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Flavio Calvino,

Antoine Dechezleprêtre,

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How can the digital transformation affect the net-zero transition? A conceptual framework for the "twin" transition

Flavio Calvino[1], Antoine Dechezleprêtre[1], Daniel Haerle[1]

Transitioning from fossil fuels to a net-zero economy is a major policy challenge at the core of the green transition. At the same time, advances in digital technologies such as artificial intelligence (AI) are rapidly changing production processes for goods and services across different sectors in the economy. This paper provides a conceptual framework to better understand how this digital transformation could influence the net-zero transition. By considering the digital transformation as linked to the emergence and diffusion of a general-purpose technology, it identifies the various channels through which this technological shift could affect the key elements of the net-zero transition, including energy efficiency and the carbon intensity of energy consumption.

[1] OECD Directorate for Science, Technology and Innovation

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Executive summary

This paper explores how the digital transformation – driven by the widespread adoption of digital technologies across the economy – may affect the pace of the transition to a net-zero greenhouse gases (GHG) emissions economy. While the green transition encompasses the broader environmental impact and therefore also other dimensions that may be affected by the digital transformation, this paper focuses on the net-zero aspect of the green transition by examining the impacts of the digital transformation on energy efficiency and the carbon intensity of energy consumption across the economy.

The net-zero transition aims to eliminate greenhouse gas emissions through the development and deployment of energy efficiency and carbon-free technologies, while the digital transformation, driven by advances in artificial intelligence (AI), other advanced digital technologies and the underlying connectivity, is rapidly changing production processes across sectors. These two transformations have been coined the "twin transition" because they happen in parallel, but also due to their potential interlinkages. However, whether and how the digital revolution can be leveraged to reach net-zero goals is not straightforward.

The two processes interact in multiple ways. On the one hand, digital technologies can lead to energy efficiency improvements and to accelerated deployment of carbon-free technologies, thanks to potential benefits from advanced digital solutions like smart metres, sensors, AI, the Internet of Things and blockchain. On the other hand, as computational needs grow and potential rebound effects come into play, the digitalisation of economic processes could also increase energy use, potentially leading to a larger GHG footprint, at least until all sources of energy have been decarbonised. Given the rapid rate at which the digital transformation is unfolding, understanding its consequences for the net-zero transition is crucial to design climate policies that best account for the digitalisation of the economy, and digital policies that accelerate rather than hinder the clean energy transition.

The paper presents a conceptual framework to analyse the economic mechanisms behind these green-digital transition linkages. The framework can help lay out an agenda for policy-relevant research aiming to quantify the importance of the different channels highlighted by the conceptual framework. As a crucial driver of the digital transformation, the arrival of new digital technologies can be thought of as linked to the emergence and diffusion of a new general-purpose technology (GPT), affecting different sectors of the economy, boosting innovation, and increasing productivity for different inputs in production. The framework focuses on how digitalisation impacts the net-zero transition by inducing changes in both the quantity and type of energy consumed in the economy. As the GPT impacts the productivity of each of the constituent parts of production, it affects their relative use as well as overall output.

The paper identifies five channels through which the digital transformation could affect the net-zero transition, through the diffusion of the digital GPT and its implications:

- Energy use of capital: the use of both digital and non-digital machines can become more energy-using. As ICT hardware becomes more important in the capital stock, the overall use of machines can become more energy-intensive due to higher computing demand, or less energy-intensive due to digitally optimised energy efficiency.

- Capital intensity: if digitalisation relatively increases the output productivity of machines (both digital and non-digital) more than that of workers, then more machines will be used, implying greater overall energy use as machines require energy to function. For example, if machines are better able to fulfil tasks, more machines and hardware will be used and relatively fewer workers will be hired. This would increase capital intensity and therefore energy consumption.
- Type of energy use: if digitalisation favours productivity of machines using clean energy (electricity, which can be generated carbon-free) compared to machines using dirty energy (fossil fuels), energy use will be less polluting. For example, optimisation driven by machine learning (ML) may benefit battery life and therefore the usage of electric vehicles more than when applied to internal combustion engine vehicles.
- Direction of innovation: digitalisation could favour R&D in either clean or dirty technologies. For example, this could be due to differences in the capacity of clean and dirty technologies to absorb digital advancements, which may reflect differences in the scientific fields they rely on and on their intrinsic proximity to advanced digital technologies.
- Scale: digitalisation may increase overall output growth, leading to higher energy demand, and therefore emissions until the economy is fully decarbonised.

The overall impact of the digital transformation on the net-zero transition remains an empirical question as the direction of the effect for each channel (except scale) is theoretically undetermined. A casual look at aggregate trends points to opposing directions across channels.

This framework highlights the policy relevance of focusing on different aspects of the link between the digital transformation and the net-zero transition, which can be affected by complementary policy levers. The various channels also show that digital and climate policies interact with each other, implying that they should each be designed taking the other into account.

1 Introduction

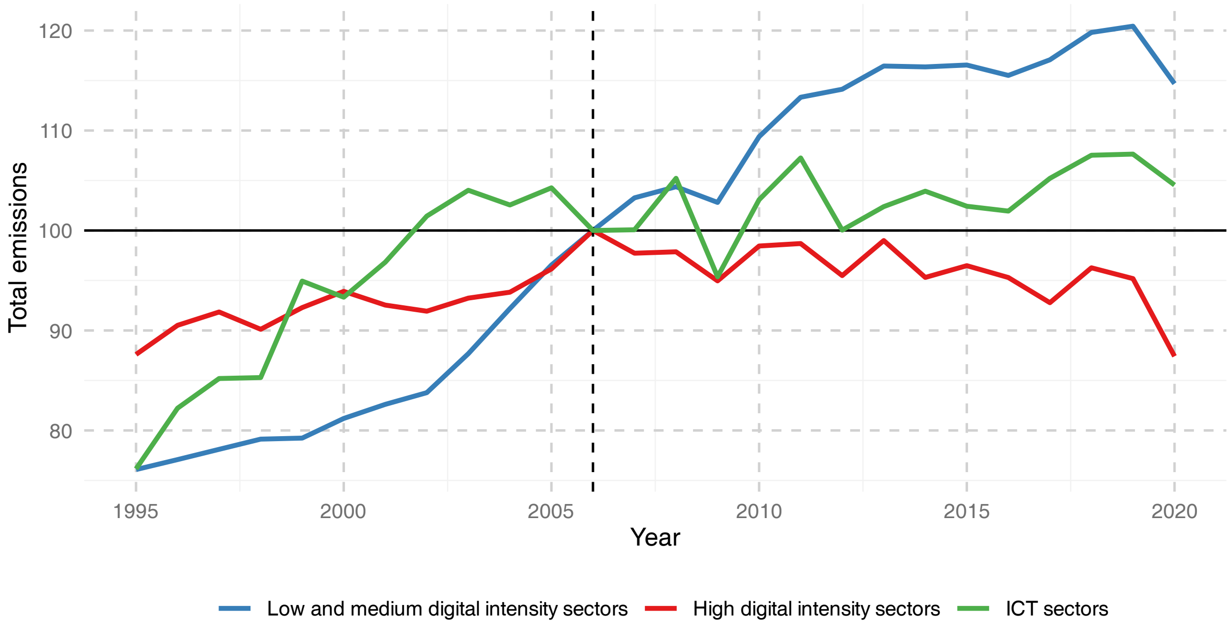
Countries representing more than 90% of world GDP have announced targets of climate neutrality by mid-century. Reaching this objective and achieving this key dimension of the "green transition" – the shift away from a form of economic growth driven by fossil fuel consumption and natural resources exhaustion – is a major challenge as it requires rapidly adopting zero-carbon energy sources and production processes across all economic sectors. Some of the low-carbon technologies necessary to reach net-zero emissions already exist, but many others are still being developed. At the same time, advances in digital technologies such as artificial intelligence (AI)[1] and their underlying infrastructure are rapidly changing production processes for goods and services across different sectors in the economy. This "digital transformation" is rapidly changing the economy in ways just as profound as the green transition.[2] These two transformations have been coined the "twin transition" because they happen in parallel but also due to their potential interlinkages. However, whether and how the digital revolution can be leveraged to reach net-zero goals is not straightforward. While the green transition encompasses multiple dimensions that may all be impacted by the digital transformation, such as material requirements as well as waste and pollutants beyond greenhouse gases, this paper focuses on the net-zero aspect of the green transition by examining the impact of the digital transformation on energy efficiency and the carbon intensity of energy consumption.

There are some obvious ways in which the two transitions may interact: on the one hand, digital technologies could be a key enabler for reaching net-zero objectives. A sizeable literature has emphasised the potential sustainability benefits of many advanced digital solutions, such as the Internet of things (e.g. smart metres and sensors) and AI (Global e-Sustainability Initiative, 2016[1]; Vidmar, Marolt and Pucihar, 2021[2]; Bican and Brem, 2020[3]; Iddri et al., 2018[4]; OECD, 2024[5]; OECD, 2025[6]). On the other hand, the digitalisation of economic processes is associated with considerable energy use, with AI on track to reach the energy needs equivalent to those of entire countries (De Vries, 2023[7]). With fossil energies still in use, the recent emergence of AI may therefore impose an increasingly large carbon footprint. Additionally, advanced digital technologies such as AI could encourage the use of (energy-using) machines as they make not only workers, but also machines more productive and thus lead to increased use of capital (OECD, 2024[5]; OECD, 2022[8]).

These opposing mechanisms are reflected in Figure 1.1: in recent years, highly digital sectors,[3] so those at the forefront of the digital transformation, have seen a reduction in their global carbon footprint, while less digital intensive sectors have continued to grow their emissions. At the same time, the Information and Communication Technologies (ICT) services sector has not reduced its emissions because of increasing energy consumption (World Bank and ITU, 2024[9]). Considering the various competing mechanisms, the way in which the digital transformation, including its most recent stages, interacts with the net-zero transition is therefore multi-faceted.

Figure 1.1. Emissions have been decreasing in highly digital sectors, but not in the ICT sector

Total CO_2 emissions by sector category



Note: Global CO_2 emissions. Index year 2006. ICT sectors only include ICT service industries (i.e. ISIC codes 61, 62 and 63), namely: Telecommunications; Computer programming, consultancy and related activities; Data processing, hosting and related activities; web portals.
Source: IEA Energy End-uses and Efficiency Indicators database.

