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Digital technology diffusion in the age of AI: Cross-country evidence from microdata

Flavio Calvino[1], Hélder Costa[1], Daniel Haerle[1]

This paper analyses firms' use of AI, big data analysis, internet of things, robotics and 3D printing across 15 OECD Member countries. It documents seven stylised facts on digital technology diffusion in the age of AI. Advanced technologies tend to build on enabling ones and diffusion varies considerably by sector and technology. Larger firms exhibit higher uptake, and this is not driven by sectoral composition. Human and technological capital – including education, ICT skills and firms' digitalisation – emerge as critical enablers. Adopters tend to be more productive than non-adopters, with the notable exception of 3D printing, but part of the observed productivity premia can be attributed to differences in human and technological capital. These factors are associated with higher productivity and contribute to explaining adopters' productivity advantages, particularly in the case of AI. Policies should combine technological, skill development and sector-sensitive measures to accelerate diffusion and unlock productivity.

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Executive summary

This paper provides a comprehensive analysis of advanced digital technology diffusion in the age of artificial intelligence (AI), leveraging official, representative microdata across 15 OECD Member countries. These data are analysed with a harmonised methodology, using a common statistical code developed by the OECD and distributed to a network of project participants with access to the source microdata. These surveys cover the period 2017-2023 and therefore do not yet fully capture the recent boom in generative AI.

This paper discusses five advanced digital technologies: AI, big data analysis, internet of things (IoT), robotics and 3D printing. Recent adoption rates of AI and 3D printing range from 4% to 10%, while big data analysis and IoT are more widespread among firms at about 25%. This broad technological scope highlights relevant interdependencies and the technology-specific patterns and drivers of diffusion, as well as the heterogeneous impact of diffusion on the economy. The analysis focuses on the key characteristics of adopters, the role of policy-relevant enablers of technology diffusion, and the links between the use of such advanced technologies and productivity. Drawing on cross-country evidence from Belgium, Canada, Denmark, Estonia, France, Germany, Ireland, Israel, Italy, Japan, Korea, the Netherlands, Portugal, Switzerland and the United Kingdom, the analysis uncovers seven stylised facts:

1. There are significant interdependencies among digital technologies: more advanced technologies tend to build on enabling ones, such as cloud computing, customer relationship management (CRM) and enterprise resource planning (ERP) software, along with fast broadband connectivity. These are, in fact, often used by firms when advanced technologies are adopted.
2. The diffusion of advanced digital technologies exhibits significant sectoral heterogeneity. This pattern is consistent across countries, with AI and big data analysis showing broader adoption in ICT and professional and scientific services, IoT displaying more widespread adoption across sectors, and robotics and 3D printing being particularly prevalent in manufacturing and utilities.
3. Larger firms are more likely to adopt advanced digital technologies, and this is not driven by sectoral composition. For example, across the countries considered, large firms are on average 20 percentage points more likely to adopt AI than small firms with similar characteristics, with this gap ranging from 5 to 37 percentage points.
4. Both human capital (in the form of ICT skills and training) and technological capital (proxied by the use of other digital technologies and digital infrastructure) are key to the adoption of advanced digital technologies. For AI, five of the six countries in which ICT skills data are available show a positive association of AI adoption with ICT skills; two of five available countries for ICT training; and all of the available nine countries for technological capital.
5. Tertiary education and technical occupations appear to be critical for the adoption of advanced digital technologies. For example, in Denmark, the Netherlands and Portugal, a one percentage point increase in the share of tertiary-educated workers is associated with a higher likelihood of AI adoption of 0.53, 0.24 and 0.15 percentage points, respectively.

6. Adopters of advanced digital technologies tend to be more productive than other firms, although this does not imply a causal link. For AI, the productivity advantage of adopters ranges from 7.7% in France to 31% in Belgium. These productivity advantages are stronger in large firms.
7. Part of the observed productivity advantages can be attributed to differences in human and technological capital. These factors are themselves associated with higher productivity and contribute to explaining adopters' productivity advantages, particularly in the case of AI and IoT. For instance, when controlling for human and technological capital, only two of ten countries retain a significant AI-related productivity advantage.

These results carry relevant policy implications. While different advanced technologies vary in their users and sectoral reach, pointing to the need for policy to tailor interventions to sector-specific dynamics, policymakers should also consider the complementarities and path dependence that shape the technology diffusion process. A broad policy mix should therefore include measures aimed at strengthening firms' digital capabilities and digital infrastructure, including connectivity, while fostering skill development for both ICT specialists and the wider workforce.

Human and technological capital are particularly critical in the age of AI. In fact, productivity premia of AI adopters depend on complementary investments, including those in specialised skills, intangible assets and technology. While the analysis suggests that productivity gains are currently more pronounced for technologies such as big data analysis, firm-level returns from AI adoption may still be in the process of fully materialising. As the technology evolves and new firm-level data become available, it is important to continue monitoring these dynamics closely – both to better understand the productivity effects of AI adoption and to assess its implications for competition along the value chain.

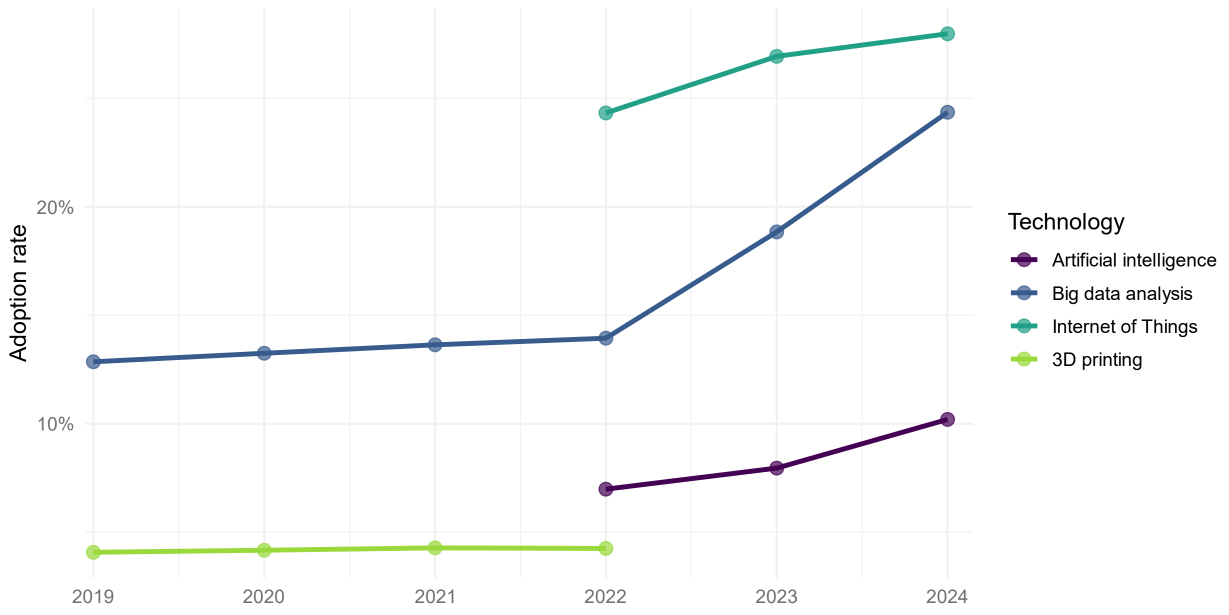
1 Introduction

The diffusion of advanced digital technologies across firms has been a topic of high interest for policymakers, given their potential to transform economies and improve economic and social outcomes. Technologies such as AI have the potential to boost productivity by increasing efficiency, fostering innovation and improving decision-making with potentially significant aggregate productivity effects (OECD, 2024[1]; Filippucci, Gal and Schief, 2024[2]; Filippucci et al., 2025[3]). As productivity growth is a key driver of wages, these technologies can also play a crucial role in improving living standards, although this depends on how the productivity gains are shared between capital and labour. Additionally, in the context of the global climate crisis, advanced digital technologies may accelerate the green transition by optimising resource use and enabling firms to adopt more sustainable practices (OECD, 2024[4]; OECD, 2024[5]). However, as computational needs grow, the digitalisation of economic processes could also increase energy use (Calvino, Dechezleprêtre and Haerle, 2025[6]). Therefore, understanding current patterns of technology diffusion across OECD Member countries, the drivers of adoption, and the links between technology use and productivity is essential for designing policies that fully harness the benefits of advanced digital technologies, while also addressing potential barriers.

As illustrated in Figure 1.1, firm-level adoption of advanced digital technologies has been steadily increasing across OECD Member countries in recent years – see, for example, OECD (2024[1]) for a comprehensive overview of recent trends in technology diffusion. Despite this aggregate upward trend, technologies such as big data analysis, IoT, 3D printing and, most notably, AI remain in use by only a minority of firms in the observed period, indicating that diffusion is still at a relatively early stage. Looking ahead, the generative capabilities of recent AI models, combined with their intuitive use, may offer firms opportunities to integrate AI more seamlessly into their processes. For instance, Chatterji et al. (2025[7]) recently documented that ChatGPT's adoption reached over 700 million weekly active users as of July 2025, with 27% of the 2.6 billion daily messages being work-related, while OECD (2025[8]) suggests that nearly a third of SMEs in some OECD countries recently used generative AI. However, aggregate patterns conceal substantial heterogeneity across countries, sectors and firms. Understanding the factors driving adoption, the interdependencies among different technologies and the implications for productivity as diffusion progresses is therefore essential for policy and research.

Figure 1.1. Aggregate trends in technology adoption

Share of technology adoption among firms, OECD averages (3-year moving average) for selected technologies



Note: OECD averages are calculated when data are available for at least 60% of OECD Member countries. As data are collected at different intervals, coverage may vary over time. Missing values are replaced, where possible, with the most recent observation from the previous three periods. Averages are then computed as a simple mean of Member countries for each indicator, using 3-year trailing moving averages. The data are based on national ICT surveys. For more details see the OECD ICT Access and Usage by Businesses database webpage: https://data-explorer.oecd.org/s/3il.
Source: OECD ICT Access and Usage by Businesses database (OECD, 2025[9]).

This paper aims to provide further evidence on the diffusion patterns of advanced digital technologies, with a focus on the firm characteristics and policy-relevant enablers associated with a higher likelihood of adoption, and the role of technology use for productivity, using network and regression analysis based on comprehensive microdata.[1] This approach offers significant advantages over the officially published descriptive statistics, as it accounts for several important confounding factors that are related to technology adoption and firm productivity, such as firm size and age, industry, and some relevant complementary assets, notably related to human and technological capital. Specifically, this paper focuses on five technologies, henceforth referred to as advanced digital technologies (AI, big data analysis, IoT, robotics and 3D printing), and covers 15 OECD Member countries: Belgium, Canada, Denmark, Estonia, France, Germany, Ireland, Israel, Italy, Japan, Korea, the Netherlands, Portugal, Switzerland and the United Kingdom.

Among advanced digital technologies, AI stands out as a likely general-purpose technology with transformative potential across all sectors (Filippucci et al., 2024[10]; Calvino, Haerle and Liu, 2025[11]). Unlike more domain-specific tools such as robotics or 3D printing, AI enables adaptive learning and decision-making, allowing firms to automate cognitive tasks, optimise complex processes, and generate new knowledge (Calvino, Reijerink and Samek, 2025[12]). Its versatility can amplify the potential of other technologies. For example, AI, IoT and robotics are increasingly converging to form highly responsive and autonomous systems, with AI providing the intelligence layer (see also OECD (2023[13]) for further discussion about AI capabilities), IoT supplying real-time data, and robotics enabling physical action (Börner et al., 2020[14]). This supports the development of autonomous, adaptive systems across sectors, reflecting a broader trend of technological co-evolution. Due to the synergies between these technologies, their joint transformative potential is often highlighted in policy discussions, such as by the European

Commission (European Commission, 2021[15]). However, these characteristics also raise unique policy challenges, from addressing skill gaps to ensuring trustworthy use, underscoring the importance of understanding AI diffusion patterns for aggregate growth.

Given the substantial heterogeneity of diffusion across countries, driven by differences in firm characteristics, policy environments and economic context, this paper contributes to the discussion through a distributed microdata approach: the Digital Diffuse project. This methodology allows for the analysis of comprehensive and representative firm-level data in a decentralised manner, producing comparable output while complying with confidentiality constraints. With respect to the study by Calvino and Fontanelli (2023[16]), which this paper builds upon, this work significantly broadens the scope of analysis by considering different advanced digital technologies beyond AI, as well as focusing in more detail on the role of human capital, including additional education and occupation measures, on the role of technological capital, further analysing technological interdependencies, and considering further productivity proxies across more countries. Broadening the technological scope is critical not only for directly addressing relevant interdependencies but also because different technologies, due to their intrinsic characteristics, can exhibit specific patterns of adoption, different drivers of diffusion and heterogeneous impacts on the economy, whose consideration can be critical for policy action.

The paper leverages data from official information and communications technology (ICT) surveys, balance sheet data and linked employer-employee data (LEED). ICT surveys are the main source of information and are representative of the underlying firm population of reference. Balance sheet data provide, for some countries, additional information on firm financials, notably relevant for productivity estimation. LEED allow zooming in on the human capital drivers of technology adoption. Balance sheet data and LEED are merged, when available, with the ICT surveys to provide additional insights by allowing for more detailed measures of productivity and human capital.

The data are analysed in the context of the Digital Diffuse project, which uses a common statistical code developed by the OECD and is run in a decentralised manner on the country-specific surveys by national experts. The Digital Diffuse program generates a set of summary statistics and regression outputs based on the abovementioned data sources, enabling a uniquely detailed outlook on technology use, its drivers and role for the economy. The main results of the analysis can be summarised in seven stylised facts.

First, looking at the role of advanced technologies within the digital technological capital in firms highlights that there are significant interdependencies among such technologies. Advanced digital technologies are, in fact, often adopted together, pointing towards their technological interrelatedness, and often build on foundational ones. Key software and digital infrastructure enablers, such as cloud computing, CRM and ERP software, along with fast broadband connectivity, play a central role in the analysed networks of technological co-occurrences. This highlights the importance of both technological and organisational interdependencies in the diffusion of digital technologies.

Second, the diffusion of advanced digital technologies exhibits significant sectoral heterogeneity. Specifically, AI and big data analysis show broader adoption across service-oriented sectors, particularly in ICT and professional and scientific services. IoT appears to be more versatile, with more widespread adoption across sectors. Conversely, 3D printing and robotics are particularly relevant to the manufacturing and utilities sectors, highlighting their industrial applications. These patterns suggest that the uptake of specific technologies is highly sector dependent.

Third, larger firms tend to be more likely to adopt advanced digital technologies. The likelihood of adoption increases monotonically with firm size for most technologies and countries. This notably holds after accounting for the sectoral composition of countries and for other firm characteristics notably firm age, which possibly suggests relevant scale advantages in the adoption of advanced digital technologies.

Fourth, human and technological capital are consistently associated with a higher likelihood of using advanced digital technologies. Human capital is proxied by the presence of ICT specialists and ICT training for non-ICT personnel, while technological capital includes measures of digital capabilities and infrastructure, as proxied by the share of adoption of other digital technologies and the use of fast broadband. These assets therefore prove to be critical and policy-relevant enablers for uptake, given their complementarities with advanced digital technology adoption.

