What next? Nations in the technological race through the 2030

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Abstract

This paper investigates the technological trajectories of nations, examining how their current specialization may influence their future technological leadership. By analysing patent data from the United States Patent and Trademark Office, we identify which countries are at the forefront of fast-growing technologies. Nations specializing in these emerging technologies are likely to experience accelerated economic growth, while others may struggle to maintain competitiveness. Additionally, countries tend to stick to areas where they have expertise, making it difficult to shift quickly to new technological fields. However, our findings partly challenge this view. Using predictive models, we project patent trends to 2030, suggesting that countries which were not technologically well-positioned in recent decades may improve their competitiveness, particularly through strategic policy interventions. We also show that future fast-growing technologies may differ significantly from the past.

Keywords: fast growing technologies, technological specialization, patents, economic growth

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Highlights

- The rate of change of patent classes indicate that the cycle of ICTs is still far from been mature and the classes "IT methods for management", "Digital communication" and "Computer technology" are still leading the race.

- The future might provide opportunities in other technological fields. Robotics, Logistics, mobility and Energy-efficient machines may constitute the base for the unfolding of a new socio-economic paradigm.

- Countries leading the technological race have lost shares in the total number of patents, with a convergence between advanced and emerging economies.

- Few countries still dominate technological development, but new countries are joining the party, leading to a relative reduction in the activities of traditional incumbents.

- Asian countries have been able to catch up technologically thanks to a strong specialization in ICT technologies, which still present technological opportunities.

- European countries have lost positions in technological activities, but they tend to specialize in those sectors that the empirical predictions foresee as the most promising in the years to come.

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1. Technology and the wealth of nations

Technological change, the driving force of economic growth, is not evenly distributed over time but appears discontinuously in swarms (Schumpeter, 1939). The clustering of innovations leads to the major role played by specific industries in determining new economic cycles that shape the techno-economic paradigms characterizing different phases of development (Perez, 2003).

Innovation and technological change enable nations to experience long-run economic development and prosperity (Abramovitz, 1989), and ideally, each nation would like to be a leader in the emerging (and most profitable) industries. Indeed, being specialized in fast-growing technologies allows countries to experience above-average growth rates thanks to the production of goods with high elasticity of demand and the returns that technological competitiveness brings from international markets (Meliciani, 2001; 2002). Patented technology provides a measure of the technological competences of firms (Patel and Pavitt, 1997), and the introduction of new technologies into production leads to learning processes that trigger a mutually reinforcing dynamic between capital accumulation and technological progress (Fagerberg, 1994). However, the innovative capabilities of nations are not randomly distributed among technological fields, and national specialization tends to be persistent (Cantwell, 1987; Pavitt, 1988; Malerba et al., 1997) because sectoral strengths and weaknesses are related to the capabilities that each nation has been able to develop in the past. The cumulative nature of innovation processes, the existence of dynamic economies in knowledge creation and learning processes, and the localized nature of knowledge spillovers tend to produce technological accumulation along spatially bounded specialization patterns (Antonelli et al., 2013). Furthermore, subsidiaries of multinational corporations with the mandate of generating new technology in accordance with the comparative advantage of a country tend to be more R&D intensive in countries with higher innovative and skill related potential (Cantwell and Mudambi, 2005). These mechanisms may lead to persistent technological asymmetries across countries (Bontadini et al., 2024).

In a competitive and strongly integrated world economy, countries tend to develop their competencies in areas where they have previously accumulated expertise. Indeed, specialization patterns are surprisingly persistent over time (Cantwell, 1987; Pavitt, 1988), and what nations can do in the future is strongly connected to what they have done in the past. The capability of countries to specialize in a differentiated set of technologies is positively associated with overall R&D investments, leading smaller countries to specialize in a narrower set of technologies (Archibugi and Pianta, 1992). However, the capability of combining different knowledge resources, and not just their level, also plays a vital role in positioning each national system of innovation (Castellacci and Archibugi, 2008). Each country has a specific set of knowledge resources, and the various ingredients of knowledge creation and capability transfer appear largely complementary and give rise to different combinations.

The persistence of nations' specialization makes it challenging to jump successfully on different technological trajectories in the short run, especially for countries close to the technological frontier: they can succeed only if they manage to carry out large investments together with commitment and integration among the various components of the national innovation system (Freeman, 1995). Catching-up and leapfrogging are possible with favourable environmental conditions, clear business strategies and appropriate political conditions (Soete, 1985). Thus, technological catch-up is largely country-specific. In recent decades, many firms from Southeast Asian countries have rapidly enhanced their technological capabilities and have caught up in specific technological fields and industries (Miao et al., 2018), often acting as drivers for the entire national economy. The process has not been homogeneous; for instance, Korean firms have performed better in technological regimes featuring low appropriability and high knowledge cumulativeness, whereas their Taiwanese counterparts seem more fitted to regimes characterized by high appropriability and low cumulativeness, generally associated with shorter technology life cycles (Park and Lee, 2006).

The persistence in countries' technological specialization combined with the changing global landscape poses a critical issue for businesses and policymakers: what will be the leading scientific and technological fields of the future, those most likely to generate abundant economic opportunities? Replying to this question is a perilous quest because predictions on future technologies are, at best, approximate (Mokyr, 2015). Indeed, the development of science and technology does not follow a linear process, especially when considering long periods of time, and new "unexpected" growth paths may arise to confute diffused expectations. Consider, for example, Thomas Watson (IBM), who in 1943 said, "I think there is a world market for maybe five computers", largely overlooking the future evolution of an infant high-tech industry that has revolutionized the world in the last decades. Systemic features and complex interactions may lead to underestimating technological development in some fields while overstating it in others (Archibugi, 2017). Nevertheless, the question is crucial for business strategies and public policies: firms and nations persisting in their traditional specializations may find themselves in a dead-end if they do not manage to evolve into the emerging technological and production opportunities.

With full awareness of the inherent risks in predicting future technologies, this study relies on patent data granted by the US Patent and Trademark Office (USPTO). This data forms the basis of our analysis of the evolution of technological advancements and the empirical predictions, offering a glimpse into technological trajectories over the next decade. In the first part of the study, we assess countries' performances and identify the fast-growing technologies over the last 20 years. We aim to depict the technological evolution of the last 20 years and provide concrete evidence about changes in the country's patent ranking and the countries' technological specialization. In the second part, we employ time series models to forecast the possible evolution of technologies until 2030. By intersecting countries' specialization with the most promising technological fields, we spot possible future technologies with high opportunities and derive a series of implications about countries' positioning and policies. The main messages arising from our exercise are two: 1) in the next decade, fast-growing technologies may be different from those of the (near) past; 2) countries that were not well technologically positioned in the last decades (e.g. EU countries) may be well positioned to compete in the (near) future. Of course, the latter will largely depend on the capacity to design appropriate policies to face the upcoming challenges in the global technology race that may reshape technological development in the coming years.

The paper is organized as follows. Section 2 provides an overview of the literature and the framework of the analysis; section 3 describes data and the used empirical methodology; section 4 provides an overview of patenting activities in the last twenty years prior to Covid-19; section 5 describes the main results of the empirical predictions; section 6 highlights the main limitations of the analysis; section 7 concludes.

2. Identifying technological trends and nations' specialization

In the last century, innovation activity has grown substantially worldwide, and today its direction is at a crossroads (WIPO, 2022). Patents are one of the most used measure of technological innovation activity, and their volume constantly increases[1]. A significant turning point in this trend was the explosion in patenting activity in the 1980s. This period marked a structural shift to higher growth rates, with the electrical and computing technology sectors largely accounting for the change but patents rising in all technology classes (Hall, 2004). The patent surge continued in the first decade of this millennium when China made a significant entry into the technological development scene. It quickly climbed positions in patenting activity, a trend that has continued to this day (Fink et al., 2016). In 2022, about 383k patents have been granted by the USPTO, a significant number, but it is dwarfed by the 798K patents granted by the China National Intellectual Property Administration (CNIPA).[2] The rising importance of China in the global patent landscape is certainly associated to the growing resources that both the public and the business sectors have devoted to R&D activities. Already in 2016 China became the country with the highest government-financed R&D expenditures (Filippetti and Vezzani, 2022).

The worldwide surge in patenting is due to different reasons, including institutional changes in patent laws (e.g., the US Boyle-Doyle Act in 1980, the Patent Law of the People's Republic of China in 1984); direct or indirect support (or discount) to patent-related R&D (e.g. patent boxes, see for instance Aalstatter et al., 2018); the increasing complexity of technologies and the intensification of patent portfolios in complex product industries like electronics (Hall, 2004). More recent is the evidence of a surge in the patenting activity related to technologies supporting the fourth industrial revolution, particularly in networked devices, where patenting firms have become progressively younger (Benassi et al., 2020).