This paper provides a conceptual framework to analyse the economic mechanisms behind these digital-green transition linkages and discusses the role of different channels and their implications for the net-zero transition. It focuses on how the diffusion of digital technologies might affect the quantity and type of energy consumption, which are key elements relevant for the net-zero transition. In this context, we consider the development and widespread adoption of the various digital technologies underlying the digital transformation as the emergence and diffusion of a new general-purpose technology (GPT), which affects different sectors of the economy, boosts innovation, and increases productivity for different inputs in production. This is consistent not only with the literature considering ICTs as a GPT, but also with recent evidence highlighting the increasing potential of AI and its applications across the economy (Basu and Fernald, 2007[10]; Fulgenzi, Gitto and Mancuso, 2024[11]; Agrawal, Gans and Goldfarb, 2019[12]; Brynjolfsson and Mcafee, 2017[13]; Goldfarb, Taska and Teodoridis, 2023[14]).

The proposed framework can help policy makers focus on different aspects of the multifaceted link between the digital transformation and the net-zero transition, each of which can be affected by different policy levers. As the digital transition influences the net-zero transition through various mechanisms, both policies aimed at guiding the digital transformation and instruments designed for climate action will interact with each other in a parallel fashion through these channels. Additionally, each of the channels can be object of further measurement and analysis, e.g. with microdata, supporting evidence-based policymaking. In this context, administrative microdata could allow exploring further the links between digital technology adoption and environmental investments, patent data could be used to further analyse innovation patterns, or granular information could enable studying recent patterns in the energy efficiency of supercomputers. This would be complementary to recent and ongoing OECD work on the links between digital technologies and economic outcomes, environmental efficiency and firm performance, and the falling labour share based on micro-aggregated data.

2 Conceptual framework

As a crucial driver of the digital transformation, the adoption and diffusion of different digital technologies, including the recent emergence of AI, can be understood as transforming the economy through the emergence of a new general-purpose technology (GPT), defined in Box 2.1.[4] Compared to other types of technologies, GPTs are characterised by their general nature as an enabling technology for a wide range of potential applications, as well as by their aggregate economic impact (Jovanovic and Rousseau, 2005[15]). As such, in order for a technology to qualify as a GPT, the literature identifies as its main features a pervasiveness across sectors, an improvement over time as well as a potential to enhance innovation (Bresnahan and Trajtenberg, 1995[16]). These characteristics have been evidenced for historical cases of GPTs such as the advent of the steam engine or electricity. At the same time, the literature has established the more recent wave of digital technologies centred around information technology (IT) as a GPT (Jovanovic and Rousseau, 2005[15]; Basu and Fernald, 2007[10]). In the context of recent advancements in digital technologies, ongoing research further points to the potential of AI and the extent to which it may qualify as a new GPT, too (Cockburn, Henderson and Stern, 2019[17]; Crafts, 2021[18]; Bresnahan, 2024[19]; Goldfarb, Taska and Teodoridis, 2023[14]).

In the following framework, this crucial aspect of the digital transformation is conceptualised as the emergence of a new GPT, which impacts the net-zero transition by focusing on the potential changes it can induce in both the quantity and type of energy consumed in the economy.[5] Considering the general nature of the GPT, its simultaneous adoption in various ways across sectors and inputs in production implies multiple channels for this impact, which are brought together in an analytical framework. A formal exposition is available in Annex A. Infographic 2.1 shows a visual representation of this framework.

The proposed framework focuses on how production inputs interact with the energy needs of production. As is common in economic models, the primary inputs are given by labour on the one hand, representing human workers,[6] and capital on the other hand, which consists of various types of machines powered by energy. Capital (machines including digital tools but not only) is therefore complementary with energy. Labour and capital are both necessary for production but can to some extent be substituted for one another. An important aspect for the net-zero transition is that not all machines are equal: some make use of "dirty" sources of energy (e.g. fossil fuel or high-carbon electricity), which are polluting, whereas others are powered by "cleaner", less-polluting energy sources (e.g. low-carbon electricity). The two types divide machine use into two sectors, as each requires their own specific set of technologies. The state of technology in each sector changes with innovation: firms invest in R&D by employing scientists to increase the productivity of the machines. Ultimately, the size of the inputs in production and innovation depends on the extent to which they can be brought to productive use. Given its general nature, the GPT impacts the productivity of each of the constituent parts of production, thereby affecting their relative use as well as overall output.

Box 2.1. General-purpose technologies

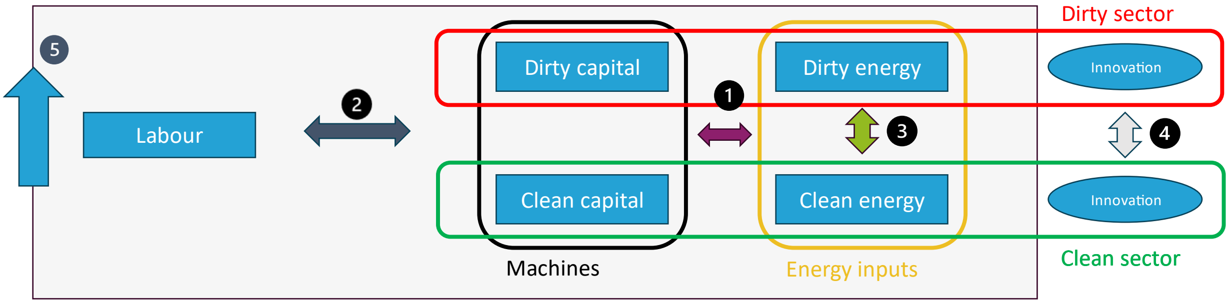
The concept of general-purpose technologies (GPTs) seeks to conceptualise the transformative impacts of certain technological developments on both the economy and, in a wider sense, society. Impacting aggregate productivity and growth, this sets them apart from marginal and/or application-specific technological innovations. The economic literature broadly identifies three features that characterise GPTs (Bresnahan and Trajtenberg, 1995[16]; Jovanovic and Rousseau, 2005[15]; Lipsey, Carlaw and Bekar, 2005[20]):

- Pervasiveness: There is widespread diffusion of the technology across sectors.
- Continuous improvement: Over time, the technology becomes increasingly useful.
- Innovation spawning: The technology aids innovation in products and processes.

Past technologies that have been characterised as GPTs include the steam engine, electricity, and ICT. A common observation across existing GPTs is that economy-wide productivity effects often take time to materialise (David, 1991[21]; Brynjolfsson, 1993[22]), a phenomenon which is often credited to the need for accumulating complementary assets (Brynjolfsson, Rock and Syverson, 2021[23]). The question of what exactly defines the GPT as compared to complementary technologies and assets is not always straightforward. In the most recent case of ICT, for example, potential technological drivers that have been identified include semiconductors (Bresnahan and Trajtenberg, 1995[16]), microprocessors (Bresnahan and Greenstein, 1999[24]), wider ICT capital (Basu and Fernald, 2007[10]) and the internet (Field, 2008[25]).

Infographic 2.1. Economic relationships affected by the digital transformation

Rectangular boxes represent the physical inputs into the economy, while the oval shapes represent R&D processes. The arrival of the new GPT affects the various relationships indicated by the arrows (composition effects). A formal exposition of the model is presented in Annex A.



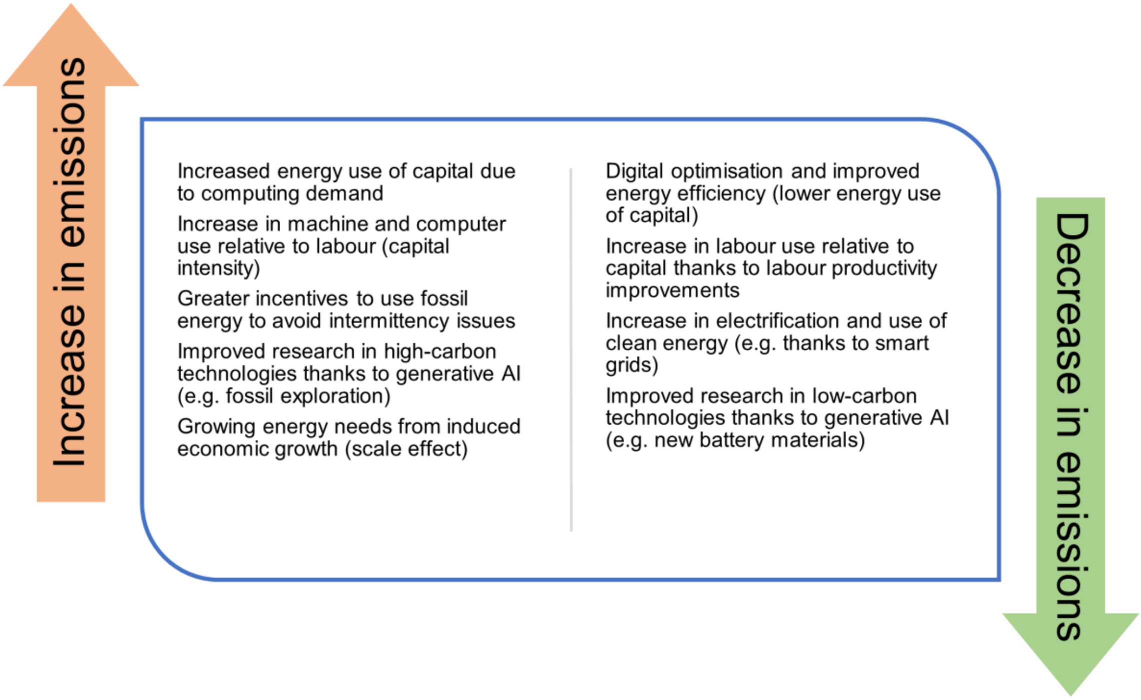
The new GPT impacts the net-zero transition through the following channels, holding other things constant, which are numbered following the diagram:

1) **Energy use of capital**: with the new GPT, the use of machines can become more or less energy-intensive. For example, as ICT hardware becomes more important in the capital stock, the overall use of machines can become more energy-intensive due to higher computing demand or less energy-intensive due to digitally optimised energy efficiency.

2) **Capital intensity**: the GPT favours productivity in both machines (capital) and workers (labour). If the productivity of machines increases relatively more than that of workers, as a result, relatively more machines will be used, implying greater energy used (of which some is polluting). For example, if machines are better able to fulfil tasks, more machines and hardware will be bought and relatively fewer workers will be hired. This would increase capital intensity and therefore energy consumption.
3) **Type of energy use:** if the GPT favours productivity in the clean sector (using electricity, which can be generated carbon-free) more than it does in the dirty sector (using fossil fuels), energy use will be less polluting. For example, optimisation driven by machine learning (ML) may benefit battery life and therefore the usage of electric vehicles more than when applied to internal combustion engine vehicles. Similarly, AI could help forecast electricity demand, thus mitigating intermittency problems and favouring renewable electricity more than fossil-based electricity. Simultaneously, increasing electricity demand from data centres could also exacerbate intermittency issues, which would favour dirty energy – the more flexible source of energy used for peak demand.
4) **Direction of innovation:** the GPT could make it easier for researchers to create new innovations. Due to differences in the capacity of clean and dirty technologies to absorb the GPT, which may reflect differences in the scientific fields they rely on and on their intrinsic proximity to the GPT, this may favour R&D either in the clean or in the dirty sector. For example, AI and ML have already helped researchers discover new perovskite materials whose properties make them good candidates for high-efficiency solar cells (Wang et al., 2024[26]).[7]
5) **Scale:** the new GPT may drive overall output growth, leading to higher energy demand. As such, total energy use may increase as a result of the various efficiency increases implied by the GPT.