Fifth, zooming in on human capital suggests that education and technical occupations appear critical for the diffusion of advanced digital technologies. In fact, leveraging detailed worker-level information from LEED in selected countries further highlights that both the share of workers with bachelor's degrees and the share of workers in technology-related occupations, so-called "techies", are positively associated with the adoption of several advanced digital technologies.

Sixth, adopters of advanced digital technologies tend to be more productive than non-adopters, although this does not imply a causal link. Both descriptive statistics and regression analyses often indicate higher productivity levels among adopting firms, with the notable exception of 3D printing. Across technologies, these productivity premia are strongest in larger firms, with a productivity premium observed also for larger firms adopting 3D printing.

Seventh, human and technological capital are also associated with higher productivity, likely explaining some of the observed productivity premia of adopters, especially in the case of AI and IoT. In fact, both human capital, in the form of ICT skills and training, and technological capital, proxied by the use of other digital technologies and digital infrastructure, are strongly associated with higher productivity levels across the countries and technologies analysed. Moreover, when controlling for these factors, the previously observed positive correlation between the adoption of advanced digital technologies and productivity diminishes. Only the adoption of big data analysis and, to some extent, the use of robots tend to remain associated with higher productivity levels across several countries. Notably, for AI, the productivity advantage of adoption is not observed in most countries when controlling for human and technological capital, implying a low productivity premium from AI adoption alone in the period under analysis.

Understanding the patterns of advanced digital technology diffusion, the role of its enablers and the links between technology adoption and productivity is essential for policymakers and businesses aiming to accelerate digital adoption and maximise productivity gains. The findings in this paper uncover key stylised facts based on comprehensive microdata covering a wide number of countries and advanced digital technologies analysed with a novel methodology and perspective.

The key findings discussed above highlight a critical role of human and technological capital in both the adoption of advanced digital technologies and productivity. This suggests the relevance for policymakers of focusing on a comprehensive policy mix that strengthens firms' digital capabilities, supports their investment in complementary assets and upskilling, and strengthens digital infrastructure, along with both technical and non-technical skills in the workforce. These implications are particularly relevant in the context of the rapid emergence of generative AI. Although often perceived as a user-friendly technology that lowers entry barriers, realising productivity gains will likely remain dependent on such enablers, with a key role for both specialised competences to develop tailor-made solutions and of critical thinking to understand when and how to use generative AI effectively (see also OECD (2024[17]) and Calvino, Reijerink and Samek (2025[12])).

The remainder of the paper is organised as follows. Section 2 discusses related literature on the adoption and productivity effects of advanced digital technologies. Section 3 discusses the data and methodology employed in the analysis across participating countries. Section 4 presents the seven stylised facts documented in this paper. Section 5 provides concluding remarks and discusses possible next steps for analysis.

2 Existing literature on advanced digital technologies: a brief overview

The literature investigating the adoption of digital technologies is extensive, with the concept of digital technology evolving over time from the simple adoption of computers (Bresnahan, Brynjolfsson and Hitt, 2002[18]) to computer-controlled machines (Bartel, Ichniowski and Shaw, 2007[19]), adoption of internet services and other web-related services (Amador and Silva, 2025[20]), to more recent advanced digital technologies such as cloud computing, big data analysis, IoT and AI (Acemoglu et al., 2022[21]; Cho et al., 2023[22]; Cette, Nevoux and Py, 2022[23]), among others.

This brief overview mainly focuses on firm-level evidence about the five advanced technologies analysed in this report, in particular AI, big data analysis, IoT, robotics and 3D printing. In this work, while highlighting the relevant technological specificities and the critical heterogeneity underpinning their characteristics and diffusion, these technologies are sometimes altogether referred to as "advanced digital technologies", considering the critical role of digital elements in characterising their key functionalities, e.g. creating physical objects from digital models, enabling industrial applications and programming to autonomously perform tasks, leveraging or interacting with, as well as collecting or exchanging, data, including through remote monitoring or control. These technologies typically require some level of digitalisation to operate. In this sense, they are more advanced than e.g. computers or standard software, are often included in the most recent waves of surveys monitoring the state of digitalisation, as further discussed in the next section, and are at the centre of debates about the most recent implications of the digital transformation.

Additionally, they tend to be technologically connected, with AI playing a crucial role in advancing the digital technology ecosystem (OECD, 2024[1]), e.g. acting as an "intelligence layer" that turns connected devices and data streams into adaptive, autonomous systems across domains (Börner et al., 2020[14]), such as in cyber-physical systems like IoT (Radanliev et al., 2020[24]; Oliveira et al., 2021[25]) or robotics (Kroemer, Niekum and Konidaris, 2021[26]; Liu et al., 2022[27]) as well as 3D printing (Goh, Sing and Yeong, 2020[28]; Ciccone, Bacciaglia and Ceruti, 2023[29]). Similarly, AI and big data analysis reinforce each other: big data pipelines make modern AI feasible, while AI unlocks predictive and autonomous analytics that traditional methods could not deliver in complex production contexts (Peres et al., 2020[30]; Gandomi, Chen and Abualigah, 2023[31]; Himeur et al., 2022[32]).

A first line of research regarding technology adoption focuses on the characteristics of firms that adopt advanced digital technologies (Cirillo et al., 2023[33]; McElheran et al., 2024[34]). This builds upon previous literature focusing on firms and digitalisation, including, for instance, the work of Bartelsman, Hagsten and Polder (2018[35]) and Bartelsman, van Leeuwen and Polder (2016[36]), which analyse previous ICT waves. A second line of research focuses more closely on the links between the use of advanced digital technologies by firms and productivity or other firm-level outcomes, building upon the broader literature on the returns to digitalisation (see Biagi (2013[37]) or Draca, Sadun and Van Reenen (2009[38]) for reviews of this topic). Further discussion of some analyses contributing to these streams of research is provided below, highlighting key findings and research gaps.

Characteristics of adopters of advanced digital technologies

Several firm characteristics are associated with a higher likelihood of adopting advanced digital technologies. The most common characteristic positively related to their use is firm size. In analyses focusing on different advanced digital technologies, the evidence suggests that adopters are, on average, larger in terms of turnover and number of employees. This has been documented by several studies, such as Zolas et al. (2020[39]) and Acemoglu et al. (2022[21]) for AI and robotics in the United States, Calvino et al. (2022[40]) for IoT, big data analysis and 3D printing in Italy, Calvino et al. (2022[41]) and Calvino and Fontanelli (2023[16]) for AI in the United Kingdom and several other OECD Member countries, and Cerqueira, Alexandre and Portela (2023[42]) for big data analysis in Portugal. This suggests the existence, for several advanced digital technologies of scale advantages, of economies of scale, or network externalities, which may lead to higher adoption by larger firms.

The relationship between firm age and the use of advanced digital technologies is less clear once not only the relevant links between firm age and size are considered, but also the characteristics of the respective technology itself. A number of studies find that younger firms are more likely to adopt advanced digital technologies, such as Acemoglu et al. (2022[21]) for AI and robotics, Calvino et al. (2022[40]) for big data analysis, IoT and 3D printing, Cerqueira, Alexandre and Portela (2023[42]) for big data analysis, and Cho et al. (2023[22]) for AI, big data analysis, IoT and 3D printing. Meanwhile, Zolas et al. (2020[39]) find the opposite for AI and robotics.

Human capital also seems to play a relevant role in the adoption of advanced digital technologies. In fact, firms adopting advanced digital technologies often seem to employ a more skilled workforce, which has been documented for earlier ICT technologies (Bresnahan, Brynjolfsson and Hitt, 2002[18]; Abowd et al., 2007[43]; Haller and Siedschlag, 2011[44]) as well as for big data analysis (Calvino et al., 2022[40]; Cerqueira, Alexandre and Portela, 2023[42]), IoT and 3D printing (Calvino et al., 2022[40]), and AI (Calvino et al., 2022[41]; Calvino and Fontanelli, 2023[16]; Mammadov et al., 2024[45]). Additionally, human capital in the form of managerial capabilities and skills has also been shown to play a role in the adoption of these technologies (Gulzar, Naqvi and Smolander, 2025[46]; Calvino et al., 2022[40]). Particularly in the case of AI, Borgonovi et al. (2023[47]) highlight that leading AI employers exhibit higher demand for AI professionals combining technical expertise with leadership, innovation, and problem-solving skills, while Green (2024[48]) finds that occupations highly exposed to AI have seen a significant rise in demand for cognitive, emotional and digital skills over the last decade. Additionally, Lane (2024[49]) finds that more skilled occupations are more exposed to AI and will likely face higher disruption. This is supported by firms reporting the need for highly educated workers in their decision to adopt AI (Lane, Williams and Broecke, 2023[50]; OECD, 2025[8]).[2]

Furthermore, the adoption of advanced digital technologies does not usually happen in isolation. Adopters were often already more digitalised, suggesting that prior digitalisation is an important enabler of adopting the most advanced digital technologies, such as AI (Zolas et al., 2020[39]; Acemoglu et al., 2022[21]; Cho et al., 2023[22]; Calvino and Fontanelli, 2023[16]; Calvino and Fontanelli, 2024[51]; McElheran et al., 2024[34]). Relevant complementarities between enabling and more advanced digital technologies are further highlighted by Calvino, Criscuolo and Ughi (2024[52]), focusing on digital technology diffusion during COVID-19 in Europe, as well as by Zolas et al. (2020[39]) in the United States. Also, technical factors such as digital infrastructure and enabling technologies have been identified as enablers of successful technology adoption (Gulzar, Naqvi and Smolander, 2025[46]).

A relevant role of other firm characteristics in the adoption of advanced digital technologies has also been documented, although less extensively studied. In particular, firms that engage in R&D (Calvino et al., 2022[40]), as well as firms that are more export-intensive (Haller and Siedschlag, 2011[44]; Koch, Manuylov and Smolka, 2021[53]), are more likely to adopt digital technologies. Finally, geographical location seems to play an important role, with adopters of advanced digital technologies more likely to be located geographically close to the presence of ICT sectors (Calvino et al., 2022[40]; Dahlke et al., 2024[54]), often in capital cities (Haller and Siedschlag, 2011[44]; Calvino et al., 2022[41]).

Advanced digital technologies, productivity and other firm-level outcomes

The productivity benefits of the adoption of advanced digital technologies by firms are not yet entirely clear and may vary by technology and timing. Some papers find no relationship between the adoption of some advanced digital technologies and productivity, consistent with the "Modern Productivity Paradox" (Solow, 1987[55]). This discrepancy between technology diffusion and productivity has been addressed by the J-curve hypothesis, which suggests that while adoption may not yield positive immediate effects, possibly even first inducing a decline in productivity, it brings about positive productivity impacts only in the medium to long run due to complementary investments (Brynjolfsson, Rock and Syverson, 2021[56]).

Indeed, for ICT more generally, Draca, Sadun and Van Reenen (2009[38]) argue that when taking into account both ICT capital and complementary organisational capital, ICT has contributed to productivity growth. Similarly, Biagi (2013[37]) emphasises the general-purpose nature of ICT technologies, which have raised productivity, accounting for both organisational changes and human capital. For the case of AI, Brynjolfsson, Rock and Syverson (2017[57]; 2021[56]) and Acemoglu et al. (2022[21]) argue that the main cause of a lack of observed productivity effects is the delay between recognition of a new technology's potential and its measurable effects. This may be especially pronounced for advanced digital technologies, such as AI, with potential general-purpose characteristics that are still evolving (Agrawal, Gans and Goldfarb, 2025[58]; Cockburn, Henderson and Stern, 2019[59]; Brynjolfsson, Rock and Syverson, 2019[60]; Crafts, 2021[61]; Klinger, Mateos-Garcia and Stathoulopoulos, 2018[62]), an example of which is the recent emergence of generative AI.[3] Indeed, McElheran et al. (2025[63]) find causal evidence of J-curve-shaped returns for the use of industrial AI and robotics, where short-term productivity losses precede longer-term benefits.

On the other hand, a recent surge in the number of analyses studying the role of advanced technologies documents a positive relationship between the adoption of digital technologies and productivity. While a link between productivity and technology adoption had already been established for a broader set of ICT technologies (Gal et al., 2019[64]; Amador and Silva, 2025[20]), such a relationship is also being observed for advanced digital technologies. In fact, Müller, Fay and vom Brocke (2018[65]), Cette, Nevoux and Py (2022[23]), Cerqueira, Alexandre and Portela (2023[42]), and Bettiol et al. (2023[66]) find a positive link between productivity and technology use for both cloud computing and big data analytics. Conti, de Matos and Valentini (2024[67]) and Andres, Niebel and Sack (2025[68]) find positive links only for big data, while Espinoza et al. (2020[69]) and Bettiol et al. (2023[66]) find a positive relationship for IoT. Cirillo et al. (2022[70]) find positive effects for IoT, robotics, big data, among others. These analyses focus on data from different countries. Additionally, a positive relationship between technology adoption and firm productivity has been found by Koch, Manuylov and Smolka (2021[53]) for robotics, Calvino et al. (2022[40]) for IoT, big data analysis and 3D printing, Acemoglu et al. (2022[21]) for AI and robotics, and Cho et al. (2023[22]) for AI, IoT, big data analysis and 3D printing. Several papers focus on AI specifically, with positive links between adoption or AI innovation and productivity further found, among others, by Damioli, Van Roy and Vertesy (2021[71]), Czarnitzki, Fernández and Rammer (2023[72]), Calvino and Fontanelli (2023[16]; 2024[51]) and Calvino et al. (2022[41]). At the worker level, findings from OECD surveys suggest that employers and workers alike see positive productivity impacts from AI adoption in firms (Lane, Williams and Broecke, 2023[50]).

However, several challenges appear when exploring the links between the use of advanced technologies and productivity. A first challenge is related to the fact that more productive firms may be more likely to adopt digital technologies in the first place. A second challenge stems from disentangling the role of digital technologies from other factors that may drive productivity.

As discussed above, relevant complementarities between the adoption of advanced digital technologies and other firm characteristics are often highlighted. These characteristics can be key to the ability of firms to extract productivity benefits. For example, Calvino and Fontanelli (2023[16]) highlight that the productivity premia of AI adopters are often linked to intangibles rather than to the use of AI itself. Barbosa and Faria (2022[73]) find that only already more productive and more digitalised firms are able to extract benefits for productivity from adoption. The importance of complementary assets, such as firms' prior digital technology intensity and the skills of its workers, in realising the productivity benefits of technology adoption is also highlighted by Bresnahan, Brynjolfsson and Hitt (2002[18]), Brynjolfsson, Jin and McElheran (2021[74]), Calvino et al. (2022[40]), Cho et al. (2023[22]) and Calvino and Fontanelli (2024[51]). Similarly, management practices have been shown to be key in extracting productivity gains from IT adoption (Bloom, Sadun and Reenen, 2012[75]; Cette, Nevoux and Py, 2022[23]; Cerqueira, Alexandre and Portela, 2023[42]).

