0.011)
Digital: *k*:Pharma	0.078* (0.046)	0.059* (0.034)	0.015 (0.012)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	3,243,802	3,243,802	3,243,802

All estimations include USPTO patents of the filing years 1990–2015 if at least one inventor has been from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, or the USA. Similar to the main text, the specifications use the number of forward citations as an indication of breakthrough innovations. The first model specification indicates a breakthrough innovation if the number of a patent's five-year forward citations is among the top 25%, the second specification is similar to the used specifications in the main text, and the third specification if the number of a patent's five-year forward citations is among the top one percent. In order to show associations in percentage points, we have multiplied the FWD-dummies by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^{*} < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 14 Technological improvement rates and breakthrough innovations: breakthrough measures across industries (part II)

Dependent variables	**IMP75**	**IMP90**	**IMP99**
Model	**(1)**	**(2)**	**(3)**
Variables			
Digital:Chemical	11.599*** (2.157)	9.024*** (1.262)	1.611*** (0.256)
Digital:Computer/ICT	7.100*** (0.882)	1.736*** (0.314)	0.027 (0.039)
Digital:Electrical	28.908*** (2.004)	13.594*** (0.686)	0.442*** (0.115)
Digital:Machinery	4.916*** (1.199)	5.103*** (0.774)	0.804*** (0.071)
Digital:Medical	27.020*** (2.060)	13.546*** (0.969)	− 0.104 (0.240)
Digital:Pharma	4.612*** (1.135)	− 1.333* (0.791)	− 1.661*** (0.186)
Non-digital: *k*:Chemical	− 0.055 (0.045)	− 0.005 (0.019)	0.003 (0.007)
Digital:Chemical	− 0.034** (0.014)	− 0.002 (0.025)	0.014 (0.010)
Non-digital: *k*:Computer/ICT	0.274*** (0.038)	0.088*** (0.016)	0.005*** (0.001)
Digital:Computer/ICT	0.135*** (0.010)	0.068*** (0.008)	0.008*** (0.001)
Non-digital: *k*:Electrical	1.627*** (0.089)	0.795*** (0.046)	0.079*** (0.006)
Digital:Electrical	0.349*** (0.019)	0.262*** (0.023)	0.075*** (0.010)
Non-digital: *k*:Machinery	0.551*** (0.083)	0.406*** (0.059)	0.056*** (0.007)
Digital:Machinery	0.158*** (0.031)	0.082*** (0.024)	0.016***(0.005)
Non-digital: *k*:Medical	0.419*** (0.038)	0.159*** (0.034)	0.005 (0.005)
Digital:Medical	0.277*** (0.027)	0.299*** (0.049)	0.130*** (0.030)
Non-digital: *k*:Pharma	− 0.122 (0.089)	− 0.151** (0.071)	− 0.016 (0.014)
Digital:Pharma	0.182*** (0.046)	0.247*** (0.041)	0.133*** (0.027)
Control variables			
inv	✓	✓	✓
num_ctry	✓	✓	✓
Claims	✓	✓	✓
bwd_cits	✓	✓	✓
Fixed effects			
Industry	✓	✓	✓
Year	✓	✓	✓
Year-Industry	✓	✓	✓
Observations	3,243,795	3,243,795	3,243,795

All estimations include USPTO patents of the filing years 1990–2015 if at least one inventor has been from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, or the USA. In order to proxy breakthrough innovations, the three specifications (1)–(3) consider an importance measure based on patent text similarity as proposed by Kelly et al. (2021). For details, see the accompanying text. In particular, the specification of column (1) indicates a breakthrough innovation if the patent's importance measure is among the top 25%, the specification of column (2) if it is among the top 10%, and the one of column (3) if it is among the top one percent. In order to show associations in percentage points, we have multiplied the IMP-dummies by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^* < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 15 Technological improvement rates and breakthrough innovations: heterogeneity between the digital and non-digital domain