The surge of patent filings and the accelerated technological change of the last decades have attracted much interest in emerging (or key enabling) technologies from policymakers and academia (Godinho and Simoes, 2023). The opportunities offered by the so-called key enabling technologies (KETs) derive from their horizontal and systemic nature that may enable different types of innovations across the economy. Indeed, European regions specialized in KETs benefit from higher economic growth, and the specialization-growth nexus is stronger for technologically backward regions (Evangelista et al., 2018). This effect can be partially ascribed to a higher capability of building new regional technological advantages over time, shown by regions specialized in KETs (Montresor and Quatraro, 2017).

Emerging technologies have instead attracted attention not only for their potential ability to remake entire industries but also for pushing firms to continuously rethink their strategies to adapt to the potential disruption of established technological trajectories (Day and Schoemaker, 2000). The attributes recognized to emerging technologies are radical novelty, fast growth, coherence, uncertainty and ambiguity, and prominent impact (Rotolo et al., 2015). In other words, emerging technologies are those technologies that fulfil a given function by using a new set of basic principles, showing relatively high growth rates, presenting a certain identity and momentum in the scientific and technological discourses, and being characterized by some degree of unpredictability of outcomes and uses, which may be unintended and undesirable, as well as of meanings associated by different social groups.

Different scientometric techniques have been operationalized to identify radical novelty, coherence, and prominent impact (Leten et al., 2007; Verhoeven et al., 2016; Confraria et al., 2021). It is certainly

[1] Nagaoka et al., 2010, confirm the increasing trend in using patent counts to measure innovation in academic research.

[2] These figures are taken from the websites of the two patent offices. The requirements for novelty and the nature of the patent systems do not allow a comparison of the total numbers. For example, the Chinese system requires filing one patent for each claim. In contrast, the US system, as in many other Western countries, allows one to group several claims in the same patent application.

important to distinguish between established and emerging technologies and one way to do it is by looking at the rate of growth of the various classes and sub-classes.

Several studies have assumed that a rapid growth signals emerging technologies. Meliciani and Simonetti (1998) and Meliciani (2001) examined the fastest-growing patent classes in the United States from 1970–74 to 1990–94 revealing at the time that Information and Communication Technologies (ICTs) dominated these rapidly expanding patent categories during the 1980s. These studies also uncovered a correlation between national specialization in these fast-growing technological domains or ICT-related patent classes and above-average growth rates in per capita GDP. A rapid growth in patents has been found associated to a higher market valuation for new entrants in complex product industries like electronic computing and communications (Hall, 2004).

Following these insights, various approaches have tried to operationalize this concept. For example, in the context of patent data, de Rassenfosse et al., 2013 suggested using the count of priority patent applications filed by a country's inventors, regardless of the filing patent office, as an indicator to identify fast growth and, by extension, potential emerging technologies. Other approaches have been explored, for instance, looking at the stage of the technology life cycle, the scope, and the potential for diffusion (Altunas et al. 2015). Despite the different methodologies based on the analysis of patents or publications, experts' opinions, or a combination of the two (for a review of future-oriented technology analyses, see Ciarli et al., 2016), most of the approaches tend to focus on specific technology niches due to the detailed information required to identify potential emerging technologies.

Approaches looking at technology from a granular perspective align with the idea that emerging technologies are components that are (or will) attract increasing research efforts among the existing paradigm and that, once they emerge, may constitute the backbone of the following one. Most of these approaches share the issues deriving from the uncertainty inherent to the level of analysis: they often work with few (sometimes sporadic) observations, and small changes in the estimated parameters (or initial opinions) may lead to large deviations in predictions.

To partially mitigate the uncertainty surrounding forecasting exercises, we look at technologies for a more aggregate level, aiming to detect and extrapolate the main trajectories of the current technological paradigm (Dosi, 1982). Specifically, we work at the level of the 35 technological fields proposed by the World Intellectual Property Organization (WIPO) to allow for cross-country and temporal comparisons of technological development at a level that mimics the sectoral classifications generally used in economic studies (Schmoch, 2008). Despite the aggregation, this level of analysis allows to capture specificities in the investments required for the development of new technologies (R&D per patent), as well as economies of scale in knowledge production and costs associated with specialization (Gkotsis and Vezzani, 2022), which contribute determining different sectoral systems of innovation (Malerba, 2002).

In the analysis, we focus on fast-growing technologies (FGT), as technology fields exhibiting sustained growth rates provide opportunities to countries able to build comparative advantages, trigger cumulative learning processes, and capitalize on increased competitiveness to boost their economic performance (Fagerberg, 1994; Pianta and Meliciani, 1996).

3. Data and methodology

3.1 Data

In the empirical analysis, we use data from the OECD's Science Technology and Patents statistics, which provides information on a country's patent at the 35 WIPO technology fields level derived from the worldwide patent statistics database (Patstat).

We gather information on patents granted at the USPTO since 2001 from the OECD data. We rely on patents at the USPTO because the USA is the leading market for information and communication-related technologies, the ones driving the current technological paradigm. In contrast, other patent offices may more prominently reflect local specificities in the shares of patents across technology fields (Dernis et al., 2015). Moreover, the USPTO was the office collecting more patent applications at the beginning of the period of analysis, which allows for good numerosity of information during the whole period considered. For example, in 2001, the USPTO issued about five times more patents than the European Patent Office (EPO), about 166k versus 35k, while patent filings at the CNIPA were much lower than those at the EPO (Fink et al., 2016). To assess the extent to which the choice of using USPTO data may provide evidence driven by the US's own dynamics, we run robustness checks excluding the USA from the analysis.

Patents are associated with countries based on the inventor's residence, which is a choice commonly used to capture where the inventive activity takes place (Picci, 2010). We include in the sample 41 countries with a level of patenting activity high enough to avoid sporadic observations for the technology fields with relatively low levels of patenting activity (see Table A.1 in the Appendix for the list of countries included in the analysis).[3] Moreover, we consider the granting date of the patented invention, allowing us to consider patents actually in force and to minimize issues related to truncation in the data series. Generally, a patent application is reported in Patstat after 18 months and may take years before a final decision on the granting right is reached.

The WIPO technological classification identifies 35 technology fields within five main technological areas: “Chemistry”, “Electrical engineering”, “Instruments”, “Mechanical engineering”, “Other fields” (the list of technology fields is reported in Table A.2). The WIPO classification is built on the International Patent Classification (IPC), used in 54 countries since 1975. The IPC contains more than 70,000 entries defined by seven-digit alphanumeric classification symbols. The patent office assigns each application to one (or more) IPC code, which is then mapped into the WIPO classification. For instance, the IPC code G06C 21/00 denotes “Programming-mechanisms for determining the steps to be performed by the computing machine”, which is mapped into the “Computer technology” WIPO field.

This WIPO technological classification allows for assessing a relatively broad range of technological areas, comparable with industrial classifications, and avoiding an excessive level of detail that can raise issues in the forecasting exercise. The analysis uses information on patents granted in the 35 technological classes from 41 countries between 2001 and 2020, to present descriptive evidence on recent technological development and estimate models to forecast technological evolution up to 2030.

3.2 Methodology

[3] In tallying the total world patents, we considered only the major European and OECD countries, except for Bulgaria, Costa Rica, Croatia, Indonesia, Singapore, North Korea, Latvia, Lithuania, and Estonia, due to the small or null number of patents in many technology classes, and with the addition of China, South Korea, Russia, Taiwan, and South Africa. As a rule of thumb, we selected countries with less than 350 missing values. The total number of countries is 41, and the total number of patents considered amounts to about 99% of the world's patents in 2001 and 98% in 2020. Therefore, the sample is representative of the worldwide trend in patenting activity. Table A.1 in the Appendix reports the countries included in the analysis.

3.2.1 The steps of the empirical analysis

Our research is centred on the crucial aspect of countries' technological specialization, a concept we define through patent indicators. Specifically, we delve into the distribution of a country's inventions across various technology fields and compare it with the global distribution of patents. This comparison allows us to gauge a country's position in fields with higher growth potential, a key factor in understanding a nation's technological landscape. The first step is identifying the technological sectors with the highest windows of opportunity. This will allow us to make some projections on which technological areas are growing in importance and which are declining. Indeed, in a globalized world economy, where innovations are quickly exploited and disseminated, the positioning concerning fast-growing technologies will affect countries' performances.

In the empirical analysis, we build on the considerations addressed in Section 2 and measure technological opportunities with the growth rate of patents. We are aware that not all technological opportunities are captured by patents and not all patents capture technological opportunities. Nevertheless, since it is costly and time consuming for firms to apply for patents and they are assessed by independent public officials, we assume that they represent a meaningful inventive and innovative activity. To explore technological trajectories, patents have the further advantage of being available for very detailed classes, much more than R&D and other scientific and technological indicators.