Infographic 2.2 summarises how the various channels affect emissions through the channels during the net-zero transition. Note that heterogeneity across industries can influence how the various effects described play out in practice, particularly in terms of their magnitude. Each channel is now reviewed in turn.

Infographic 2.2. Potential effects of the digital transition on the net-zero transition



Energy use of capital

Perhaps the most apparent way in which advanced digital technologies affect energy usage is the technology's very own energy needs. Recently, this has become especially prominent, in the context of the debate surrounding the computational needs of AI. While machines have always required the input of energy in order to function, highly digitally-powered operations come with substantial energy needs in the form of electricity used for computing power, oftentimes outsourced to datacentres which provide the processing of data and computing power (IEA, 2024[27]; OECD, 2022[8]). As a result, the energy use of capital may increase during the digital transition as increasingly energy-intensive ICT capital is added to the capital stock. In Infographic 2.1, this is represented by channel (1). Without any adjustment to the inputs to production, this increase in energy use is potentially immense, with the energy use of a search request using current generative AI models alone constituting a multiple of a simple web search (De Vries, 2023[7]).[8] However, how large the increases in demand for AI-powered computation will be remains uncertain. Similarly, projections about the computational energy costs are riddled with just as large of an uncertainty due to the importance of the underlying computation architecture, differences between the different life-cycle phases (such as training and inference), and large differences between AI models (Hwang, 2018[28]; De Vries, 2023[7]). In this vein, the adoption of operational best practices for the responsible use of AI along various dimensions (model, machine, mechanisation and location) can potentially reduce energy consumption and, depending on the type of energy source, carbon emissions by multiple orders of magnitude (Patterson et al., 2022[29]). Alongside the emergence of green datacentres (OECD, 2022[8]), this paints a more optimistic picture of the evolution of AI's carbon footprint. Indeed, it seems to be the case that the AI compute hardware has been seeing efficiency gains, with data centres remaining at a steady share of 1% of global electricity demand despite a 25-fold growth of workloads and data traffic since 2010 (OECD, 2022[8]; IEA, 2023[30]).[9]

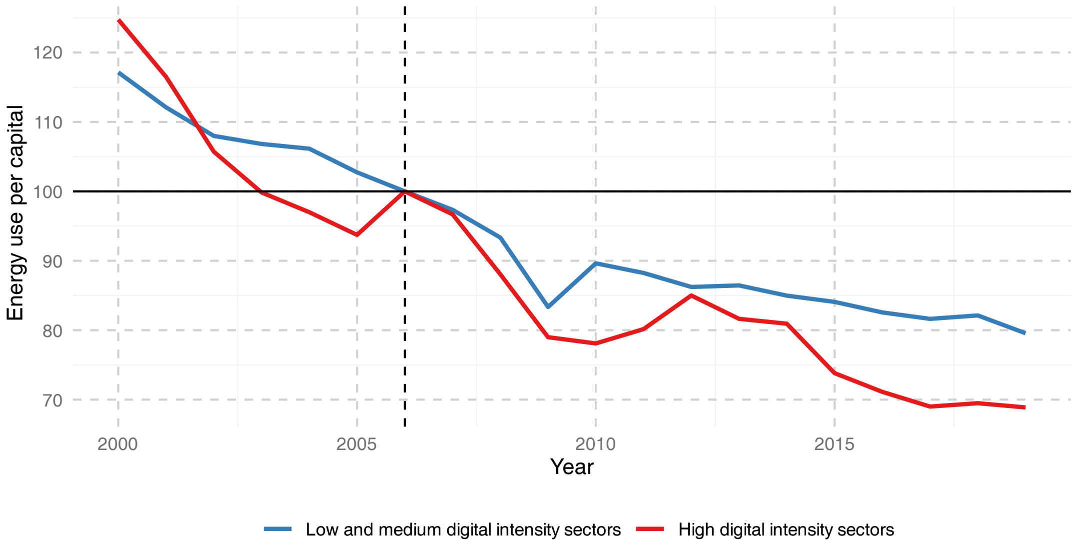
At the same time, digital technologies and, most recently, AI and ML solutions can also make digital and non-digital machines more energy efficient, potentially lowering the energy intensity of the overall capital stock. For example, smart energy and grid management systems can ensure the efficient use of energy inputs in production (Yao et al., 2022[31]; Yin et al., 2018[32]) and AI applied to communication networks can reduce energy consumption through optimised network management (OECD, 2022[33]; OECD, 2025[6]). Similarly, there are potential energy efficiency improvements associated with the use of industrial robots and the Internet of Things (Liu et al., 2022[34]; Tomazzoli, Scannapieco and Cristani, 2020[35]). In this vein, a recent cross-country study by Wang, Lee and Li (2022[36]) finds that the application of industrial robots has contributed to improving the energy efficiency of the capital stock in the manufacturing sector. Thus, AI also has a potential for sizeable energy savings. For instance, a recent experimental study identifies the energy savings potential of AI to be 35% in buildings; 25% for heating, ventilation and air conditioning equipment; 50% in artificial lighting systems; up to 70% in information transfer and communication; and 20% power demand reduction in the factory (Lee, Chen and Chao, 2022[37]). An expanding body of literature analyses the potential of ML in climate and energy efficiency for uses such as predictive maintenance, remote sensing, and forecasting. These uses will likely grow as the digital transformation further unfolds (Rolnick et al., 2019[38]; Kaack et al., 2022[39]).

Therefore, while digital technologies inherently increase energy demand due to their computational needs, they also offer significant opportunities for energy savings through optimisation and efficiency improvements, and these effects may be particularly pronounced in the case of AI. Both opposing effects are subject to a high degree of uncertainty and will ultimately depend on the path the technology will take. In addition, both AI's own energy needs and applications for energy saving will respond to prices and the policy environment in energy markets.

Until recent years, concerns of an exploding energy use in highly digital sectors have not materialised. In fact, Figure 2.1 shows that across OECD Member countries, the most digital intensive sectors (including both ICT manufacturing and services, but also transport equipment, financial and various other services) have been experiencing larger reductions in energy use than less digitally exposed sectors up until 2019.[10] While this dynamic may change with a more widespread adoption of computationally intensive AI technologies, this suggests that energy saving effects of the digital transformation may have dominated its energy needs in the observed period.

Figure 2.1. The energy intensity of the capital stock has declined faster in highly digital sectors

Energy intensity of net capital stock in manufacturing sectors, OECD average



Note: Energy intensity computed as energy end use per net capital stock (chain-linked volume, reference year 2015) for select sectors. Sectors in sample (ISIC Rev. 4 2-digit classification): 10-12, 13-15, 16-18, 19, 20-21, 23, 24, 29-30, 31-32. Sectors are classified as digital intensive following the taxonomy by Calvino et al. (2018[40]). Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in sample: Austria, Belgium, Canada, Czechia, Denmark, Finland, France, Japan, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, United Kingdom, United States.
Source: IEA Energy End-uses and Efficiency Indicators (IEA, 2024[41]), OECD STAN database for Structural Analysis.

Capital intensity

The energy use of adopting advanced digital solutions is also determined through a second mechanism: as AI and other digital technologies boost productivity in both machines and humans, their widespread adoption potentially affects the relative use of capital and labour in the production of goods and services. This is relevant since, as laid out above, operating capital is inherently energy-consuming, which implies that the energy need of production will be impacted if labour and machine operations are substituted for each other. For example, if work that has previously been manually executed by a human worker is now more efficiently carried out by an autonomous machine powered by digital technologies, a larger energy input will be required, other things being equal.

However, the impact of the digital transformation on the share of capital — and thereby also labour — in production is not obvious, as digital technologies, including those related to AI, may have productivity-enhancing applications in both capital and labour. The impact of these aspects of the digital transformation on energy use will depend on how they will impact the share of labour in production. This, in turn, will depend on whether technical change is more capital or labour augmenting and on the degree of substitutability between labour and capital; that is, to what extent labour and capital need to be employed together or whether they can replace each other. Many digital technologies such as the Internet of Things and robotics complement the use of machinery by making it more productive and efficient. If this leads to more machines being employed compared to workers in production, more energy will be needed as an input. Evidence shows that in the case of R&D in science and engineering, AI-driven idea production is more capital-intensive than traditional R&D (Besiroglu, Emery-Xu and Thompson, 2022[42]).