Finally, other firm-level outcomes also appear to be linked to the use of advanced digital technologies. For instance, Rammer, Fernández and Czarnitzki (2022[76]) find that the adoption of AI is relevant for more ambitious product innovations, while Bartel, Ichniowski and Shaw (2007[19]) and Niebel, Rasel and Viete (2018[77]) relate IT investments to higher efficiency of the production process. Babina et al. (2024[78]) document several effects of investments in AI, such as growth in sales, employment and market valuations. DeStefano, Kneller and Timmis (2023[79]) find positive effects of the adoption of cloud computing on employment and revenue for young firms. For incumbent firms, the effects appear to be concentrated in the reallocation of the workforce between establishments. Furthermore, Caldarola and Fontanelli (2025[80]) find that cloud services positively impact the growth rates of firms, with smaller firms experiencing more significant benefits compared to larger firms, while Bisio et al. (2025[81]) further analyse the links between technology adoption and firm resilience.

Key insights and gaps

Evidence on the diffusion of advanced digital technologies shows that adoption is influenced by several firm characteristics, with larger firms more likely to adopt several of these technologies due to scale advantages and network externalities, while the relationship between adoption and firm age is more mixed. Additionally, human capital in the form of workforce skills and managerial capabilities as well as technological capital given by digital infrastructure and enabling technologies appear to play a relevant role in technology adoption. Regarding productivity outcomes, while some literature suggests a J-curve effect where initial productivity declines precede longer-term benefits, recent analyses have documented positive links between adoption and productivity across various advanced digital technologies. Crucially, complementary investments and organisational changes appear critical for realising productivity growth.

Much of the empirical evidence in the literature discussed above is, however, country-specific, which limits its representativeness across countries. Furthermore, many studies rely on aggregated information, such as at the sector level, and focus on a single technology. Additionally, many studies focus only on either the determinants of technology adoption or its productivity implications.

This paper addresses these gaps by providing comprehensive cross-country evidence from 15 different countries, leveraging detailed and representative microdata across several advanced digital technologies, offering a unique and comprehensive picture of advanced digital technology adoption, its determinants, and its relationship with productivity.

3 Data and methodology

This section discusses the data and methodology employed to investigate the use of advanced digital technologies by firms across countries. It covers firm-level surveys across countries as well as the distributed microdata approach utilised to analyse the data – the Digital Diffuse program.

Firm-level surveys across countries

This section provides an overview, for each country, of data coverage for ICT surveys and when applicable, balance sheet data and LEED. Key features of the different sources are briefly summarised below, with additional comprehensive information on the national surveys and the metadata reported in Annex A and Annex B, respectively.[4]

Official ICT surveys provide representative data containing relevant information on the use of advanced digital technologies by firms. The common features of these sources are their representativeness, as they are generally collected by national statistical offices, and the presence of information about the use by businesses of several digital technologies, notably including advanced ones, together with key firm characteristics.

Information on technology use is generally binary (i.e. firms are asked whether they use a given technology or not). ICT surveys in different countries contain information on relevant advanced digital technologies, notably including AI, big data analysis, cloud computing, IoT, robotics and 3D printing, among others. For selected advanced technologies, such as AI, firms are also asked for additional information, e.g. whether the technology was developed internally or acquired from a third party.

Information on firm characteristics generally includes key measures, notably the sector of activity of the firm, its size (employment) and turnover, which allow building a proxy for labour productivity.

The data are typically repeated cross-sections, based on stratified sampling methodologies. This allows on the one hand, when survey weights are present, for the analysis to be representative of the population under consideration (typically enterprises with 10 or more persons employed). On the other hand, also considering the typical focus on technology use rather than on the date of first adoption, this makes the analysis oriented towards exploring changes in adoption behaviour more challenging.

A key challenge for a multi-technology analysis across different countries is ensuring the harmonisation of the reported information, which can differ in terms of time, sectoral and size coverage, as well as the definitions used.

In some cases, in order to carry out a more detailed analysis, it is possible to combine the information in ICT surveys with additional information available in other micro-level data sources, such as balance sheet data or LEED, depending on data availability and data access. Together, these data sources contain additional information on firm characteristics, financial indicators of firm performance and information about the human capital of firms. For countries where such data are available, details on data availability are provided.

Digital Diffuse: a distributed microdata project

This section discusses the distributed microdata approach used. The evidence is based on representative firm-level data sourced from official firm-level surveys containing information on the use of ICTs from 15 countries. For countries where balance sheet data and/or LEED are available, additional evidence leverages these sources.

Building upon the AI diffuse project (Calvino and Fontanelli, 2023[16]), Digital Diffuse uses a common statistical code developed by the OECD Digital Diffuse team. This is commonly referred to as a distributed microdata approach. First, the code is run in a decentralised manner on the country-specific surveys by national experts from statistical offices, academia, other institutions, or directly by the OECD Secretariat. Then, the country-specific outputs of the program are sent back to the OECD for cross-country analysis. Before analysis, consistency checks and metadata validation steps are carried out in collaboration with experts from each country. This strategy effectively deals with challenges related to cross-country microdata access while preserving confidentiality.

The Digital Diffuse program runs in a Stata environment and generates a set of summary statistics and regression outputs based on firm-level survey data on technology adoption. Summary statistics and regressions are computed in both weighted and unweighted forms conditional on the availability of sampling (probability) weights, or of a business register from which these can be calculated. The Digital Diffuse program can run flexibly on different data sources but requires the following information: firm-level employment, turnover, sector of activity, binary variables identifying technology use by firms, and the year of observation.

Furthermore, the program is able to scale up the analysis in a modular manner to leverage information from balance sheet data and LEED. If balance sheet data are available, additional measures of firm-level productivity are computed, such as value added over employment and measures of multifactor productivity (MFP). The availability of LEED allows the analysis to include additional measures of human capital at the firm level, both for descriptive statistics and regression analysis. These measures include average years of formal education, share of individuals with tertiary education and share of individuals with a master's or PhD degree. These measures can be calculated for the entire workforce, and, conditional on data availability, for managers and workers in a non-managerial position. Additional human capital measures are the share of workers in a technical occupation, in an ICT technical occupation and in a non-ICT technical occupation.

The code has been designed to analyse the use by firms of various digital technologies, including both advanced and widely adopted ones. This study defines advanced digital technologies as AI, big data analysis, IoT, robotics and 3D printing, which are at the core of the present analysis. Other technologies, such as cloud computing services, customer relationship management (CRM) software, e-commerce, and enterprise resource planning (ERP) software, are also analysed, but in the present analysis related information is used only to assess their role as enablers of the use of the abovementioned advanced digital technologies. For the current analysis, the code allows to investigate the role of ICT skills (proxied by the presence of ICT specialists and training for non-ICT specialists) and digital infrastructure (ultra-fast broadband connection), information that is often directly available in firm-level surveys.

Further details on the Digital Diffuse program are provided in Annex A.

4 Seven stylised facts about advanced digital technologies and firms

This section presents seven stylised facts about the adoption of advanced digital technologies by firms across 15 countries. These stylised facts provide evidence based on summary statistics and regression analyses examining firm characteristics associated with a higher likelihood of adopting each advanced digital technology. The analysis also explores the role of human and technological capital in technology adoption and provides evidence on the co-occurrence patterns among different digital technologies. Finally, the analysis explores the relationship between technology adoption and firm-level productivity, and the role of relevant confounding factors. Where possible, these dimensions are explored at more granular levels, highlighting trends across countries and technologies. To the best of our knowledge, this is the first study to provide international evidence using regression analysis carried out with a harmonised methodology on the diffusion and role of multiple advanced digital technologies in the age of AI.[1] While great efforts were made to harmonise the methodology, as discussed above, cross-country comparisons should be made with caution given differences in definitions and reference periods across countries (further details are available in the Annex).

Stylised fact 1: There are significant interdependencies among digital technologies and more advanced technologies tend to build on enabling ones

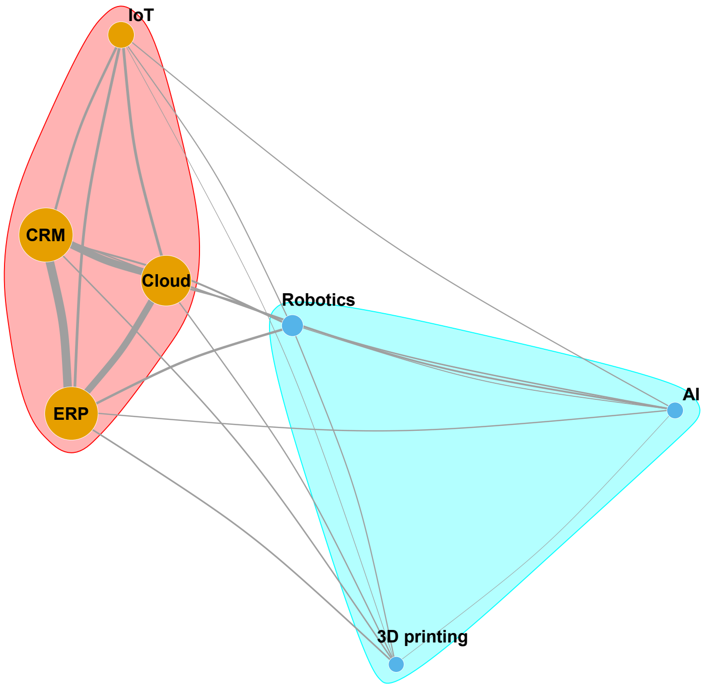
Looking at the role of advanced technologies within the digital technological capital in firms is key to understanding the determinants of adoption and any associated productivity advantages. This section focuses on the extent to which digital technologies are interdependent, highlighting that they are often adopted together, with more advanced technologies building on foundational ones. Leveraging the analysis of co-occurrences in technology adoption, that is, the simultaneous observation of a given technology pair within a firm in a given survey year, a network of technologies can be constructed to analyse the role of technological capital through co-adoption patterns. A typical example of such a technology network is shown in Figure 4.1: Foundational technologies such as ERP, CRM and cloud take a central position in the network, as indicated by the node size. Community detection reveals that they tend to be adopted together. In particular, technologies that take a central role in this network are often observed to be present simultaneously with other technologies and are therefore likely to be important for other technologies, suggesting a role for them as technological "enablers". This is also confirmed by the analysis of conditional adoption probabilities between technologies for various countries.[2] Conversely, data-driven advanced digital technologies centred on AI tend to be adopted together and form their own community. Specifically, in many countries, the adoption of the related technologies of AI and big data analysis, as well as other advanced technologies, is often observed together when they are present in the same wave.

[1] See Calvino and Fontanelli (2023[16]) for a previous cross-country study that focuses on the diffusion and role of AI specifically.

[2] See Figure A C.1 in the appendix for a representation of conditional probabilities for the case of Switzerland in 2019.

Interestingly, IoT tends to cluster with enabling technologies, potentially suggesting a broader integration in the firm technology portfolio. Indeed, this is supported by the overall adoption rates of IoT, as illustrated in section 1. Additionally, as shown in detail in stylised fact 2, IoT also has broad adoption across sectors.

Figure 4.1. Typical network of technology co-occurrences: Switzerland

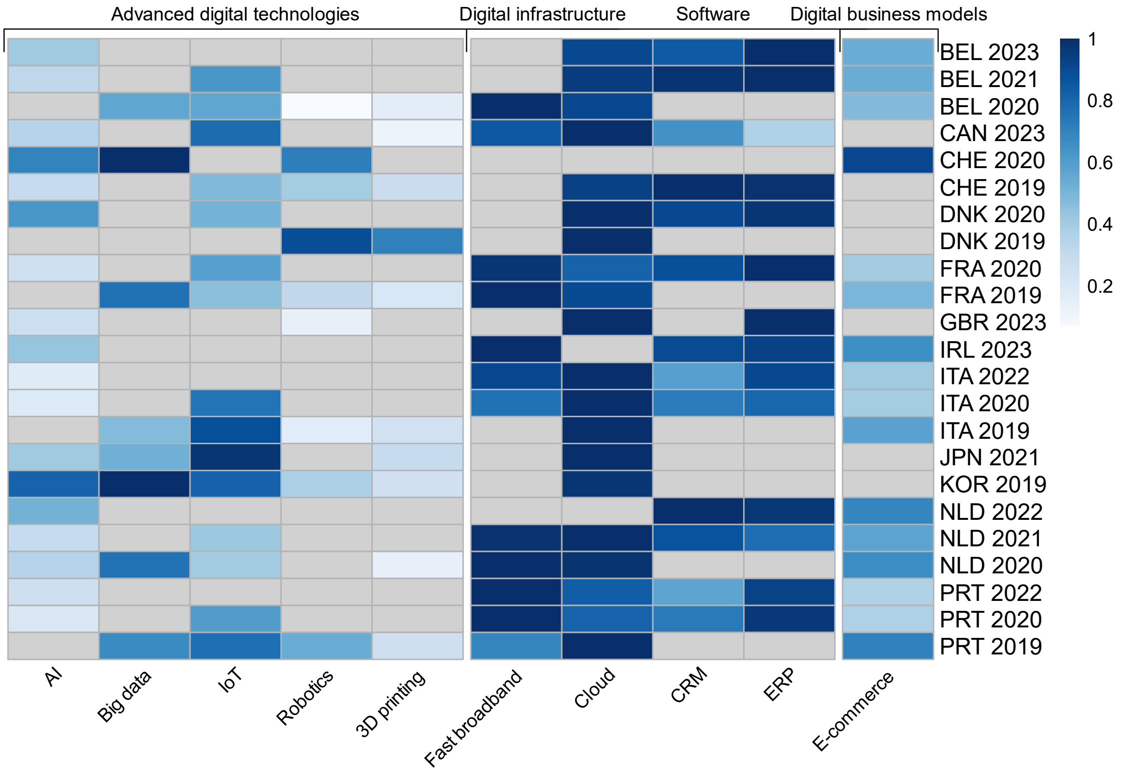


Note: Node size is scaled by eigen centrality, and the edges are scaled by the number of co-occurrences. Communities are represented by clouds and identified using the springclass community detection algorithm ($\gamma = 1$). The data refer to the year 2019.
Source: Authors' calculations based on microdata from the KOF Enterprise Panel.

Moving to a cross-country picture, Figure 4.2 illustrates the eigenvector centrality[5] of technologies within the networks of technology co-occurrences based on surveys across various countries and years. Here, every row represents an undirected network in a country-year, with the nodes given by the technologies and the edges defined by the observed number of co-occurrences between each technology pair. A clear pattern emerges: the most central technologies, which frequently coincide with the adoption of others, are foundational technologies such as cloud computing, key business software applications such as those related to CRM and ERP software, along with digital infrastructure such as fast broadband connectivity, pointing towards their role as enablers of more advanced digital technologies.