We focus on fast-growing technologies since they represent a signal of technological dynamism, reflecting rapid innovation in emerging fields, and often indicating areas of significant industrial development. Recent studies highlight that fast patent growth often occurs in high-R&D fields, signalling transformative innovation potential (OECD, 2018; Breschi et al., 2019). We therefore share the OECD (2009) opinion that patent growth rates are a robust indicator of emerging technological trends.

Of course, patent counts present the drawback that not all inventions are patented, and the propensity to patent may differ across fields, firms, and countries. Nevertheless, these issues are less critical when growth rates are computed.[4].

Our research methodology involves dividing the sample into sub-periods: the first sub-period spans from 2001 to 2004, the second from 2011 to 2014, and the third from 2017 to 2020. To capture the dynamism of technology fields, we calculate total patent growth rates over the 2001-2020 period (between the first and the third sub-period). We then identify the most dynamic technology fields as those falling within the first quintile of growth rates. These are the so-called fastest-growing technologies for any given sub-period (henceforth, FGT). Additionally, we also report technology fields falling within the second quintile of growth rate distribution, which we define as medium-growing technologies (MGT).

The second step is to identify nations' technological strengths and weaknesses. By doing so, we compute the index of "revealed technological advantage" (henceforth, RTA) to identify the specialization of each country in the different technology fields; RTAs in different technologies provide a country's technological specialization profile. The RTA is defined as follows:

$$RTA_{ij} = \frac{P_{ij} / \sum_j^J P_{ij}}{\sum_j^J P_{ij} \,/\, \sum_i \sum_j P_{ij}}$$

[4] Hall et al., 2005 used patent citation data to show that technologies with increasing citations over time are markers of innovation intensity, particularly in sectors like biotechnologies and ICT. They also represent larger windows of opportunity, as fast-growing technological sectors, such as AI, biotechnologies, and renewable energy, tend to be subject to rapid advancements.

Where P stands for patents, i is referred to countries, and j to technology fields, with RTA taking values between 0 and $\propto$ and is computed for each year of observation. The index is computed for each country-technology pair within each sub-period under analysis; values higher than one indicate that a country is specialized; values higher than 1.5 indicate that the country is highly specialized; values lower than one indicate that the country is not specialized.

Once FGT, MGT and RTA are obtained, we can assess each country's technological specialization profile concerning the most dynamic technologies and compare the main patterns at the beginning and the end of the period under analysis (from 2001/2004 to 2017/2020).

The third step of the analysis consists of making empirical predictions at the technology level over the 2021–2030 time span. To do so, we run 35 regressions, one for each WIPO technological class, using different specifications and selecting the most suitable one. To make reliable forecasting estimates, we assess the validity of different specifications for each technological class by conducting "pseudo" out-of-sample forecasts, keeping a shorter time horizon to estimate the parameters (2001-2016) and assessing the goodness of fit of our predictions with observational data (2017-2020).

Once the best model is selected, we conduct the "true" forecast estimates from 2021 to 2030, considering the whole 2001-2020 period as the in-sample data, and derive the forecasted values at the technology and technology-country levels. Lastly, we compute RTAs and growth rates over the 2011/14-2027/30 period to assess the possible specialization profile of each country and their specialization in FGT and medium-growing technologies (MGT) in the near future.[5] Specifically, we first assess whether there have been some changes in the dynamics at the level of technology fields. Indeed, registering changes in the growth rates of technology classes allows us to infer plausible indications about declining and growing technologies. Then, we investigate whether the specialization of countries is skewed towards those technology fields exhibiting the highest growth rates. We interpret the finding of a high specialization pattern in declining technological classes as evidence of lower potentiality to register higher innovativeness and income growth rates in the future and embark upon a sustained development path. By contrast, countries exhibiting a wide array of specializations in FGT have a great potential to capture the technological opportunities offered by the most dynamic technologies.

The last step of the analysis consists of computing the Chi-squared and the Herfindahl-Hirschman (henceforth, HHI) indexes to assess the overall distribution of countries' technological development over time. The former index measures dissimilarity from the "representative" technological specialization profile. The index is defined as follows:

$$\chi_i = \frac{(\frac{P_{ij}}{\sum_i^N P_{ij}} - \frac{\sum_j^J P_{ij}}{\sum_i \sum_j P_{ij}})^\wedge 2}{\sum_j^J P_{ij} \,/\, \sum_i \sum_j P_{ij}}$$

The latter measures the country's technological concentration of patenting activity in different WIPO technology fields. The index is defined as:

$$HHI_i = [\sum_j^J (\frac{P_{ij}}{\sum_i^N P_{ij}})^\wedge 2] * 100$$

[5] In other words, we specify the number of technological specializations (RTA > 1) of the leading advanced countries in the sample in the first quintile, the FGT, and the second quintile, including the medium-growing technologies, MGT.

Where, again, P stands for patents, i is referred to countries, and j to technology fields, with χ taking values between 0 and 2.587, and HHI values between 0 (uniform distribution of patents across technologies) and 100 (all patents pertain to only one technology). Both indexes are computed for each country within each sub-period of analysis. The Chi-squared and the HHI allow us to assess the technological activities of the countries in our sample further.

3.2.3 Estimation framework

We run 35 panel regressions, one for each technological class, to select a model between three different specifications through a "pseudo" out-of-sample forecasting strategy. Then, using the selected model, we conduct forecasting estimates until 2030.

With the first model, we assume that patent granting at the technology level follows a simple autoregressive process of order one and a stochastic component; with the second model, we assume that patent grants move following an autoregressive process of order 2 (two lags) and a stochastic component; with the third model, we assume that patenting activity at the technology level follows an autoregressive process of order 1 with the addition of a common trend (common across countries) and a stochastic component. All three models also include fixed effects capturing country-specific unobserved heterogeneity. For each technology field, the relative equations are:

$$P_{it} = \alpha P_{i,t-1} + u_i + \varepsilon_{it}$$

$$P_{it} = \alpha P_{i,t-1} + \beta P_{i,t-2} + u_i + \varepsilon_{it}$$

$$P_{it} = \alpha P_{i,t-1} + t + u_i + \varepsilon_{it}$$

where P indicates patents, i refers to country and t to year, u_i captures country-level unobserved heterogeneity, and ε is included as the stochastic disturbance. To test the validity of different specifications and choose the one that best fits the data, we select the model with the largest predictive ability, i.e., the one with the lowest associated root mean squared forecast error (henceforth, RMSFE). The RMSFE is equal to $\sqrt[2]{\frac{\sum_{t=1}^{T}(P_{it}-\hat{P}_{it})}{T}}\ \forall\, i, t > 2020$, where $\hat{P}_{it}$ indicates forecasted patent values. To compute it, we explored the pseudo out-of-sample properties of the panel series. Generally, one chooses a time horizon $T_0 < T$, and the resulting forecasting errors $\{\varepsilon_{it}\}_{t=T_0+1}^{T}$ are used to estimate the model's out-of-sample forecasting ability. We chose to hold the time series as late as 2016 ("in-sample" period) to assess its forecasting capacity between 2017 and 2020 ("out-of-sample" forecasting) by comparing the actual data with the forecasted data generated by each model. The model that best fit the actual data (with the lowest RMSFE index) was chosen to estimate the forecasted values from 2021 to 2030. Although this data-driven methodology is reliable in several respects, the results should be taken cautiously since forward-looking estimates are gradually less reliable over time, given the several exogenous factors that could intervene to generate unforeseen shocks that undermine their credibility.

Table A.3 in the Appendix reports the model validation analysis results based on the minimum value of the RMSFE index. Notably, all three classes representing the core of ICTs, "Digital technology", "IT methods for management", and "Computer technology," are best predicted by the model with one autoregressive component and a common trend. Overall, the evidence is mixed, with some technologies better described by models with one autoregressive component (one lag order), other fields moving following both a one lag order and a common trend, and others following a two lag orders autoregressive process (Table A.4 reports the model selected for each technology). Once the best model fit has been chosen, we forecast until 2030 to compute the specialization pattern of countries included in the analysis and compare them with the growth rates of technologies.

We also perform a sensitivity analysis through two robustness checks. In one case, we include patent information for 2021 and 2022, which brings into the analysis the COVID-19 crisis years. In the other case, we evaluate whether the main findings are substantially affected by the exclusion US patent data. In the first case, we want to assess the effect of the COVID-19 pandemic on the empirical predictions; in the latter case, we aim to verify the robustness of our results to the "home bias" effect induced by the large share of US patents granted at the USPTO.