Dependent variable	FWD90	
Model	**(1)**	**(2)**
Variables		
Digital	2.991*** (0.691)	
k	0.148*** (0.022)	
Digital: k	− 0.125*** (0.023)	
Digital: Chemical		8.035*** (0.704)
Digital: Computer/ICT		2.062*** (0.232)
Digital: Electrical		6.985*** (0.391)
Digital: Machinery		1.260*** (0.254)
Digital: Medical		7.333*** (0.690)
Digital: Pharma		1.501*** (0.431)
k:Chemical		0.191*** (0.021)
k:Computer/ICT		0.086*** (0.017)
k:Electrical		0.415*** (0.030)
k:Machinery		0.167*** (0.016)
k:Medical		0.227*** (0.044)
k:Pharma		0.087** (0.039)
Digital: *k*:Chemical		− 0.196*** (0.024)
Digital: *k*:Computer/ICT		− 0.067*** (0.012)
Digital: *k*:Electrical		− 0.290*** (0.036)
Digital: *k*:Machinery		− 0.128*** (0.014)
Digital: *k*:Medical		− 0.207*** (0.042)
Digital: *k*:Pharma		− 0.028 (0.037)
Control variables		
inv	✓	✓
num_ctry	✓	✓
Claims	✓	✓
bwd_cits	✓	✓
Fixed effects		
Industry	✓	✓
Year	✓	✓
Year-Industry	✓	✓
Observations	4,259,239	3,243,802

All estimations include USPTO patents from Canada, China, France, Germany, Japan, South Korea, Switzerland, the UK, and the USA of the filing years 1990–2015. If a patent has inventors from more than one of those countries, it will only take into account once. The first model specification shows estimations across all industries. The second considers interactions for selected industries. In order to show associations in percentage points, we have multiplied the FWD90-dummy by 100. The industry fixed effects are at the level of the six industries included in the interaction terms. The standard errors in parentheses are also clustered at this industry level. Significance levels for the coefficients are indicated as: $p^{*} < 0.1$; $p^{**} < 0.05$; $p^{***} < 0.01$

Table 16 Breakdown of the average technology improvement rate by digital, non-digital, and all patents for different countries and industries