Figure 4.2. Centrality of technologies

Eigen centrality of technologies by country and survey year



Note: The colour gradient represents the eigen centrality for each available technology (column) in the network of observed technology co-occurrences for each country-year (row). A high value indicates an influential position of the technology in the network. Greyed out cells correspond to technologies either not surveyed or not available in a given country-year. Networks with blanked co-occurrences due to confidentiality or a low number of available technologies are excluded.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

As these technologies play a central role in the network, it positions them as drivers in technological co-adoption by, for instance, reducing adoption costs or helping realise potential productivity benefits of adopting advanced digital technologies. For example, fast broadband ensures the necessary connectivity for reliable and quick data transfer, which is essential for advanced digital technologies and crucial for applications like cloud and edge computing in IoT (OECD, 2022[82]). The availability of fast broadband connection therefore impacts the efficiency and viability of advanced digital technologies, reinforcing its role as a foundational technology. Similarly, cloud computing services can offer scalable infrastructure capable of handling large datasets and computing capacity without the need for physical hardware investment (Berisha, Mëziu and Shabani, 2022[83]). These services are often integrated with AI-specific tools, facilitating the adoption of big data analytics, AI and IoT. Additionally, many approaches to adopting advanced technologies such as AI include their integration with existing software in the firm, such as CRM (Ledro, Nosella and Dalla Pozza, 2023[84]) and ERP systems (Goundar et al., 2021[85]), which in turn are often cloud-based, an enabler itself. With these key enablers playing a central role in the network of technological co-occurrences, this highlights the importance of both technological and organisational interdependencies in the diffusion of digital technologies.

Stylised fact 2: The diffusion of advanced digital technologies exhibits significant sectoral heterogeneity

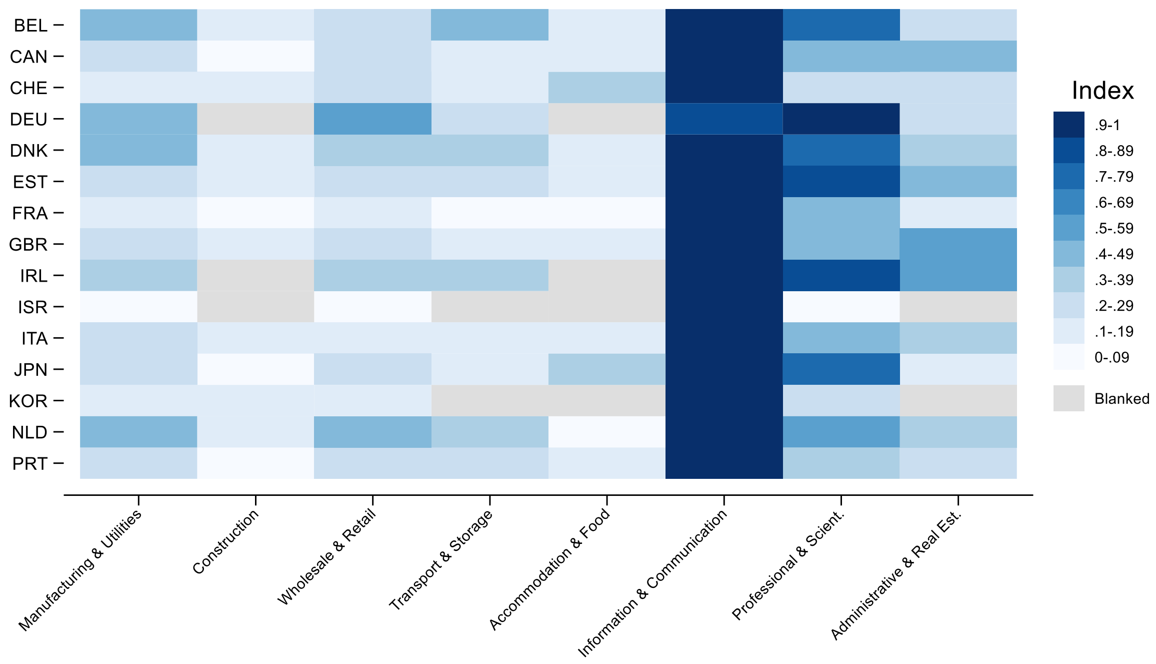
Given the different technological and organisational contexts in different industries, the applications of the technologies considered in the current analysis vary across sectors, leading to different levels of diffusion. This stylised fact highlights the different patterns of diffusion of advanced digital technologies across sectors for the countries considered. Figures 4.3-4.7 present the relative adoption rates of each advanced digital technology across countries and sectors of the economy. The ICT sector often emerges as a leader in digital technology adoption, yet notable differences exist among technologies. The use of relative indicators may facilitate comparisons between countries, considering that – as previously highlighted – definitions may vary across countries and statistics may refer to different years (further details are provided in the figure notes and in Annex C).

The ICT sector stands out as the leading adopter of AI in all countries except Germany, where its adoption rate is second highest after professional and scientific activities.[6] This is illustrated in Figure 4.3, which presents AI adoption patterns across countries and sectors, revealing a distinct sectoral distribution concentrated in this sector. This result has also been documented by Calvino and Fontanelli (2023[16]) and may reflect the high concentration of AI innovation and human skills required in this sector.[7]

The professional and scientific activities sector also emerges as a significant adopter of AI in several countries. In contrast, manufacturing and utilities, the leading adopter of robotics and 3D printing, shows considerably lower AI adoption rates. This suggests that while AI may play an important role in optimising industrial processes, for instance, when embedded in advanced robotics, its adoption across firms in the manufacturing and utilities sector is not as deep as it is in service-oriented and knowledge-intensive sectors.[8]

Furthermore, relevant heterogeneity across countries is observed. In particular, unreported adoption levels reveal that Denmark tends to exhibit relatively high adoption of AI across several sectors, while countries such as Italy, Japan and Portugal tend to show generally lower adoption rates, except in the ICT sector.

Figure 4.3. Relative adoption rates of AI by industry and country – different years



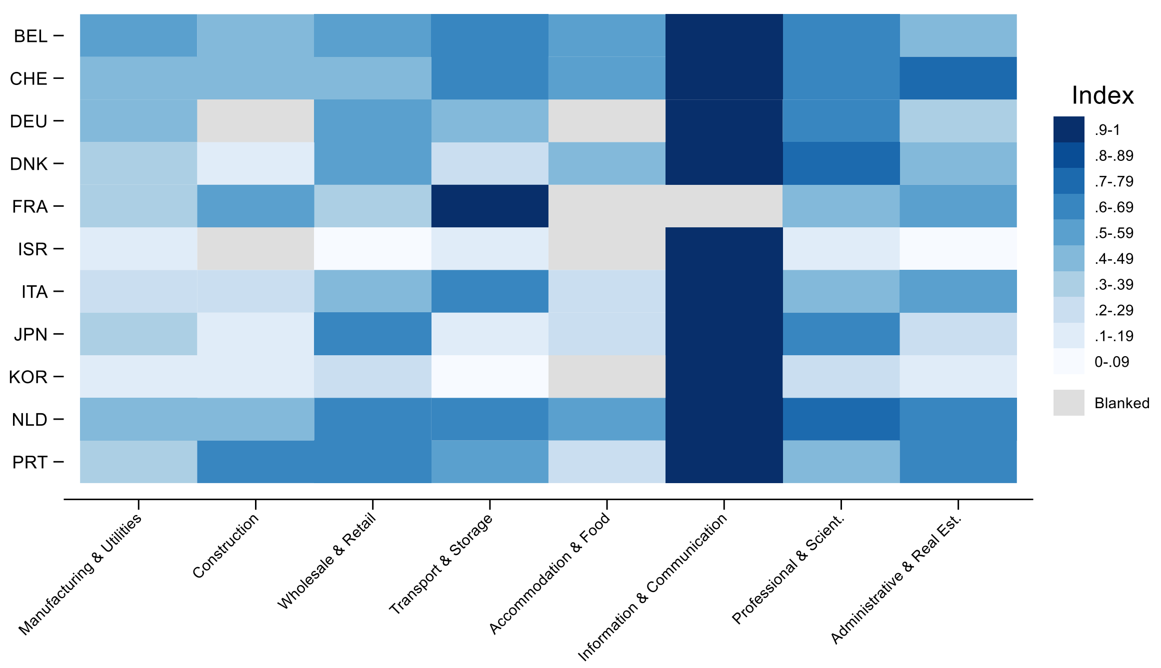
Note: This figure reports the relative adoption rates of AI across sectors. Within each country, the adoption rates are normalised such that the sector with the highest rate is equal to one. Values are weighted for all countries except for Germany, Ireland and Korea. Some cells are blanked for confidentiality reasons. The year of reference for each country is 2023 for Belgium, 2023 for Canada, 2020 for Switzerland, 2020 for Germany, 2020 for Denmark, 2023 for Estonia, 2022 for France, 2023 for the United Kingdom, 2023 for Ireland, 2020 for Israel, 2023 for Italy, 2019-2021 for Japan, 2019 for Korea, 2021 for the Netherlands and 2022 for Portugal. Owing to methodological differences, figures may deviate from officially published national statistics.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure 4.4 presents the relative adoption rates of big data analysis. The use of this technology follows a pattern similar to AI, with the ICT sector consistently reporting the highest adoption rates across most countries. This reflects the fundamental role of data analytics in digital services, where businesses leverage large-scale data processing for decision-making and machine learning applications.

However, in contrast to AI, big data analysis shows higher overall relative adoption rates beyond the ICT sector. The diffusion of big data analysis is also strong in the professional and scientific activities sector, which reports the second highest adoption rates for 7 of the 11 countries analysed. In contrast, manufacturing and utilities and construction consistently present lower adoption rates across countries.

As with AI, there appears to be significant heterogeneity across countries, with some economies exhibiting broader sectoral adoption while others more concentrated in select industries. For example, Belgium, Switzerland, Denmark and the Netherlands show a relatively more even diffusion of big data across sectors, whereas Israel, Korea and to some extent Italy seem to show a stronger contrast between the ICT sector and the rest of the economy. Once again, comparisons between countries should be taken with caution, also considering differences in survey years.

Figure 4.4. Relative adoption rates of big data analysis by industry and country – different years

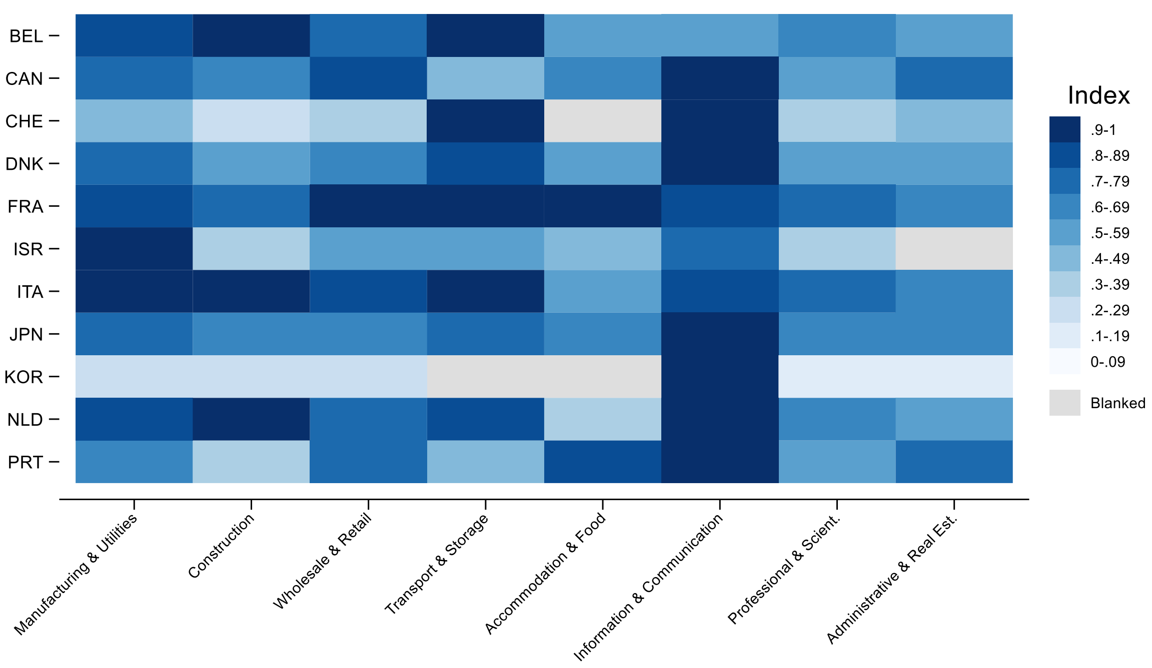


Note: This figure reports the relative adoption rates of big data analysis across sectors. Within each country, the adoption rates are normalised such that the sector with the highest rate is equal to one. Values are weighted for all countries except for Germany and Korea. Some cells are blanked for confidentiality reasons. The year of reference for each country is 2020 for Belgium, 2020 for Switzerland, 2018 for Germany, 2018 for Denmark, 2019 for France, 2020 for Israel, 2020 for Italy, 2019-2021 for Japan, 2019 for Korea, 2020 for the Netherlands and 2019 for Portugal. Owing to methodological differences, figures may deviate from officially published national statistics.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure 4.5 presents the relative adoption rates of IoT across countries and sectors. As with AI and big data analysis, the ICT sector generally presents the highest adoption rates. However, IoT exhibits a distinct, broader pattern compared to other advanced digital technologies. In fact, in countries such as Belgium, France, Israel and Italy, the construction, manufacturing and utilities, and transport and storage sectors surpass the adoption rates found in the ICT sector. This suggests that the industrial applications of IoT – such as predictive maintenance, process automation, and supply chain management, as well as logistics for the transport and storage sector – are key drivers of its diffusion in these economies.

In contrast, lower adoption rates are observed in sectors such as administrative and real estate and professional and scientific activities, suggesting that IoT applications in some service-based industries tend to remain relatively limited. Overall, the adoption of IoT aligns with sectors that rely on physical infrastructure and logistics rather than purely data-driven sectors. The ICT sector is the only service-based sector where the diffusion of this technology is pervasive.