4. An overview of patenting trends

4.1 The patent surge and the changing ranking of countries

Table 1 presents a comprehensive view of the 20 countries that have registered the highest number of patents at the USPTO, both in the initial sub-period (2001-2004) and the final sub-period (2017-2020) of the observational data. This data is significant as it reveals a doubling of patents granted at the USPTO over the 20-year period under consideration. The world economy is becoming increasingly based on patents (Fink et al., 2016). This surge may capture the shift toward more complex products and industries where the ratio of patents per R&D invested is particularly high, and specialization costs are low (Gkotsis and Vezzani, 2022). The patent surge is only partially due to an increase in the total amount of resources devoted to knowledge since R&D expenditure has also grown but at a much lower rate. This has raised critical views on patents because they might reflect an increasing appeal to property rights for lobbying and rent-seeking (Boldrin and Levine, 2013) and because making knowledge (too) proprietary may have a detrimental effect on the growth of the common knowledge pull (Archibugi and Filippetti, 2018). That said, patents can capture the development of new technical solutions and, as such, are a useful device for understanding the rate and direction of technological change.

Table 1: Patent granted to top 20 countries, 2001/04 versus 2017/20

Country	2001/04	%	Country	2017/2020	%	Δ rank
United States	345,347	52.1%	United States	622,320	47.2%	=
Japan	139,154	21.0%	Japan	202,582	15.4%	=
Germany	44,816	6.8%	South Korea	84,135	6.4%	+2
Taiwan	22,079	3.3%	China	70,479	5.3%	+15
South Korea	15,715	2.4%	Germany	69,061	5.2%	-2
France	15,379	2.3%	Taiwan	46,349	3.5%	-2
United Kingdom	14,930	2.3%	United Kingdom	28,844	2.2%	=
Canada	13,869	2.1%	Canada	28,511	2.2%	=
Italy	6,810	1.0%	France	27,708	2.1%	-3
Sweden	6,205	0.9%	India	19,928	1.5%	+11
Switzerland	5,394	0.8%	Israel	17,449	1.3%	+2
Netherlands	5,342	0.8%	Italy	12,082	0.9%	-3
Israel	4,269	0.6%	Sweden	12,040	0.9%	-3
Australia	3,607	0.5%	Netherlands	11,409	0.9%	-2
Finland	3,355	0.5%	Switzerland	11,324	0.9%	-4

Belgium	2,729	0.4%	Australia	7,099	0.5%	-2
Austria	2,256	0.3%	Austria	6,088	0.5%	=
Denmark	1,898	0.3%	Finland	6,054	0.5%	-3
China	1,428	0.2%	Belgium	5,403	0.4%	-3
Spain	1,196	0.2%	Denmark	4,650	0.4%	-2
Total	663,327	100.0%	Total	1,318,646	100.0%	
World share of top 20		*98.9%*	*World share of top 20*		*98.1%*	

Note: Patents granted at the USPTO by inventors' country of residence. The share of United States is subject to home bias.

The United States ranks first in both sub-periods. However, this performance incorporates the well-known phenomenon known as *home bias*, where proportionate to their inventive activity, domestic applicants tend to file more patents in their home country than foreign ones (Dernis and Khan, 2004). The table highlights the massive increase in patents among Asian countries and the generally poor performance of European countries that have lost or, at best, defended their position in the worldwide ranking. Among the top performers, China and India, thanks to a spectacular increase in patents, have gained 5 and 11 positions in the ranking. Korea experienced a fivefold increase in patenting, reaching third place in the world ranking at USPTO behind Japan, while patents from Israel-based inventors quadrupled.

4.2 Fast growing technologies and countries' specialization

In this Section, we present the crucial stylized facts that shed light on the growth of patents by technology and the relative specialization of countries. The country's performance in terms of overall patenting activity is significantly influenced by its technological specialization. Therefore, we will delve into the intersection of these two dimensions, namely patent growth rates and technological specialization, to provide a comprehensive understanding of the subject matter.

Table 2 presents the WIPO fast-growing technologies from 2001/04 to 2017/20. In the last column of the table, we report the technologies with the highest growth rates over the two decades and the FGT, considering the whole period. Among the seven technology fields with the highest growth rates during the 20 years considered (last column), only one, "Digital communication", has been constantly on the top in the two decennia. "IT methods for management", the technology with the highest growth rate overall, does not show up among the top growing technologies in the 2011/14 to 2017/2020 period.[6] Fast-growing technologies differ according to the period considered. Moreover, the correlation between the growth rates of technologies in the two periods is relatively low (only 0.02). In other words, despite a strong presence of IT-related technologies among those with high growth rates, the growth performance of technological fields does not exhibit strong persistence, suggesting that short windows of opportunities may arise in different fields within the overall pattern dictated by the technological paradigm.

Table 2: Technologies with high growth rates in the 2001/04 – 2017/20 period.

[6] The increasing use of patents related to "IT methods for management" can partly reflect a USPTO specificity on the way software patents are treated (in EPO, software patents are admitted if they also contain some hardware related feature).

	From 2001/04 to 2011/14		From 2011/14 to 2017/20		From 2001/04 to 2017/20	
	WIPO filed	Growth	WIPO field	Growth	WIPO field	Growth
FGT	IT methods for management	480%	Digital communication	114%	IT methods for management	634%
	Computer technology	228%	Thermal processes and apparatus	112%	Digital communication	568%
	Digital communication	212%	Micro-structural and nano-tech.	97%	Computer technology	259%
	Telecommunications	106%	Transport	76%	Micro-structural and nano-tech	230%
	Surface technology, coating	95%	Engines, pumps, turbines	58%	Control	165%
	Control	83%	Other special machines	53%	Medical technology	145%
	Medical technology	73%	Analysis of biological materials	46%	Electrical mach., apparatus, energy	117%
MGT	Audio-visual technology	73%	Electrical mach., apparatus, energy	45%	Thermal processes and apparatus	96%
	Micro-structural and nano-tech.	68%	Control	45%	Transport	88%
	Pharmaceuticals	55%	Materials, metallurgy	44%	Analysis of biological materials	86%
	Electrical mach., apparatus, energy	50%	Other consumer goods	43%	Measurement	82%
	Basic communication processes	39%	Medical technology	42%	Civil engineering	73%
	Food chemistry	38%	Civil engineering	41%	Audio-visual technology	72%
	Environmental technology	37%	Mechanical elements	36%	Food chemistry	72%

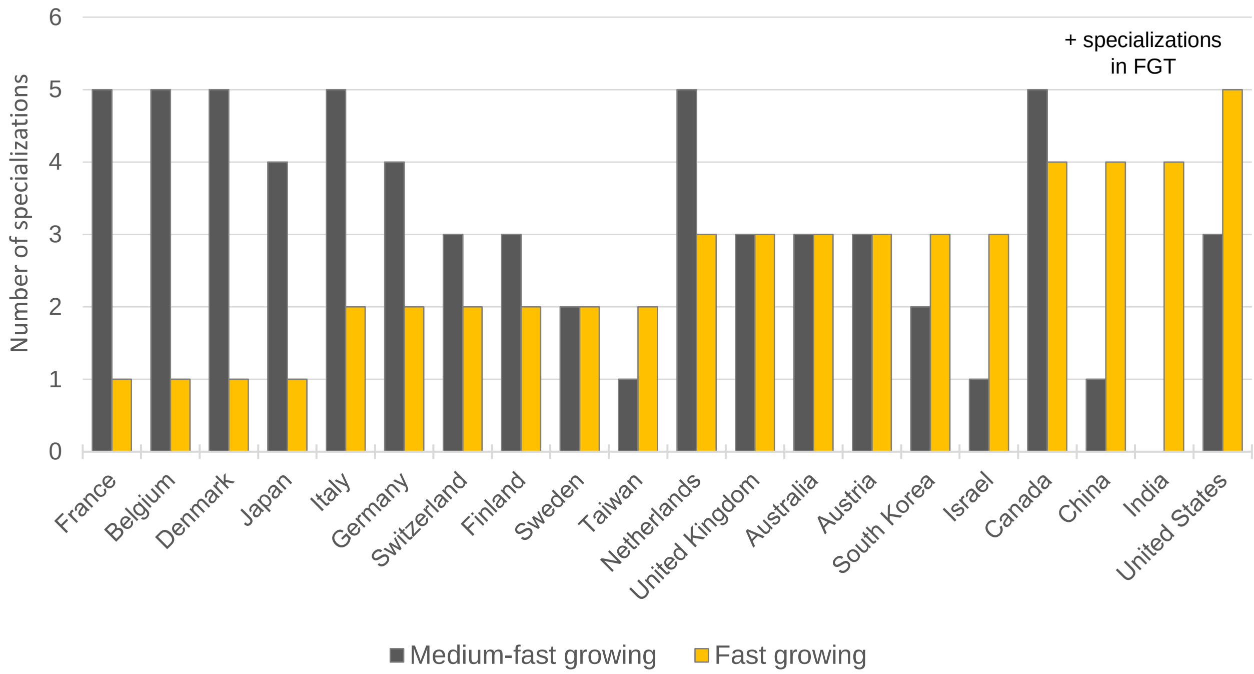
Note: Patents are considered according to their date of grant at the USPTO.

