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Technological profiles, upgrading and the dynamics of growth: Country-level patterns and trajectories across distinct stages of development

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ABSTRACT

We investigate the dynamic and qualitative nature of technological change in 96 countries between 1980 and 2021 from a structuralist technology upgrading perspective. First, drawing from patent data, we map the dynamics of technological knowledge by exploring the growth rates and significance of technology clusters. Second, we explore whether there is a relationship between specific technology clusters and economic growth. Third, we examine whether countries at different levels of development share similar or heterogeneous technology upgrading profiles and how patterns of technology upgrading have changed over time. We use a long-term, technology-level, cross-country patent dataset, and to address the issues identified we apply two complementary analytical methods: Generalized Method of Moments (GMM) panel data analysis and Fuzzy Set Qualitative Comparative Analysis (fs/QCA). We find a significant association between growth dynamics and country-level specific technology clusters that is driven by the ongoing ICT-based technological revolution and enabling nanotechnology, biotechnology and automation tools. Heterogenous trajectories in technological profiles allowed us to distinguish between more productive and less productive technology upgrading profiles at different income levels. Our results suggest that innovation policy should go beyond mission oriented policies focused solely on newly emerging technologies. Instead, it should develop policy mixes conceived as portfolios of missions focused on technology clusters with disparate objectives, requirements and institutional setups.

1. Introduction

'*Add successively as many coaches as you please, you will never get a railway thereby*' so said Schumpeter (1934: 64). This is probably one of the most famous Schumpeter quotes in the innovation studies literature, and epitomizes the significance of technology as the driver of economic structural change. Indeed, the relationship between structural change and growth has been a central theme in the economy for centuries (Syrquin, 1988). However, the structural shift Schumpeter talks about refers to qualitative change or the changing nature of technology - although in his quotation, proxied by products. The problems related to addressing technology directly or indirectly as in Schumpeter's quote via products have persisted.

As a solution to this issue, a line of research has emerged which proxy technology indirectly, via products and industries. On the one hand, in formal models, technology tends to be viewed as an aggregate phenomenon. In its most aggregate form, technology is represented by 'total factor productivity' (Solow, 1957), by labour productivity, or using indicators such as R&D or patents (Fagerberg, 1987; Romer, 1990). On the other hand, technology is perceived as a multi-faceted, multi-level phenomenon proxied using various indicators that aggregate different facets of technology into a composite indicator (see Archibugi et al., 2009; Radosevic and Yoruk, 2018).

While aggregate and multidimensional treatments have improved our understanding of the relationship between technology and economic growth, they overlook the structural dimension of technological change. Patterns of technological change evolve in specific directions, defined by technological trajectories and technology paradigms (Dosi, 1982; Perez, 2010). Hence, in the context of economic growth, technology is not just about increased technology intensity or deeper knowledge about

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existing technologies. It is also about the emergence of new technologies and the recombination of the existing knowledge in new directions (Arthur, 2009). These emerging novel or combinatorial innovations are driven largely by the transformative features of General Purpose Technologies (GPTs) and enabling technologies[1] (Bresnahan and Trajtenberg, 1995; Teece, 2018). By measuring technology only through its increasing intensity or 'macro-indicator' scale – whether TFP or R&D or an aggregate composite - we lose sight of the dynamic and qualitative nature of technological change. Also, from a policy perspective, in periods of intensive technological change, the direction and structural features of a technology are much more important than its intensity.

In light of these issues, empirical research and conceptual research have explored the issue of the structural differences between different products, technologies, sectors, regions and countries. The differences in the R&D intensity of different sectors and the distinction between high-, medium- and low-tech industries, implicitly recognise the importance of differences in the technology knowledge base. Research on the complexity of products shows, indirectly, that the knowledge bases underlying different products matter for economic development (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009). Research that explores different diversification patterns – related or unrelated – in regions also recognises that the structure of knowledge matters (Boschma et al., 2014; Pinheiro et al., 2022). Research on technology upgrading suggests that the dynamic and qualitative nature of technological change is dependent not only on knowledge generation but also on the inherent structural differences at distinct levels of development (Radosevic and Yoruk, 2018).

Studying the differences in the technological opportunities provided by different technological trajectories is essential to understanding their differential effects on economic growth. This has been grasped only by a few Schumpeterian economists who show that, in specific historical periods, specialisation in particular technologies is critical to understand differences in growth across economies (Freeman and Perez, 1988; Lee, 2013; Dosi et al., 2021). For example, Dosi et al. (2021) show that sectoral technological opportunities matter for growth. Lee (2013) shows that for a group of Asian economies, the catching-up process was driven by planned capability accumulation in short cycle technologies.

We build on and advance this line of research by using direct proxies for technological knowledge. As expected, this has pros and cons, but, overall, allows us to address directly the relationship between growth and the 'content' of the knowledge bases underlying different technologies (Fischer et al., 2020). It is hoped that this will overcome the limitations related to proxying technology using products (including industries as their aggregates) which, increasingly, are technology systems comprising different levels of technical equipment and value-added stages.

Specifically, we address three issues. First, we map current technological knowledge dynamics by exploring the growth rates and significance of technology clusters. To do this, we develop a technology growth-share matrix which leads to our conceptual framework based on the crucial transformative role played by GPTs and enabling technologies. Second, we explore the relationship between specific technology clusters and economic growth. Third, we investigate whether countries at different levels of development share similar or heterogeneous technology profiles and how patterns of technology upgrading have changed over time.

These three 'structuralist' questions ultimately address the issue of whether a country's technological profile matters and, if so, what are their effects across distinct development stages. These are relevant questions for innovation policy and, especially, in the current period of profound technological transformation driven by the digital and newly emerging technologies. There is a huge body of research on the ongoing technological transformation at different levels – firm, sector and globally. However, none of these works offer more rigorous examination of the link between different types of technology (technology clusters) and economic growth. In particular, to our best knowledge, there are no papers that explore these issues for a large sample of countries and over a relatively long time period. We assume this is primarily due to the methodological difficulties in trying to capture a variety of technologies and distinct technology profiles of individual countries. Our research includes some necessary simplifications, but tries to overcome these methodological difficulties.

The empirical setting chosen to address these questions involves data on the patenting activity in 96 countries over 40 years (1980–2021). We use these data to search for patterns that reveal the types of technologies that were instrumental in driving economic growth. In particular, we are interested in the relationship between technology profiles and shifts of countries from lower to higher income groups. We develop a taxonomy of technology classes rather than considering them in aggregate.

Patent data have been used frequently to track technological activity (e.g., Boschma et al., 2014; Granstrand, 1998; Griliches, 1990). The novelty offered by our paper is that we develop a simple classification of technology groups, based on their individual rates and shares of growth. We then investigate whether the orientation towards specific technology clusters drives economic growth. We explore individual economies' technology profiles (portfolios) and how they changed in different periods. We apply two complementary methods of analysis: Generalized Method of Moments (GMM) panel data analysis and Fuzzy Set Qualitative Comparative Analysis (fs/QCA). This allows us to investigate the relationships between technological profiles and growth in countries with different levels of development.

We find a significant association between growth dynamics, shifts in income levels and countries' involvement in specific technology clusters. The heterogenous trajectories of countries' technological profiles allow us to detect more and less productive technology upgrading profiles for different country groups. We also detect changes in technology profiles over time and increasing technology gaps among high-, medium- and low-income economies in terms of their capacity to benefit from their respective technology profiles. For example, some low-income economies appear stuck in technological profiles (portfolios) that offer no opportunities for sustained development. Our results suggest that innovation policy should try to support those technology profiles that are the most compatible with the level of economic development and provide opportunities for economic growth. In summary, we find that the choice of technology and the policies implemented to support this choice matters.

Section 2 elaborates the 'structuralist' perspective on technology change and upgrading and presents our conceptual framework. Section 3 describes the country data and technology cluster measures. Section 4 addresses our three questions. Section 4.1 presents a technology cluster growth-share matrix; Section 4.2 reports results of econometric tests of the relationships between specific technology clusters and economic growth; Section 4.3 explores the technology profiles of different country groups and their changes over time. Section 5 discusses results and Section 6 concludes the paper and draws policy implications.

[1] Enabling technologies are defined by Teece (2017) as 'discoveries arising from advanced science and engineering activity that allow the creation or improvement of products and services across a wide product scope. They have platform-like features and often exhibit strong complementarities with existing and/or new technologies'. They are closely related to the concept of GPTs. Teece (2018, 1369) likens enabling technologies to junior GPTs, meeting GPT criteria for capability of ongoing technical improvements and enabling complementary innovations in application sectors but not yet as pervasive or in wide use as GPTs.

2. 'Structuralist' perspective on technology upgrading and economic growth

2.1. Technology upgrading and economic growth

Technological differences among countries are the prime cause of per capita GDP differences (Fagerberg, 1987; Dosi, 1988; Castellacci, 2011). These differences pertain to both the different levels of technology and the structure of their technology portfolios. Countries with similar levels of technology can have different structures in terms of their technology portfolios. For example, countries with broadly similar levels of R&D intensity or patenting activity may have a technology portfolio with different mixes of low-, medium- and high-tech sectors, which result in different impacts on their growth. As pointed out in the introduction, aggregating technology ignores that technology is also a driver of structural economic transformations. A long-term economic growth is linked inextricably to the differential opportunities of different sectors to engage in ongoing technological transformation.

These differential opportunities suggest that the type of technologies on which the country should focus matter. For example, Lee and Lim (2001) and Lee (2013) point to the importance for countries' catch-up process of different technology portfolios. Based on evidence from Korea, Taiwan, Brazil, Argentina, India and China, they differentiate between short and long cycle sectors and related technology upgrading paths with path-following, stage-skipping, and path-creating strategies. Based on longitudinal patent and patent citation data they distinguish short-cycle ICTs from other technologies, which allow exploitation of windows of opportunity.[2] Lee (2013) provides robust evidence that focusing on short-cycle technologies significantly accelerates the catching up and subsequent forging ahead processes. The rapid growth of Korea and Taiwan up to 1999 is explained by their specific focus on technologies with shorter cycles: semiconductors and electrical/electric machinery. Once countries achieve high-income status, innovation systems tend to focus on long-cycle technologies with higher entry barriers (Lee et al., 2021), indicating a dynamic shift in the technology upgrading path.

Countries that adopt predominantly imitative approaches focus on technologies owned and developed by technology leaders whose accumulated technological capabilities constitute barriers to entry. Lee (2013) shows that technological diversification rather than imitation is a significant factor in catch-up to high-income levels. As countries move from middle- to high- income levels, imitative technologies are insufficient and 'smart diversification' into new areas is required. This applies particularly to the case of middle-income economies taking 'detours' towards short-cycle technologies as ways to transition from a middle- to a high-income level. In technology upgrading terms, the next stage - transition from catch-up to post-catch-up – involves a shift from technology diversification to frontier technology activities (Radosevic and Yoruk, 2016).

A lack of structural upgrading results in stagnation in technology upgrading, which hinders catch-up capacity (in the case of followers) and the capacity to remain competitive (in the case of advanced economies) (Agénor, 2017). This is critical for low- and middle-income countries whose opportunities for growth are limited by their exploitation of low-cost resources and imitation (Perez-Sebastian, 2007; Vandenbussche et al., 2006). Radosevic and Yoruk (2018) identify the structural shift required to effectively promote technology upgrading and show that high-income countries demonstrate much stronger impact of structural upgrading. Zhou et al. (2021) report similar findings.

The present article takes a somewhat narrow, but focused approach to exploring the role of structural shifts in technology generation as the determinants of growth. We examine technological diversification as reflected solely in changes in the structure of patenting as proxy of knowledge generation activities (Radosevic and Yoruk, 2018: 60).

2.2. Technologies facilitating technology upgrading and economic growth

Technologies follow particular advancement trajectories which are shaped by their knowledge bases or a scientific research programme (Dosi, 1982). Some technologies that were dominant in the past lose prominence and are overtaken by new technologies that can generate superior solutions to existing problems. Mature technologies experience continuous and incremental changes along their respective trajectories while new technologies emerge as the result of discontinuities or spin-offs from a combination of dominant technology fields. At any point in time, an economy's technology profile (portfolio) is a composite of technologies with different growth dynamics. However, these technology combinations are not random collections; rather, they are portfolios of technology clusters which, cumulatively, reflect the dominant and newly emerging technology paradigms.