Figure 4.5. Relative adoption rates of IoT by industry and country – different years

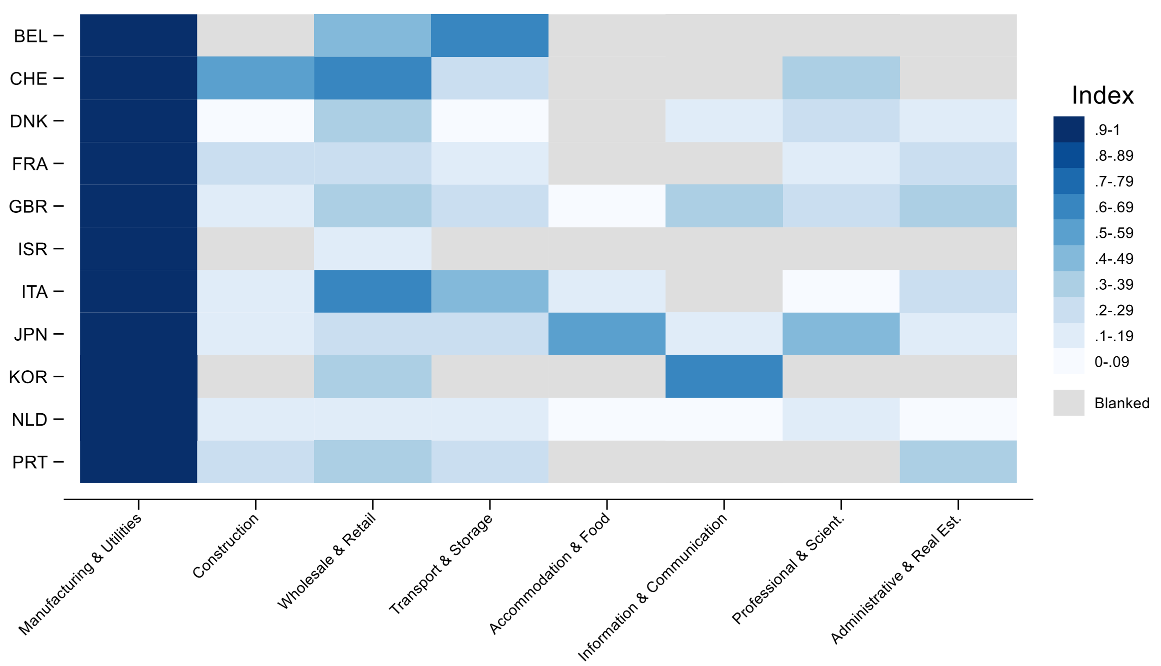


Note: This figure reports the relative adoption rates of IoT across sectors. Within each country, the adoption rates are normalised such that the sector with the highest rate is equal to one. Values are weighted for all countries except for Canada and Korea. Some cells are blanked for confidentiality reasons. The year of reference for each country is 2021 for Belgium, 2023 for Canada, 2019 for Switzerland, 2020 for Denmark, 2020 for France, 2020 for Israel, 2021 for Italy, 2019-2021 for Japan, 2019 for Korea, 2021 for the Netherlands and 2020 for Portugal. Owing to methodological differences, figures may deviate from officially published national statistics.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure 4.6 presents the adoption rates of robotics across countries and sectors. Unlike some other advanced digital technologies considered, robotics adoption is concentrated in industrial sectors rather than services, such as the ICT sector. In fact, for all countries, the highest adoption of robotics is observed in the manufacturing and utilities sector. This aligns with the relevance and long-standing use of robots to automate manufacturing processes, suggesting that this technology might be particularly effective in enhancing productivity and efficiency in industrial settings.

The figure also reveals varying levels of robotics adoption across sectors. After manufacturing and utilities, wholesale and retail reports the highest adoption rates in five of the nine countries analysed.

Figure 4.6. Relative adoption rates of robotics by industry and country – different years

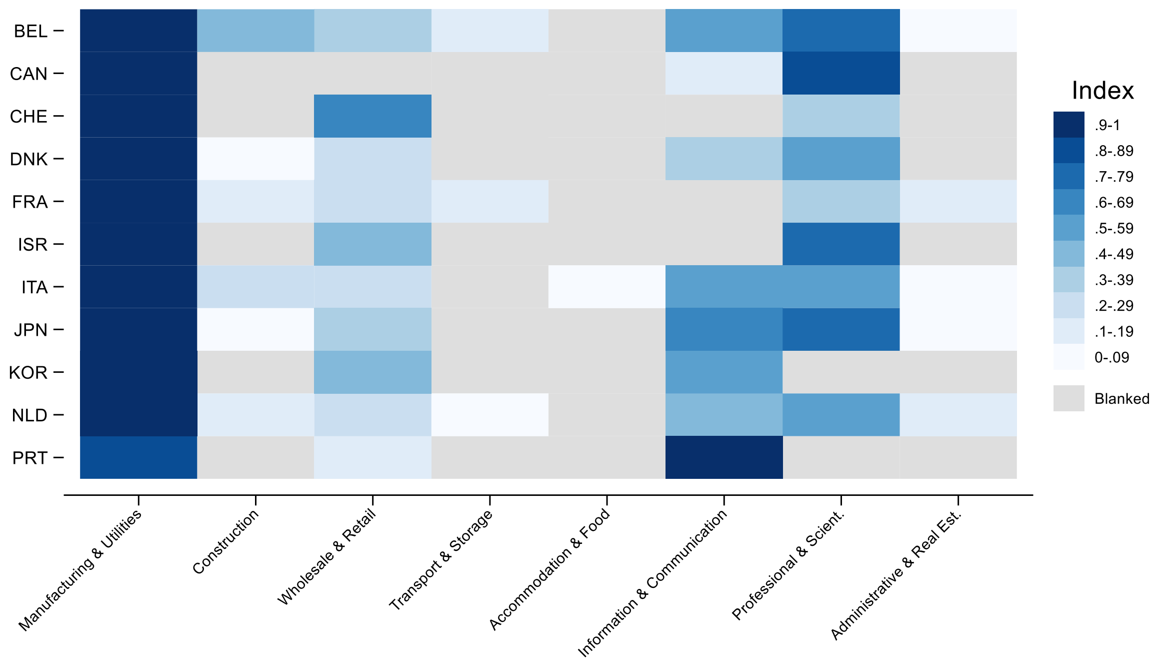


Note: This figure reports the relative adoption rates of robotics for Belgium (BEL), Switzerland (CHE), Denmark (DNK), France (FRA), the United Kingdom (GBR), Israel (ISR), Italy (ITA), Japan (JPN), Korea (KOR), the Netherlands (NLD) and Portugal (PRT) across sectors. Within each country, the adoption rates are normalised such that the sector with the highest rate is equal to one. Values are weighted for all countries except for Korea. Some cells are blanked for confidentiality reasons. The year of reference for each country is 2020 for Belgium, 2020 for Switzerland, 2019 for Denmark, 2019 for France, 2023 for the United Kingdom, 2020 for Israel, 2020 for Italy, 2019-2021 for Japan, 2019 for Korea, 2021 for the Netherlands and 2019 for Portugal. Owing to methodological differences, figures may deviate from officially published national statistics.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Finally, Figure 4.7 presents the relative adoption rates of 3D printing, revealing substantial variation in diffusion across sectors and countries. Similar to robotics, 3D printing is more prevalent in manufacturing and utilities, followed by the professional and scientific activities and ICT sectors. This pattern aligns with its industrial applications, including the production of complex and high-precision components, prototyping, tooling and small-batch production, among others (see OECD (2017[86]) for an in-depth discussion of the application and impact of 3D printing). Notably, Portugal is the only country for which manufacturing and utilities does not have the highest adoption rate of 3D printing, where it is surpassed by the ICT sector.

The professional and scientific activities sector exhibits notable adoption levels in certain countries, likely due to the use of 3D printing in research, design and engineering applications. In contrast, the ICT sector does not consistently emerge as the leading adopter, suggesting that while digital innovation plays a crucial role in 3D printing, its primary applications remain in physical production and development rather than in purely digital or service-oriented sectors. Moreover, some heterogeneity in diffusion patterns is also observed across countries, with some differences in adoption rates between sectors more pronounced in certain countries, while more homogeneous in others. These variations might stem from differences in industrial composition within broad sectors, policy measures, specific technological needs of each economy, or differences in the timing of the surveys.

Figure 4.7. Relative adoption rates of 3D printing by industry and country – different years



Note: This figure reports the relative adoption rates of 3D across sectors. Within each country, the adoption rates are normalised such that the sector with the highest rate is equal to one. Values are weighted for all countries except for Canada and Korea. Some cells are blanked for confidentiality reasons. The year of reference for each country is 2020 for Belgium, 2023 for Canada, 2019 for Switzerland, 2019 for Denmark, 2019 for France, 2020 for Israel, 2020 for Italy, 2019-2021 for Japan, 2019 for Korea, 2020 for the Netherlands and 2019 for Portugal. Owing to methodological differences, figures may deviate from officially published national statistics.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Overall, the adoption of advanced digital technologies varies significantly across sectors and, to some extent, across countries, highlighting specificities in sectoral applications. AI and big data analysis show broader adoption in service-oriented industries, particularly in ICT and professional and scientific sectors. IoT appears to be more versatile, with more widespread adoption across sectors. Robotics and 3D printing are particularly relevant to the manufacturing and utilities sector, highlighting their industrial applications. These patterns suggest that the uptake of specific technologies is highly sector-dependent.

Similarly, the patterns of co-adoption discussed in the previous stylised fact also show some sectoral heterogeneity, as shown in Figure A C.2 and Figure A C.3 of Annex C for the ICT and manufacturing sectors, respectively, two sectors with each high and distinct adoption patterns. In the ICT sector, AI and big data analysis are not only widely diffused, but also appear to play a more central role in the network of technology co-occurrences compared to the survey average as they are often adopted together with other technologies. Concerning IoT, on the other hand, while adoption rates observed in the ICT sector are higher than in other sectors of the economy, it does not appear to take a central position in the network, pointing to more standalone adoption patterns of this technology in the ICT sector. In the manufacturing sector, conversely, while IoT, robotics and 3D printing are widely diffused, only 3D printing and, to a lesser extent, robotics take a more central position in the network than it does in other sectors, implying a greater integration of these technologies with other technologies and digital infrastructure in the manufacturing sector. These technological interdependencies may help explain the heterogeneous patterns observed across sectors.

Understanding the sectoral patterns of adoption is essential for policymakers and businesses aiming to accelerate digital adoption and maximise productivity gains across sectors. Taking them into account through regression analysis is critical for a better understanding of the dynamics and implications of the diffusion of advanced digital technologies.

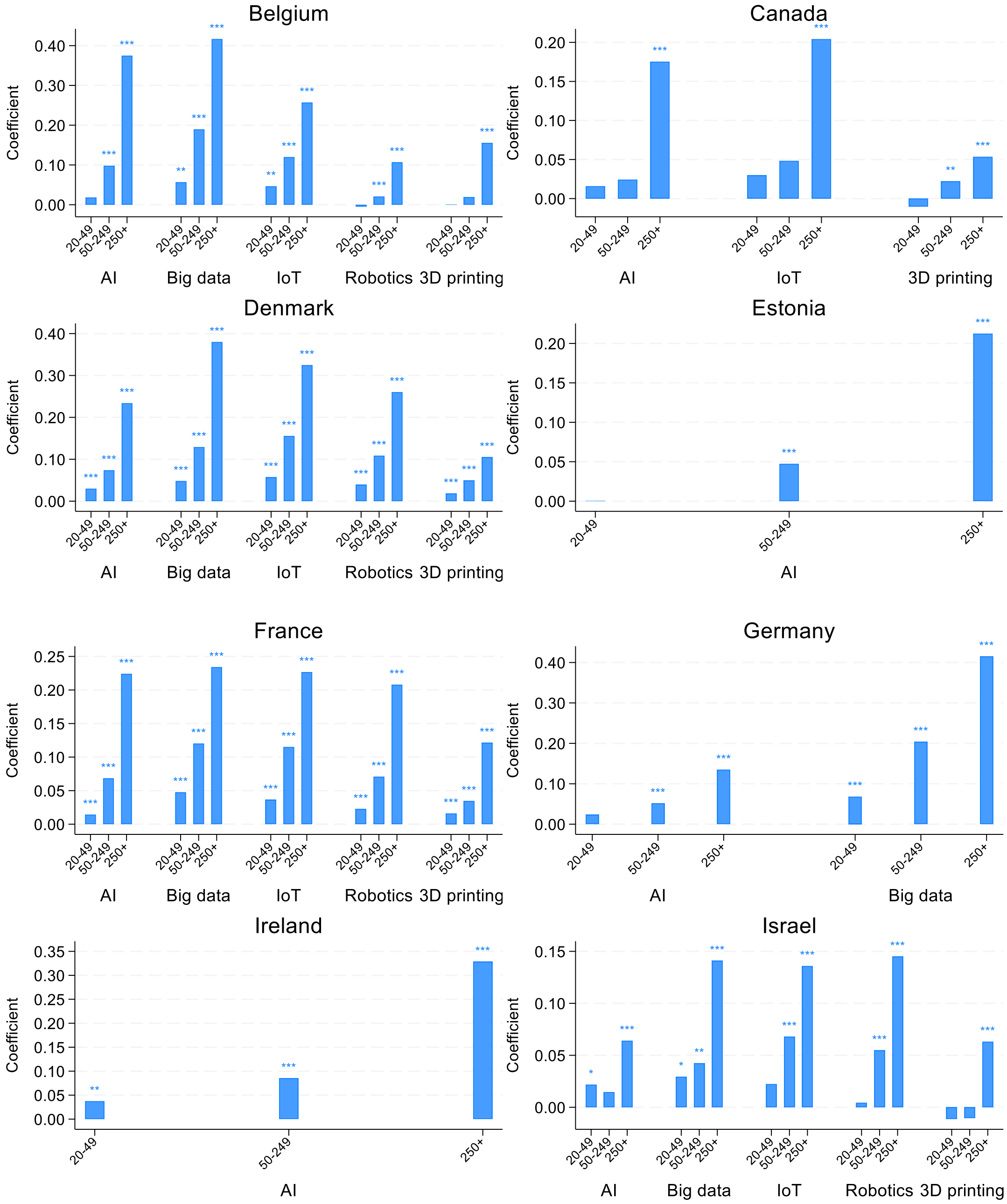
Stylised fact 3: Larger firms are more likely to adopt advanced digital technologies