The FGT reported in the last column exhibit growth rates above 100%, higher than the overall growth of patenting activity (98.8%). In other words, while many technological fields experienced high growth rates, the patent surge between 2001 and 2020 has been largely driven by ICT-related technologies.

Figure 1 reports the number of specializations in the medium-growing and FGT over the 2017-2020 period for the 20 countries with the largest number of patents. The United States present the highest number of total specializations (RTA > 1) in the FGT (showing specialization in 5 out of 7). The US has been able to direct its R&D and innovative efforts toward the most promising technology fields and to confirm its leadership in the high-tech patenting activity. More than 30 years ago, many commentators discussed the decline of the US technological leadership associated with a decrease in the share of high-tech trade and patents (Nelson and Wright, 1992); yet, after such a long cycle, it seems that so far the American economy has successfully managed a transition from the previous to the current techno-economic paradigm.

Also, India, China, and Canada register a high number of specializations (4) in FGT; Canada shows a diversified portfolio with also five specializations in the MGT. Overall, the intense efforts of China and India to position themselves as technological competitors with the most advanced economies have been based on a careful positioning in the most promising technological fields. On the contrary, most EU countries do not show many specializations in FGT but have mostly specialized in MGT.

Figure 1: Number of specializations for medium- and fast-growing technologies by country in 2017/20



Notes: FGT are the 20% technologies with highest growth rates during the 2001-2020 period; medium-fast growing the those with the second quintile in terms of growth rates. Elaborations on OECD data, patents granted at the USPTO in 2020 by inventors' country of residence.

Table 3 shows which FGT countries are specialized, considering their patenting activity during the 2017/20 period. The table is sorted according to the number of specializations exhibited by a country. As highlighted above, the FGTs feature three IT-related technologies, together with technologies related to "Control," "Electrical machinery, apparatus, energy," "Medical technology," and "Micro-structural and nanotechnology" fields. Remarkably, China and India have a specialization in all IT-related technologies, while European countries do not present specializations in ITs apart from the UK ("Computer technology" and "Digital communication") and Sweden ("Digital communication"). Several EU countries instead specialized in "Medical Technologies" (related to medical devices) and "Micro-structural and nanotechnology".

Table 3: Today countries' specializations in FGTs

Country	Computer technology	Control	Digital communication	Electrical machinery, apparatus, energy	IT methods for management	Medical technology	Micro-structural and nano-technology
United States	Spec.	Spec.	Spec.		Spec. (+)	Spec.	
China	Spec.		Spec. (+)	Spec.			Spec.
Canada	Spec.	Spec.	Spec.		Spec.		
India	Spec. (+)	Spec.	Spec. (+)		Spec. (+)		
South Korea	Spec.		Spec.	Spec.			
United Kingdom	Spec.		Spec.			Spec.	
Israel	Spec. (+)		Spec. (+)			Spec. (+)	
Netherlands				Spec.		Spec.	Spec. (+)

Australia	Spec. (+)			Spec.	Spec. (+)	
Austria	Spec.		Spec. (+)			Spec. (+)
Germany			Spec.			Spec.
Taiwan			Spec.			Spec. (+)
Italy			Spec.			Spec. (+)
Sweden		Spec. (+)			Spec.	
Switzerland					Spec. (+)	Spec.
Finland		Spec. (+)				Spec. (+)
Japan			Spec. (+)			
France						Spec.
Belgium						Spec.
Denmark					Spec. (+)	

Notes: Specializations are computed considering the patent distribution across technologies for the 2017/2020 period. *Spec* stands for “specialization (RTA > 1)”; Spec. (+) stands for “high specialization (RTA > 1.5)”.

Overall, the Asian economies that have climbed the world ranking in patenting activity show a specialization in IT-related technologies[7]. Moreover, all the countries with a high number of FGT specialisations include "Computer technology" and "Digital communication."

Finally, let us notice that the relative specialization of countries does not show particularly high levels of persistence during the period considered. In particular, the correlation of within country-technology RTAs observed at the beginning (2001/04) and at the end (2017/20) of the period is not high and equal to 0.37. Since the first identification and measurements of technological accumulation (Cantwell, 1987; Pavitt, 1988), we know that countries' technological capabilities are characterized by stickiness because of the advantages offered by the cumulativeness of knowledge and the difficulties and costs of redirecting innovative efforts, mainly when operating close to the technological frontier. One may expect that this is reflected in a slowly changing nature of specialization patterns, at least in the medium term. However, RTA measures specialization in relative terms and incorporates changes in technological capabilities both at the country and at the global level: a country may end up losing its specialization in each technology because its knowledge accumulation is low compared to the one experienced by other countries.

5. A look into possible future patterns

In this section, we first perform a sensitivity analysis based on two different plausible scenarios: the exclusion of US patents and the inclusion of COVID-19 years. Then, we replicate the descriptive analysis of section 4 using the projections resulting from the estimated panel models. Specifically, we first look at potential candidates' classes that are among the fastest-growing ones, and then we look at the country's specialization in these technologies. To conclude, we also look at some long-term properties of the countries’ specialization profiles.

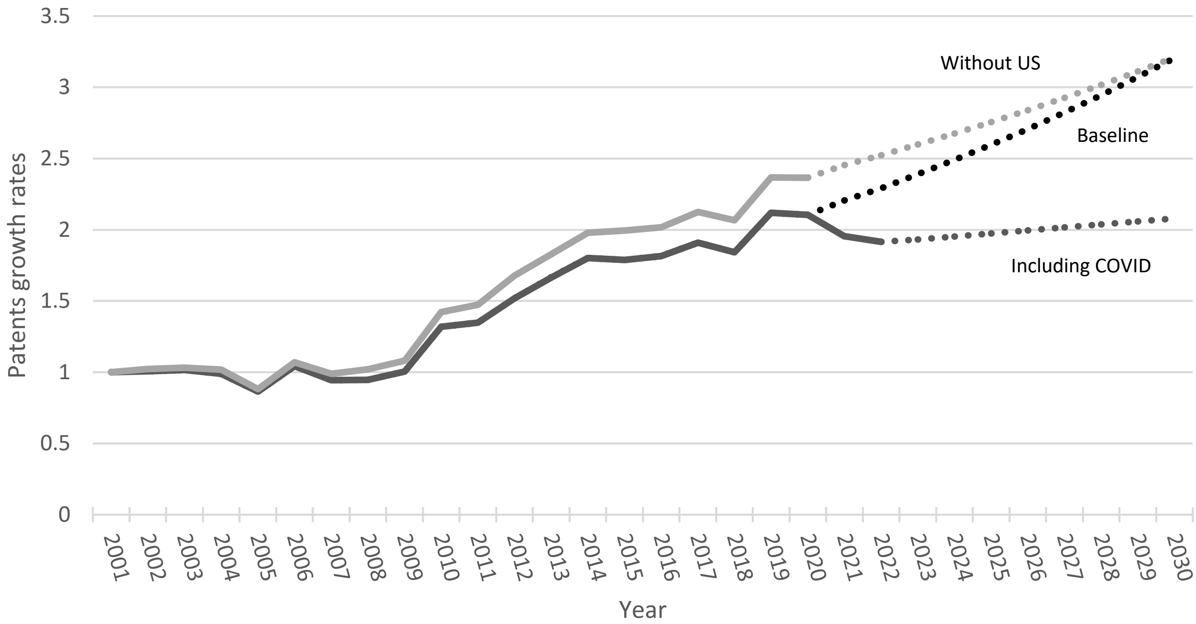
5.1 Robustness checks

Before discussing the main results, we compare the overall dynamic of patenting activity – in sample and forecasted – in our sample (baseline) with that resulting from the exclusion of US patents and the

[7] Not only China and India, but also South Korea.

inclusion of 2021 and 2022 (COVID-19 years) in the estimation of underlying parameters (see Figure 2). To facilitate the comparison, we normalize values for each series with respect to 2001.

Figure 2: Patent dynamics, baseline versus robustness checks (excluding US, and including 2021/22)



Note: Patents growth rates at the USPTO by inventors' country of residence, for the baseline sample, excluding US data, and including COVID-19 years, i.e., 2021 and 2022.

Including 2021 and 2022 brings the effects of the COVID pandemic into the analysis. Indeed, a drop in granted patents is visible in 2021 and 2022, right after the sanitarian shock hit the world economies. This drop is incorporated in the forecasting exercise at the technology level, leading to an overall sluggish patent dynamic until 2030. In other words, including the years of the pandemic gives the shock a structural characterization projecting a conjuncture phenomenon into the future. We do not think this is plausible, but it is a sign of the importance of carefully inspecting data when performing estimation exercises and cautiously reading forecasting results such as ours.