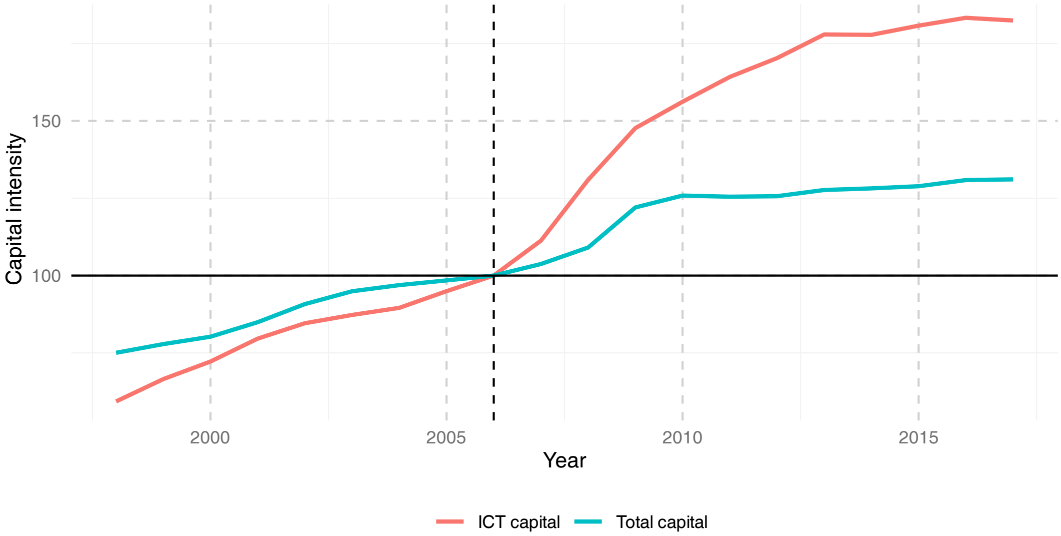
On the other hand, certain digital technologies, particularly generative AI, have the potential to impact capital intensity by considerably raising worker productivity and making more efficient use of human resources. Although there are still ongoing debates around the aggregate implications of AI, some studies predict significant labour productivity and output increases from large language models (LLM) and generative AI (Baily, Brynjolfsson and Korinek, 2023[43]; Goldman Sachs, 2023[44]).[11] One study finds that the use of ChatGPT, a generative AI chatbot, significantly increased productivity in professional writing tasks (Noy and Zhang, 2023[45]). It has been estimated that 15% of all worker tasks in the economy could be significantly impacted by LLM (Eloundou et al., 2023[46]). With continuous improvements to the underlying models and ever-new applications, this share may increase in the future.[12] Note that, depending on the skill intensity of the workforce, the impact of digital technologies on labour productivity may differ across sectors. While previous generations of digital technologies appeared to overall favour the productivity of high-skilled workers,[13] an emerging literature now suggests that AI may improve the productivity of low-skilled workers more than that of high-skilled ones (Noy and Zhang, 2023[45]; Choi, Monahan and Schwarcz, 2023[47]; Brynjolfsson, Li and Raymond, 2023[48]). With the digital transformation affecting both capital and labour, the extent to which it will impact capital intensity in production also hinges on the degree of automation of human tasks and thus relates to the labour share in income. There is mixed theoretical and empirical evidence regarding the effect of automation on the labour share. Automation (as embodied in total factor productivity growth) has benefitted employment, but at the same time lowered the labour share in the United States over the last four decades (Autor and Salomons, 2018[49]). Conversely, it has been argued that automation in its traditional form has not had a large effect on the labour share in France (Aghion et al., 2021[50]). More recent economic frameworks about automation consider the role of the creation of new tasks (Acemoglu and Restrepo, 2018[51]). Evidence suggests that the adoption of robotics has raised labour productivity, but negatively affected the labour share and employment (Acemoglu and Restrepo, 2020[52]). The latest wave of digital technologies, and generative AI specifically, may be different from previous waves of automation: AI replaces not only routine tasks, but also tasks that are traditionally high-skilled. While as a result of this transformation, the possible outcome of a fully labour-driven economy in the long run is also explored by Acemoglu and Restrepo (2018[51]), most economic models point either towards a constant labour share or even the risk of AI replacing labour altogether (Trammell and Korinek, 2023[53]; Erdil and Besiroglu, 2023[54]).[14]

Empirically, the labour share has been considered rather stable for a long time (known as one of the “Kaldor facts”), but some argue it has recently begun to decrease in many advanced economies, often credited to the diffusion of information and computer technologies (Karabarbounis and Neiman, 2014[55]; Cho, Manaresi and Reinhard, 2024[56]). Early evidence suggests that digital technologies such as cloud and big data may have lowered the share of labour in the manufacturing sector in France through increased labour productivity (Cette, Nevoux and Py, 2022[57]). On the flipside, DeStefano, Kneller and Timmis (2020[58]) found ICT to be capital-saving in the United Kingdom. Additionally, evidence from the People’s Republic of China (hereafter, ‘China’) indicates that the digitalisation of firms has increased the labour share (Li et al., 2023[59]).

It can be seen in Figure 2.2 that, across several OECD Member countries, capital deepening (defined as the increase in the capital-labour ratio) has been more pronounced in ICT capital compared to the overall capital stock despite ICT capital constituting only a small yet growing part of the overall capital stock.[15] This suggests an increasing demand for ICT capital, explained among other factors by the falling prices in ICT capital relative to labour.[16] As ICT capital plays an increasingly important role in the economy relative to labour, the digital transformation may contribute to increasing the intensity of the energy-using capital stock. As such, the channel counteracts any simultaneous decreases in the energy intensity of the capital stock and thus contributes to a rising energy demand. For the net-zero transition, it is therefore crucial to which extent such energy demand is covered by clean or dirty energy.

Figure 2.2. Capital deepening in ICT capital has outpaced capital deepening in other forms of capital

Capital intensity in the manufacturing sector over time, average over selected OECD Member countries



Note: Capital intensity computed as the chain-linked volume measure of the capital stock (reference year 2015) over the number of full-time equivalent jobs. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in the sample: Austria, Czechia, France, Italy, Netherlands, Norway, United States.
Source: OECD STAN database for Structural Analysis.

Type of energy use

With the GPT increasing machine productivity under the digital transformation, there may be differences regarding the types of capital benefitting the most. In the context of the net-zero transition, this is most relevant if machines using cleaner technologies, that is, technologies making use of low-polluting energy sources, are affected differently from machines using dirty technologies.

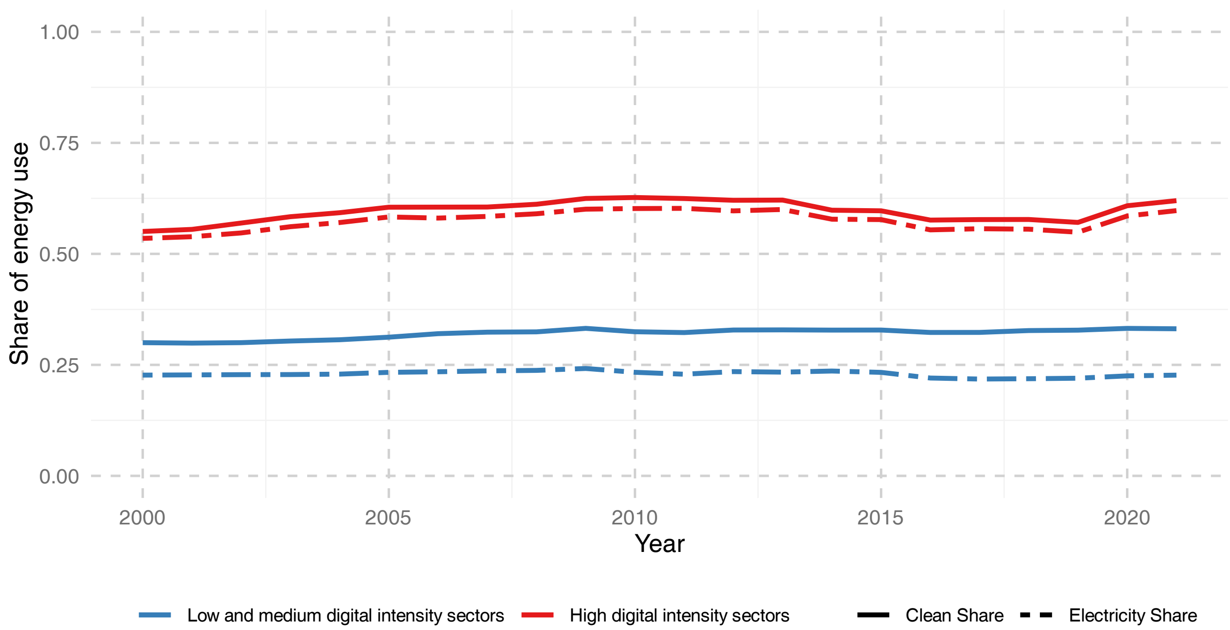
On the one hand, advanced digital technologies such as AI and ML are proving useful for the exploration of extraction fields for the oil and gas industry, allowing them to lower the cost of providing dirty energy (Hanga and Kovalchuk, 2019[60]), with similar applications in mining (Maroufkhani et al., 2022[61]). Further, both the onshore and offshore oil and gas industries are set to benefit significantly from advancements in robotics technologies (Shukla and Karki, 2016[62]; Shukla and Karki, 2016[63]). Such applications of digital technologies encourage the use of dirty energy and of machines that make use of dirty energy. Additionally, when adopting digital technologies improves efficiency in energy use, this may not only lead to energy savings: as dirty energy becomes less costly to use, demand may increase as a result, a phenomenon known as the rebound effect (OECD, 2024[64]). Such an effect was already known to be present for early digital technologies (Berkhout and Hertin, 2004[65]). Energy and carbon rebound effects have been further documented empirically recently (Peng, Zhang and Liu, 2023[66]; Peng and Qin, 2024[67]; Zhu and Lan, 2023[68]). Moreover, the energy demand from data centres not only increases overall energy demand, but it also requires stable energy supply (Bhattacharya et al., 2013[69]). Until now, fossil energy sources are better able to satisfy such inflexible electricity supply. This aspect of the digital transformation could therefore be argued to encourage dirty energy.

On the other hand, given a long history of continuous improvement and innovation in technologies considered dirty, such as fossil fuel-based power plants for electricity provision or the internal combustion engine in passenger vehicle transportation, machines using cleaner energy could be argued to have a larger potential for improvement. It has been shown that adopting AI and digital tools can support efficiency in network and power flow management in electric grids, benefitting in particular renewable energy such as wind and solar due to their innate supply fluctuations (IEA, 2023[70]). In this vein, a recent study confirmed the increasing importance of the integration of AI into the energy system for the performance of the clean energy sector (Zhang et al., 2024[71]).

Similarly, challenges related to energy storage are crucial for the clean energy transition (Kittner, Lill and Kammen, 2017[72]). Here, the predictive maintenance applications of AI are a useful tool to address these issues and may be also applied to other connected sectors of the economy, such as cars. In the automotive sector, AI applications are likely to benefit electric vehicles (EV) considerably more than conventionally powered vehicles (Ahmed et al., 2021[73]; Rigas, Ramchurn and Bassiliades, 2015[74]; Paret, Finegan and Narumanchi, 2023[75]). The reason for this is that charging efficiency and battery performance have been one of the most persistent barriers to EV adoption, aspects which can potentially profit substantially from AI applications. Additionally, another study found that the use of industrial robots had a beneficial impact on the ecological footprint of production, especially in more advanced economies (Chen, Cheng and Lee, 2022[76]). Therefore, as advanced digital solutions are adopted throughout the economy, this could disproportionately boost efficiency and productivity in clean energy, a short- to medium-term effect that has the potential to alter the relative balance of clean and dirty technologies.

Figure 2.3. Highly digital sectors use relatively cleaner energy

Share of clean energy and electricity use in manufacturing sectors over time, OECD average



Note: Energy use here is considered clean when based on one of the following sources: Electricity, Renewable municipal waste, Ambient heat (heat pumps), Biodiesels, Biogases, Industrial waste (non-renewable), Heat, Primary solid biofuels, Geothermal, Liquid biofuels, Solar thermal. Sectors aggregated by energy use in 2015. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Countries in sample: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Norway, Poland, Portugal, Romania, Slovak Republic, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States.
Source: IEA Energy End-uses and Efficiency Indicators (IEA, 2024[41]), World Input-Output Database Environmental Accounts (Corsatea et al., 2019[77]), OECD STAN database for Structural Analysis.