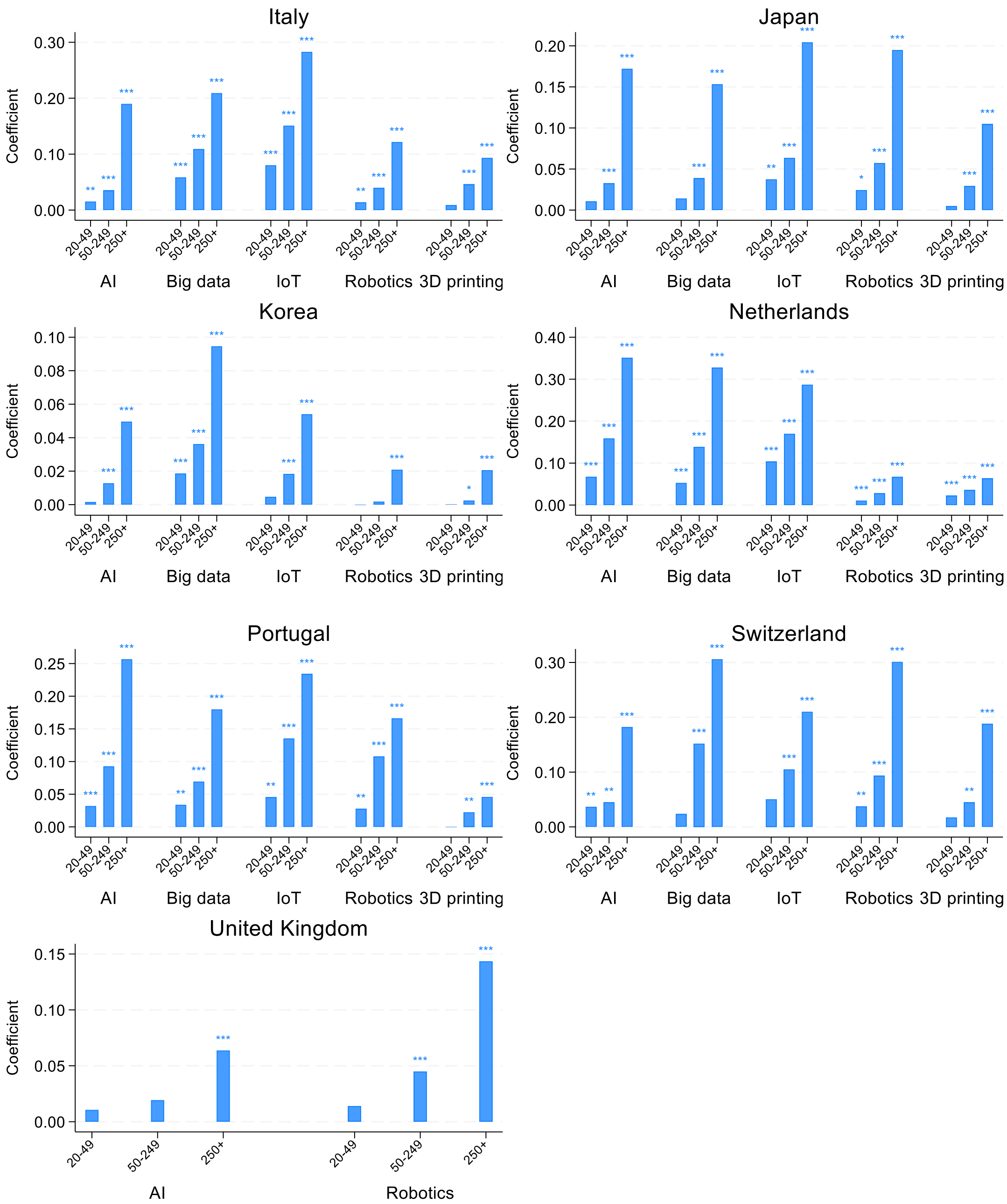
This stylised fact focuses on the link between the use of advanced digital technologies and firm size, highlighting the higher propensity of advanced technology use by larger firms. The analysis focuses on the latest available data on advanced digital technologies, accounting for a number of relevant confounding factors in the size-technology relationship using a regression analysis. In particular, Figure 4.8 presents the coefficients of the size class dummies from adoption regressions, where the dependent variable is the use of an advanced digital technology. These regressions are estimated separately for each country and technology. The estimated models include controls for year, age and industry fixed effects. Given the observed sectoral heterogeneity in adoption discussed in stylised fact 2, this approach allows to better understand the link between firm size and the use of advanced digital technologies by accounting for key dimensions, such as industry composition. All reported coefficients are to be interpreted relative to the baseline category of firms, i.e. those with 10 to 19 persons engaged (see Box 4.1 for further details on the econometric strategy).

It is apparent that the likelihood of adoption increases monotonically with firm size for almost all technologies and countries considered. A coefficient of 0.4 – such as that observed for large Belgian firms (250 or more persons engaged) adopting AI or big data analysis – indicates that being a large firm increases the likelihood of adopting that specific advanced digital technology by 40 percentage points compared to a firm with 10 to 19 persons engaged. There is, however, relevant heterogeneity in adoption patterns both across technologies within countries and across countries. For example, firm size seems to be a less important predictor of adoption for 3D printing across most countries, compared to other technologies. Furthermore, for some countries and some technologies, such as AI for Belgium, Canada, Germany, Japan, Korea and the United Kingdom, only higher size classes appear to exhibit statistically significant coefficients.

These results suggest that even when controlling for key firm-level characteristics such as sectoral heterogeneity and firm age, larger firms remain more likely to adopt advanced digital technologies, consistent with a role for scale advantages in their diffusion. By contrast, while Calvino and Fontanelli (2023[16]) and Zolas et al. (2020[39]) identify a relevant association between firm age with technology adoption, a heterogeneous picture emerges for the role of age across countries and technologies once firm size is taken into account, as shown in Figure A C.4 in Annex C.

Figure 4.8. Adoption regression coefficients for size class dummies





Note: This figure reports the coefficients of size class dummies for Belgium, Canada, Denmark, Estonia, France, Germany, Ireland, Israel, Italy, Japan, Korea, the Netherlands, Portugal, Switzerland and the United Kingdom. The adoption regression includes age classes and year dummies, when available. Each regression includes 2-digit NACE rev. 2 sector dummies. All estimated regressions are weighted except for Germany, Ireland and Korea. See Table A B.2. for the sample coverage years of each technology adoption regression. See Table A C.1 – Table A C.5 for the complete list of coefficients. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Box 4.1. Econometric strategy for adoption regressions

Adoption regressions are used to evaluate which firm-level characteristics are associated with the use of advanced digital technologies. The results presented in this paper rely on a series of linear probability models, estimated using the following equation:

$$\text{Technology use}_{\text{it}} = \beta_0 + \beta_1 \text{SizeClass}_{\text{it}} + \beta_2 \text{AgeClass}_{\text{it}} + \delta_{\text{s}} + \gamma_{\text{t}} + \varepsilon_{\text{it}}$$

where $\text{Technology use}_{\text{it}}$ is a binary variable indicating whether firm *i* uses an advanced digital technology in year *t*. The equation is estimated separately for each technology. $\text{SizeClass}_{\text{it}}$ and $\text{AgeClass}_{\text{it}}$ represent fixed effects based on size and age classes, respectively. δ_s and γ_t capture sector and, where available, year fixed effects. Finally, ε_{it} denotes the error term. The inclusion of variables in the model, particularly age class and year fixed effects, depends on data availability.

To analyse the role of additional factors relevant to the adoption of advanced digital technologies, specifically human and technological capital, the equation above is extended as follows:

$$\text{Technology use}_{\text{it}} = \beta_0 + \beta_1 \text{SizeClass}_{\text{it}} + \beta_2 \text{AgeClass}_{\text{it}} + \beta_3 \text{X}'_{\text{it}} + \delta_{\text{s}} + \gamma_{\text{t}} + \varepsilon_{\text{it}}$$

where X'_{it} is a vector of binary variables that identify relevant factors. These include, where available, the presence of ICT specialists and ICT training to capture the role of human capital, use of fast broadband to capture digital infrastructure and the share of other digital technologies adopted. Fast broadband is defined as having a broadband connection with at least 100 Mbit/s. The share of other digital technologies is computed as the number of digital technologies that firm *i* has adopted in year *t* out of all technologies surveyed. The following technologies are considered, conditional on survey coverage: AI, big data analysis, cloud computing services, IoT, robotics, 3D printing, customer relationship management (CRM), enterprise resource planning (ERP) and e-commerce. The availability of such information varies across countries and years. The technology under analysis is excluded from this calculation.

Stylised fact 4: Human and technological capital are key to the adoption of advanced digital technologies

Some assets, such as human and technological capital in the form of intangibles and digital infrastructure, may affect the uptake of advanced digital technologies by providing the necessary tools and skills to identify use cases or leverage their potential, enabling technology adoption. It has been, in fact, found that the adoption of new technologies is linked to technological and organisational complements (Brynjolfsson and Milgrom, 2013[87]). For example, the adoption of predictive analysis is positively correlated with IT infrastructure, human capital in the form of educated employees and high flow efficiency processes (Brynjolfsson, Jin and McElheran, 2021[74]), and AI exhibits relevant complementarities in adoption with human capital and firms' digital capabilities (Calvino and Fontanelli, 2023[16]).

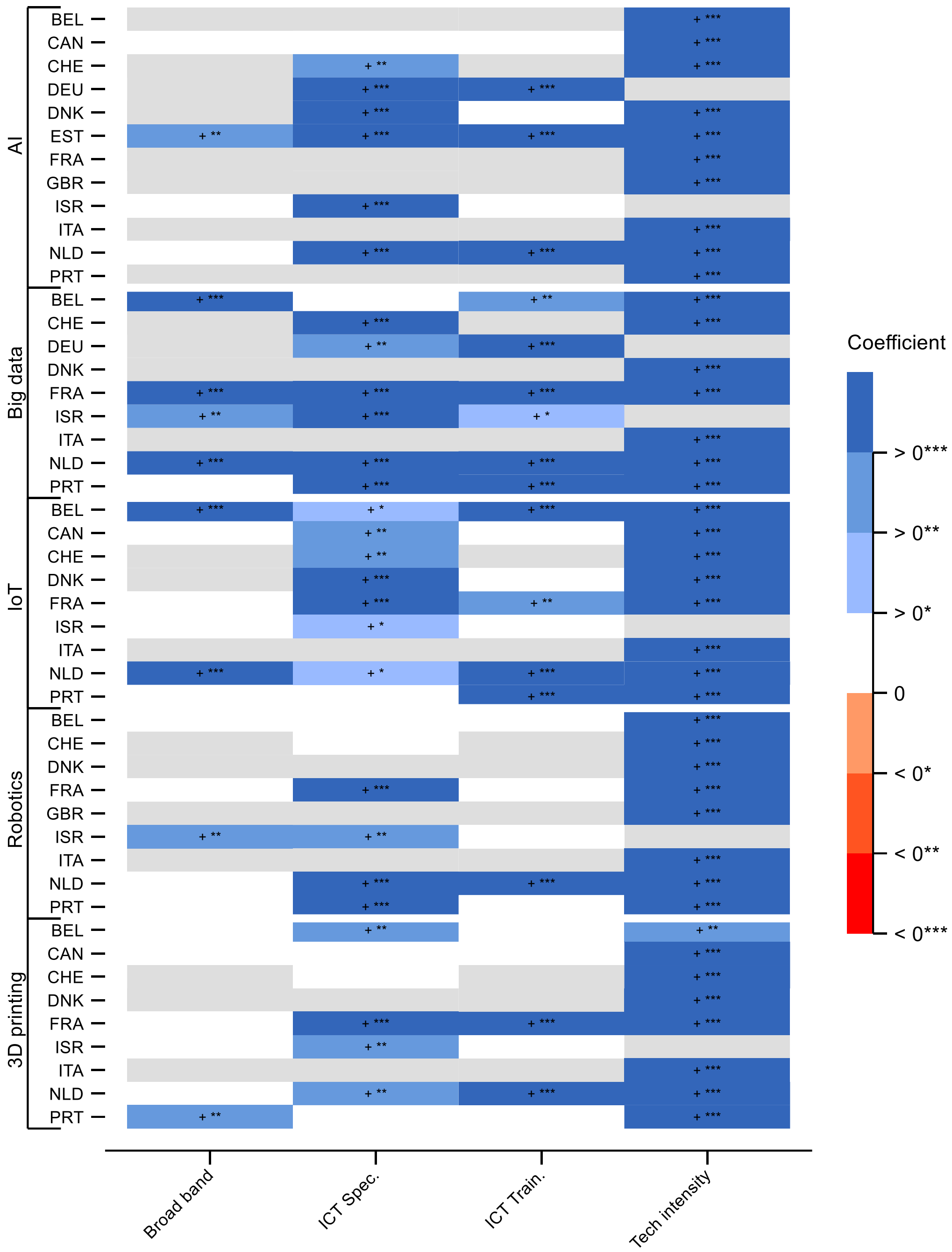
To explore the role of human and technological capital, the analysis builds on the econometric strategy discussed above (see Box 4.1 for details). The use of each advanced digital technology is analysed as a function of firm-level characteristics, including firm size, firm age and relevant assets proxying the role of human and technological capital: the presence of ICT specialists, ICT training for non-ICT personnel, use of fast broadband internet and the share of other technologies adopted. The presence of ICT specialists and ICT training for non-ICT personnel in ICT surveys provides a first proxy of human capital. Meanwhile, the adoption rate of other digital technologies serves as a proxy for a firm's digital capabilities or technology intensity. Additionally, the use of fast broadband proxies the role of high-quality digital infrastructure. Both are crucial components of a firm's technological capital. The inclusion of each explanatory variable depends on data availability in each country.

Figure 4.9 presents the sign and statistical significance of selected coefficients from adoption regressions across advanced digital technologies and countries, conditional on data availability. With respect to the role of human capital, the presence of ICT specialists and ICT training is widely associated with higher adoption rates across most technologies and countries. However, ICT specialists appear not to be significantly associated with the adoption of 3D printing in Switzerland, Portugal and Canada. Similarly, ICT training does not significantly influence the adoption of both 3D printing and robotics in Belgium and Portugal.

The results also show that digital capabilities and, to some extent, digital infrastructure play a crucial role in the uptake of advanced digital technologies, highlighting the role of different forms of technological capital as relevant complementary assets for advanced digital technology adoption. The share of other digital technologies adopted, including both other advanced digital technologies as well as enabling technologies, is positively associated with the adoption of all advanced digital technologies for which data are available. This suggests that firms' prior digital technology intensity is an important factor in the adoption of new technologies. The presence of fast broadband appears to have a positive but, to some extent, weaker link with the use of these technologies, possibly due to its high diffusion in the most recent years. In fact, for most countries of the analysis, the share of businesses with a broadband download speed of at least 100 Mbit/s is higher than 60%.

These findings highlight a key enabling role of assets related to human and technological capital, notably skills and digital capabilities, in the adoption of advanced digital technologies, suggesting the existence of relevant complementarities. In fact, a positive and significant relationship between different complementary assets – notably related to proxies of human and technological capital – and technology use holds across several technologies and countries. Furthermore, since some technologies are more widely diffused across specific sectors, this relationship does not appear to be sector-specific. Stylised facts 1 and 5 further investigate the role of human and technological capital by considering the roles of education, ICT occupations and technological co-occurrences in technology adoption.

Figure 4.9. Regression results on adoption of advanced digital technologies, human and technological capital



Note: This figure reports the sign and statistical significance of coefficients from adoption regressions. All regressions are weighted except for Germany. For some countries, technologies or cells are omitted due to not being covered. See Table A B.2. for the coverage years of each technology adoption regression. See Table A C.6 – Table A C.10 for the complete list of coefficients. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Stylised fact 5: Education and technical occupations appear critical for the adoption of advanced digital technologies

This stylised fact further zooms in on the role of human capital in the adoption of advanced digital technologies, leveraging more detailed information from LEED. The discussion focuses on Denmark, the Netherlands and Portugal, where merging ICT surveys with LEED was possible.

More detailed human capital proxies are constructed in two ways, conditional on data availability: the first proxy is the share of a firm's workforce with tertiary education qualifications, and the second is the share of the workforce employed in technology-related occupations ("techies"). The techie classification follows Harrigan, Reshef and Toubal (2021[88]; 2023[89]), and is further disaggregated into ICT techies and non-ICT techies following Fontanelli et al. (2025[90]), using the International Standard Classification of Occupations (ISCO-08).[9]

The use of information from LEED provides significantly more detail with respect to the information on human capital commonly available in ICT surveys discussed above, which often only indicate whether a firm employs ICT specialists or provides ICT training, lacking granular detail on workforce qualifications and roles. A further limitation is the inconsistent availability of human capital data in ICT surveys, since these are not included in every survey wave. Combined with the surveys' rotating panel design, this limits the analysis to certain countries and technologies, as shown in Figure 4.9.