Excluding patents from US inventors shifts the in-sample dynamic up, largely because of the higher growth rates of Asian countries between 2001 and 2020. However, this leads to a slightly lower aggregate growth in the upcoming years (catch-up may have already happened) and a relative number of patents for 2030 in line with the one resulting from our baseline estimations. The exclusion of US patents has a much lower impact on the forecasted patent dynamic than the inclusions of the years incorporating the COVID-19 shock.

5.2 Reading the empirical predictions

In this section, we summarize and describe the main statistics arising from the empirical predictions resulting from the baseline scenario. Table 5 reports the estimated technologies with the highest growth rates for the 2017/20 to 2027/30 period; to assess the robustness of our results, we compare the list of technologies with the highest estimated growth rates with the one resulting from the exclusion of US patents. Among the FGT, we find some overlap with the observational data discussed above (see Table

2). “IT methods for management,” “Digital communication”, “Control”, and “Medical technology”, which rank at the top during the last 20 years, will still stay among the 20% of technology classes with the highest growth in patenting activity, thus retaining considerable technological opportunities. Once we make a comparison with the last ten years of observational data, the overlapping is still good despite some technologies being slightly different: “Food chemistry”, “Thermal processes and apparatus”, and “Other special machines” appear for the first time among FGT. Finally, when comparing results from the baseline specification and those excluding US patents, we find a substantial overlap of technological classes in the first two quintiles of growth rate distribution; 10 of the 14 technologies in the table are the same. Naturally, some differences arise; for example, “Food chemistry” and “Computer Technology” are not among the top growing estimated technologies when excluding US patents but, overall, the correlation of estimated growth rates is rather high (0.75).[8]

Table 5: Technologies with the highest predicted growth rates (2017/20 – 2027/30)

	WIPO fileds	Top growth also excluding USA	WIPO fields excluding patents from US
FGT	Thermal processes and apparatus	Yes	IT methods for management
	Other special machines	Yes	Digital communication
	Food chemistry		Thermal processes and apparatus
	IT methods for management	Yes	Medical technology
	Digital communication	Yes	Control
	Medical technology	Yes	Engines, pumps, turbines
	Control	Yes	Transport
MGT	Transport	Yes	Measurement
	Engines, pumps, turbines	Yes	Macromolecular chemistry, polymers
	Computer technology		Electrical machinery, apparatus, energy
	Measurement	Yes	Analysis of biological materials
	Materials, metallurgy		Other special machines
	Handling		Other consumer goods
	Electrical machinery, apparatus, energy	Yes	Civil engineering

Note: Patents per technology are estimated according to the methodology presented in section 3.

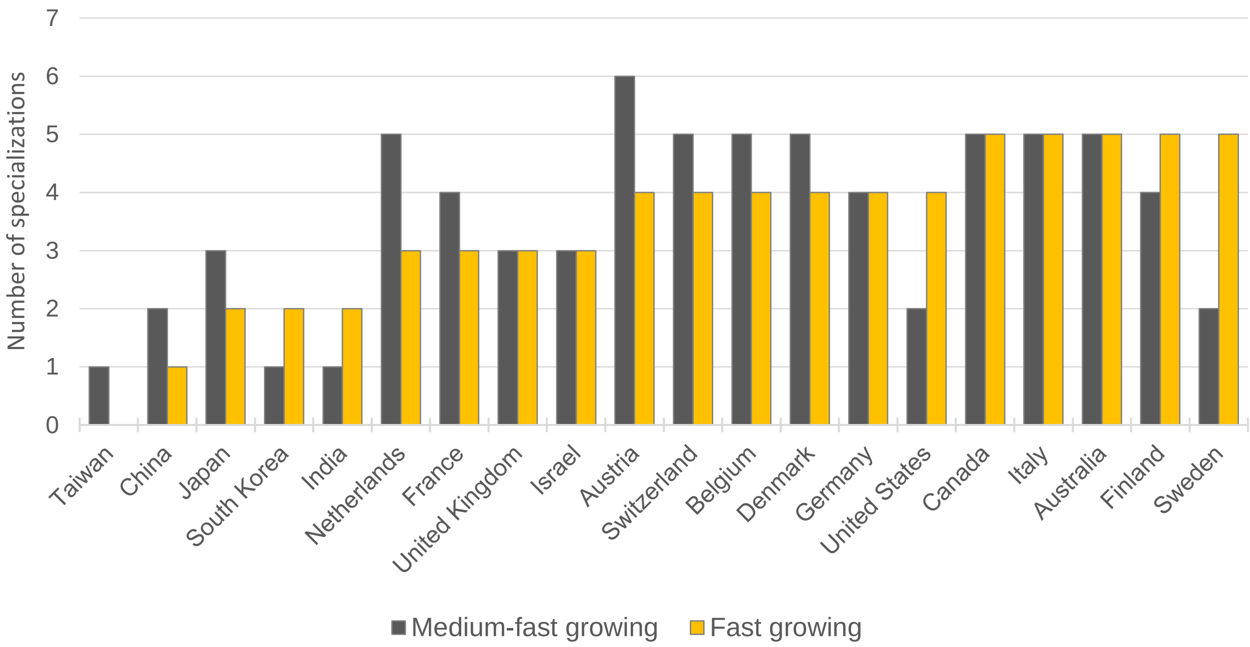
Interestingly, along with the core of IT-related technologies characterizing the last decades, from the table, a set of technologies related to transport, logistics, engines, and advanced machines and materials emerges as the one offering high technological opportunities in the years to come. Overall, these changes suggest a shift in the relative importance of technologies in the unfolding of the current techno-economic paradigm, indicating that the maturity reached by IT technologies will allow for a renewal of the knowledge base in other technological fields. While we do not know exactly what the next techno-economic paradigm will look like, it seems likely to involve technologies linked to digital systems, environmental transition, and a possible explosive growth in robotics boosted by recent advancements in digital technologies such as artificial intelligence (Pratt, 2015). When a specific area becomes a general-purpose technology, it likely generates associated innovations in areas which were originally simply recipients of the technology, spanning additional innovation and capabilities (Brynjolfsson & Mitchell, 2023). Artificial intelligence is already affecting the way research is conducted in different fields and may further push scientific understanding in the near future (Krenn et al., 2022), as well as redesigning

[8] The correlation of growth rates in the observational data is closer to one, 0.98, implying that the exclusion of US patents has an even more marginal impact on the descriptive evidence provided above.

innovation management as a data-driven process (Cockburn et al., 2018). Our data suggest that advancements in digital technologies can lead to cascade effects even in a post-IT revolution era.

In Figure 3, we report the number of specializations of the top patenting countries in our dataset for medium-growing technologies (MGT) and FGT in 2027/2030. Differently from what was observed in Figure 1, European countries tend to present more specializations in the potential FGT of the next decade. On the contrary, Asian economies may register fewer specializations in the most dynamic sectors at the end of the next decade. Of course, these results should be taken *cum grano salis*. They will largely depend on the capacity of Asian economies to diversify their science and technology efforts into new fields and on European ones to exploit their comparative advantages in the future. As the saying goes, creating a new "European Silicon Valley" may be a dream of the past, but new challenges are there to be taken.

Figure 3: Number of specializations by country in 2027/2030 (RTA > 1)



Notes: number of specializations for each country in patents cohorts with different compound annual average growth rates over the 2010-2030 period (forecasted values). Authors' elaborations on OECD data on patents grants at the USPTO by date of grant, inventor's country of residence.

In Table 6, we report which potential future FGT countries would be specialized in during the 2027/30 period. The table provides a somewhat different picture from Table 3: specialization in the potential FGT of the future appears much more widespread across countries. Specifically, 13 out of the 20 countries present a potential specialization in "Other special machines"; a similar situation can be observed in the "Medical Technologies" and "Engines, pumps, turbines" fields. The result should be interpreted in light of the forecasting exercise. Many countries have the potential to play a major role in these technologies. However, only a few will likely be able to trigger the necessary positive dynamics in the innovation system to get the lead.

Table 6: Potential countries' specializations in upcoming FGTs, 2027/30

Country	Control	Digital communication	Engines, pumps, turbines	Medical technology	Other special machines	Thermal processes and apparatus	Transport
Canada	Spec.	Spec.	Spec.		Spec.	Spec.	
Italy			Spec. (+)	Spec.	Spec. (+)	Spec. (+)	Spec.
Sweden		Spec. (+)	Spec.	Spec.	Spec.	Spec.	
Australia	Spec. (+)		Spec.	Spec. (+)	Spec. (+)	Spec.	
Finland		Spec. (+)	Spec.	Spec.	Spec. (+)	Spec. (+)	
United States	Spec.	Spec.		Spec.			Spec.
Germany	Spec.		Spec. (+)		Spec.		Spec. (+)
Switzerland			Spec.	Spec. (+)	Spec.	Spec.	
Austria			Spec.	Spec.	Spec. (+)	Spec. (+)	
Belgium			Spec. (+)	Spec.	Spec. (+)	Spec. (+)	
Denmark			Spec. (+)	Spec. (+)	Spec. (+)	Spec. (+)	
United Kingdom	Spec.	Spec.	Spec.				
France			Spec. (+)		Spec.		Spec. (+)
Israel		Spec.		Spec. (+)	Spec.		
Netherlands				Spec. (+)	Spec. (+)	Spec.	
Japan	Spec.						Spec. (+)
South Korea		Spec.					Spec.
India	Spec.	Spec. (+)					
China		Spec. (+)					
Taiwan							

Notes: Specializations are computed considering the possible patent distribution across technologies for the 2027/2020 period. *Spec* stands for "specialization (RTA > 1)"; *Spec.* (+) stands for "high specialization (RTA > 1.5)".