A technology paradigm is "an outlook, set of procedures, a definition of the relevant problems and of the specific knowledge related to their solution" that can be developed and improved according to a set of heuristics or principles (Dosi, 1988:150). Since paradigms embody strong prescriptions on the directions of technical change (Dosi, 1982) they result in (path-dependent) technological trajectories. Technology paradigms and technology trajectories are central to diffusion of technologies as they operate as 'focusing devices' to continuous technological improvements and complementary innovations (Freeman and Perez, 1988). They take the form of General Purpose Technologies (GPTs) (Bresnahan and Trajtenberg, 1995) or enabling technologies (Teece, 2018). GPTs are more revolutionary than enabling technologies; they tend to dominate for longer and belong to a small group of technologies. Enabling technologies (of which there are many hundreds) may be more difficult to identify, but, potentially, can be mission-critical and can generate combinatorial innovations (Teece, 2018). Both GPTs and enabling technologies have potential to allow improved performance across a wide range of products and thus are linked closely to economic growth (Freeman and Perez, 1988; Helpman and Trajtenberg, 1994; Bresnahan and Trajtenberg, 1995; Carlaw and Lipsey, 2006, 2011; Gambardella et al., 2021).[3] Steam engines, electricity, computers and ICTs are all GPTs. Youtie et al. (2008) studied new technologies and, in particular, nanotechnology and whether it can be considered a GPT. They draw parallels between nanotechnology and computers in terms of their respective pervasive effects. Archibugi (2017) acknowledges the role of ICTs as GPTs, but is more doubtful about whether biotechnology should be considered a GPT. In 2009, the European Union identified nanotechnology, industrial biotechnology, advanced materials, photonics and advanced manufacturing as enabling technologies (Commission of European Communities, 2009 cited in Teece, 2018) while the UK Government's list of enabling technologies includes similar technologies such as the Internet of Things (IoT), electronics, sensors and photonics, robotics and autonomous systems, cybersecurity and big data (Innovate UK, 2022). Teece (2018) contends that the enabling technology of Artificial Intelligence (AI) has the potential to become a GPT and Perez discusses whether blockchain can be considered a GPT (Perez, 2020). Efforts are ongoing, also, to foresee emerging technologies that will drive economic growth, including works that define emerging technology based on specific characteristics (Cozzens et al., 2010;

[2] These cycles are measured by backward patent citations (time between application/grant years of citing and cited patents) with shorter times indicating faster catch up by the country.

[3] The notion of technological paradigm is inextricably linked to the notion of techno-economic paradigm which denotes the whole range of economic and institutional transformations associated with a particular technological change (Perez, 2010). For methodological and analytical simplicity we have confined our analysis to knowledge generation and related policy issues.

Rotolo et al., 2015).

The moment when GPTs become revolutionary is when their impact extends beyond the boundaries of the new industries they trigger (Perez, 2010). Their transformative impact spreads throughout the whole economy, raise productivity levels in all sectors, rejuvenate mature industries and lead to new innovation trajectories in technologies whose application has modernisation effects on all other industries and activities (Perez, 2010). The diffusion of these massive changes and their economic and social effects constitute a 'great surge of development' (Perez, 2010). For instance, Petralia (2020) found a positive association between sectoral GPT adoption rates, based on United States Patent and Trademark Office (USPTO) GPT patents and sectoral growth. GPTs as clusters of related technologies get embedded into mature technologies, synergize complementary technologies and thus rejuvenate the whole industrial fabric. A similar effect is observed in the case of enabling technologies that generate novel or combinatorial (but less transformative) technology forms (à la Arthur, 2009). Teece (2018) offers the example of lasers, developed in the field of photonics but used also in supermarket checkouts, on military bases and by cargo containers. They help to reduce the transportation costs of products with large economic and societal impacts and are making cargo shipping containers more high-tech and efficient through integration with Internet of Things technologies.

This process is characterised by its range of application areas and sequential generation of new knowledge with spread of enabling technologies and GPTs throughout the economy. Fig. 1 is a stylised representation of the technological transformation of different technologies across three sectors. Appendix A provides the empirical evidence behind Fig. 1, that is, the patent growth-share matrix.

Technological transformation originates from the technology sector, which is driving the pace and scope of its transformation. In the context of the ICT paradigm, technology sector includes diffusion of ICT networks and hardware ICT installations in phase one of Digital Wave (i.e. computer and electronic product manufacturing (334), telecommunications (517), data processing, hosting, and related services (518), other information services (519), and computer systems design and related services (5415)) (Srnicek, 2017) as well as artificial intelligence, big data and other digital transformations in the second phase of Digital Wave (WIPO, 2022a). However, this technology sector also provides technologies and knowledge which are deployed in other sectors of economy. These advances take place in hard sciences such as nanotechnology, biotechnology, medical technologies, new materials, environmental technologies, agri-food and transport with breakthrough innovations in Deep Science Wave (WIPO, 2022a). GPTs and enabling technologies that originate from technology sector are used in carrier branches predominantly as digital and automation solutions.

Carrier branches (sectors) produce the highest number of digital solutions and are the most intensive users of automation. For example, around 80 % of the installed industrial robots in the world are in the automotive, computers and electronic equipment, and electrical appliances sectors (Van Roy et al., 2019); they increase labour productivity (Fu et al., 2021; Ballestar et al., 2021) and radical innovation (Rammer et al., 2022). Also, high-tech sectors, such as medicine, aeronautics and vehicles are primary users of AI patents. Carrier branches are the most visible and active users of these inputs and represent paradigmatic products spreading the word about the new opportunities offered by computers, software and mobile phones for instance.

The third sector is 'induced branches', which refers to traditional (old) industries and services, not central to the current technological transformation, but which are - or will be - affected to various degrees by digitalisation and AI. For example, in traditionally less technology-intensive fields, such as agriculture, textiles and paper, the number of AI patents shows rapid growth (Van Roy et al., 2019). Also, there are some new products and services for which demand is created by changes in production, commercial practices and lifestyles. These are often a direct result of the technology revolution or policies that encourage specific types of innovation and, currently, are related to provision of health services and organic food. These products and services might be related to lower levels of productivity, but are effective for creating jobs (Perez and Leach, 2018).

The number of different technologies and clusters that emerge, their direction, and their technology field and persistence are history and context contingent. However, in our view: a) emerging technologies will show higher rates of growth than old technologies; b) technologies will be developed in carrier sectors which are intensive users of GPTs and enabling technologies; and c) as the technological distance between old and new technologies reduces through a process of 'combinatorial evolution', enabling technologies and GPTs will be deployed by induced sectors at slower rates (Arthur, 2009).

From the perspective of economic growth, what matters is the relative scale of different technologies i.e. their relative share in overall technology activities. Large scale and high growth technology clusters in either core technology or carrier sectors represent greater opportunities for technology based growth. These are the 'excelling' technologies in Fig. 1. Other technologies may show high rates of growth, but related to small scale activities and are described as 'opportunity-driven' technology cluster. Opportunity-driven technologies have yet to establish a full presence in the market, but given their high rates of growth should be able to do so. Technology clusters with low share and low growth rates are described as 'lagging' technologies. These clusters have yet to exploit the opportunities offered by enabling technologies and/or GPTs, and reduce use of technologies related to the old paradigm. However, this quadrant can also include inventions made by induced sectors associated with the new technological paradigm which explains the label 'lagging' rather than 'declining'. Some technologies (lower right quadrant) show low rates of growth, but have high shares in total technology activities. We describe these clusters as 'established', since the technologies are deployed in induced sectors in large-scale technology activities, involving high employment and value-added, but lower than average growth rates.

In the growth-share matrix, emerging technologies are the drivers of the technological transformation. Despite their small shares, they show exceptionally high growth rates, especially in the early stages of 'emergingness' (Fig. 1). Identification of emerging technologies is not a trivial issue. Corrocher et al. (2003), Srinivasan (2008), Cozzens et al. (2010), Rotolo et al. (2015), Small et al. (2014) and Lee et al. (2018) proposed some features characterising an emerging technology field. All of these studies particularly emphasise 'fast growth rate' and 'novelty/newness'.[4] Daim et al. (2006) and Kim and Bae (2017) used forecasting techniques, such as trend extrapolation, based on patent growth rates and growth curves. Some level of discontinuity in emerging technology is inherent in these approaches. Cozzens et al. (2010) highlight the 'transition to something new', while Rotolo et al. (2015) emphasise radical novelty, uncertainty and ambiguity. Similar to Dosi (1982), Srinivasan (2008) proposes a broader definition of emerging technology which takes account of both continuity and discontinuity. His definition includes revolutionary technologies emerging from new technologies, and incremental technologies which arise from the convergence among existing technologies (Srinivasan, 2008: 634), that is, technologies 'constructed, put together, assembled from previously existing technologies' (Arthur, 2009: 2).

Fig. 1 depicts our analytical framework and the hypotheses we test in this paper. It would be difficult to collect and define data on a specific technology paradigm and, thus, the range of GPTs and enabling technologies associated solely to that paradigm. Empirically, our growth-share matrix is populated by technologies from both the new and old

[4] The reader can refer to these contributions for a list of the other characteristics attributed to emerging technologies. For the purposes of our research, we focus on the characteristics of high growth rate and novelty, which are common to all of the contributions referred to.

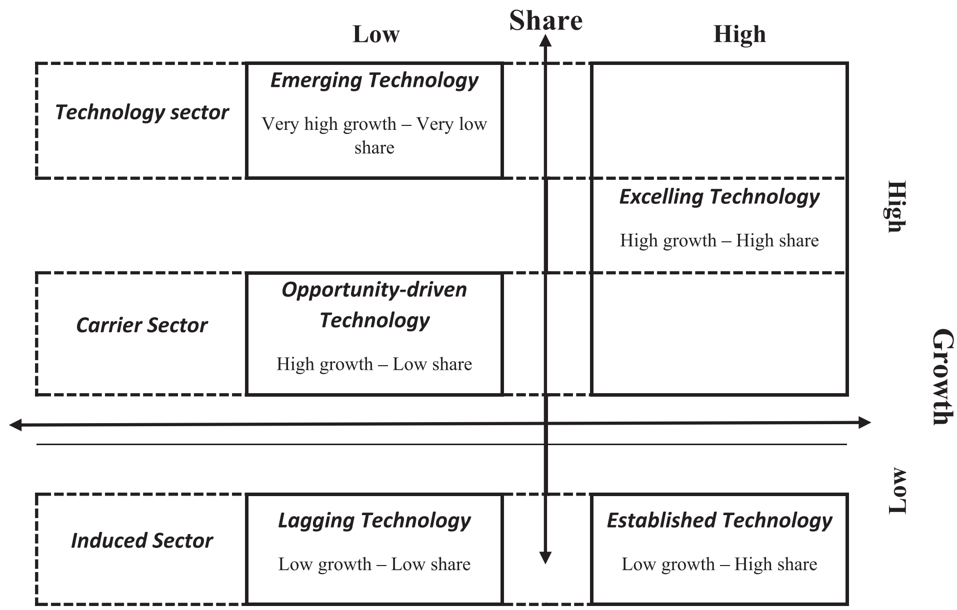

Fig. 1. Technological transformation and its dynamics across sectors. (We are grateful to Carlota Perez for discussion and comments on our development of this framework.)

technology paradigms. We would expect their location in the growth-share matrix quadrants to predict the economy's growth dynamics. Also, an economy's technology profile is composed of various technology clusters, represented by the different shares of each of the five technology clusters depicted in Fig. 1. Hence, we expect specific technology profiles to be associated with particular growth patterns and levels of development. For example, we expect technology profiles with predominantly excelling and opportunity-driven technologies to be valid predictors of future economic growth whereas economies with high shares of lagging and to some extent established technologies are likely to show lower future economic growth. However, we also predict 'inadequate' technology profiles (portfolios), resulting from policy choices not reflective of global technological trends or mismatches in national innovation systems, which result in low economic growth.

2.3. *Technology upgrading meets mission-oriented innovation policy*

Our framework is focused, primarily, on knowledge generating activities. However, most developing economies grow based not on technology generation, but use of technologies created elsewhere. Most developing countries are imitators rather than technology frontier innovators and are upgrading based on adoption and assimilation of existing technologies. However, successful catching up economies pursue stage-skipping or stage-defying paths (Lee, 2013). High performing economies, engaged in frontier technology generation, follow path-creating routes of technology upgrading. However, they can also fall into lock-and-lose industrial leadership (Arthur, 1989; Lee and Ki, 2017).[5]

A diversity of technology upgrading paths shows that technology profiles, i.e. directions and the qualitative content of technological change matter (Mazzucato, 2018; Saviotti and Pyka, 2004).[6] A shifting of the innovation system towards technologies that trigger effective economic growth thus becomes issue of high policy relevance (Mazzucato and Perez, 2015). This requires an emphasis on the shaping and creating of markets for new technologies and on desirable technology transformation (Mazzucato, 2016; Daimer et al., 2012). The capacity to steer structural rationalisation to achieve upgrading in a specific direction becomes essential (Zhou et al., 2020). However, such mission-oriented intervention may comprise policy mixes based on portfolios of missions focused on technologies with disparate objectives rather than cherry-picking of one single overarching technological mission. Our focus is on the relationship between technology profiles (portfolios) and economic growth which leads to consideration of increasingly fashionable mission-oriented policies. However, in the context of development innovation policy should also recognise other sectors that drive economic growth including employment. Here we highlight only those issues which seems directly linked to our focus on technology upgrading: infrastructure, absorptive capacity, Global Value Chains (GVCs) and the overall institutional context.