In this context, recent survey data suggest that the adoption of advanced digital technologies is positively correlated with green investments in firms in the both the European Union and the United States (European Investment Bank, 2023[78]). Indeed, Figure 2.3 shows that in the manufacturing sector, highly digital firms make use of significantly cleaner inputs compared to less digital firms. Despite recent improvements in less digital sectors,[17] this shows that the digitalisation of sectors is positively correlated with cleaner energy use.[18] The figure also highlights the significant role of electricity among clean energy sources, where it accounts for the largest share. This pattern is particularly pronounced in highly digital sectors, which rely more heavily on electricity as an energy source. Consequently, digitalisation is likely to further increase the use of electricity due to its complementarities with ICT capital and computer-based technologies. While electricity has the potential to drive the transition to green energy, the impact of the digital GPT on the type of energy use will partly be contingent on the shares of renewables in electricity generation and thus the greening of the electricity sector. Due to the importance of the electricity mix for clean energy provision, policy can therefore play an important role in shaping the type of energy use. If adopting the GPT indeed makes the economy's capital stock greener, the digital transformation may contribute to reducing the economy's carbon footprint in the short run while at the same time providing the potential for the greening of innovation, and thereby longer-run growth in the clean sector, as is explored in the next channel (OECD, 2022[8]).

Direction of innovation

While the digital transformation may help with the adoption of machines using green energy, digital technologies can also assist researchers themselves, enabling useful applications in R&D and fostering innovation (Hinings, Gegenhuber and Greenwood, 2018[79]; Ciarli et al., 2021[80]; Appio et al., 2021[81]). For example, digital transformation and digital connectivity have been shown to positively impact innovation (Wu and Li, 2024[82]; Cheng and Miao, 2025[83]). AI in particular, and most recently generative AI, have been attributed a transformative potential as they might allow for the autonomous discovery of ideas and for machines to be self-improving. The potential growth possibilities from this property on innovation are suggested to be significant in some of the theoretical literature (OECD, 2023[84]; Trammell and Korinek, 2023[53]). Some analyses of the topic even consider AI's capacity to be the invention of a method of inventing (IMI)[19] and serve as a research tool by "automating discovery", with profound implications for knowledge accumulation in the long run (Jovanovic and Rousseau, 2005[15]; Besiroglu, Emery-Xu and Thompson, 2022[42]).

The target of achieving net-zero requires significant advances in low-carbon technologies.[20] The "Net-Zero by 2050" IEA report (IEA, 2021[85]) makes it clear that the carbon neutrality objectives cannot be reached simply by deploying currently existing technologies at scale. While most of the global reductions in CO_2 emissions through 2030 in the net-zero scenario come from technologies readily available today, almost half of the reductions in 2050 will have to come from technologies that are currently at the demonstration or prototype phase.

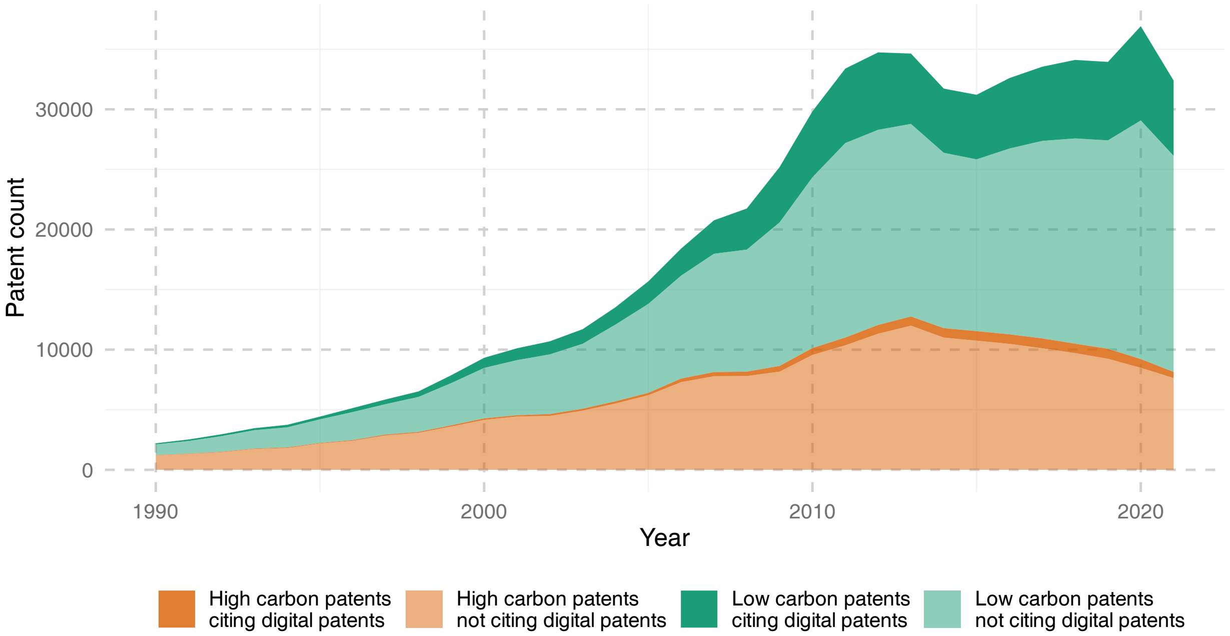
Particularly relevant in this context is the concept of directed technical change: innovation follows economic incentives, which in turn follow from path dependencies in technologies, innovation potential, and policy measures. With transformative digital technologies such as AI impacting R&D and potentially the method of inventions itself, a crucial consideration for the net-zero transition will be how this may change the profitability of research in clean energy technologies compared to the profitability of research in their dirty counterparts, potentially altering the direction of technical change and the course of the net-zero transition.

The boost to productivity in R&D may especially benefit research in technologies related to clean energy, where the potential for improvement is highest, as illustrated by the recent rapid cost declines in renewable energy sources (Glenk and Reichelstein, 2022[86]). Recent empirical evidence indicates that R&D in clean technologies has a higher capacity to absorb knowledge generated in the digital area than R&D in dirty technologies (Andres, Dugoua and Dumas, 2022[87]). This disparity could potentially be attributed to catching-up dynamics: the benefits of digital technologies on knowledge accumulation may be more pronounced in clean energy technologies because they have historically trailed behind dirty energy technologies. An example of this is carbon capture, utilisation and storage (CCUS), a relatively young technology, for which AI has been shown to be both an accelerating tool and an integral part of a research framework for the development of crucial nanomaterials (Chen et al., 2023[88]). Beyond the energy sector, AI has also been evidenced to boost advances in synthetic biology that can enable bio-based solutions in various sectors such as agriculture and environmental management. For example, the recent Nobel Prize in Chemistry was awarded to David Baker, Demis Hassabis and John Jumper for their groundbreaking work in computational protein design and the development of AlphaFold, an AI model that predicts protein structures, with potentially massive implications for developing a bioeconomy and decarbonising the chemical industry (Royal Swedish Academy of Sciences, 2024[89]; OECD, 2023[84]; OECD, 2023[90]).

As depicted in Figure 2.4, clean technologies benefit from digital knowledge spillovers much more than high-carbon technologies. Measured by the number of patents citing digital technologies, both the absolute number of low-carbon patents citing digital patents and the relative share of digital citations in low-carbon patents exceed their high-carbon counterparts. This trend has been growing over time and supports the idea that clean technology research could benefit more from improvements driven by the digital transformation than high-carbon technologies. In other words, the digital transformation may help the net-zero transition by encouraging a shift towards clean research. A few recent empirical studies have shown a positive impact of digital technologies on green innovation in firms (Cicerone et al., 2023[91]; Timmermans et al., 2023[92]; Liu, Liu and Ren, 2023[93]; Wang, Sun and Li, 2023[94]). Additionally, patented inventions in twin transition technologies (technologies that are both green and digital) have been growing faster than digital or environmental technologies alone (Aklilu, Dussaux and Verrier, 2025[95]).

Figure 2.4. Low-carbon technologies build on digital knowledge much more than dirty technologies

Low-carbon and high-carbon patents citing vs not citing digital technologies, by year



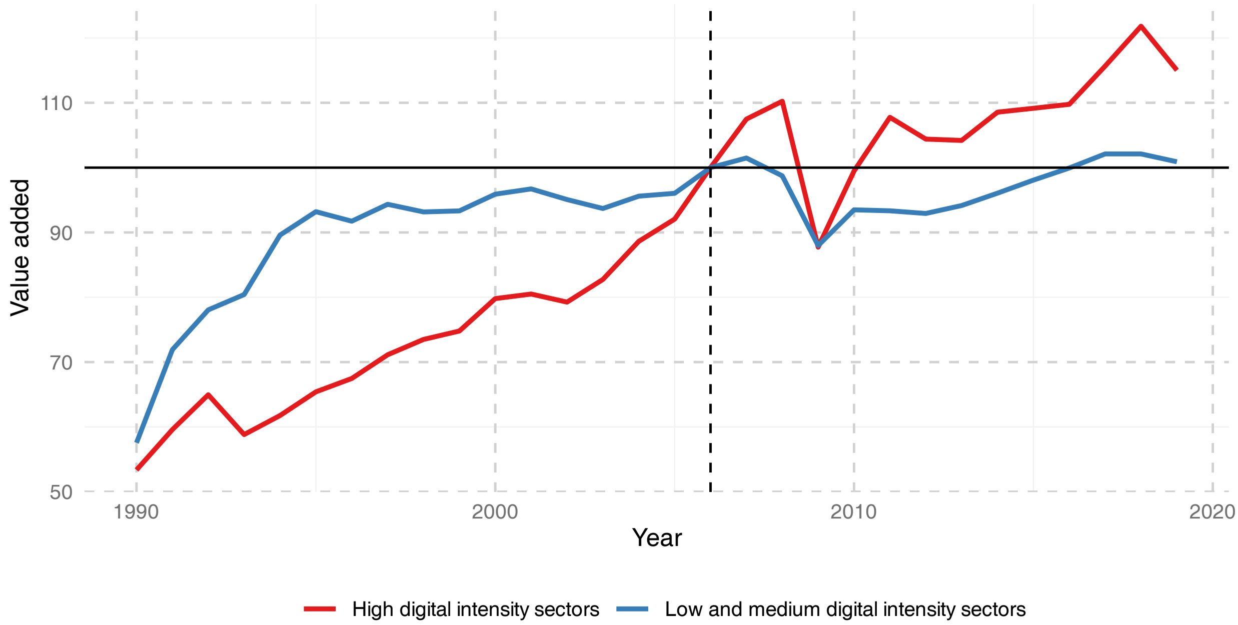
Note: Data refer to patent applications filed under the Patent Cooperation Treaty (PCT) by earliest filing date. Green technologies are identified using the taxonomy developed by Haščič and Migotto (2015[96]). Patents in high-carbon technologies include grey patents and are derived from the taxonomy developed by the IEA and EPO in 2021 (IEA, 2021[97]). Digital technologies rely on the taxonomy developed in Inaba and Squicciarini (2017[98]).
Source: OECD, STI Micro-data Lab: Intellectual Property Database, May 2024.