Another result standing out from the table is the narrow specialization of South Korea, India, and China around "Digital technologies". Will they be able to diversify into new high-opportunity fields? China is a vast country with substantial financial resources and active policies targeting industries and technologies of interest, with growing strengths in Electric Vehicle (EV) batteries and putting pressure on Western countries (Yang, 2023). Also, other Asian economies, like South Korea and Japan, sowed a strong dynamism in the development of battery technologies in the last twenty years (Metzger et al., 2023). As we said, European countries are well positioned regarding potential upcoming FGT. "Control," "Engines, pumps, turbines", "Other special machines", "Thermal process apparatus", and "Transport" are all technology fields related to the core of the innovative capacity of the European manufacturing sector. In one way or another, these are also technologies related to climate change, which the EU has traditionally played a leading role in.

However, the increasing technological tensions between the US, EU and China, for example, in electric vehicles or legacy chips, will likely influence future opportunities and restrict the possibilities for cooperation that were open in the past. This will have nontrivial implications for the future of worldwide technology development, and much will depend on the willingness to accompany the industry's needs to develop new technological solutions that will lead to sustainable long-term growth without fuelling technological fragmentation.

Finally, we conclude our analysis by presenting some indicators highlighting the main features of the countries' technological specialization throughout the analysis. Table 7 reports the Chi-squared statistic and the HHI index computed on the WIPO technological fields for USPTO's top 20 patenting countries. The former measures a country's technological profile's dissimilarity with respect to the “average” country (or to the global profile of technological development), and the latter measures the technological concentration of its patenting activity.

The Chi-square highlights a general convergence process in the countries’ technological profiles. For most countries, the reported values also decrease in the estimation sample, consistent with what happened in observational data; the trend contrasts with the increasing divergence observed in the 1980s (Archibugi and Pianta, 1992). Particularly marked is the convergence in specializations shown by India, Finland, Denmark, and Belgium. While convergence seems to be the rule, some countries do instead persistently show technological profiles differing from the average one, particularly visible in the case of Taiwan. Also, countries like Japan and the Netherlands do not seem to follow the general rule.

Table 7: Technological specialization of countries, dissimilarity, and concentration

	Technological dissimilarity (Chi squared)				Technological concentration (HHI)			
	2001/04	2011/14	2017/20	2027/30	2001/04	2011/14	2017/20	2027/30
India	273.70	83.46	78.37	47.66	10.35	21.27	18.58	17.40
Finland	142.58	84.04	40.49	27.28	7.42	10.55	8.74	10.17
Denmark	94.40	93.93	75.29	43.80	5.03	5.42	5.39	7.53
Belgium	90.30	62.68	40.94	27.05	4.74	4.30	3.96	6.72
Taiwan	72.51	49.25	100.98	99.70	8.96	8.63	11.45	9.76
China	64.38	26.92	23.10	20.54	7.73	8.18	8.51	10.42
South Korea	48.75	45.28	29.52	28.89	8.07	8.89	8.31	8.82
Israel	48.56	40.73	48.26	33.51	6.70	13.37	14.22	13.88
Australia	47.10	76.01	33.04	36.86	4.37	6.02	5.62	7.63
Switzerland	41.96	46.10	36.53	29.46	4.35	4.99	5.35	6.96
Austria	39.75	32.75	34.31	17.16	3.89	4.02	4.95	6.45
Sweden	39.09	38.37	49.63	34.98	4.58	6.56	10.33	12.79
Germany	32.18	29.68	27.89	25.32	4.32	4.44	4.75	5.58
Italy	31.42	36.23	37.80	23.58	4.02	4.32	4.17	5.66
Japan	24.27	28.93	30.11	40.51	5.93	6.67	5.84	6.11
France	23.72	20.97	20.82	18.77	3.95	4.68	4.53	5.64
Canada	23.67	18.10	16.06	12.14	3.84	7.33	6.20	7.51
Netherlands	22.66	29.79	47.57	30.63	4.33	4.49	4.73	6.14
United Kingdom	18.57	14.51	12.18	8.34	3.89	5.78	6.01	7.53
United States	3.58	6.57	5.73	3.86	4.13	6.65	6.22	7.08

The convergence of technological profiles goes hand in hand with a generalized increase in the concentration of the countries’ technological activities. In countries like Israel and Sweden, the concentration index has more than doubled between 2001/04 and 2017/20, and we do not observe signs of reversion of this tendency in the forecasted data. India, which showed an exceptionally high value of technological concentration in the 2011/14 period, shows instead a tendency toward a lower concentration, suggesting that after a period of solid growth in patenting activity around a few technological fields, the country has started a process of diversification of its technological efforts. If we combine the two tendencies, the table returns an image where countries increasingly focus their innovation activities on the same set of technologies. While this evidence is purely descriptive, the extent and the speed at which this process increases the technological competition of countries and decreases the set of alternative development patterns is an issue that would deserve some reflection from the policy and academic communities.

6. Limitations of our analysis

Our analysis has some obvious limitations. First, we assume that a single indicator, such as patents, equally reflects the technological advancements in all fields. This is certainly not the case since there are critical knowledge-intensive industries where it is less likely to recur to patents. Some sectors of the economy, such as entertainment and media, banking and insurance and health services, even if very knowledge-intensive, have a lower propensity to patent than other sectors. Nations which are successfully active in these industries may be well off even without showing high performances in terms of patents. Similar remarks were made back in the 1980s and 1990s when it was (rightly) stressed that patents were a good indicator of the technological activities of the manufacturing sector but much less for the service economy (Evangelista, 2006). However, service companies, including IBM, Alphabet and Microsoft, are nowadays among the very top patent assignees (Grassano et al., 2021), indicating that today's techno-economic paradigm is largely driven by innovation from the service sector that have been spread through the economy to transform the way production and distribution is performed.

Second, patents at the USPTO are a subset of the total patents at the world level, which over-emphasize the US technology market compared to the European or Asian ones (Dernis et al., 2015). We show, however, that the exclusion of US inventors does not change the overall figures significantly. Moreover, the fact that we consider the growth rates in each technology class should hopefully reduce the potential distortion associated with the fact that we use only one national institution.

Third, our projections are not tailored to detect specific emerging technologies. As they will likely emerge in some individual countries, these are the one that will benefit more in terms of future performance. With our methodology, we look at macro trajectories in technological development. However, specific technology niches with high potential may arguably play a determinant role in the future but their identification would require tailored combinations of scientometric techniques and expert judgment.

Finally, the increasing relevance of industrial and technology policies, as illustrated in Made in China 2025 and the Inflation Reduction Act in the US, is changing policymaking and may influence future technological trajectories. The increasing direct intervention in industrial and technological development from two world leader countries will put pressure on other economies and may lead to a redefining of the "rules of the game" in the upcoming years. In other words, technological rivalry driven by the quest to achieve dominance over technologies with critical strategic importance increases the uncertainty inherent to forecasting future technological development.

7. Conclusions: rays of opportunities

In this work we present an analysis of technological trajectories for a panel of 41 countries and provide forecasts until 2030. We also outline countries' specialization profiles and establish whether they are specialized in those technology fields associated with larger windows of opportunity. To do so, we consider the most dynamic technological classes measured by patent growth rates and associate them with the revealed technological advantages of countries. This allows us to detect the number of specializations in fast-growing and medium-growing technologies.

The first and foremost finding is the possible change of the techno-economic paradigm, or the unfolding of a new paradigm boosted by the maturity and pervasiveness of digital technologies. Indeed, while most of the fast-growing technologies in the last decades were associated with ICTs-related technologies like "IT methods for management", "Digital communication" and "Computer technology", the future might look slightly different because development in other technological fields can be accelerated by the recent advancements in digital technologies. Our analysis suggests that technological domains related to robotics, logistics, mobility and energy-efficient machines may constitute the base for the unfolding of a new socio-economic paradigm.

Second, countries leading the technological race have lost shares in the total number of patents, with a convergence between advanced and emerging economies. Few countries still dominate technological development, but new countries are joining the party, leading to a relative reduction in the activities of traditional incumbents. This trend, widely recognized for main economic variables such as production and trade, is also visible in an indicator specific to technological activities. The fact that we have considered patents granted at the US patent office further reinforces the finding.