Important in this context is the provision of effective knowledge infrastructure to support technology upgrading. This is important for all countries at all income levels, but matters especially for low- and middle-income economies which often do not have the foundations required to promote knowledge generation, absorption and diffusion (Abramovitz, 1986; Dahlman et al., 1987; Lall, 1992; Verspagen, 1991; Esterhuizen et al., 2012).

Technology infrastructure is inseparable from the level of the absorptive capacity (AC). AC, through R&D activities, is the key in driving technological diffusion and sustained growth not only in high-income but also in low- and middle-income countries (Khan, 2022; Minniti and Venturini, 2017; Fagerberg and Verspagen, 2002). On the other hand, absorptive capacity may not be sufficient condition for effective technology upgrading. Instead, the dynamics of National Systems of Innovation (NIS) is driven by the co-evolution between innovative capabilities and absorptive capacity, allowing countries to go beyond only adoption of foreign technologies and knowledge (Castellacci and Natera, 2016, 2013; Eum and Lee, 2022).

How countries couple local technology efforts with knowledge that potentially can be assimilated via GVCs has been and continues to be relevant to technology upgrading. Integration in GVCs have demonstrated significant impacts in terms of innovation-led economic growth (Eum and Lee, 2022; Radosevic and Yoruk, 2018; Castellacci and Natera,

[5] See, e.g., Lee and Ki (2017) for leadership takeover by Japan from the USA and South Korea from Japan, in the science-based steel industry segment.

[6] The qualitative content of innovation activity refers to the composition of products, services and activities that represent economic systems (Saviotti and Pyka, 2004). Thus, qualitative shifts can be related to sectoral profiles and intra-sectoral changes in terms of technological orientation.

Table 1
Income category shifts for 96 countries between 1980 and 2021.

	1980–82	2019–21	Country
	LI	LMI	India, Kenya, Kyrgyzstan[2], Nigeria, Pakistan, Sri Lanka, Tajikistan[2], Uzbekistan[2], Viet Nam[5], Zambia, Zimbabwe.
	LI	UMI	Armenia[2], Azerbaijan[2], China, Moldova[2].
II	LMI	LMI	Bolivia, Egypt, Indonesia, Morocco, Philippines, Ukraine[5].
	LMI	UMI	Albania[1], Belarus[2], Botswana, Colombia, Costa Rica, Georgia[2], Kazakhstan[2], Lebanon, Mauritius, Peru, Romania[2], Thailand, Turkey.
	LMI	LHI	Chile, Poland[2].
	Moving between LMI and UMI		Algeria, Iran, Jordan, Tunisia
III	UMI	UMI	Argentina, Brazil, Bulgaria, Cuba, Ecuador, Malaysia, Mexico, Panama, South Africa, Venezuela.
	UMI	LHI	Barbados, Croatia[3], Cyprus, Czech Republic[2], Estonia[4], Hungary[2], Latvia[4], Lithuania[3], Malta, Oman, Portugal, South Korea, Slovakia[3], Trinidad & Tobago, Uruguay.
	Moving between UMI and LHI		Russia[5]
IV	LHI	LHI	Bahamas, France, Greece, Italy, Israel, New Zealand, Saudi Arabia, Slovenia[3], Spain.
	LHI	UHI	Australia, Hong Kong, Netherlands, Singapore.
	UHI	UHI	Denmark, Luxembourg, Norway, Sweden, Switzerland, USA.
	Moving between LHI and UHI		Austria, Belgium, Canada, Finland, Germany, Iceland, Ireland, Japan, Kuwait, UAE, UK.

LI: low-income, LMI: lower middle-income, UMI: upper middle-income, LHI: lower high-income, UHI: upper high-income.
Starting period is not 1980–82 but 1. 1986–88, 2. 1992–94, 3. 1995–97, 4. 1998–00, 5. 1989–91.
Source: World Bank historical classification of income levels.

2013). On the other hand, the relationship between GVC and local technology upgrading is not linear. Instead, catching-up countries have demonstrated that periods of reduced participation in international trade can be beneficial for technological accumulation, followed by reinsertion in GVCs with higher value-added products and services (Lee et al., 2018).

Finally, quality and appropriateness of institutions conducive to a specific technological trajectory is inextricably linked to processes of technology upgrading (Fagerberg and Verspagen, 2002). Rodrik (2000) considered that in less developed economies institutions can be 'shaky'. From a technology policy perspective, this can result in ambiguities and can hamper implementation of long term initiatives and plans (Roca et al., 2021; Yu et al., 2020; Choung and Hwang, 2019) that require accumulation of dynamic technology capabilities. Institutional instability may result in suboptimal investment in obsolete technology or may fail to achieve effective technology upgrading due to weak organisational capabilities of enterprises and other organisations in local innovation system.

In nutshell, not only technology choices and technology profiles (portfolios) matter, but also they are inseparable from other factors in national innovation systems. Their interdependence is manifested in the existence of 'technology clubs' that are associated with countries' levels of development (Castellacci and Archibugi, 2008). They underscore the pivotal role of industrial policy in 'steering' not only mission oriented technologies but the overall NIS in the direction of acquiring and developing capabilities that are conducive to growth (Cimoli et al., 2019). Section 3 describes the data and analytical methods used to test the relevance of our conceptual framework and apply it to our three research questions.

3. Methods

3.1. Sample

Our sample includes data on 96 countries from 1980 to 2021. The High-Income (HI), Middle-Income (MI) and Low-Income (LI) subsamples in our unbalanced panel dataset are based on the World Bank's historical income-level country classifications.

Table 1 shows countries' positions in the broader income leagues during 1980–82 and 2019–21 and the shifts to higher income levels. Armenia, Azerbaijan, Moldova and China (Category I) jumped from Low-Income (LI) in 1980 to the Upper Middle-Income (UMI) in 2021. Bahamas, Greece, France, Italy, Israel, New Zealand, Saudi Arabia, Slovenia and Spain (Category IV) remained Lower High-Income (LHI) countries over the whole period while Australia, Hong Kong, the Netherlands, and Singapore moved from Lower High-Income (LHI) to the Upper High-Income (UHI). The High-Income (HI) group includes countries that persisted as HI countries. In the same period, several countries, such as Austria, Belgium, Canada, Finland, Germany, Iceland, Ireland, Japan, Kuwait, UAE and the UK moved between LHI and UHI.

Table 2
Summary of the shifts in income groups (1980–2021).

Income group	Stable	Improvers	Catching-up
I	0	11	4
II	10	13	2
III	11	15	0
IV	26	4	0

Source: Table 1.

Table 2 categorises the income group shifts in Table 1 into three types: 'Stable' indicating economies whose income category did not change; 'Improvers' which moved up a category; and 'Catching-up' economies which jumped two income categories in the period 1980–2021. As expected, over the period analysed, the smallest number of shifts (6) is in the catching up economies, compared to 43 that moved to a higher income group and 47 that either remained in the same group or fluctuated between two adjacent groups. We observe that a) a shift to a higher income category is most frequent for the lower-income economies, b) catching up is less frequent for the shift from UMI to UHI or LMI to LHI, which is in line with the literature on the middle-income trap, and c) moving up a category or catching up above a low high-income level are less frequent. From a Schumpeterian perspective, this would seem plausible. Economic growth at higher income levels is driven by technological capabilities that require accumulated capabilities in diverse industries and technologies of higher technological opportunities.

3.2. Data and measures

Our indicators for technology clusters are based on patent data. The limitations of patent data for measuring innovation dynamics are well known. These include country-level heterogeneity in terms of patenting propensity driven largely by differences in industrial structure (OECD, 2004; Pavitt, 1985). Particularly in lower income economies this may lead to misrepresentation of economic sectors that do not rely on patents as a critical strategy. Patents, on their own, do not readily capture the technological capabilities in a country, since other activities such as

R&D, design and shop-floor engineering are important in accumulation of technological capabilities (Archibugi, 1992). However, patent data provide standardized and reliably quantifiable statistical picture of knowledge generation capabilities allowing international comparison over time (Jiang et al., 2019; Boschma et al., 2014; Frietsch et al., 2014; Trappey et al., 2012; Mancusi, 2012; Granstrand, 1998; Griliches, 1990; Pavitt, 1985).

Patent data are available by technology classes. The World Intellectual Property Office (WIPO) uses the IPC scheme to collate technologies according to eight sections and around 24 sub-sections, 120 classes, 640 sub-classes and 70,000 groups. WIPO's PATENTSCOPE search system uses this classification to identify individual patents. A reclassification of the IPC-based technology classification for 35 technology classes, was created for WIPO to allow country-level comparison (Schmoch, 2008). WIPO uses the IPC-technology concordance table to assign the 35 technological codes/classes. Since a single patent can be linked to several IPC codes, it can belong to more than one technological fields. In this case, WIPO uses fractional counting, i.e. they assign equal portion of different technology for the same patent.[7]

WIPO reports granted patents by technology classes, at country level, starting in 1980, using Schmoch's (2008) classification. Data include all granted patents, in the 35 technology classes, registered by a specific country's residents in all patent offices worldwide. Thus, the data capture national capability to generate new technological knowledge. Since we investigate shifts in technology generation, we use total number of patent grants by technology counted by applicant's country of origin. For instance, a French inventor who applied to Algerian Patent Office, if granted the patent, will be included in granted patents of France. If they are not yet granted a patent and it is just in application phase, they will not be counted in this dataset.[8] Griliches (1990) considers total patents to be a better measure than domestic patents of a technology frontier shift. Also, WIPO data allow reliable cross-country comparison because they eliminate geographical bias emerging from the tendency to patent in neighbouring countries.

Since the patenting system involves a three-year time lag, on average (Tijssen, 2001), we use patent data up to and including 2021. Technology clusters, as defined in our classificatory framework (Fig. 1), are our independent variables. They are measured as the share of patents in each technology cluster in the country's total patents in a given year. We generated pooled cross-section and time-series data for 96 countries. Each observation corresponds to a three-year average, which smooths the values for granted patents. The dependent variable in the panel regressions is growth rate of per capita Gross National Income (GNI). We match each country's per capita GNI for each three-year interval with income level, using the World Bank guide to income levels which provides LI, LMI, UMI and HI threshold levels (Table 3).

To avoid omitted variables bias, in the regression models we include several indicators used in growth models as baseline control measures. We add R&D expenditure, Gross Fixed Investment (GFI), trade openness and tertiary school enrolment to capture the usual determinants of knowledge driven growth. Data on R&D expenditure as a percentage of GDP, GFI formation in GDP, trade openness by total exports and imports as a percentage of GDP and tertiary school enrolment are taken from the World Bank database (Table 3).[9] These variables control for the interplay between National Systems of Innovation dynamics and growth trajectories, thus providing a good coverage of conditioning factors related to innovation capabilities and absorptive capacity at the macro

[7] See https://www.wipo.int/ipstats/en/ for further information on WIPO data and indicators.

[8] We gathered data from WIPO IP Statistics Data Center (https://www3.wipo.int/ipstats/index.htm?tab=patent) for patents, i.e. Indicator: 5 – Patent grants by technology and Report type: Total count by applicant's origin.

[9] Appendix B provides the descriptive statistics and correlation matrix for the indicators used in the regressions.

Table 3
Sources of indicators used in GMM and fs/QCA analyses and operationalisation of calibration thresholds in fs/QCA analysis.