Scale

In the context of the net-zero targets, what matters is ultimately not only relative measures of emissions per unit of economic output, but also absolute amounts of greenhouse gas emissions. This dimension is especially relevant in the case where the digital transformation fundamentally alters the economy's long run growth dynamics. Growth in production implies a higher use of inputs, and therefore also a higher use of energy. Likewise, if the growth effect of the digital transformation is negative — a possible outcome in some economic models[21] — so will be the scale effect. With the widespread adoption of AI, many models predict increases in long run economic growth, with some even predicting explosive growth dynamics (Trammell and Korinek, 2023[53]; Erdil and Besiroglu, 2023[54]). With the net-zero transition largely incomplete and much of energy production still relying on polluting fossil fuels, such growth effects would be environmentally unsustainable due to the increasing demand for energy (some of which will be dirty). This overall growth effect could be further amplified or mitigated by the cross-sector heterogeneity in changes in the composition of demand. If sectors that grow more relative to others are particularly energy-intensive, this would further increase energy consumption.

Figure 2.5. Growth in digital intensive sectors has exceeded growth in other sectors

Growth in value added in manufacturing sectors, OECD average



Note: Deflated values. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in the sample: Austria, Belgium, Canada, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States.
Source: OECD STAN database for Structural Analysis.

As depicted in Figure 2.5, the trend in value added growth of highly digital intensive sectors has outpaced growth in less digitalised sectors since 2010.[22] This is in line with mounting evidence that the ICT sector has significantly outperformed growth in the broader economy over the past decade (OECD, 2024[99]). Indeed, recent evidence shows that growth in these highly digital intensive sectors has been a main driver of energy demand, with scale effects from digitalisation exceeding any reductions related to energy efficiency and sectoral composition (Hambye-Verbrugghen et al., 2024[100]). Moreover, this divergence in trends could further pick up momentum as new digital applications continue to emerge and the potential of AI keeps growing. It is known from the literature on past GPTs that many productivity and growth effects tend not to materialise until later in the adoption cycle, when sufficient complementary assets and technologies have been accumulated and organisations have successfully adapted to new methods (Brynjolfsson, Rock and Syverson, 2021[23]; Bresnahan, 2024[19]). Such effects may therefore still materialise, particularly in sectors with a current lower digital intensity. Conversely, the observed higher growth in digital sectors could also be driven by a mere correlation between the sectors' capacity to absorb digital technologies and their growth potential. It remains to be seen whether the digital transition will transform growth further as more sectors adopt AI and other digital technologies.

Overall effect

Understanding the interplay of the different aspects detailed above is crucial in determining how the digital transformation, including its most recent stage related to the diffusion of AI and related advanced digital technologies, will affect the net-zero transition and its pace. The literature extensively explores the role of innovation and path dependencies for the direction of technical change. The impact of the digital transformation on the direction of technical change in the long run will depend on the relative magnitudes of effects on clean and dirty machines and the state of their technologies. In the short run, potential increases in energy use, either from the direct use of energy or from increasing use of capital, may also have environmental effects and pose additional challenges to the net-zero transition.

Ultimately, which effects dominate is an empirical question. This depends on the magnitudes of the various effects, the boost to productivity in both production and innovation, and the degree of substitutability between labour and capital/energy and between clean and dirty technologies. Furthermore, the overall effect may be heterogeneous across countries, e.g. due to differences in sectoral composition or regulation.

This understanding is vital for shaping policies and strategies for a successful net-zero transition. This conceptual framework has provided some preliminary illustrative insights about the potential direction of the various channels, which are summarised in Table 2.1. It is important to keep in mind that these insights are based on recent aggregate trends, which do not allow to establish causal relationships, and may change further as the digital transformation and net-zero transition evolve. So far, despite concerns about the energy needs of computing, the capital stock in highly digital sectors has been decreasing its energy intensity faster than other sectors, pointing towards a possible beneficial outcome – at least in relative terms – for the net-zero transition. In a similar fashion, both capital using clean energy and R&D in clean technologies are positively influenced by digital technologies, indicating a potential for the digital transition to benefit clean energy. Conversely, the capital stock most directly related to digital technologies, ICT capital, is growing at a much higher rate than traditional capital. As the increasing capital stock requires energy, this could pose a challenge for the net-zero transition. Finally, aggregate sectoral growth trends suggest a potential growth effect related to digital intensity. As the digital transformation further unfolds, this could possibly imply a scale effect on the net-zero transition.

Table 2.1. Summary of the channels discussed and potential outcomes

Summarising the channels by their potential outcome for the net-zero transition based on initial aggregate insights

Channel	Potential effect on the net-zero transition's pace based on recent trends
Energy use of capital	Positive
Capital intensity	Negative
Type of energy use	Positive
Direction of innovation	Positive
Scale	Negative

Note: A positive effect on the net-zero transition refers to an accelerated decrease in emissions, while a negative effect refers to a slowing down of the net-zero transition.
Source: authors' elaboration.

3 Concluding remarks and next steps

Understanding the extent to which the digital transformation can accelerate or derail the net-zero transition is particularly relevant from a policy perspective, at a time when governments seek to both foster a sustainable digital transformation and to decarbonise the economy. However, given the complexity and multifaceted nature of the interactions between the digital transformation and the net-zero transition, it may be challenging for policy makers to design appropriate policy responses.

This paper presents an analytical framework conceptualising key economic mechanisms through which the digital transformation can affect the net-zero transition. The framework focuses on the quantity and type of energy consumed, which are key elements relevant for the net-zero transition. It considers the digital transformation as linked to the emergence and diffusion of a new general-purpose technology (GPT), which affects different sectors of the economy, boosts innovation and increases productivity for different inputs in production. The conceptual framework helps to outline key mechanisms that can be related to relevant policy levers.

Five key channels through which the digital transformation can impact the net-zero transition are outlined: i) the energy use of capital, i.e. the extent to which machines become more or less energy-using; ii) the capital intensity, i.e. the extent to which the relative balance between labour and capital may change; iii) the type of energy use, i.e. the extent to which the digital transformation may improve efficiency relatively more for clean than for dirty machines; iv) the direction of innovation, i.e. the extent to which the GPT can disproportionately boost innovation in the clean or dirty sector; v) the scale, i.e. the extent to which aggregate emissions may increase due to higher output resulting from digital-related productivity improvements.

Initial evidence based on aggregate trends, aiming at illustrating the channels proposed, has been reported, along with some tentative implications in terms of the possible direction of outcomes. However, the extent to which the digital transformation can be leveraged to reach net-zero targets remains an empirical question and a question of how societies choose to use digital tools.

The framework this paper proposes holds significant implications for policymaking. Each of the economic mechanisms can be influenced by distinct policy levers. Policies that are designed to steer the digital transformation and those intended for climate action are likely to interact through these channels in a parallel manner. It is also crucial for policy to consider the temporal differences among these channels and the heterogeneity of their effects across sectors. This understanding can pave the way for evidence-based policymaking, enabling policymakers to concentrate on diverse aspects of the complex relationship between the digital transformation and the net-zero transition.

While comprehensive into several respects, the current framework – due to its conceptual nature – does not fully explore some dimensions of heterogeneity (e.g. across firms or sectors). Sectoral heterogeneity is explored more in detail in complementary OECD work. Notably, Calvino, Dechezleprêtre and Losma (forthcoming[101]) aim at assessing the links between the digital transformation and the green transition at the sectoral level and measuring the extent to which sectors are embracing the digital and the green transitions. Building upon previous work on the digital intensity of sectors (Calvino et al., 2018[40]) and on the framework presented in this paper, the analysis focuses on key indicators of output, capital formation, labour, and innovation.

Endnotes

[1] An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment (OECD, 2019[116]).

[2] The digital transformation has been defined by the OECD as the economic and societal effects of digitisation and digitalisation, where (1) digitisation is the conversion of analogue data and processes into a machine-readable format and (2) digitalisation is the use of digital technologies and data as well as interconnection that results in new or changes to existing activities (OECD, 2019[117]). This paper more casually refers to the "digital transformation" not only as the effects of the use of digital technologies (e.g. on productivity) but also as digitalisation itself, i.e. the widespread adoption of digital technologies across the economy.

[3] Based on the taxonomy of digital intensive sectors by Calvino et al. (2018[40]).

[4] Not to be confused with generative pre-trained transformers in the context of generative AI. In this paper, we denote GPT to mean general-purpose technology.

[5] Even though energy consumption is not the only relevant element of the green transition, its quantity and type are key indicators in tackling climate targets. However, the digital transformation may have implications for other outcomes beyond energy consumption, such as, for instance, waste production (including e-waste), material requirements and associated pollution from mining, and emissions of other pollutants, e.g. PFAS, which are left outside the scope of the current framework for simplicity. Future work could broaden the framework presented in this paper by taking these additional elements into account.

[6] The role of labour may differ across sectors depending on the skill composition of the workforce. In this framework, we abstract from cross-sector heterogeneity in skill intensity, although this would be a relevant element to consider more explicitly in further analysis. See also the additional discussion in the capital intensity subsection.

[7] https://actu.epfl.ch/news/machine-learning-accelerates-discovery-of-solar-ce/

[8] The estimates brought together by de Vries (2023[7]) indicate an electricity of use of 2.9 Wh per query for ChatGPT and 6.9-8.9 Wh for AI-powered Google Search request as compared to a self-reported electricity use of 0.3 Wh per conventional Google Search.

[9] See also OECD (2023[112]) for further OECD work on compute capacity for artificial intelligence.

[10] This trend is even more apparent when distinguishing low and medium digital intensity sectors, see Figure A B.1 in the appendix.

[11] On the contrary, Acemoglu (2024[110]) argues that as future effects will depend on hard-to-learn tasks, productivity gains from AI adoption may in fact not be very large.

[12] For example, recent advances make use of LLM for modelling complex simulations (Park et al., 2023[103]; Gao et al., 2023[104]; Wu et al., 2023[105]).

[13] See the stream of literature discussing the skill-biased (and routine-biased) technological change hypotheses [e.g. Autor et al. (2003[114]) or Autor et al. (2015[115]); see also Taniguchi and Yamada (2022[113]) who show that ICT equipment appears more complementary to skilled rather than unskilled labour across OECD Member countries].

[14] The extent to which the digital transformation affects differently high-skilled and low-skilled labour might also impact globalisation and the international organisation of production, with in turn possible implications for the green transition, which are however left outside of the scope of the current discussion.

[15] Note that this also holds when including non-manufacturing sectors, see Figure A B.2 in the appendix. This is in line with the literature: see, e.g. Colecchia and Schreyer (2002[106]) and O'Mahony and Vecchi (2005[107]).