Industry	**Country**	$\mu_{non-dig}$		$share_{non-dig}$		μ_{dig}		$share_{dig}$		μ_{all}
Chemical	South Korea	11.9	*	0.82	+	27.2	*	0.18	=	14.7
Chemical	Japan	11.9	*	0.80	+	24.1	*	0.20	=	14.4
Chemical	China	11.3	*	0.91	+	27.8	*	0.09	=	12.9
Chemical	UK	11.8	*	0.95	+	32.8	*	0.05	=	12.8
Chemical	Canada	11.2	*	0.87	+	16.9	*	0.13	=	12.0
Chemical	USA	11.4	*	0.94	+	21.9	*	0.06	=	12.0
Chemical	Germany	11.3	*	0.96	+	25.3	*	0.04	=	11.9
Chemical	Switzerland	10.8	*	0.97	+	22.4	*	0.03	=	11.2
Chemical	France	10.5	*	0.97	+	22.7	*	0.03	=	10.8
Computer/ICT	Canada	20.3	*	0.03	+	95.5	*	0.97	=	92.9
Computer/ICT	UK	20.5	*	0.03	+	91.8	*	0.97	=	89.5
Computer/ICT	USA	20.1	*	0.05	+	90.9	*	0.95	=	87.5
Computer/ICT	Switzerland	18.0	*	0.07	+	83.1	*	0.93	=	78.6
Computer/ICT	China	17.7	*	0.09	+	79.9	*	0.91	=	74.2
Computer/ICT	France	18.7	*	0.05	+	71.5	*	0.95	=	68.9
Computer/ICT	Germany	19.2	*	0.07	+	72.3	*	0.93	=	68.7
Computer/ICT	South Korea	16.7	*	0.04	+	63.5	*	0.96	=	61.6
Computer/ICT	Japan	18.6	*	0.07	+	60.8	*	0.93	=	57.9
Electrical	Japan	14.7	*	0.83	+	26.8	*	0.17	=	16.7
Electrical	China	15.1	*	0.88	+	24.4	*	0.12	=	16.2
Electrical	South Korea	13.6	*	0.87	+	30.3	*	0.13	=	15.7
Electrical	Germany	13.8	*	0.87	+	25.4	*	0.13	=	15.3
Electrical	France	13.3	*	0.82	+	24.2	*	0.18	=	15.3
Electrical	USA	12.9	*	0.87	+	28.0	*	0.13	=	14.9
Electrical	UK	13.1	*	0.88	+	22.5	*	0.12	=	14.2
Electrical	Canada	12.9	*	0.90	+	26.3	*	0.10	=	14.2
Electrical	Switzerland	12.6	*	0.94	+	23.4	*	0.06	=	13.2
Machinery	South Korea	13.6	*	0.46	+	45.4	*	0.54	=	30.9
Machinery	Japan	14.6	*	0.38	+	36.0	*	0.62	=	27.9
Machinery	China	9.8	*	0.61	+	45.3	*	0.39	=	23.7
Machinery	UK	10.4	*	0.75	+	49.8	*	0.25	=	20.4
Machinery	USA	10.8	*	0.72	+	42.7	*	0.28	=	19.9
Machinery	Canada	9.6	*	0.74	+	40.2	*	0.26	=	17.4
Machinery	France	10.5	*	0.79	+	42.9	*	0.21	=	17.3
Machinery	Switzerland	10.5	*	0.80	+	42.4	*	0.20	=	16.8
Machinery	Germany	12.2	*	0.86	+	38.1	*	0.14	=	15.8
Medical	UK	19.3	*	0.88	+	44.8	*	0.12	=	22.5
Medical	Japan	19.4	*	0.77	+	26.2	*	0.23	=	21.0
Medical	South Korea	18.5	*	0.80	+	27.6	*	0.20	=	20.3
Medical	Germany	18.9	*	0.82	+	26.2	*	0.18	=	20.2
Medical	France	17.8	*	0.90	+	38.8	*	0.10	=	19.9
Medical	Canada	17.7	*	0.86	+	33.3	*	0.14	=	19.9
Medical	USA	18.9	*	0.91	+	28.4	*	0.09	=	19.8
Medical	Switzerland	18.8	*	0.86	+	22.6	*	0.14	=	19.3
Medical	China	15.9	*	0.82	+	30.7	*	0.18	=	18.6
Pharma	South Korea	7.8	*	0.86	+	19.7	*	0.14	=	9.4
Pharma	Japan	8.0	*	0.88	+	15.1	*	0.12	=	8.9
Pharma	USA	7.8	*	0.94	+	12.8	*	0.06	=	8.1

Table 16 (continued)

Industry	Country	$\mu_{non-dig}$		$share_{non-dig}$		μ_{dig}		$share_{dig}$		μ_{all}
Pharma	UK	7.8	*	0.96	+	15.1	*	0.04	=	8.1
Pharma	Germany	7.8	*	0.94	+	12.1	*	0.06	=	8.1
Pharma	Switzerland	7.8	*	0.97	+	12.5	*	0.03	=	8.0
Pharma	France	7.8	*	0.97	+	12.7	*	0.03	=	8.0
Pharma	China	7.6	*	0.96	+	13.3	*	0.04	=	7.9
Pharma	Canada	7.6	*	0.92	+	10.6	*	0.08	=	7.9

Abbreviations

AI	Artificial Intelligence
ICT	Information and Communication Technology
IPC	International Patent Classification
R&D	Research and Development
UPC	US Patent Classification System
USPTO	United States Patent and Trademark Office

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Author contributions
MN contributed to the conceptual idea, text, and literature; CR contributed to the conceptual idea, text, literature, data processing, data visualization, and empirical estimates. Both authors have read and approved the final version of the manuscript.

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Availability of data and materials
Data for technology improvement rates are available with permission from the authors of Singh et al. (2021) at https://zenodo.org/record/4779832#.Yjstn-fMK38. USPTO patent data can be freely accessed at https://patentsview.org/download/data-download-tables. Data on patent families and patent to industry crosswalks can be accessed from Patstat at https://data.epo.org/expert-services/index.html based on an annual subscription.

Declarations

Competing interests
The authors declare that they have no competing interests.

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