Panel data analysis, Year coverage 1980–2021			fs/QCA analysis Calibration thresholds (fully in, crossover point, fully out)					
			1992–94			2019–2021		
Indicator	Description	Source	HI subsample	MI subsample	LI subsample	HI subsample	MI subsample	Calibration criteria
GNIpc	Gross National Income per capita	World Bank	(21,860, 10,930, 0)	(2453, 1227, 0)	(608, 304, 0)	(49,339, 24,670, 0)	(4233, 2117, 0)	(WB historical income threshold, midway between fully in and fully out values, 0)
Newly emerging	Share of newly emerging technologies in total patents of the country (3-yearly average)	WIPO	(0.001, 0.0003, 0)	(0.0004, 0.0001, 0)	(0,0,0)	(0.037, 0.015, 0)	(0.027, 0.012, 0)	(Average value of technology cluster for countries which are above the crossover point, average value of technology cluster for all countries in the subsample, 0)
Excelling	Share of excelling technologies in total patents of the country (3-yearly average)	WIPO	(0.363, 0.294, 0)	(0.418, 0.280, 0)	(0.317, 0.200, 0)	(0.552, 0.440, 0)	(0.478, 0.352, 0)	
Opportunity-driven	Share of opportunity-driven technologies in total patents of the country (3-yearly average)	WIPO	(0.166, 0.122, 0)	(0.188, 0.108, 0)	(0.350, 0.121, 0)	(0.152, 0.118, 0)	(0.192, 0.110, 0)	
Established	Share of established technologies in total patents of the country (3-yearly average)	WIPO	(0.375, 0.310, 0)	(0.359, 0.268, 0)	(0.490, 0.345, 0)	(0.312, 0.221, 0)	(0.337, 0.215,0)	
Lagging	Share of lagging technologies in total patents of the country (3-yearly average)	WIPO	(0.339, 0.273, 0)	(0.510, 0.343, 0)	(0.454, 0.272, 0)	(0.273, 0.208, 0)	(0.375, 0.255, 0)	
R&D expenditures	R&D expenditures as percent of GDP	World Bank	–	–		–	–	–
Trade openness	Total exports and imports as percent of GDP	World Bank	–	–		–	–	–
GFI	Gross fixed investment formation in GDP	World Bank	–	–		–	–	–
Tertiary school	Ratio of total tertiary school enrolment, regardless of age, to the population of the age group that officially corresponds to tertiary level education	World Bank	–	–		–	–	–

level (Eum and Lee, 2022; Radosevic and Yoruk, 2018; Castellacci and Natera, 2013, 2016).

3.3. Model specifications

The role of technology-related structural shifts have been examined using a range of analytical lenses to analyse their effects on economic growth and development. We employ panel data analysis and fs/QCA, which are complementary and were chosen deliberately for their specific strengths in relation to our research questions. They allow us to investigate how the connections among technological profiles (portfolios) unfold over time in countries in different stages of development.

3.3.1. Regression model specification

Panel data analysis is used to address our first research question: whether economic growth is associated with specific technologies. The panel regressions use income level subsamples. We apply Generalised Method of Moments (GMM) estimations to our panel data. Since our panel time dimension (T) is comparatively short, fixed-effects estimation is not appropriate (Baltagi, 2005). We conducted a Breusch-Godfrey autocorrelation test for time series data to check whether our dynamic panel data analysis could be implemented including lagged dependent variables in the model. For all subsamples, we cannot rule out serial correlation, so we chose not to include lagged dependent variables in the panel data model.[10]

The model is specified as:

$$GNIpc_{it} = \beta_0 + \beta_1 X^{'}_{i,t} + \beta_2 Z^{'}_{i,t} + \mu_i + \varepsilon_{i,t}$$

where $X_{i,t}$ is a vector of the technology clusters, that is, newly emerging, excelling, opportunity-driven, established and lagging technologies, and $Z_{i,t}$ is a vector of the baseline controls for R&D expenditure, GFI, trade openness and tertiary school enrolment.

We expect GNIpc to be influenced by technology generation and technology upgrading, but it is possible that GNIpc might also contribute to technology generation and upgrading. We conducted GMM estimation to check for this endogeneity problem (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). We used STATA's *xtabond2* command to run a series of regressions. GMM estimation is suitable for our panel data for several reasons. First, it controls for endogeneity by accounting for simultaneity in the strictly not exogenous independent indicators, through the internal Instrumental Variables (IV) process. We use the IV function for both level and difference equations by including in the model the lagged values of all the dependent and independent indicators as IVs. We consider all IVs to be endogenous or potentially endogenous. We restrict lags to 1, since if T is fairly large (>7–8), which applies to our panels, Baum (2013) notes that an unrestricted set of lags will introduce a large number of instruments and loss of efficiency. Second, our panels include slightly more countries than the number of time periods, that is, 'large N small T' panels (Roodman, 2009b).

GMM estimations can take two forms: difference GMM and system GMM. Difference GMM estimations transform all the regressors by differencing and adding the lagged values of the indicators as IVs in the difference equation (Hansen, 1982; Holtz-Eakin et al., 1988; Arellano and Bond, 1991). System GMM augments the difference GMM by building a system of two equations, the original and the transformed equation, and allows for the inclusion of more IVs (Arellano and Bover, 1995; Blundell and Bond, 1998). We report the system GMM results. Since the number of countries is not a great deal higher than the number of years in our panels we ran the one-step GMM estimation. In the case of small samples, the standard errors of the two-step GMM estimation coefficients are likely to be biased downwards (Bond et al., 2001; Windmeijer, 2005). Finally, we ran the Arellano-Bond test to check for serial correlation and the Sargan test for overidentifying restrictions regarding the validity of the IVs. We report the results in Section 4.2.

3.3.2. Configurational model specification and calibration procedure

We use fs/QCA to examine technology profiles (or, in QCA terminology, configurations) associated with economic growth. QCA allows investigation of whether the configurations of several technology upgrading profiles are driving economic growth. We conduct fs/QCA at two points (1992–94[11] and 2019–21) to observe shifts in technology profiles in countries with different income levels (see Section 4.3). As a case-oriented approach, fs/QCA overcomes cross-national diversity in countries' technology upgrading profiles and accounts for heterogeneous effects across country groups (Ragin, 2000). This allows us to explore whether growth is dependent on several causal profiles and to identify the countries that conform to these profiles (Fiss, 2007; Ragin, 2008a).

We specify the configurational model as follows:

$$\text{Emerging tech*Excelling tech*Opportunity} - \text{driven tech*Established tech*Lagging tech} \rightarrow GNI_{\text{per capita}}$$

Fs/QCA requires calibration of conditions (variables). Table 3 presents the measures and calibration thresholds. To implement fsQCA, we developed a three-value fuzzy set for all the indicators in the HI, MI and LI groups –full membership, full non-membership, and the crossover point or the point of maximum ambiguity for neither 'fully in' nor 'fully out' cases. As the outcome variable, we used per capita GNI and World Bank historical income thresholds for the next income level. The calibration process in QCA (see Table 3) allows us to benchmark each condition against specific values and to identify strong and weak conditions associated with the outcome. We set the upper calibration threshold for 'fully in' value as the historical threshold above which the country shifts to the next income level. The crossover point is the midpoint between 'fully in' and 'fully out' values.

In terms of causes, that is, technology clusters, we calculated the average value (share of technology) for each technology cluster, for all the countries in the subsamples. We set these values as the crossover points. Then, the average values for each technology cluster for countries above the crossover point are taken as the upper threshold points of 'fully in'.

[10] Roodman (2009a) warns that per capita GDP is a highly persistent series, which makes lagged per capita GDP a weak instrument for subsequent changes in GMM estimation. When using a small sample, our model also showed evidence of adverse effects. Including the lagged dependent variable resulted in not significant results; therefore, we specified the model excluding the lagged dependent variable, but were able to run the GMM estimation using the xtabond2 command in Stata which offers this flexibility (Drukker, 2008).

[11] Patent data were not available for most of the ex-USSR and Soviet bloc countries pre-1990.

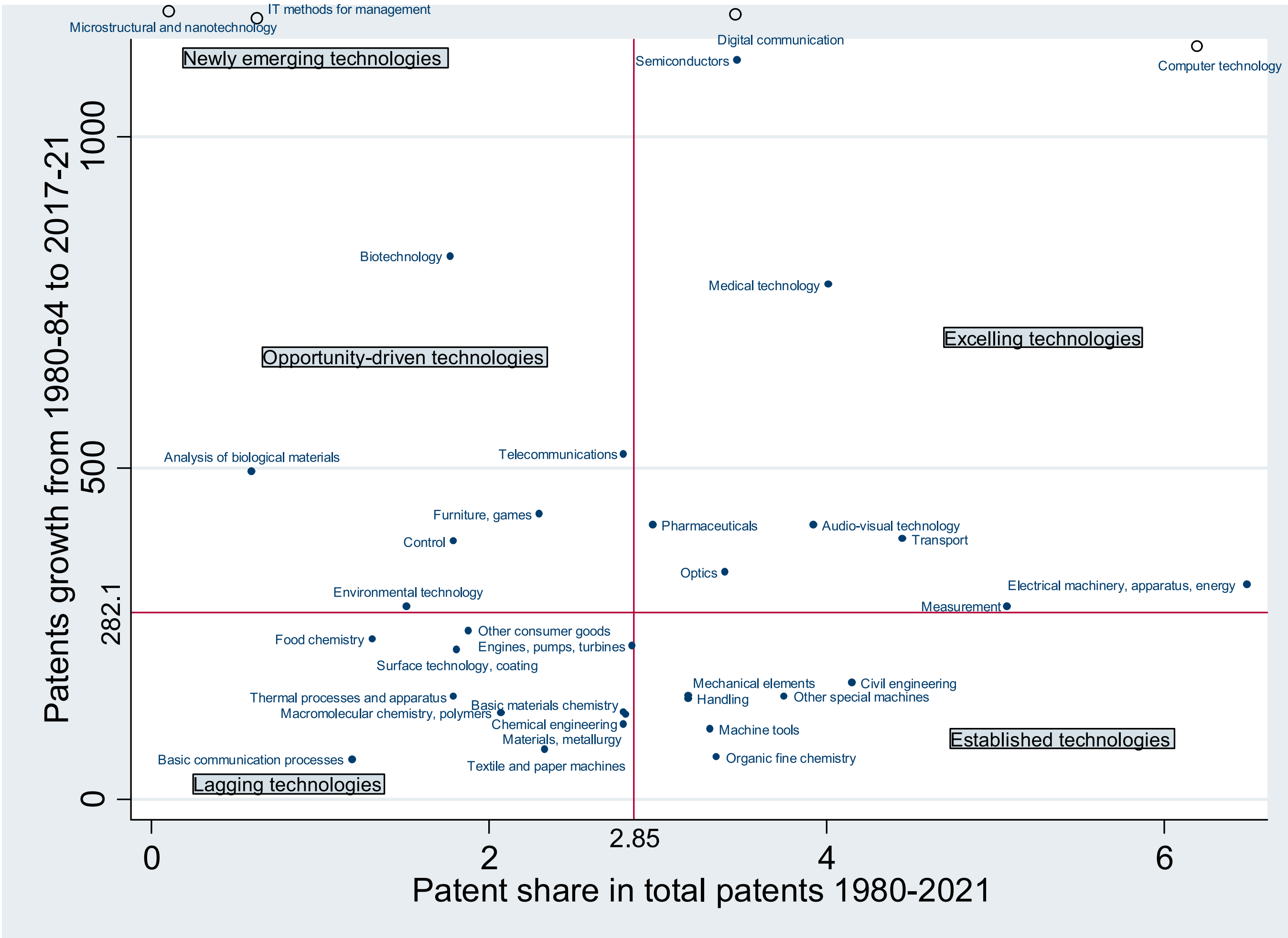

Fig. 2. Technology clusters by growth in granted patents and share in total patents (1980–2021).

4. Results

4.1. Mapping technology clusters in a growth-share matrix

In our framework, patent data organised in technology clusters reflect current and past technology paradigms (see Fig. 2 for the patent growth-share matrix). The 40-year history of the ICT paradigm allow differentiation among the different stages of the present technology transformation, which develops as an evolutionary process from the emergence of the technology to its deployment.

The upper left quadrant in Fig. 2 represents *emerging technologies cluster*, which include classes of Microstructural and Nanotechnology and Information Technology (IT) methods for management. IT management methods are the fastest growing area of the ICT paradigm and reflect recent advances in AI. This technology cluster includes special purpose software for data processing, for example, adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes (Schmoch, 2008: 8). Web platforms enable online ordering, organising project management teams, childcare facility platforms, an AI-based model for predicting energy use, or management of data for health. These are all examples of patents obtained in IT methods for management technologies. Microstructure and Nanotechnology, spin-off technologies from chemistry and physics, might appear to belong to some other category. However, according to the US National Nanotechnology Initiative, their effects span from memory and logic chips to cars and computers, based on diminishing the size of the artefacts and increasing their operative speed using super high-density microprocessors (NRC, 2006).[12] Rafols and Meyer (2007) identified nanotechnology patenting activity in 21 other technology classes in the period 1980 to 2004.

The *excelling technologies cluster* in the upper right quadrant in Fig. 2 includes computer technologies, digital communication technologies and semiconductors, as GPT or enabling technologies in the ICT paradigm. This category also includes medical technologies, pharmaceuticals, audio-visual technologies, optics, transport, measurement and electrical machinery from the carrier sector. In Fig. 2, computer technologies, digital communication and semiconductor patents are distinguished from other excelling technologies by their very high growth rates and the high share. One of the fastest-growing technology clusters in 1980–2021 was digital communication technologies, which are characterised by the speed, quality and ability to transfer large volumes of information over long distances. This information includes transfer of images by telegraph, radio, television, mobile phone or the Internet. Petralia (2020) observes a similar pattern and identifies computer and communication technologies as potential GPTs enabling other technologies. The high share of computer technology reflects its relative age compared to digital communication technologies. The high rates of

[12] The effects of nanotechnology on computers and communication technologies are less obvious, since they are largely confined to the laboratory.