Figure 4.10 presents the regression coefficients for the share of workers with tertiary education across the five advanced digital technologies considered in the three countries for which this information is available. The estimated model includes this additional variable in the baseline adoption model (see Box 4.1 for details). Other human capital proxies available in ICT surveys (such as the presence of ICT specialists or training) are excluded from these specific regressions.

The relationship between a firm's share of tertiary-educated workers and its adoption of advanced technologies shows both common patterns and notable differences across the Netherlands, Portugal and Denmark.

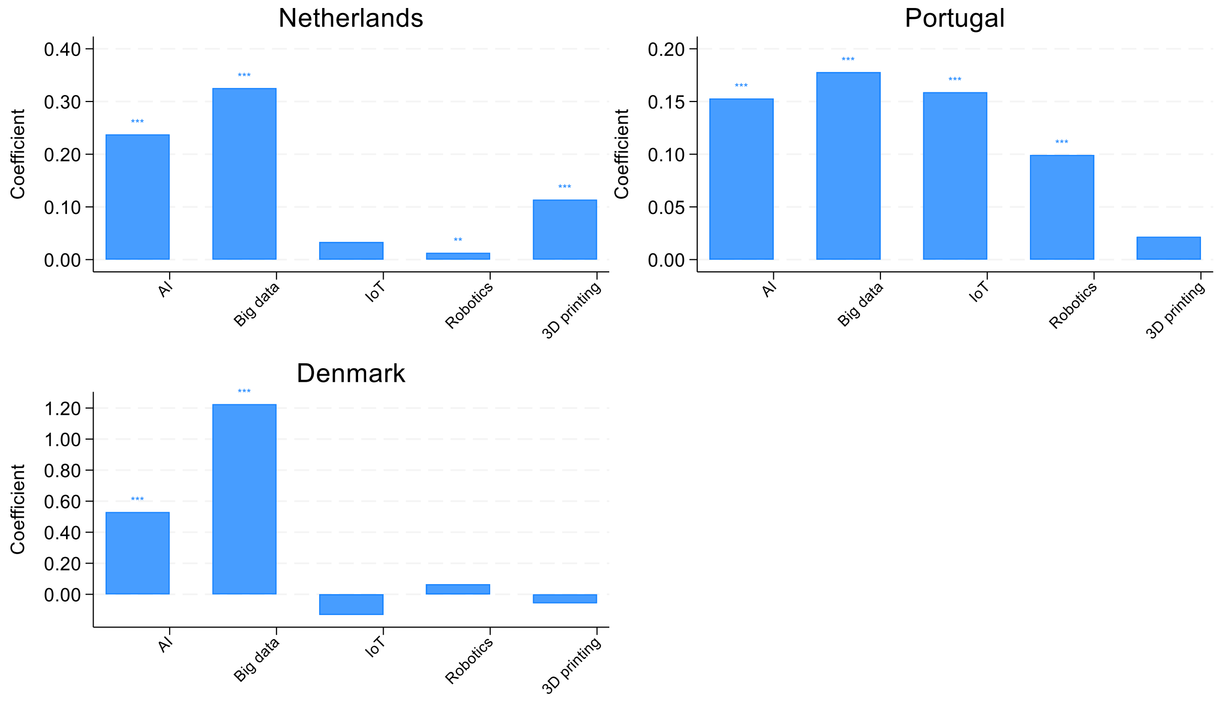
In the Netherlands, a higher share of workers with tertiary education is positively associated with the adoption of AI, big data analysis, robotics and 3D printing. This relationship is particularly strong for big data analysis: a one percentage point increase in the share of tertiary-educated workers is associated with a more than 0.3 percentage point higher likelihood of adoption. In contrast, the association is only marginal for robotics and is not statistically significant for IoT.

The findings for Portugal are broadly consistent, showing a positive association for most technologies, with the main exception being 3D printing. A key difference emerges for IoT, where, unlike in the Netherlands, the baseline model shows a significantly positive relationship with workforce education.

The results for Denmark also show a strong positive relationship for AI and big data analysis - and it is even more pronounced in this case. A one percentage point increase in the tertiary education share is associated with a 0.5 percentage point higher likelihood of AI adoption and a 1.2 percentage point increase for big data analysis adoption. However, unlike in the Netherlands, there is no significant association for either robotics or 3D printing in Denmark.

A consistent finding across all three countries is the robust role of tertiary education in the adoption of AI and big data analysis. Unreported results confirm that the positive association between tertiary education and the adoption of each of the two technologies remains significant even after controlling for a firm's overall digital intensity. For other technologies such as IoT and robotics in the Netherlands, and IoT in Portugal, this is not the case, suggesting their adoption is more closely linked to a firm's existing technological capital rather than human capital alone.

Figure 4.10. Adoption regression coefficients for tertiary education

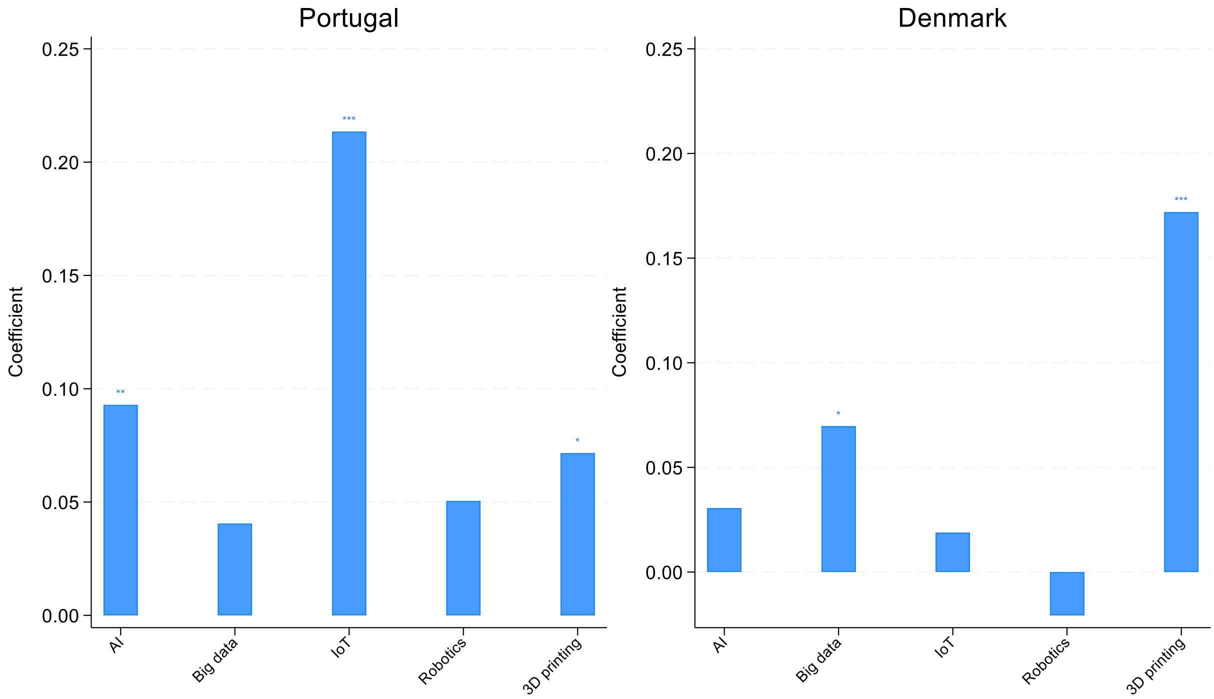


Note: This figure reports the sign and statistical significance of coefficients for the share of workers with tertiary education. All regressions are weighted. The dependent variable is the adoption of an advanced digital technology. All models include size and age classes, and industry and year fixed effects. See Table A B.2. for the coverage years of each technology adoption regression. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys and LEED See section 3 for details on the methodology and the Annex for details on the different sources.

Focusing further on the role of occupational composition, Figure 4.11 presents the regression coefficients of the share of techies for the adoption of each advanced digital technology in Denmark and Portugal. In Portugal, the results suggest that technical skills are positively correlated with the adoption of AI, IoT and 3D printing, whereas in Denmark this is the case for big data analysis and 3D printing.[10] In Portugal, a higher share of techies is particularly associated with IoT: a one percentage point increase in the share of workers with technical skills is associated with a 0.21 percentage point higher likelihood of IoT adoption. In Denmark, by contrast, a significant positive association is found for big data analysis and 3D printing, with the latter showing a similarly strong magnitude.[11]

Together with the findings in Box 4.3, these results further corroborate the relevance of specialised human capital for the adoption of advanced digital technologies.

Figure 4.11. Adoption regression coefficients for technical occupations measures



Note: This figure reports the sign and statistical significance of coefficients for the share of workers with technical occupations. All regressions are weighted. The dependent variable is the adoption of an advanced digital technology. All models include size and age classes, and industry and year fixed effects. See Table A B.2. for the coverage years of each technology adoption regression. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Estimations based on country-specific firm-level surveys and LEED. See section 3 for details on the methodology and the Annex for details on the different sources.

Box 4.2. Spotlight on the role of human capital in adopting and developing AI

Using a similar methodology, Fontanelli et al. (2024[91]) explore how firms' occupational composition influences the adoption of AI in France. For this purpose, the authors leverage information from ICT surveys, balance sheet data and LEED. These provide detailed information on AI use and the share of workers in higher intellectual (e.g. managers, executives, engineers) and intermediate (e.g. supervisors, foremen, technicians) occupations. Within these two broad categories, it is possible to distinguish between human capital related to ICT and non-ICT technical and non-technical human capital, and to disentangle more detailed occupational categories (e.g. ICT engineers).

The analysis finds a positive relationship between the share of ICT engineers and the likelihood of adopting AI, a link primarily driven by ICT engineers specialised in R&D. A positive link emerges between ICT engineers and both the acquisition of AI systems from external providers and the development of in-house AI systems.

Moreover, the role of ICT engineers appears particularly relevant in fostering AI adoption in Wholesale and Retail, ICT business services and Professional, Scientific and Technical services. This highlights the importance of advanced ICT knowledge in sectors dealing with large datasets or requiring high levels of ICT and R&D competencies. Still, non-ICT engineers play an important role in AI development, suggesting the relevance of a broader set of skills to design and maintain AI systems.

These findings further underscore the critical role of highly qualified human capital in supporting the diffusion of advanced technologies such as AI.

Stylised fact 6: Adopters of advanced digital technologies tend to be more productive than other firms

This subsection analyses the relationship between firm productivity and the use of advanced digital technologies. For this purpose, it leverages regression results from 14 countries, highlighting the different productivity profiles of adopters of each advanced digital technology.

Overall, the results – which are not to be interpreted causally but just as conditional correlations – show that firms adopting advanced digital technologies tend to be, on average, more productive. This pattern is observed across most technologies considered, with some country-specific exceptions.

The relationship between the adoption of advanced digital technologies and productivity is investigated through a simple regression analysis. As previously discussed, unlike descriptive statistics, regression analysis controls for other key dimensions that might be related to firm productivity.[12] This includes accounting for sectoral specificities, which contributes to the robustness of the analysis. Figure 4.12 presents the baseline productivity regressions for AI, big data analysis, IoT, robotics and 3D printing. The regressions are estimated separately for each country and technology. The dependent variable is firm productivity, as proxied by the ratio of turnover and employment, while the main explanatory variable is the use of the respective advanced digital technology. Additional controls include firm size, firm age, industry and time fixed effects, conditional on data availability (see Box 4.3 for details on the econometric strategy).

Box 4.3. Econometric strategy for productivity regressions

To assess the link between the use of advanced digital technologies and firm productivity, the following equation is estimated:

$$\log(\mathrm{Productivity})_{\mathrm{it}} = \beta_0 + \beta_1 \mathrm{Technology\ use}_{\mathrm{it}} + \beta_2 \mathrm{SizeClass}_{\mathrm{it}} + \beta_3 \mathrm{AgeClass}_{\mathrm{it}} + \delta_{\mathrm{s}} + \gamma_{\mathrm{t}} + \varepsilon_{\mathrm{it}}$$

where $\log(\mathrm{Productivity})_{\mathrm{it}}$ is the logarithm of a firm's productivity, measured as the ratio of turnover to the number of persons engaged. The main explanatory variable, $\mathrm{Technology\ use}_{\mathrm{it}}$, is a binary variable indicating whether firm *i* has adopted a given advanced digital technology in year *t*. The equation is estimated separately for each technology. $\mathrm{SizeClass}_{\mathrm{it}}$ and $\mathrm{AgeClass}_{\mathrm{it}}$ represent fixed effects based on size and age classes, respectively. δ_s and γ_t capture sector and, where available, year fixed effects. Finally, $\varepsilon_{\mathrm{it}}$ denotes the error term. The inclusion of variables in the model, particularly age class and year fixed effects, depends on data availability.

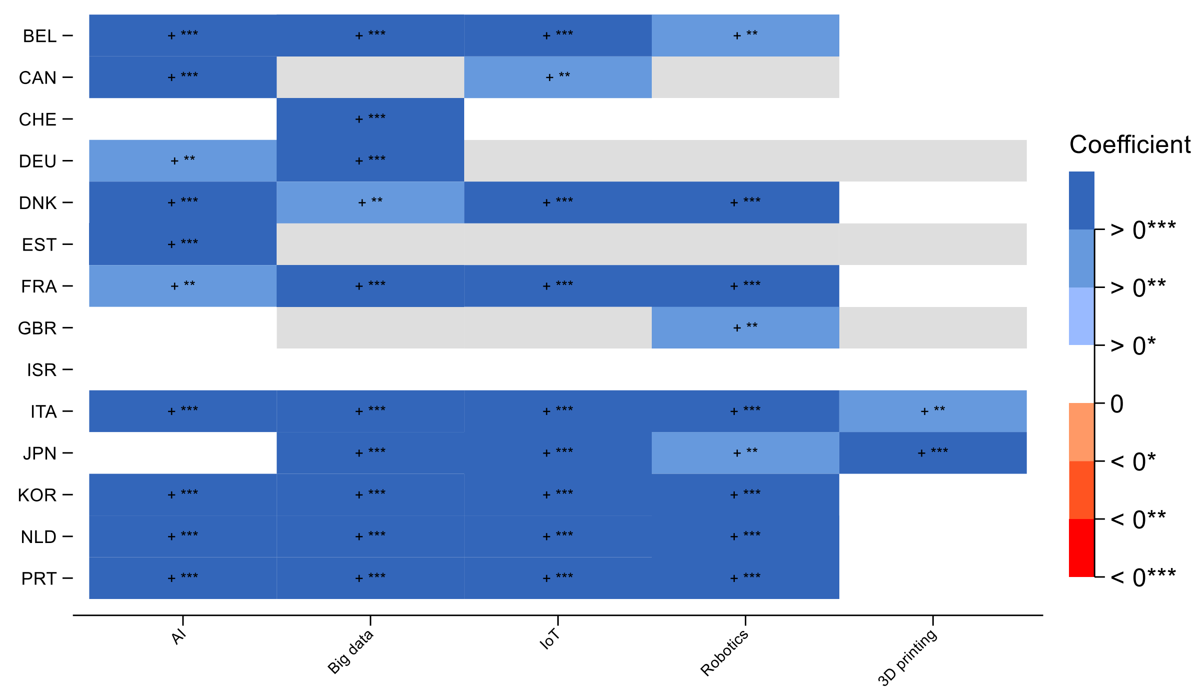
As robustness checks, the same equation is re-estimated using the ratio of value added to the number of persons engaged in logarithmic form as the dependent variable. These robustness checks are limited to countries where balance sheet data can be merged with the ICT survey data.