[16] In fact, a decrease in the relative price of ICT capital could also correspond to an increase in its volumes as a share of overall capital. Further extensions to the current analysis may further explore the role of ICT and non-ICT capital. Complementary ongoing work is also focusing on sectoral patterns of ICT capital formation in the context of developing a taxonomy of sectors according to the extent to which they are embracing the digital and green transitions.

[17] See Figure A B.3 in the appendix.

[18] This also holds when distinguishing low and medium digital intensive sectors, see Figure A B.4 in the appendix.

[19] Cockburn et al. (2019[17]) propose the idea that deep learning can represent a novel general-purpose invention of a method of invention; see also Bianchini et al. (2022[111]) for further discussion.

[20] Most net-zero pathways underlying climate ambitions assume the use of technologies which are not yet ready for deployment (IEA, 2021[108]).

[21] Mostly in the context of AI, either due to "catastrophic" effects or because of the lack of innovation incentives (Aghion, Jones and Jones, 2019[109]; Acemoglu and Restrepo, 2018[51]; Trammell and Korinek, 2023[53]).

[22] Note that the reported figure hides a considerable degree of within-sectoral heterogeneity, with some firms increasing value added and gaining market shares likely at the expenses of others, as well as some cross-sectoral heterogeneity. In fact, as shown in Figure A B.5 in the appendix splitting low and medium digital sectors further, low digital intensity sectors experienced higher growth than medium digital intensive

sectors throughout the observation period, potentially due to exceptionally high growth in low digital intensive industries for circumstances unrelated to the digital transformation. A similar pattern is observed for the broader economy, see Figure A B.6.

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Annex A. Formal framework

Consider an economy where the final good at time t is produced using labour as well as clean and dirty energy inputs with each a complementary capital stock. For exposition, assume a nested constant elasticity of substitution (CES) function for the final good Y_t:

$$Y_t = \left((\alpha_L L_t)^{\frac{\varepsilon-1}{\varepsilon}} + Y_{Et}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

Equation 1

Where ε is the elasticity of substitution between the labour input L_t and a combined energy-capital good Y_{Et}. This energy good is in turn produced using a range of machines x_{jit} with individual productivities A_{jit} that together make use of energy E_{jt}. Following the exposition in Acemoglu et al. (2012[102]), the energy good further combines input from two energy sectors $j \in (c, d)$: a clean and a dirty sector that each make use of complementary machine equipment.

$$Y_{Et} = \left(\left(\alpha_c E_{ct}^{\gamma} \int_0^1 A_{cit}^{\gamma} x_{cit}^{1-\gamma} di \right)^{\frac{\sigma-1}{\sigma}} + \left(\alpha_d E_{dt}^{\gamma} \int_0^1 A_{dit}^{\gamma} x_{dit}^{1-\gamma} di \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

Equation 2

Where $\gamma \in (0,1)$ is the output elasticity of energy, σ is the elasticity of substitution between the clean and dirty inputs. A number of scientists $s_{jt} \in S = 1$ is allocated to each sector to research improvements to the machines. Every scientist is randomly allocated to a machine. The probability of a successful innovation in each of the sectors $j \in (c, d)$ in each period is given by β_j. Defining aggregate technology levels as $A_{jt} \equiv \int_0^1 A_{ji} di$, this implies the following law of motion in each sector:

$$A_{jt+1} = (1 + \beta_j s_{jt}) A_{jt}$$

Equation 3

At time $t = t_{GPT}$, a new GPT arrives. Due to its general nature, its productivity increases will affect the various inputs of production as well as the creation of innovation itself. This implies a discontinuous increase in α_L,α_c,α_d,β_c,β_d and γ, which will lead to different effects:

1. α_L: the new GPT may augment labour. Workers become more productive by using the GPT in their daily lives.
2. α_c: the new GPT makes clean energy more productive. One can think of the “smart” applications of AI in grid management for e.g. wind power.
3. α_d: at the same time, the new GPT makes dirty energy more productive as well. AI and accompanying digital technologies can e.g. improve the management of oil exploration or enhance the efficiency of production processes that make use of fossil fuels. Together with an increase in α_c the productivity increase contributes to augmenting the energy-capital factor Y_E vis-à-vis labour in the final output.

4. β_c: new research methods implied by the GPT potentially imply more effective research in clean technologies.
5. β_d: in a similar fashion, research in traditionally dirty technologies may be improved as well.
6. γ: new digital technologies such as AI tend to come with large energy use due to data centres and energy used for computing power. As a result, with the adoption of the new GPT, the energy share within the Cobb-Douglas specification of the capital good may be affected.

Define each energy sector's mass of machines as $X_{jt} \equiv \int_0^1 x_{jit} di$, where $X_t = X_{ct} + X_{dt}$ represents the aggregate capital stock. Similarly define aggregate energy use as $E_t = E_{ct} + E_{dt}$. "Relevant for the green transition" can be considered anything affecting the (relative) quantity of energy use, in particular dirty energy E_{dt} (which is polluting). How the different channels influence this variable depends on the relative magnitudes of the different variables as well as the substitution elasticities ε and σ.

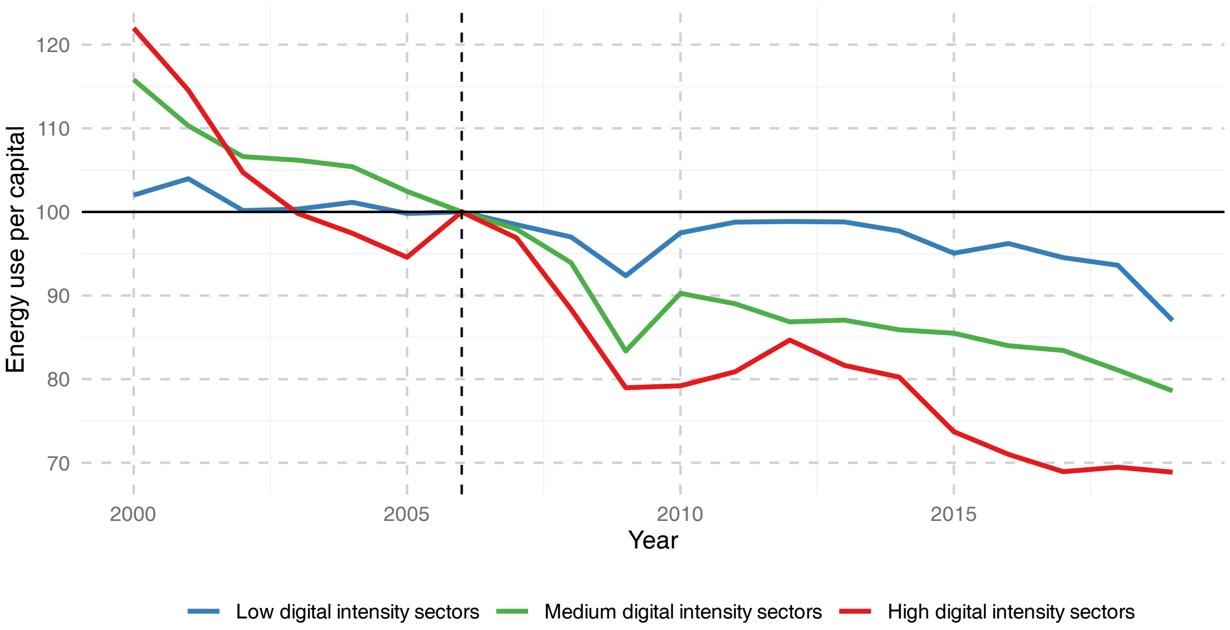
1. Energy use of capital: $\Delta \frac{E_t}{X_t}$
2. Capital intensity: $\Delta \frac{X_t}{X_t + L_t}$
3. Type of energy use: $\Delta \frac{E_{ct}}{E_{dt}}$
4. Direction of innovation: $\Delta \frac{\dot{A}_{ct}}{\dot{A}_{dt}}$
5. Scale: ΔE_t

Additionally, for $j \in (L, c, d)$ it is the case that:

$$\alpha_j = \begin{cases} 1, & t < t_{GPT} \text{ (before GPT)} \\ \geq 1, & t \geq t_{GPT} \text{ (with new GPT)} \end{cases}$$

Annex B. Supplementary graphs

Figure A B.1. Energy intensity, distinguishing medium and low digital intensive sectors



Energy intensity computed as energy end use per net capital stock (chain-linked volume, reference year 2015) for select sectors. Sectors in sample (ISIC Rev. 4 2-digit classification): 10-12, 13-15, 16-18, 19, 20-21, 23, 24, 29-30, 31-32. Sectors are classified as digital intensive following the taxonomy by Calvino et al. (2018[40]). Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in sample: Austria, Belgium, Canada, Czechia, Denmark, Finland, France, Japan, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, United Kingdom, United States.
Source: IEA Energy End-uses and Efficiency Indicators (IEA, 2024[41]), OECD STAN database for Structural Analysis.

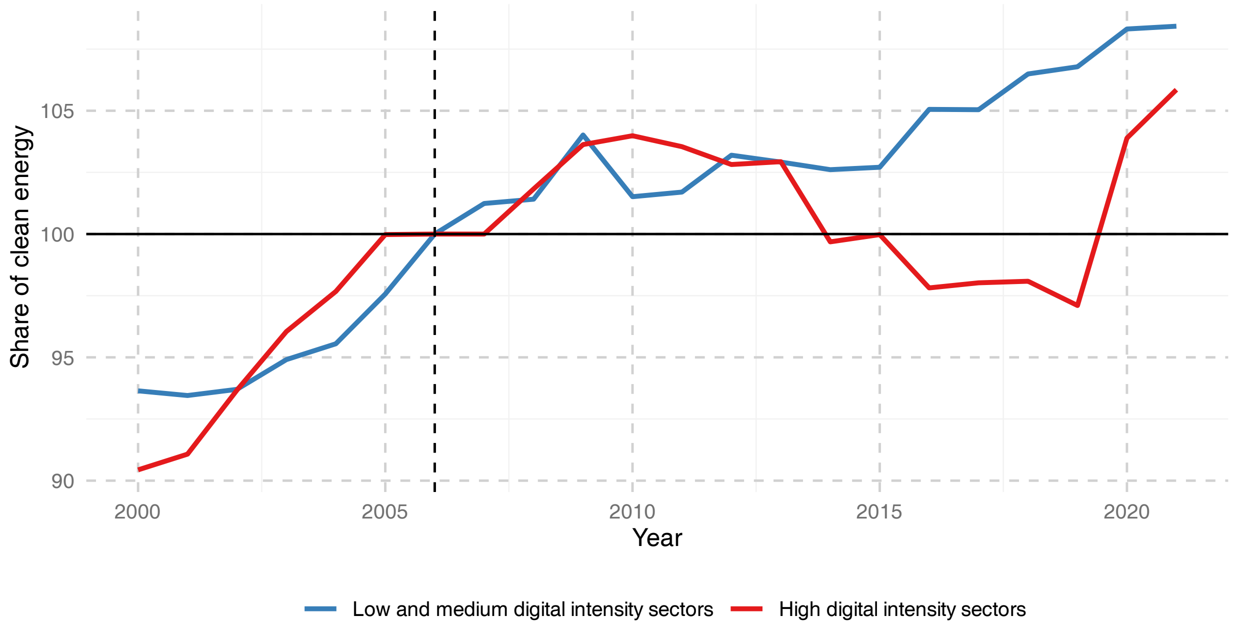
Figure A B.2. Capital deepening of ICT capital and total capital in the wider economy

Capital intensity across manufacturing and non-manufacturing sectors over time, average over selected OECD Member countries

Note: Capital intensity computed as the chain-linked volume measure of the capital stock (reference year 2015) over the number of full-time equivalent jobs. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in the sample: Austria, Czechia, France, Italy, Netherlands, Norway, United States.
Source: OECD STAN database for Structural Analysis.