Table 4
Growth in number and share of granted patents by technology field and time period, 1980–2021.

	Granted patents 1980–84 avg	Granted patents 2017–21 avg	Granted patents growth from 1980–84 to 1996–2000 (%)	Granted patents growth from 2001–2005 to 2017–21 (%)	Granted patents growth from 1980–84 to 2017–21 (%)	Granted patents share in total patents 1980–2021 (%)
Emerging technologies						
22 - Micro-structural and nano-technology	1.4	3341	10,386	588	238,557	0.1
7 - IT methods for management	116	20,371	688	853	17,431	0.7
Excelling technologies						
4 - Digital communication	1447	90,485	410	535	6152	3.5
6 - Computer technology	7635	132,704	209	318	1638	6.3
8 - Semiconductors	4190	50,913	356	97	1115	3.5
13 - Medical technology	8257	72,377	122	209	777	4.0
16 - Pharmaceuticals	7974	40,983	73	97	414	3.0
2 - Audio-visual technology	9786	50,287	157	81	414	3.9
32 - Transport	14,532	71,610	54	151	393	4.5
9 - Optics	9477	41,991	125	70	343	3.4
1 - Electrical machinery, apparatus, energy	25,469	108,053	11	204	324	6.5
10 - Measurement	21,893	85,759	-2	232	292	5.1
Opportunity-driven technologies						
15 - Biotechnology	3339	30,713	171	181	820	1.8
3 - Telecommunications	5792	35,994	171	68	521	2.8
11 - Analysis of biological materials	1545	9194	90	153	495	0.6
33 - Furniture, games	6611	35,085	83	164	431	2.3
12 - Control	6595	32,274	31	223	389	1.8
24 - Environmental technology	5899	23,101	22	158	292	1.5
Established technologies						
35 - Civil engineering	20,993	57,948	4	142	176	4.1
31 - Mechanical elements	16,221	41,522	2	114	156	3.2
29 - Other special machines	19,922	50,884	0	129	155	3.8
25 - Handling	16,558	41,732	5	128	152	3.2
26 - Machine tools	21,047	43,447	−23	154	106	3.3
14 - Organic fine chemistry	21,322	34,826	−15	64	63	3.3
Lagging technologies						
34 - Other consumer goods	7326	26,013	50	116	255	1.9
18 - Food chemistry	4508	15,410	31	91	242	1.3
27 - Engines, pumps, turbines	12,047	39,962	18	128	232	2.8
21 - Surface technology, coating	7623	24,859	22	137	226	1.8
30 - Thermal processes and apparatus	9934	25,322	−6	146	155	1.8
23 - Chemical engineering	16,442	37,990	−14	143	131	2.8
17 - Macromolecular chemistry, polymers	10,903	25,111	8	94	130	2.1
19 - Basic materials chemistry	15,360	35,023	−6	118	128	2.8
20 - Materials, metallurgy	17,144	36,670	−23	158	114	2.8
28 - Textile and paper machines	12,789	22,426	22	38	75	2.3
5 - Basic communication processes	6772	10,875	10	20	61	1.2

Source: Authors' elaborations of WIPO data based on classificatory framework (see Fig. 1).

growth of semiconductor technologies reflect their capital goods nature and thus narrower scope of patenting. Semiconductor chips are major enabling technologies driving, especially, the electronics industry (Langlois and Steinmueller, 1999; Huggins et al., 2022). Overall, the technology classes included in the excelling cluster are enabled by the Internet, computers and semiconductors. However, most patents related to the excelling technologies cluster were granted to carrier sectors, that is, those sectors that are intensive users of enabling ICT and biotechnologies, such as medicine, pharmaceuticals and optics which carry the potential to drive the Deep Science Wave. The electrical machinery class is an intensive user of ICT GPTs and has the highest share of all technology classes (6.5 %; see Table 4).

Five of the technologies in the *emerging/excelling technologies* quadrant reflect three overlapping generations in the ICT paradigm cumulative (computers, digital and AI), that is, they build on one another. The diffusion of computers was a precondition for their connection via the Internet. Digitalisation is an essential technical and organisational precondition for the spread of AI (McKinsey, 2019).[13] Also, three generations of technologies show markedly different diffusion patterns.[14] The cumulative nature of these changes suggests that they are complementary and form the base of the emerging technological system.[15]

The upper/middle left quadrant exhibits a similar pattern of coexisting enabling technologies and shows the high growth in patenting rates for *opportunity-driven technologies* which include biotechnology, telecommunications, analysis of biological materials, furniture and games, control and environmental technologies. However, their share in total patents is below average. This quadrant also contains ICT-related patents (telecommunications) and patents derived from the carrier sector. In these sectors, opportunities for digitalisation and 'greening' (environmental technologies) are in their early stages. This quadrant also contains patents that are unrelated to current dominant ICT GPTs, but are related to enabling technologies such as biotechnology and biological materials.

In the two lower quadrants in Fig. 2 are those technology clusters exhibiting growth rates lower than the world average for all technologies which is characteristic of mature technologies. The *established technologies cluster* has a higher than average share of total patents. This cluster includes many technologies in the areas of civil engineering, organic chemistry, machine tools, mechanical elements and handling with very high numbers of patents. From negative growth rates between 1980 and 2000, rates increased substantially between 1980 and 2021 though significantly less compared to opportunity-driven and excelling technologies (Table 4).

Finally, the *lagging technologies cluster* shows below world average growth rates for patenting and share in total patents lower than the average value for all technologies. This cluster includes mainly basic science and mature engineering technologies, related to basic materials chemistry, engines, pumps, turbines, chemical engineering, macromolecular chemistry, thermal processes and apparatus, other specialist machines, basic communication processes, materials and metallurgy, surface technologies and coating, other consumer goods, food chemistry and textile and paper machines. These technologies are important for many middle- and low-income economies. Albuquerque (2000) considers that in developing countries, technological activities in mature sectors are important locally, but are not at the international level. These activities include imitation, local learning and adaptations of foreign innovations, which might be patentable at the national level. However, cutting-edge inventions related to mature technologies have shifted to newly emerging technologies. An example of this is 3D printing technology, which moved from the specialised machines technology to the nanotechnology and digital communication technology classes.

Table 5
Technology cluster cycle times.

Technology cluster	Cycle time (years)
Emerging technologies (Information storage only)	5.91
Excelling technologies	7.73
Of which ICTs	6.48
Of which optics/electricals/drugs/transport	8
Opportunity-driven technologies	9
Established technologies	9.71
Lagging technologies	9.61

Source: Authors' calculations using data in Tables 3.5 and 3.6 in Lee (2013, 70-71).

Finally, the global nature of our data allow us to check whether clusters that originated from the technology and carrier sectors offer better technology opportunities. Lee's (2013) concept of short cycle technologies can be used to proxy for technological opportunities. Cycles are measured by backward patent citations, that is, the time difference between application/grant year of citing and cited patents. Table 5 uses data from Lee (2013) and shows approximate cycle times for our technology clusters based on matching Lee's technology classes with the 35 technology classes in our data. We find that emerging and excelling ICTs, such as information storage, computers and semiconductors, have short cycle times, ranging from 5.91 to 6.48 years in the 1980–95 period.[16] Excelling technologies such as optics, electrical, transportation and drugs, and opportunity-driven technologies, such as biotechnology, telecommunications, furniture, environmental technologies, have medium-cycle times ranging between 8 and 9 years. We found that established technologies, such as machine tools and handling, chemistry and lagging technologies, have long cycle times of over 9 years. Thus, our technologies classification broadly supports Lee's short versus long cycle technologies classification.

4.2. *Are specific technology clusters correlated to economic growth and do they differ across income levels?*

We next investigate whether the technology clusters are associated with economic growth and how these effects unfold at different income levels. We conducted GMM estimation using panel data to assess within country temporal variations; this revealed significant relationships between a change in country patenting activity and its citizens' per capita income.

Tables 6, 7 and 8 present the results for HI, MI and LI countries, using several models. We find that the technologies in the excelling technology cluster are correlated to economic growth at all levels of development, but the significance of the other clusters differs across income levels.

Emerging, excelling and partly opportunity-driven technologies at the HI level are significant predictors of per capita income. Lagging technologies do not seem to contribute to growth, while the contribution of established technologies changes depending on the controls. If we control for R&D and tertiary education, established technologies do not contribute to growth. This is intuitive since it would be unlikely that

[13] McKinsey's (2019) survey of large EU firms found that only 23 % consider AI diffusion to be independent of both previous digital technologies and the capabilities required to use those technologies. This confirms the cumulative nature of the emerging techno-economic paradigm and suggests, also, that we can expect further divergences in productivity gains across firms and regions.

[14] E.g., all firms in EU countries and regions can access the Internet, but not all can access high-speed Internet and only a small percentage uses cloud computing and big data. The EU is lagging behind the US and China for share of 'digital ICTs' in GDP and the AI gap with these countries is increasing the EU's already significant digital gap with them (McKinsey, 2019).

[15] E.g., McKinsey (2019) shows that AI diffusion relies on the technical and organisational capabilities accumulated from previous adoption of digital technology (exhibit 10, p. 19).

[16] To benchmark cycle times with Keun Lee's data, we calculated cycle times using our data for the 1980–1995 period.

Table 6
Panel data estimations (System GMM), high-income countries.

Dependent variable: GNIpc										
Model	I		II		III		IV		V	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Emerging	**140,491**	**0.000**	**146,747**	**0.000**	**164,518**	**0.000**	**126,200**	**0.000**	**119,189**	**0.000**
Excelling	**47,697**	**0.000**	**37,610**	**0.000**	**52,029**	**0.000**	**47,829**	**0.000**	**38,877**	**0.000**
Opportunity-driven	**15,536**	**0.001**	−1296	0.823	5690	0.315	**10,549**	**0.052**	**−32,726**	**0.000**
Established	1224	0.699	**−11,313**	**0.001**	2291	0.568	−2203	0.572	−4957	0.114
Lagging	2809	0.400	**−6350**	**0.085**	4141	0.331	3291	0.428	−1286	0.708
R&D expenditures			**5629**	**0.000**						
Gross Fixed Investment					**−323**	**0.000**				
Trade openness							**24**	**0.000**		
Tertiary school									**213**	**0.000**
Constant	7029	0.016	**10,045**	**0.001**	**13,219**	**0.001**	**7155**	**0.053**	**8148**	**0.004**
N	534		475		509		519		450	
Number of groups	49		47		48		48		49	
Number of instruments	475		436		457		466		414	
Wald chi2 (sig)	20,232.2 (0.000)		21,040.4 (0.000)		20,242.5 (0.000)		20,970.1 (0.000)		19,603.0 (0.000)	
AR(2)	0.717		0.796		0.155		0.806		0.607	
Sargan	0.000		0.000		0.000		0.000		0.000	

Technology (% in country's total patents).
Number of instruments are high but not higher than number of observations. In all of the models tested, Stata reports that Sargan test is not robust but not weakened by many instruments.
Significant coefficients in bold (at 10%, 5% and 1%).

mere participation in these sectors would contribute to growth without some investment in R&D and skills. Established technologies are core engineering technologies with long cycles, that require skilled human capital and substantial R&D investment. Overall, HI economies are characterised by knowledge generation.

We find for the MI category, emerging, excelling and partly opportunity-driven technologies have positive and statistically significant effects on income per capita. Established and lagging technologies do not contribute to growth. MI economies have weaker skills and research investment compared to HI economies, hence, the weaker effect of established technologies on their economic growth. However, their knowledge generation is driven by ICT diffusion. If we control for R&D, fixed investments, trade openness or tertiary education, the contribution of some of the technology clusters becomes not significant or even demonstrate negative effects. This suggests a mixed picture; economic growth seems not to be driven by the generation of new knowledge and patenting, but rather by acquisition of knowledge via skills, trading or R&D through absorptive function.

As expected, the coefficients of emerging, excelling and opportunity-driven technologies for MI economies are significantly smaller and less significant in all the specifications. This indicates a significantly lower contribution of knowledge generation to MI economic growth than in HI economies. Nevertheless, despite the smaller coefficients related to MI economies, we find a statistically significant impact of emerging

Table 7
Panel data estimations (System GMM), middle-income countries.