Third, Asian countries have been able to catch up technologically thanks to a strong specialization in ICT technologies, which still present technological opportunities but might need to diversify their technological specialization to remain among the leading players in the technological landscape.

Finally, while European countries have lost positions in technological activities, they tend to specialize in those sectors that the empirical predictions foresee as the most promising in the years to come. All in all, European countries are well-positioned at the starting blocks, and a lot will depend on which public policy decisions will be taken. For more complex products, technological specialization is likely to be associated with stronger productive capabilities, and selective innovation policies may be usefully complemented with interventions aimed at increasing productive capacity (Caravella et al., 2024). The EU has been traditionally refractory to active industrial policies, preferring to act through regulations; it may be time to develop public strategies to sustain technological development in areas with high opportunities to reap the benefits deriving from the fields where Europe is at the frontier.

Recent years have been characterized by a renewed interest in industrial policies and an evolution of the geopolitical panorama characterized by rising geopolitical stances. The issue today seems to be how to accompany the industry's need to develop new technological solutions that will lead to future sustainable long-term growth without fuelling technological fragmentation at the global level.

Credit authorship contribution statement

Daniele Archibugi: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Vitantonio Mariella:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Antonio Vezzani:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix

Table A.1: List of countries included in the analysis.

Australia	Colombia	Hong Kong	Japan	Portugal	Sweden
Austria	Czech Republic	Hungary	Luxembourg	Russia	Switzerland
Belgium	Denmark	Iceland	Mexico	Slovak Republic	Taiwan
Brazil	Finland	India	Netherlands	Slovenia	Turkey
Canada	France	Ireland	New Zealand	South Africa	United Kingdom
Chile	Germany	Israel	Norway	South Korea	United States
China	Greece	Italy	Poland	Spain	

Table A.2: The WIPO technological classification

Technology area	Technology field	Patents 2001/04	Patents 2017/20
Chemistry	Basic materials chemistry	12,815	17,024
	Biotechnology	14,890	23,590
	Chemical engineering	13,392	20,931
	Environmental technology	6,514	10,956
	Food chemistry	4,199	7,220
	Macromolecular chemistry, polymers	12,601	13,013
	Materials, metallurgy	9,004	12,142
	Micro-structural and nano-technology	721	2,376
	Organic fine chemistry	18,384	22,415
	Pharmaceuticals	18,808	31,380
	Surface technology, coating	10,288	16,255
Electrical engineering	Audio-visual technology	36,022	62,065
	Basic communication processes	13,910	17,369
	Computer technology	53,821	193,357
	Digital communication	18,651	124,628
	Electrical machinery, apparatus, energy	41,888	91,096
	IT methods for management	3,176	23,315
	Semiconductors	44,396	74,689
	Telecommunications	25,050	40,810
Instruments	Analysis of biological materials	3,526	6,550
	Control	10,391	27,555
	Measurement	32,467	59,239
	Medical technology	32,818	80,522
	Optics	34,497	47,871
Mechanical engineering	Engines, pumps, turbines	19,598	33,301
	Handling	16,123	23,689
	Machine tools	17,108	18,930
	Mechanical elements	18,617	30,386
	Other special machines	18,908	30,517
	Textile and paper machines	17,057	12,888
	Thermal processes and apparatus	6,503	12,775
	Transport	29,410	55,236
Other fields	Civil engineering	17,101	29,521
	Furniture, games	18,122	26,177
	Other consumer goods	12,549	18,862

Table A.3: Model validation of the technological fields

WIPO patent classes	MODEL 1 1 lag	Model 2 2 lags	MODEL 3 1 lag + trend
		RMSFE	
Audio-visual technology	**87.85**	88.65	89.08
Basic communication processes	**45.13**	45.38	46.37
Basic materials chemistry	**18.04**	26.21	19.01
Biotechnology	**26.41**	29.79	27.21
Chemical engineering	**36.99**	38.76	37.20
Macromolecular chemistry, polymers	**19.10**	21.31	19.16
Mechanical elements	**51.07**	58.40	51.29
Micro-structural and nano-technology	**10.64**	17.58	10.79
Optics	**97.08**	103.00	97.31
Organic fine chemistry	**32.45**	33.18	34.00
Pharmaceuticals	**45.83**	58.43	46.01
Semiconductors	**98.68**	100.40	100.50
Telecommunications	**59.98**	62.38	61.36
Transport	**86.56**	104.60	87.59
Control	60.70	**54.14**	60.70
Analysis of biological materials	16.60	**15.84**	16.68
Civil engineering	53.68	**49.87**	54.11
Electrical machinery, apparatus, energy	151.30	**141.70**	151.10
Environmental technology	23.91	**21.30**	23.85
Furniture, games	58.06	**57.22**	57.99
Measurement	123.10	**99.70**	123.10
Other consumer goods	37.38	**36.30**	37.18
Textile and paper machines	29.96	**26.32**	30.08
Computer technology	445.40	462.20	**445.30**
Digital communication	255.90	285.50	**255.20**
Engines, pumps, turbines	70.86	73.70	**70.57**
Food chemistry	23.72	26.30	**23.65**
Handling	41.38	42.45	**41.25**
IT methods for management	155.20	162.20	**154.90**
Machine tools	35.48	44.07	**35.14**
Materials, metallurgy	24.28	28.98	**24.07**
Medical technology	254.60	298.60	**254.30**
Other special machines	62.93	68.96	**62.80**
Surface technology, coating	22.41	31.82	**22.39**
Thermal processes and apparatus	45.80	50.60	**45.60**

Notes: the table reports model validation analysis for each WIPO technological class. In yellow, we highlighted the model chosen in the "pseudo" out-of-sample analysis to conduct forecasting estimates (minimum RMSFE).

Table A.4: Parameters for the selected models

	Lag 1	Lag 2	Trend	R2 within	R2 overall
Audio-visual technology	0.894*** (0.018)			0.774	0.985
Basic communication processes	0.588*** (0.027)			0.386	0.986
Basic materials chemistry	0.935*** (0.016)			0.821	0.987
Biotechnology	0.963*** (0.019)			0.778	0.992
Chemical engineering	0.971*** (0.019)			0.787	0.991
Macromolecular chemistry, polymers	0.779*** (0.023)			0.617	0.981
Mechanical elements	1.023*** (0.016)			0.848	0.989
Micro-structural and nano-technology	0.880*** (0.017)			0.780	0.908
Optics	0.875*** (0.019)			0.742	0.991
Organic fine chemistry	0.873*** (0.019)			0.748	0.986
Pharmaceuticals	0.939*** (0.017)			0.804	0.983
Semiconductors	0.920*** (0.016)			0.817	0.989
Telecommunications	0.833*** (0.018)			0.751	0.982
Transport	1.132*** (0.014)			0.905	0.991
Analysis of biological materials	0.786*** (0.037)	0.242*** (0.042)		0.723	0.985
Civil engineering	0.916*** (0.039)	0.165*** (0.043)		0.845	0.989
Control	0.616*** (0.034)	0.547*** (0.038)		0.928	0.992
Electrical machinery, apparatus, energy	0.745*** (0.037)	0.369*** (0.040)		0.920	0.993
Environmental technology	0.668*** (0.040)	0.335*** (0.041)		0.791	0.990
Furniture, games	0.871*** (0.039)	0.093** (0.040)		0.768	0.989
Measurement	0.437*** (0.040)	0.640*** (0.040)		0.804	0.995
Other consumer goods	1.097*** (0.039)	-0.060 (0.042)		0.822	0.989
Textile and paper machines	0.988*** (0.036)	-0.229*** (0.035)		0.712	0.982
Computer technology	0.952*** (0.012)		3.868 (2.541)	0.909	0.984
Digital communication	1.079*** (0.008)		1.477 (0.993)	0.968	0.989
Engines, pumps, turbines	1.122*** (0.015)		0.602** (0.278)	0.888	0.990
Food chemistry	1.005*** (0.020)		0.341*** (0.116)	0.787	0.981
Handling	0.913*** (0.022)		0.992*** (0.263)	0.727	0.989
IT methods for management	0.980*** (0.019)		1.009 (0.729)	0.790	0.933
Machine tools	0.695*** (0.027)		0.749** (0.302)	0.483	0.978
Materials, metallurgy	0.983*** (0.021)		0.473*** (0.129)	0.762	0.985
Medical technology	1.045*** (0.014)		2.330* (1.188)	0.888	0.983
Other special machines	1.074*** (0.018)		1.142*** (0.353)	0.835	0.987
Surface technology, coating	0.847*** (0.019)		0.497* (0.279)	0.739	0.978
Thermal processes and apparatus	1.186*** (0.018)		0.524*** (0.139)	0.856	0.980

*Note: technology regressions with country fixed effects. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$*