Figure A B.3. Trends in clean energy use

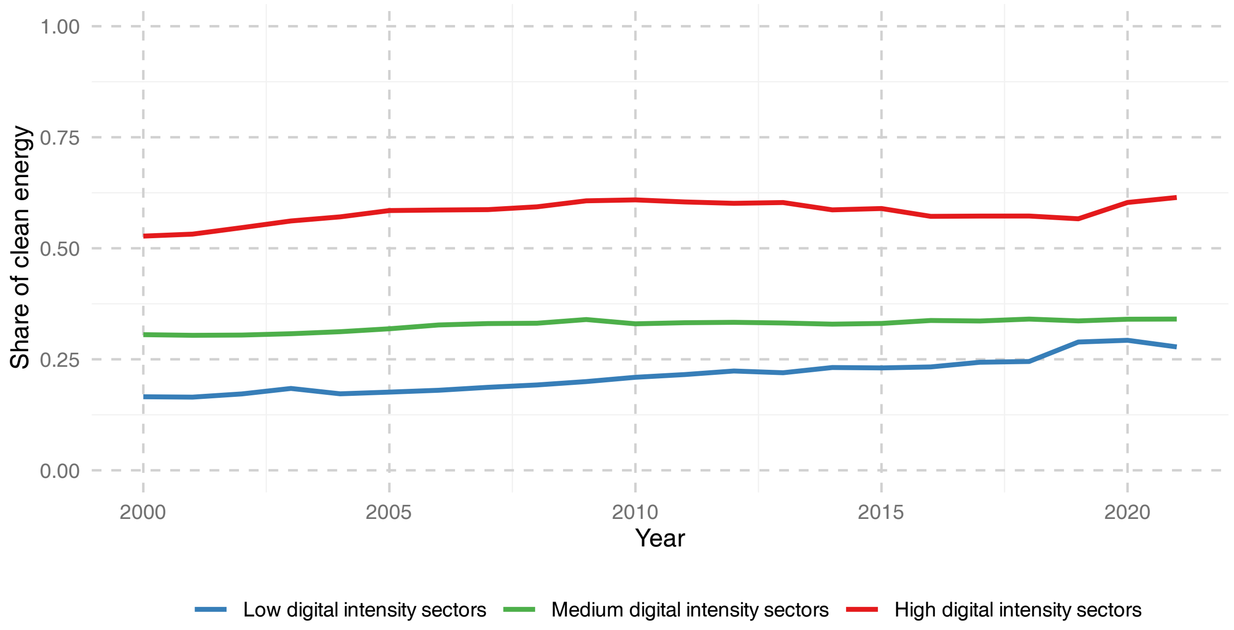
Growth in the share of clean energy use in manufacturing sectors over time, OECD average



Note: Energy use here is considered clean when based on one of the following sources: Electricity, Renewable municipal waste, Ambient heat (heat pumps), Biodiesels, Biogases, Industrial waste (non-renewable), Heat, Primary solid biofuels, Geothermal, Liquid biofuels, Solar thermal. Sectors aggregated by energy use in 2015. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in sample: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Norway, Poland, Portugal, Romania, Slovak Republic, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States.
Source: IEA Energy End-uses and Efficiency Indicators (IEA, 2024[41]), World Input-Output Database Environmental Accounts (Corsatea et al., 2019[77]), OECD STAN database for Structural Analysis.

Figure A B.4. Clean energy shares, distinguishing medium and low digital intensive sectors

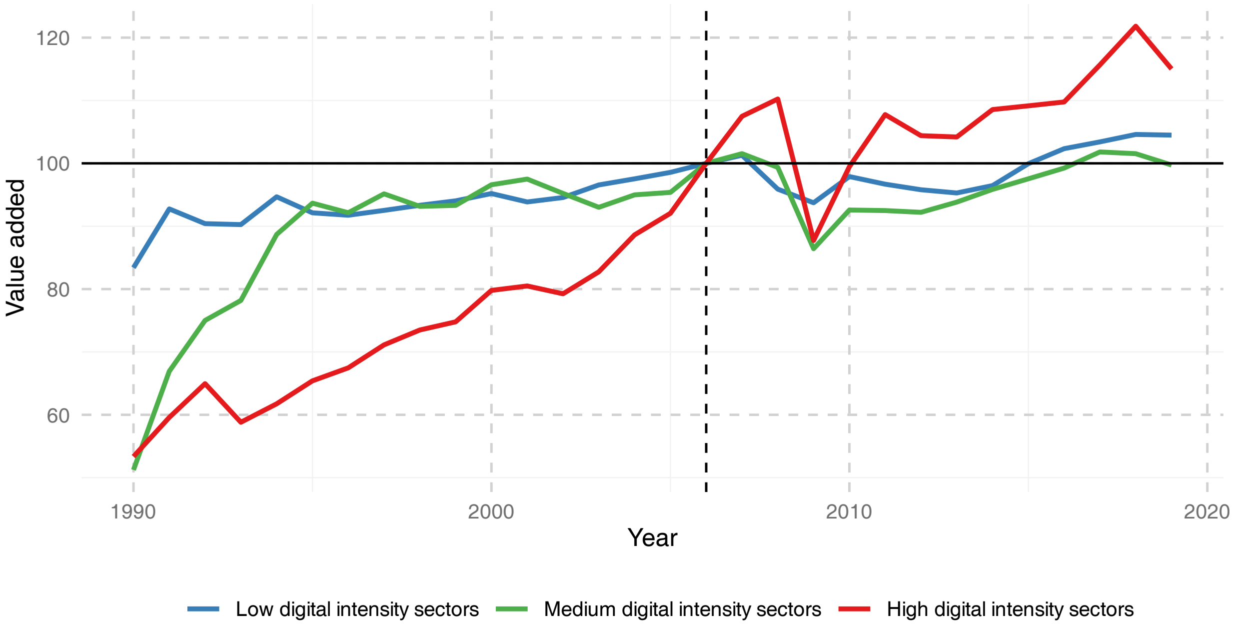
Share of clean energy use in manufacturing sectors over time, OECD average



Note: Energy use here is considered clean when based on one of the following sources: Electricity, Renewable municipal waste, Ambient heat (heat pumps), Biodiesels, Biogases, Industrial waste (non-renewable), Heat, Primary solid biofuels, Geothermal, Liquid biofuels, Solar thermal. Sectors aggregated by energy use in 2015. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Countries in sample: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Norway, Poland, Portugal, Romania, Slovak Republic, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States.
Source: : IEA Energy End-uses and Efficiency Indicators (IEA, 2024[41]), World Input-Output Database Environmental Accounts (Corsatea et al., 2019[77]), OECD STAN database for Structural Analysis

Figure A B.5. Growth trends when distinguishing low and medium intensive sectors

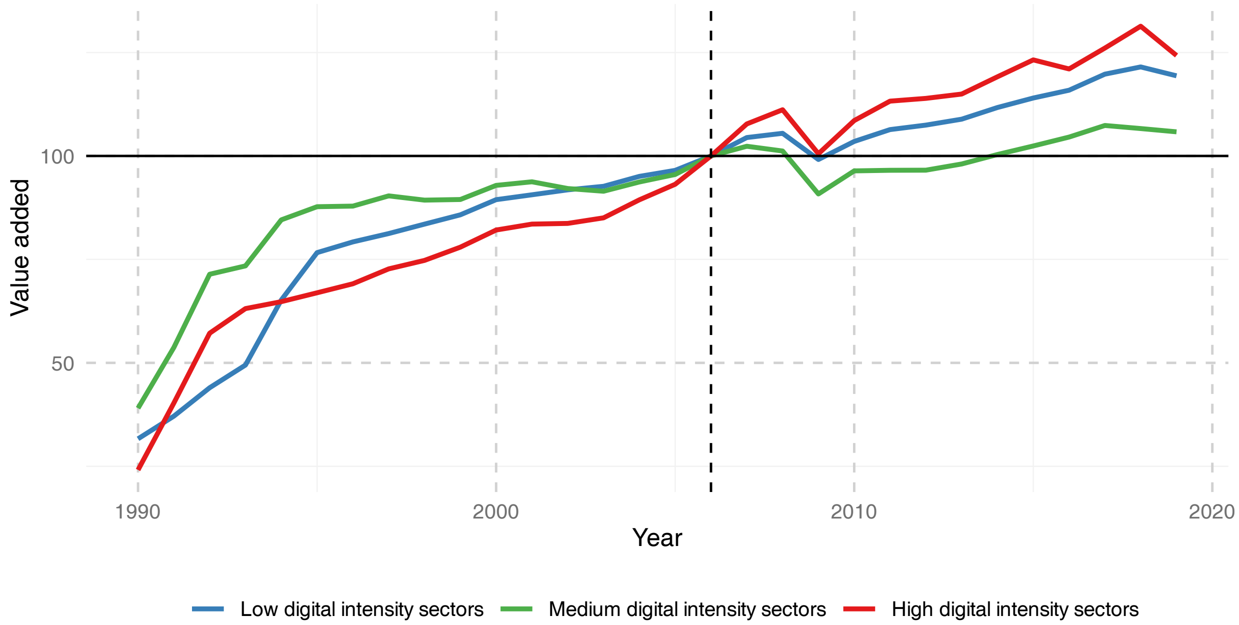
Growth in value added in manufacturing sectors, OECD average



Note: Deflated values. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in sample: Austria, Belgium, Canada, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States.
Source: OECD STAN database for Structural Analysis.

Figure A B.6. Growth in sectors by digital intensity in the wider economy

Growth in value added across manufacturing and non-manufacturing sectors, OECD average



Note: Deflated values. Average over countries weighted by GDP by expenditure approach, US $, volume, constant PPPs, reference year 2015. Index year 2006. Countries in the sample: Austria, Belgium, Canada, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States.
Source: OECD STAN database for Structural Analysis.