Dependent variable: GNIpc										
Model	I		II		III		IV		V	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Emerging	**24,041**	**0.000**	**34,543**	**0.000**	**23,403**	**0.000**	**22,761**	**0.000**	**18,948**	**0.000**
Excelling	**860**	**0.001**	**1233**	**0.001**	**1265**	**0.000**	**1304**	**0.000**	**−1756**	**0.000**
Opportunity-driven	401	0.233	**1767**	**0.000**	**799**	**0.026**	**881**	**0.013**	−362	0.357
Established	**−1325**	**0.000**	408	0.208	**−735**	**0.006**	**−763**	**0.003**	**−1585**	**0.000**
Lagging	−334	0.187	324	0.383	−18	0.947	−80	0.760	**−2380**	**0.000**
R&D expenditures			**2425**	**0.000**						
Gross Fixed Investment					**−19**	**0.002**				
Trade openness							**18**	**0.000**		
Tertiary school									**83**	**0.000**
Constant	**3805**	**0.000**	**1428**	**0.000**	**3870**	**0.000**	**2769**	**0.000**	**2825**	**0.000**
N	634		531		603		605		536	
Number of groups	67		61		66		66		66	
Number of instruments	515		459		512		513		450	
Wald chi2 (sig)	11,325.9 (0.000)		8954.1 (0.000)		10,790.3 (0.000)		10,975.6 (0.000)		11,788 (0.000)	
AR(2)	0.002		0.063		0.022		0.006		0.058	
Sargan	0.000		0.000		0.000		0.000		0.000	

Technology (% in country's total patents).
Number of instruments are high but not higher than number of observations. In all of the models tested, Stata reports that Sargan test is not robust but not weakened by many instruments.
Significant coefficients in bold (at 10%, 5% and 1%).

Table 8
Panel data estimations (System GMM), low-income countries.

Dependent variable: GNIpc										
Model	I		II		III		IV		V	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Emerging	**31,315**	**0.006**	**29,118**	**0.013**	**29,858**	**0.009**	**29,417**	**0.013**	**25,672**	**0.060**
Excelling	**120**	**0.024**	**209**	**0.009**	**158**	**0.007**	**104**	**0.057**	30	0.674
Opportunity-driven	21	0.723	−56	0.615	47	0.470	22	0.722	**384**	**0.002**
Established	**189**	**0.000**	64	0.298	**242**	**0.000**	**191**	**0.000**	103	0.123
Lagging	**190**	**0.000**	**190**	**0.000**	**237**	**0.000**	**197**	**0.000**	**173**	**0.004**
R&D expenditures			23	0.647						
Gross Fixed Investment					**2.3**	**0.095**				
Trade openness							0.5	0.406		
Tertiary school									**2.4**	**0.065**
Constant	**320**	**0.000**	**332**	**0.000**	**231**	**0.000**	**306**	**0.000**	**299**	**0.000**
N	106		78		95		100		82	
Number of groups	18		15		17		18		18	
Number of instruments	101		76		91		97		75	
Wald chi2 (sig)	2206.9 (0.000)		1637.4 (0.000)		2064.6 (0.000)		2033.5 (0.000)		1340.4 (0.000)	
AR(2)	0.885		0.916		0.949		0.906		0.293	
Sargan	0.000		0.000		0.000		0.000		0.000	

Technology (% in country's total patents).
Number of instruments are high but not higher than number of observations. In all of the models tested, Stata reports that Sargan test is not robust but not weakened by many instruments.
Significant coefficients in bold (at 10%, 5% and 1%).

technologies in MI economies. This result is consistent with the notion that MI countries can benefit from focusing on short-cycle technologies that provide economic systems with a competitive edge. Also, this may suggest that many MI economies have prioritised investments in 'IT methods for management' even though they are not yet widely used in downstream sectors (Carriers and Induced). Among the HI and MI economies, we observe a degree of convergence in the results for emerging and excelling technologies, but not opportunity-driven technologies. This is as expected given the trend towards global diffusion of ICT-based GPTs and enabling technologies.

The regressions for LI economies also identify emerging and excelling technologies as drivers of growth. This result suggests that LI category is able to capitalise on short-cycle technologies and diffusion of ICTs via the technology sector. This effect is largest for emerging technologies, but much smaller for excelling technologies with marginal economic impact due to smaller coefficients compared to MI and LI categories. Opportunity-driven, established and lagging technologies are significant contributors in LI category indicating that a diversified model of technology generation drives growth in this category. All of the control variables are also significant predictors of growth suggesting the importance of infrastructure in upgrading and reinforcing growth in tandem with technology generation. As expected, LI economies have poor knowledge generation capacity, but some level of technology implementation capacity related to use of technologies generated elsewhere (Lee et al., 2021). However, we can state that the effect of the technology sector on the carrier and induced sectors is observable even for LI economies, although compared to the MI and HI categories, this effect is marginal.

Our results confirm the relevance of our conceptual framework for understanding technology generation as a driver of economic growth, especially for MI and HI economies. We show that our classification of technology classes is broadly in line with Lee's (2013) findings about the short versus long cycles and their effects on growth, with emerging and excelling technology clusters having the highest coefficients. The association between technology cluster and per capita income is robust to the inclusion of economic and socioeconomic control variables. This supports the hypothesis that technology clusters are significant predictors of per capita income, even controlling for aggregate economic and socioeconomic variables such as R&D expenditure, trade openness, fixed investment and education level.

4.3. Diversity of technology upgrading profiles

In Section 4.2, we showed that certain technology clusters are associated with economic growth at a particular development level. Here, we predict that, equally important for economic growth, is smart combination or portfolio of technology clusters. We investigate whether countries at different levels of development show distinctive technology upgrading profiles and how these change over time. Specifically, we are interested in whether countries with similar or different income levels share similar or different technology profiles. Our aim is to show whether there are productive and less productive technology upgrading profiles, within and across income levels or, in other words, whether there are particular profiles or portfolios of technology which facilitate a shift from a lower to a higher income level.

fs/QCA is used to identify combinations of technology clusters which lead to a shift to a higher income level.[17] The highest level of per capita GNI is the 'fully-in' at threshold level which allows a shift to the next income level. We use fsQCA software 3.0 (Ragin and Davey, 2016) and set the frequency threshold to 1 and the consistency cut-off value to above 0.75, as suggested by Ragin (2008b).[18] Tables 9 and 10 report the findings related to the causes of "present" outcomes.

In statistical terms, for the HI group, solutions I and II, for 1992–94 and 2019–21, respectively, show acceptable overall solution consistency

[17] fsQCA analysis differs from cluster analysis in the sense that the conditions related to a configuration can be associated with an outcome indicator. For instance, the outcome informs about the growth rates of countries arranged according to the threshold income level that leads to a shift to a higher income level, while the conditions inform about the technology clusters that collectively form technology upgrading profiles.

[18] Frequency refers to the number of cases in the sample that are explained by a configuration. A lower frequency threshold increases sample coverage, although each combination refers to a smaller number of sample cases. The consistency threshold distinguishes between configurations that are or are not subsets of the outcome.

Table 9
Technology upgrading profiles/configurations enabling shift to the next income level (all HI samples for 1992–94; selected HI samples[a] for 2019–2021, average patent outputs).

Solution	I										II				
	1992–1994										2019–2021				
Configurations	1	2a	2b	3	4a	4b	5	6	7a	7b	1a	1b	2	3	4
Emerging technologies			⊖		⊖	⊖	⊖	⊖	●	●		⊖	⊖	⊖	●
Excelling technologies	●	●	●	●			⊖			⊖	●	●	⊖	⊖	
Opportunity-driven technologies	⊖	●	●	⊖	⊖		●	●	●	●		⊖		●	●
Established technologies	⊖	⊖		●	●	●		●	⊖		⊖	⊖	●		⊖
Lagging technologies						⊖	●	⊖			⊖			●	⊖
Raw coverage	0.30	0.24	0.27	0.26	0.40	0.36	0.31	0.28	0.18	0.16	0.45	0.32	0.40	0.35	0.27
Unique coverage	0.06	0.00	0.00	0.01	0.06	0.00	0.03	0.00	0.00	0.00	0.08	0.03	0.05	0.01	0.00
Raw consistency	0.96	0.96	0.90	0.97	0.97	0.93	1	1	1	1	0.97	0.94	0.79	0.86	0.95
Overall solution coverage	0.70										0.72				
Overall solution consistency	0.93										0.84				
Cases with >0.5 membership in configuration	CYP	HKG	HKG	SGP	BEL	AUS	AUT	AUS	CAN	CAN	CAN	FIN	AUS	BEL	CAN
	GBR	ISR	KOR	SVN	CHE	ISL	FIN	DEN	ISR	DEN	EST	FRA	AUT	CHL	EST
	JPN	KOR		SWE	DEU	ESP		ESP			GBR	ISL	BEL	DEN	HGK
	LUX				ISL	GRC		GRC			HKG	ISR	CHL	ESP	LTU
	NLD				ITA	NOR					IRL	JAP	CZE	HRV	
	USA				NOR	NZL					ISL	NLD	DEU	LVA	
					NZL	PRT					ISR	URY	ESP		
					PRT	SGP					KOR		GRC		
					SGP	SVN					NZL		HUN		
					SVN						SGP		ITA		
											SWE		LVA		
											USA		NOR		
													POL		
													PRT		
													SVK		
													SVN		

● Core causal condition (present); ⊖ core causal condition (absent). Blank spaces denote 'don't care'.
Truth table frequency cut-off = 1, consistency cut-off = 0.86. Combination of intermediate and parsimonious solutions are presented.
[a] Oil-rich and small island countries are excluded from the sample.

values of ≥0.75.[19] In all the configurations, raw consistency values are above the acceptable threshold value of 0.75. Overall, solution coverage informs that the configurations related to solutions I and II jointly explain 70 % and 72 % of memberships in the present outcomes. Unique coverage statistics suggest that configurations 1 and 4a have the highest significance in solution I, that is, 0.06, and configuration 1a has the highest significance in solution II, that is, 0.08, in terms of frequency of occurrence of the outcome. According to the raw coverage statistics, conditions explain the configurations in solutions I and II between 16 and 45 %.[20]

Table 9 (HI group) shows, first, that in the period 1992–94, three major technological upgrading profiles are associated with similar income levels. The first, second and third profiles centre on the excelling technologies supported by either opportunity-driven or established technologies; the fourth on the established; the fifth and sixth profiles on the opportunity-driven technologies clusters, and the seventh profiles on emerging technologies. In the 2019–21 period, three technology upgrading profiles are centred around excelling or established technologies clusters, and two are centred around the opportunity-driven technologies cluster combined with either the emerging or lagging technologies clusters. These results show the diversity of technology upgrading patterns in HI economies, which is in line with our econometric results (Table 6). The highest number of configurations, with excelling, opportunity-driven and established technologies clusters, are associated with HI status. They are also significant drivers or predictors of income growth in GMM models, although fs/QCA shows that the emerging technologies cluster is an above-average contributor to technology upgrading in only a few configurations (Tables 9, paths 7a & 7b in 1992–94 period and 4 in 2019–21). Also, lagging technologies which are either not significant or are negative contributors to income growth (Table 6), have above average shares in two significant profiles in the HI group (Table 9).

Second, there is a shift from diversified to less diversified patterns of technological activity between the two periods. In the second period, most countries' technology profiles focus on excelling or established technologies and both the emerging and lagging technologies clusters lose their relatively stronger presence. While this might be expected for the lagging technologies clusters, the case of the emerging technologies clusters is somewhat puzzling. This shift towards excelling and established technologies may indicate progression of technology paradigm, i. e. a shift towards technologies whose economic relevance has increased.

There are several reasons for the reduced presence of emerging technologies cluster in the technology upgrading profiles in the second period, including the fact that they are supported by the nanotechnology field. Munari and Toschi (2014) highlight legitimisation and institutionalisation issues related to nanotechnology patenting, including the practice of 'patent thicketing'. Patent thicketing refers to the issuing multiple patents for a single invention, which can hinder further development or cause temporary stagnation. Youtie et al. (2021) argue that the development of nanotechnology towards commercialisation means that patenting is not the firm's main strategy any more. Schmoch (2007), Rothaermel and Thursby (2007) and Shapira et al. (2011)

[19] Consistency measures the degree to which configurations and the solution as a whole (overall solution consistency) are subsets of the outcome (Ragin, 2008b, p. 85). Overall solution consistency denotes the extent to which cases correspond to the set-theoretic relationship expressed in a solution (Fiss, 2011, p. 402).

[20] Coverage measures how much of the outcome is explained by each configuration (represented by raw coverage and unique coverage) and by the solution as a whole (overall solution coverage) (Ragin, 2008b, p. 85). Raw coverage measures the proportion of memberships for each condition in the outcome, while unique coverage measures the proportion of cases that follow the specific configuration leading to the outcome (Ragin, 2008b, p. 86).

Table 10
Technology upgrading profiles/configurations enabling shift to the next income level (all MI samples in 1992–94 and 2019–2021, average patent outputs.)

	Low-income			Middle-income															
Solutions	I			II							III								
	1992–1994			1992–1994							2019–2021								
Configurations	1	2	3	1a	1b	2a	2b	3	4a	4b	1a	1b	1c	1d	2a	2b	3a	3b	4
Emerging technologies	Θ	Θ	Θ	Θ	Θ	Θ	Θ	Θ	Θ	Θ	Θ		Θ	Θ				●	●
Excelling technologies	●			●	●		Θ				Θ	Θ				●	Θ		●
Opportunity-driven technologies			Θ		Θ			●	Θ	Θ	Θ	Θ		Θ	●	●		Θ	
Established technologies		●			Θ	●	●	●		Θ			Θ	●	Θ		●	●	Θ
Lagging technologies	Θ	Θ	●	Θ		Θ		Θ	●	●		●	●	Θ	Θ	Θ	●	●	Θ
Raw coverage	0.46	0.48	0.63	0.49	0.17	0.42	0.41	0.25	0.48	0.22	0.31	0.30	0.31	0.18	0.27	0.30	0.30	0.19	0.24
Unique coverage	0.03	0.06	0.32	0.07	0.01	0.02	0.01	0.02	0.06	0.00	0.03	0.01	0.06	0.01	0.02	0.02	0.01	0.00	0.04
Raw consistency	0.94	0.89	0.93	0.90	0.90	0.88	0.92	0.99	0.90	0.85	0.85	0.97	0.97	0.81	0.93	0.97	0.99	1	0.94
Overall solution coverage	0.84			0.83							0.70								
Overall solution consistency	0.89			0.86							0.87								
Cases with >0.5 membership in configuration	ARM PAK UZB ZAM ZWE	ALB KGZ PAK ZAM ZWE	AZE CHN IND KEN MDA LKA TJK	BLR CUB DZA ECU EST GEO HRV IDN JOR LTV MUS OMN RUS TTO TUN UKR URY	IDN IRN MUS URY	ARG BLR CZE DZA ECU EGY EST GEO HUN JOR KAZ PAN PER POL RUS UKR	BRB BRA BGR CZE EGY HUN KAZ LEB MEX PAN PER PHL POL SVK TUR	HUN PAN PER ZAF	BRB BOL BWA BRA BGR CHL CRI COL LEB MYS MEX MOR ROM PHL SVK THA TUR VEN	BOL BWA CHL IRN MYS VEN	ALB BLR BOL BWA ECU GEO IDN JOR KAZ KEN KGZ PER ZAM ZWE	ALB BOL GEO IDN JOR KAZ KEN MEX PER LKA	ARM BOL CRI JOR KEN PER ROM THA TUR UZB VNM	AZE BLR ECU KGZ TJK ZWE	DZA CHN CUB IRN LEB NGA PAK	DZA ARG CHN CUB IRN MYS MUS PAK RUS	ALB BRA COL GEO IND KAZ MEX ZAF	MDA MEX	CHN EGY IND PAK PHL TUN

● Core causal condition (present); Θ core causal condition (absent). Blank spaces denote 'don't care'.
Truth table frequency cut-off = 1, consistency cut-off = 0.86 (for MI subsample), 0.88 for LI subsample. Combination of intermediate and parsimonious solutions is presented.
Note: Vietnam has no patent activity in 1992–94 period. Nigeria patented only in opportunity-driven technologies.

suggest that the major nanotechnology actors have become large incumbents, more interested in capturing the benefits of application and commercialisation than in patenting.

Patenting of IT management methods increased sharply from 2010 and shows the second highest growth of all fields (see Table 4). IT management technologies allow access to services such as accounting, inventory management, programming, project management, etc. provided by distant rather than proximate suppliers (Harris, 1998). This is leading to business changes based on conversion of information from analogue to digital information which is embedded in new business models (Kraus et al., 2021). The effects of IT-driven strategies are increasing for both large and small businesses. The increased use of these technologies by small firms will likely have a major impact on business operations.

In the first period, many countries focused on established technologies with below-average shares of excelling and emerging technologies. These trajectories are led by countries, such as Germany and Italy, with long experience in capital-intensive engineering and chemical technologies, that is, industry-based science with rapid transfer of research results to production (Grupp et al., 2003). Eastern European countries that rely on Germany's industrial strategy and have strong links to German companies, shifted from the MI level in the 1990s to a HI level in 2021. The emphasis of southern European countries, such as Spain, Portugal and Greece, on established technologies allowed them to shift income levels from MI to HI. Their upgrading profile also shows a significant share of opportunity-driven technologies (see configuration 3) in 2019–21 period.

Countries categorised as MI during the 1990s, were able to make the shift to HI in the 2010s, based on use of established technologies. However, use of established technologies was not sufficient for LHI countries to shift to UHI levels. Italy seems stuck in the LHI group, while Germany and Belgium moved between LHI and UHI. In their study of German engineering sectors, Fromhold-Eisebith et al. (2021) suggest that an industry-specific historical trajectory may lead to lock-in and, combined with weak specialisation in advanced ICTs, can hamper technological upgrading in traditional sectors such as textiles.

Third, we observe that technology upgrading based on excelling technologies is the most prominent in the group of large and technologically leading economies (USA, Japan, Sweden, Canada, France). Some small countries shifted towards a more diversified technology upgrading profile in the period 2019–21. This suggests that the major 'improvers' in terms of shifting to the next income level or remaining in the HI group, have focused on ICT-driven, short-cycle technologies. This likely allowed development of the carrier and even the induced sectors to the next stage of digitalisation and automation.

In statistical terms, the LI and MI groups, solutions I, II, III, show acceptable overall solution consistency values of $\geq$0.75. For all the configurations, raw consistency values are well above the acceptable threshold value of 0.75. Overall solution coverage shows that the configurations included in solutions I, II and III explain 84 %, 83 % and 70 % of current positions. Unique coverage statistics suggest that configuration 3 in solution I, configuration 1a in solution II and configuration 1c in solution III have the highest outcome occurrence significance. The raw coverage statistics suggest that conditions explain between 18 % and 63 % of the configurations in solutions I, II and III.

Table 10 shows that the technology profiles of the LI and MI groups do not differ substantially from the profiles of the HI economies, with the exception of lagging and emerging technologies whereby the latter do not contribute to LI and MI groups' technology profiles. This is expected, since the technology efforts in these economies put more emphasis on technology use than on knowledge generation and lagging technologies play a more important role in this group. Also, it should be noted that a similar technology profile, especially in technology clusters in LI economies, does not imply more than a marginal contribution to economic growth.

During the 1992–94 period, MI economies show four distinctive technology upgrading profiles, each focused on a specific technology cluster and including profiles with a lagging technologies cluster (Table 10). Emerging technologies did not contribute to countries' technology profiles in that period. In the period 2019–21, the emerging technologies cluster appears as present condition in MI group. The GMM regressions show that, for the MI group, emerging technology cluster has a statistically significant impact on economic growth. The results of both our analyses suggest that, despite their very low shares in the MI group technology portfolios, emerging technologies influence carrier sectors which, for MI economies, are macroeconomically or economically relevant.

Summarising shifts in technology upgrading profiles of MI shows the following: First, between 1992 and 2021, there was a shift from less diversified to diversified patterns of technology upgrading. This leads to a no-distinctive technology profile in some countries, similar to profile 1a solution III (Table 10). This contrasts with HI economies which are less diversified in the second period. These findings are in line with Lee and Li (2014), who show that MI economies diversify their knowledge bases. Second, greater diversification means a focus on more technology clusters whether excelling, opportunity-driven, established or lagging technologies. Third, in the 2019–21 period, a few countries (China, India, Malaysia, Pakistan, Tunisia), active in excelling technologies, and emerging technologies (China, India, Moldova, Pakistan) moved to a higher income level and show more diversified patterns of technology upgrading. "Improver" countries, focused on excelling technologies in the entire period 1992 to 2021, shifted to the next income level. The positive and statistically significant effects of excelling technologies are reported in regressions for the MI group. We add to this our fs/QCA analysis which shows the transformative effects of the ICT paradigm on some LI and MI economies.

Although in the 1990s, many MI countries made efforts in excelling technologies, in most cases these efforts had been abandoned by 2019 – China is an illustrative exception. However, most profiles show evidence of technology upgrading linked to clusters in established and lagging technologies. This could be the result, in part, of integration of these countries (Turkey, Vietnam, Romania, India) via GVCs and involvement in low value-adding activities. For some economies, especially some of the largest emerging markets (Argentina, Brazil, Mexico, Indonesia, South Africa), result was a lock-in in non-dynamic clusters.

5. Discussion

This paper addresses the association between countries' technological profiles and their respective economic growth dynamics. Specifically, we: (a) explored the changing dynamics of current technology clusters based on a growth-share matrix which shows the strong effect of GPTs and enabling technologies; (b) conducted econometric testing of the associations between specific technological clusters and economic growth; and (c) explored the range of technology upgrading profiles of different income groups, and how these profiles shifted between 1992 and 2021.

Based on our interpretative framework of technology, carrier and induced sectors, we identified five technological clusters: emerging, excelling, opportunity-driven, established and lagging. Our results show that the country's technological profile plays a significant role in predicting its growth prospects and possible shift to a higher income level.

First, we have shown that, during the 1980–2021 period, if the country was focused on technology generation, particularly in newly emerging short-cycle technology fields, driven by the ICT paradigm and enabling technologies, and displayed fast growth in patenting in those areas, its chances of moving to the next income league increased substantially.

Second, we found heterogeneous technological profile trajectories co-existing within and across income levels, suggesting that competing strategies for macro-level productive technology profiles may have equivalent outcomes. However, this does not mean that technology upgrading profiles do not matter. In the MI and HI groups, lagging technologies contributed nothing to growth despite their substantial shares in some economies. Emerging, opportunity-driven and excelling technologies, had positive and statistically significant effects on income per capita in both the MI and HI groups; however, the role of established technologies varied.

Third, in the period 1992 to 2021, strong technology upgrading resulted in less diversification in the HI group and more diversification of the technology clusters in MI economies. Our results suggest that countries which focused on technology clusters that have a weak effect on economic growth, might be stuck in technological paths that offer few opportunities for a move to a higher income level. These structurally 'stable' countries were observed at all income levels. 'Lock-in' to an unproductive technology ugrading path can prevent catch-up and close routes to a path-creating or stage-skipping paths (Lee, 2013).

Our results show that, although some technological clusters are associated strongly with economic growth, their combined effect is decisive for technology transformation. It seems that what matters is not just the individual technology cluster, but the combination of complementary clusters. Technology transformation is a continuous dynamic process driven not only by newly emerging technology clusters but more by complementarities among different clusters. Some clusters are generators of radical new knowledge while others are economically more important as adaptors and users of new or established technologies. This calls for policy mixes, combining different instruments for a 'mix' of objectives, applicable to a range of different domains but which consider the structural idiosyncrasies of economic and innovation systems (Kergroach, 2019; Rogge and Reichardt, 2016; Flanagan et al., 2011). Policy mixes conducive to technology transformation need to go beyond emerging technologies' mission oriented policies. Goal setting and establishment of priorities based on expectations about *which technologies* can accelerate economic growth is essential (Mazzucato, 2018, 2016). However, mission oriented policy (MOP) need to be combined with the *coordination of complementary technology clusters and dimensions of the innovation system* (Mazzucato, 2016; Kattel and Mazzucato, 2018). MOP are in line with Lee (2013), who suggests that path-creation or stage-skipping routes are crucial for catching up and forging ahead. Our analysis suggests that this is *necessary but not sufficient*. Promoting technology transformation requires policy focus *on all technology sectors and clusters.* For some economies that could mean focus on new and unrelated technologies. Pinheiro et al. (2022) demonstrate that more developed NIS facilitate the shift towards involvement of unrelated technologies and policies with different priorities. On the other hand, Zabala-Iturriagagoitia et al. (2020) argue that related and unrelated diversification can co-exist with traditional industries having capabilities concentrated in mature technologies. In these cases, policy should support diversification in other industries and technologies.

Our analysis suggests that MOP should be conceived as portfolio of missions with different objectives for different technology clusters. Established and lagging technology clusters may be crucial from economic and employment perspectives. Newly emerging, excelling and opportunity-driven clusters may be essential as sources of knowledge to be used by carrier and induced sectors.

Portfolios of missions require a mix of instruments but also adequate governance and coordination structures (Hekkert et al., 2020). Given the variety of missions with different objectives, state-led, highly centralized initiatives are likely to be ineffective (Poel, 2003). Instead, mission-oriented strategies should aim to coordinate the actors involved in technological upgrading, to achieve decentralization of government decision-making and the formulation of enabling complementary policies (Mazzucato, 2018; Soete and Arundel, 1993).

It takes time for the effects of policy initiatives that involve structural shifts in technology upgrading profiles to emerge. This requires institutional stability (Roca et al., 2021). However, there is a lack of consensus about what constitutes effective institutions and how it can be achieved. Choung and Hwang (2019) argue that in the context of technological discontinuity, existing institutional frameworks can stifle innovation by encouraging lock-in effects. Although institutional stability is desirable, institutions also need to co-evolve with the focal technology upgrading process, provide agents with appropriate incentives, remove regulatory uncertainty (Yu et al., 2020; Choung and Hwang, 2019) and facilitate links to Global Value Chains (Brandt and Thun, 2016). From a micro perspective, Bernat and Karabag (2019) point out that technology upgrading is an iterative process, in which monitoring, strategizing, aligning and learning are critical. It is likely that these elements are also important at the macro-level policy making.

In a nutshell, technology transformation requires policy mixes conceived as portfolios of missions with disparate objectives, requirements and institutional setups. In that respect, they go well beyond often simplified pictures of the entrepreneurial state focused solely on newly emerging technologies.

Knowing which technology combinations trigger economic growth does not equate with certainty about which technological domains will be as effective in the future. The position of technologies in individual clusters can change both in terms of growth and shares. This makes mission oriented policies prone to uncertainty and heightened risks though forecasting exercises can somewhat reduce these risks. However, this further reinforces the need for thorough examinations on the mechanics of impact of particular technologies on economic development.

6. Concluding remarks

This paper investigated the role of technological profiles in economic growth and shifts in income levels. We conducted analyses of patenting activities of 96 countries over 40 years (1980 to 2021). We tried to identify why some countries moved from LI to MI, and to HI levels and others did not. Our analysis shows that specific technological domains – depending on their relative weight and growth dynamics – are associated with different patterns of economic growth. More importantly, we identified distinct technological upgrading paths and explored shifts in their profiles at different levels of income.

Our findings show that economic growth is a process of constant transformation and shifting of technology portfolios rather than adjustment to a long-run fixed technology target (Fagerberg and Verspagen, 2002: 1302). This process is guided by market forces but it also requires government intervention. This latter is indispensable as markets can be poor allocators of investments in early stages of new technologies (cf. renewables). Decision-makers need to be aware of shifts in the global technological landscape and their potential effects on technology transformation and the prospects for growth. This requires foresight to understand which technologies will provide the greatest opportunities in coming decades.

Our conceptual framework and our results suggest that technological domains are not substitutable in terms of their capacity to generate economic growth and development. Each technology cluster plays different technological and economic roles and has different socio-economic impacts. In that respect, strategic choice of technologies does matter (Lee, 2013). This shows, also, that the structure of technology clusters is pivotal in this debate (Mazzucato, 2018; Saviotti and Pyka, 2004). Policy should aim to shift innovation system towards technologies able to trigger strong economic growth (Mazzucato and Perez, 2015). However, our analyses suggest that focusing only on emerging sectors and disregarding the role of other technology clusters would have limited impact on long-term growth. The capacity to steer structural rationalisation for technological progress and upgrading is vital for effective innovation policy (Zhou et al., 2020; Cimoli et al., 2019).

Emerging technologies have been associated with the strongest impacts in terms of generating income growth. On the other hand, these technologies are seldom part of the configurations of low- and middle-income countries, thus representing the challenges for these economies to engage in frontier technologies that require 'path-defying' strategies. In this respect, excelling technologies appear to be a more reasonable driver of growth, demonstrating significant effects across all income levels, as well as being a key part of several configurations conducive to growth. A more in-depth scrutiny of which specific technologies have more potential to spur growth – and what are its underlying mechanisms – is warranted as a critical avenue for future research. Our research has shown that although excelling technologies are predominantly driven by ICT-related technologies, hard science such as nanotechnology, biotechnology, medical sciences, environmental technologies, new materials and transport are also part of emerging and, excelling technologies representing the Deep Science Wave in the coming (WIPO, 2022a). In particular, policy focus on portfolio of missions, on different functions of each technology cluster and how they complement each other should be a priority.

In sum, our GMM analysis indicates that HI countries can achieve economic growth mainly based on developing capabilities in Emerging and Excelling technologies, i.e., by engaging with innovation at the technological frontier. In turn, MI countries present growth patterns strongly associated with Emerging technologies whereas for the case of LI economies, Lagging technologies can provide relevant sources of growth as they can form part of the initial stages of technological upgrading compatible with their industrial structure. Interestingly, Established technologies appear to be consistently associated with negative growth rates in HI and MI countries. This is in accordance with the notion of middle-income traps for countries that strongly engage in developing these technologies. As Lee (2013) laid out, especially MI economies cannot achieve sustained growth when focusing on such long-cycle technologies. In HI economies a focus on these technologies may result in a lock-in. Escaping the middle-income trap seems highly unlikely in the absence of orientations of the National Systems of Innovation towards the frontier, short-cycle technologies.

However, our configurational approach using fs/QCA reveal that these patterns should not be taken as 'universal truths' for industrial policy and that alternative combinations of technological portfolios can lead to growth. In the next decades, the rejuvenating effect of digitalisation and AI might generate a very different role for established, opportunity-driven and even lagging technologies.

In this respect, the novelty of our research concerns the multiplicity of technology paths required for income shifts and how these conditions change across different levels of economic development. In this respect, there are serious limits for innovation policies focused solely on emerging technologies. Instead, our assessment outlines the relevance of technological portfolios, and comprehending the differential impacts and roles of these technologies in triggering growth.

Having a thorough comprehension of how technology clusters and their combinations can foster growth is key in establishing priorities for innovation policy. Illustratively, our empirical exercise identified the limits of established and lagging technologies in driving growth, except in the case of low-income countries. This represents specific challenges for countries in middle-income traps. This might require policy shifts that go beyond related diversification. Initiatives targeted at promoting capability 'leaps' towards new technological domains might be needed – an issue that requires also institutional and socioeconomic transformations.

Our study is not without limitations. First, the limitations of the patent statistics to cover the full variety of technological activities in economy. Technologies with low propensity to formal protection could not be accounted in our assessment. Due to the complex nature of our investigation we could not include indicators such as R&D expenditures and industrial design in our analyses. So, patent bias limits the generalizability of our findings. Second, our aggregate study builds on clusters based on patterns of growth dynamics and shares of technological clusters. This does not allow us to address the heterogeneous impacts of specific patents in promoting market competitiveness and economic growth. Also, different approaches to combining technologies, which rely on other clustering parameters (e.g., technological proximity), might provide a different picture of the association between technological diversification and economic activity.

Future research in this area could extend this research in several ways. First, it can examine the technological dynamics of specific fields more closely and investigate their relation to economic growth in countries at different stages of development. This would allow a better assessment of GPTs (ICT, nanotechnology, AI and biotechnology for instance). We would suggest both deductive and inductive research to delve deeper into the specificities of these phenomena and their interplay with broader economic and institutional aspects. For instance, assessing how policies targeting these technological clusters affect technological ugrading could inform further theoretical advances. Second, industrial design data can be used to complement the patent data. Recently, some middle-income economies (i.e. China, Turkey, Brazil, Morocco, India, Thailand) have shown particular strengths in industrial design as compared to high-income economies albeit mostly in medium- and low-tech sectors (WIPO, 2022b: 99–100). Third, our growth-share matrix as a dynamic framework captured not only ICT Wave but also Deep Science Wave technologies (i.e. nanotechnology, biotechnology, health technologies, environmental technologies, transport and new materials) that show the potential to drive economic growth specifically enhanced with advances in AI technology. Further research can run forecasting analysis to identify specific technologies for their effect on growth. We hope that this article will be useful to motivate research in these topics.

CRediT authorship contribution statement

Esin Yoruk: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Slavo Radosevic:** Conceptualization, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Bruno Fischer:** Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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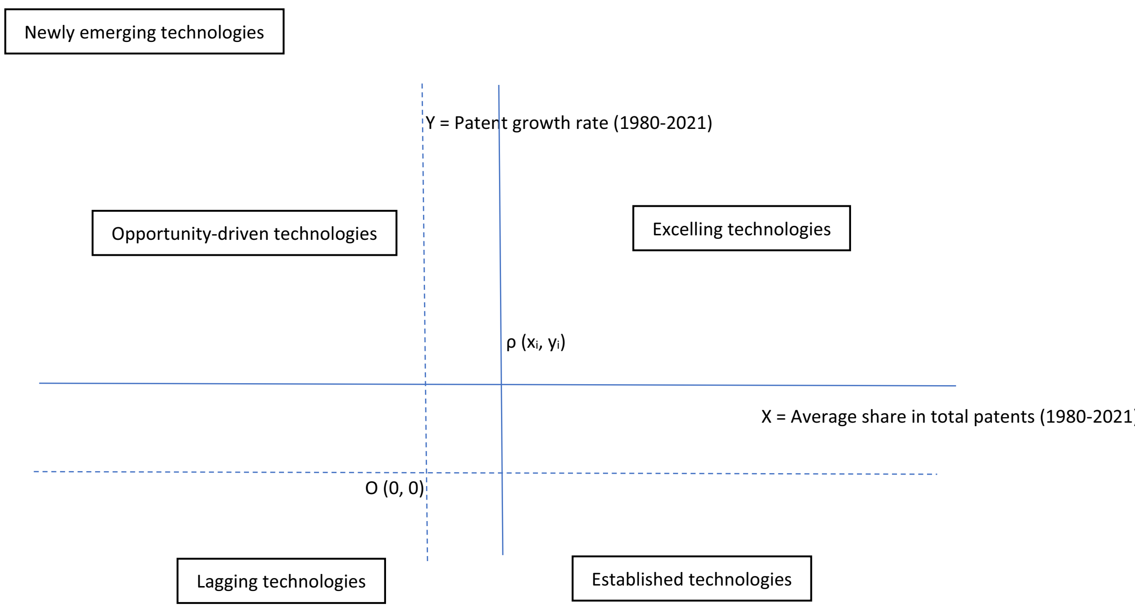
Appendix A. Operationalisation of patent growth-share matrix

Our conceptual framework (see Fig. 1) is based on the operational framework depicted below for mapping technologies based on their growth rate and share in total patents. Fast versus slow growth rates and novelty versus maturity (associated with a small number of patents in an emerging technology field or many patents in a mature technology field) guided our formulation. Similar clustering was operationalised, in the context of emerging technologies, by Breitzman and Thomas (2015) who use patent citation rates and shares. The technology clusters in our research are mapped according to the direction and rate of change measured by patent growth rates in the period 1980 to 2021, and average share of patents in technology clusters in total patents during 1980–2021. The coordinates of the intersection point ρ (x_i, y_i) in Fig. 2 are important for interpreting the framework. X_i is the mean value of the share of each technology cluster in total world patents during 1980–2021. X_i is 2.85 %. We are interested in which technology clusters show shares above and below this value. Y_i is the growth rate of granted patents in all technologies from 1980 to 2021. We calculated this value, 282.1 %, by smoothing the patent statistics using 1980–84 and 2017–21 averages as two points in time. In this average value, we do not include the five outlier technologies of micro-structural and nano-technology, IT methods for management, digital communication, computer technology and semiconductors (see Fig. 2). Table 4 presents the results including figures on the growth rates of technology clusters during the 1980–1997 and 1998–2021 periods.



Appendix A. Operational framework for technology clusters by patent growth rate vs. average share of patents in worldwide patenting (1980–2021).

Appendix B
Overview and descriptive statistics for indicators used in the analyses (full sample).

Indicator	No of obs	Min	Max	Mean	SD	Emerging	Excelling	Opportunity-driven	Established	Lagging	R&D expenditures	Trade Openness	GFI	Tertiary school
GNIpc	1276	153.3	101,226.7	13,260.7	16,251.8									
Emerging	1276	0	0.19	0.005	0.013	1								
Excelling	1276	0	1	0.306	0.170	0.170	1							
Opportunity-driven	1276	0	1	0.117	0.106	−0.019	−0.034	1						
Established	1276	0	1	0.270	0.166	−0.111	−0.356	−0.248	1					
Lagging	1276	0	1	0.274	0.160	−0.089	−0.355	−0.189	−0.187	1				
R&D expenditures	1087	0	5.29	0.97	0.93	0.052	0.338	0.010	−0.084	−0.178	1			
Trade openness	1228	6.38	209.67	42.0	29.4	0.115	0.157	−0.018	−0.037	−0.104	0.050	1		
GFI	1211	3.11	87.67	23.2	6.2	0.028	−0.064	−0.019	−0.011	−0.031	0.050	0.085	1	
Tertiary school	1072	0.016	149.70	38.5	25.8	0.199	0.351	0.082	−0.092	−0.158	0.532	0.106	−0.111	1

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