Similarly to adoption regressions, to analyse the role of other key firm-level assets in explaining firm productivity, the equation above is extended as follows:

$$\log(\mathrm{Productivity})_{\mathrm{it}} = \beta_0 + \beta_1 \mathrm{Technology\ use}_{\mathrm{it}} + \beta_2 \mathrm{SizeClass}_{\mathrm{it}} + \beta_3 \mathrm{AgeClass}_{\mathrm{it}} + \beta_4 \mathrm{X}'_{\mathrm{it}} + \delta_{\mathrm{s}} + \gamma_{\mathrm{t}} + \varepsilon_{\mathrm{it}}$$

where $\boldsymbol{X'_{it}}$ is a vector of binary variables that identify additional relevant factors, notably related to human and technological capital. These include, where available, the presence of ICT specialists and ICT training, use of fast broadband and share of other digital technologies adopted (see Box 4.1 for details on variable definitions).

Figure 4.12. Estimation results of the baseline productivity regressions



Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the baseline productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Canada, Germany and Korea. Although not reported, the model includes controls for firm size and age classes, as well as sector and year fixed effects, where available. For further details, see Box 4.3. See Table A C.11 – Table A C.15 for the complete list of coefficients. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

With respect to the relationship between AI use and firm productivity across countries, the figure shows that in most countries there is a positive and statistically significant association between AI adoption and the proxy for labour productivity analysed. Relevant exceptions appear to be Japan, where, however, AI adoption is proxied by machine learning, which represents only a subset of AI technologies, Israel, Switzerland and the United Kingdom. The productivity advantage of AI adopters is estimated to range from 7.7% in France to 31% in Belgium, highlighting relevant cross-country variation. These results align with those discussed at greater length by Calvino and Fontanelli (2023[16]).

Similarly, Figure 4.12 reveals a strong and statistically significant relationship between the use of big data analysis and firm productivity in the vast majority of countries. The estimated productivity advantages range from approximately 5% in France to nearly 28% in Korea.

The results for the links between IoT use and firm productivity suggest that the use of this technology is associated with a productivity advantage in 9 of the 11 countries analysed, with premia for IoT adopters ranging from 9% in the Netherlands to 23% in Korea. For a few countries, including Switzerland and Israel, no statistically significant relationship is observed between the use of IoT and firm-level productivity. Overall, these findings suggest that firms leveraging IoT technologies tend to be, on average, more productive than their non-adopting counterparts.

Similar to findings on other advanced digital technologies, robotics is associated with sizeable productivity advantages in most countries, ranging from around 14% in Denmark to 21% in Italy.

Finally, the results suggest that the adoption of 3D printing is associated with higher productivity levels in only 2 of the 11 countries analysed: Italy and Japan. The estimated productivity advantage for adopting firms here ranges from around 8% to 20%.[13] However, no statistically significant relationship is identified in the other countries analysed, suggesting a different role for 3D printing compared to other advanced digital technologies.[14]

For most countries in the sample, the observed productivity advantages are strongest in large firms. The importance of firm size becomes evident when these results are contrasted with the aforementioned findings. For example, while Figure 4.12 reveals a positive productivity association with 3D printing on average across all firms in only 2 of 11 countries, further unreported analysis suggests the existence of productivity advantages for large firms in 9 of the 10 countries for which data are available. This trend also holds for other technologies: premia for large firms are observed in 8 of 12 countries for AI; 7 of 9 for big data analysis; 6 of 10 for IoT; and 7 of 10 for robotics.

Beyond the adoption of advanced digital technologies, unreported results from the models estimated in Figure 4.12 suggest a strong relationship between firm size, firm age and productivity. The advantage of older firms is particularly robust for those older than 10 years, with positive and statistically significant effects across most technologies and countries. With respect to firm size, larger firms also tend, overall, to be more productive than other firms.

Unreported results using value added per employee as an alternative productivity measure in Belgium, the Netherlands and Portugal tend to qualitatively confirm the overall findings. While the estimated coefficients for technology adoption tend to be smaller, they remain statistically significant for the Netherlands and Portugal. In Belgium, however, the positive coefficients for big data analysis, IoT and robotics are no longer statistically significant.

It should be stressed that the positive relationship documented between advanced digital technologies and firm productivity should not be interpreted as causal. The implemented econometric strategy may be subject to endogeneity, selection and simultaneity issues. Importantly, more productive firms may be more likely to adopt advanced digital technologies in the first place. Parallel to their importance previously discussed in the context of technology adoption, the next stylised fact addresses some of these issues by exploring the role of enablers related to human and technological capital in firm productivity.

Stylised fact 7: Human and technological capital are associated with higher productivity, explaining part of the productivity premia of adopters

This stylised fact explores the extent to which the relationship between firm productivity and the use of advanced digital technologies is related to human and technological capital, key assets complementary to adoption, namely the presence of ICT specialists, ICT training for non-ICT personnel, use of fast broadband internet and digital technology intensity. The analysis builds on the previous stylised fact by including these complementary assets in the productivity regression (see Box 4.3 for details on the econometric strategy).

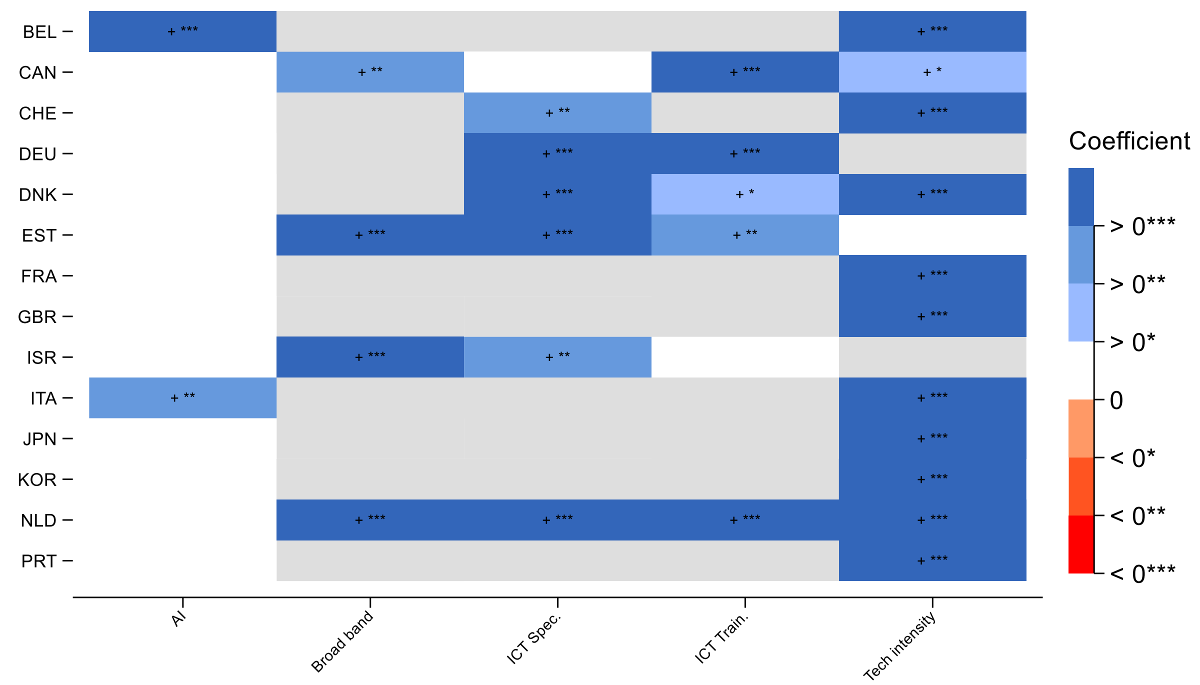
By accounting for these assets, this section aims to better understand whether higher productivity levels are primarily driven by the adoption of advanced digital technologies or rather by broader firm capabilities or assets, such as human capital, digital capabilities and digital infrastructure.

Figures 4.13–4.17 present the regression results for each advanced digital technology. The overall findings indicate that proxies for both human and technological capital are strongly associated with higher productivity levels across the countries and technologies considered. Moreover, when controlling for these factors, the positive link between the adoption of advanced digital technologies and productivity highlighted in the previous stylised fact weakens considerably. Notably, only the adoption of big data analysis and, to some extent, the use of robots remain associated with higher productivity levels across several countries.

Figure 4.13 presents the regression results for the role of AI adoption and complementary assets in firm productivity across countries. For European countries following Eurostat guidelines, the surveys that covered AI often did not include all measures of complementary assets, in particular human capital proxies such as the presence of ICT specialists or ICT training. As a result, Figure 4.13 only includes the full set of explanatory variables for Estonia and the Netherlands.

The results highlight two key findings. First, controlling for firms' digital technology intensity alone significantly weakens the productivity premia of AI adopters. Among the ten[15] countries that exhibit a productivity advantage in Figure 4.12, only two retain a significant premium, but substantially lower in magnitude in both cases, and with lower statistical significance in Italy. Second, complementary assets remain consistently associated with higher productivity levels. Overall, this suggests that firms benefiting from AI adoption tend to be those that are already highly digitalised, rather than the technology itself being the sole driver of productivity gains. This corroborates the findings discussed by Calvino and Fontanelli (2023[16]). Given the timing of the surveys considered, it is noteworthy to highlight that the analysis does not yet fully reflect the impacts of the recent boom in generative AI. Future work will focus on those more closely as new data become available.

Figure 4.13. Estimation of productivity regressions including complementary factors – AI



Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Canada, Germany and Korea. Although not reported, the model includes controls for firm size and age class, as well as sector and year fixed effects, where available. Regressions for Germany include a dummy equal to 1 if the firm has export activities. For further details, see Box 4.3. See Table A C.16 for the complete list of coefficients. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Box 4.4. AI adoption and productivity: evidence from Denmark using a production function approach

In a forthcoming paper, Warzynski (forthcoming[92]) examines the relationship between AI adoption, productivity and labour composition in Denmark, which has seen a rapid diffusion of AI among firms, increasing from 7% in 2017 to 36% in 2021. Drawing on the 2017-2021 ICT surveys merged with balance sheet data and LEED, the analysis confirms that adopters were typically larger and more productive, and they significantly increased their share of techies (defined as two-digit ISCO-08 code 25) prior to and after adoption, particularly in ICT-related sectors.

To assess the impact of AI on firm performance, the study employs two complementary approaches. First, a forward-looking growth model compares early adopters to other firms over a two-year horizon, showing that AI adopters experienced 3.7% higher growth in value added per worker and a 7.1% increase in the share of techies. Second, a production function framework is used to estimate the contribution of AI alongside traditional inputs. The baseline specification follows a Cobb–Douglas functional form with value added as the dependent variable and inputs including capital, tech labour, non-tech labour, and an AI adoption indicator. Estimation relies on the Wooldridge proxy-variable method (Wooldridge, 2009[93]) and OLS for robustness.

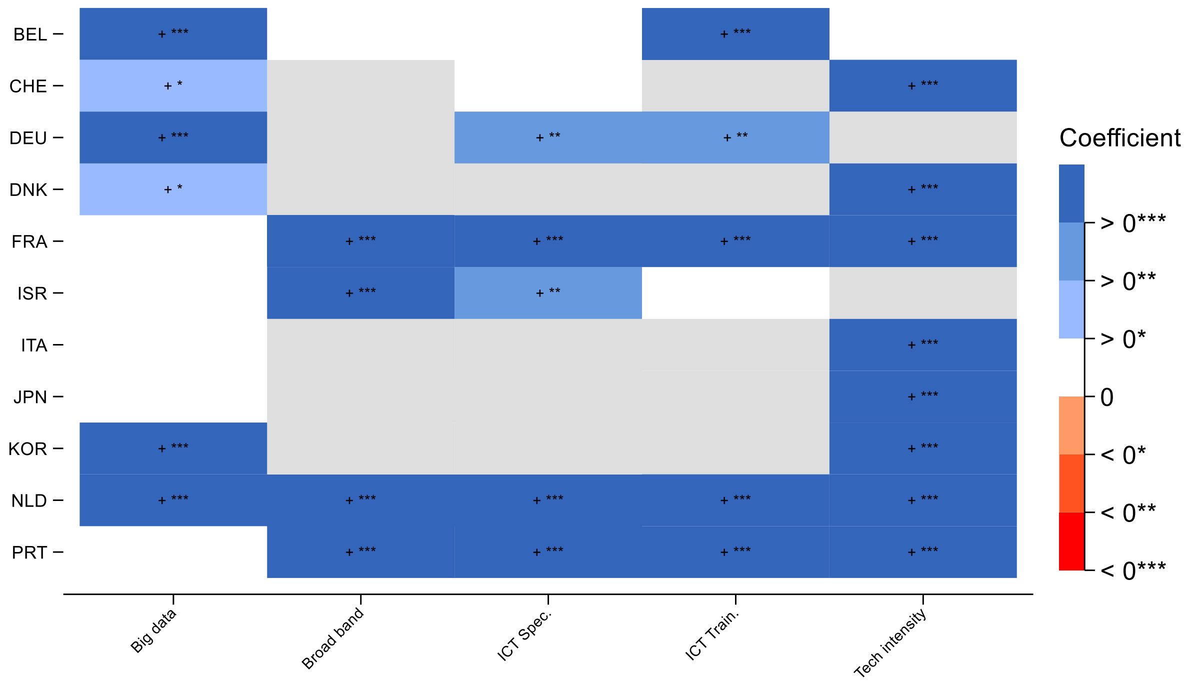
The results indicate that AI adoption is associated with a modest direct effect on value added (around 3%), but when interaction terms are introduced, complementarities become evident: the contribution of tech and non-tech labour rises significantly in AI-adopting firms, while traditional capital appears less productive, suggesting that intangible AI-related capital plays a distinct role. These findings provide further evidence about the “Productivity J-Curve” hypothesis (Brynjolfsson, Rock and Syverson, 2021[56]) and align overall with the cross-country evidence in this paper: AI adoption alone does not guarantee productivity gains, but rather, its impact depends on complementary investments in human capital and organisational change.

Figure 4.14 presents the regression results for the role of big data analysis and complementary assets in firm productivity across countries. Consistent with the findings for AI, the results suggest that the available measures of human and technological capital are generally positively and significantly associated with productivity levels. Notable exceptions include the presence of ICT specialists in Belgium and ICT training for non-ICT personnel in Israel, for which no statistically significant coefficients are observed.

While the productivity advantages of firms leveraging big data analysis significantly decline in magnitude, they remain positive and statistically significant in many countries. However, in France, Italy, Japan and Portugal – one of the two countries where all complementary asset variables are available – the productivity premia are no longer observed.

These findings suggest that the productivity benefits of big data analysis may be less dependent on pre-existing firm characteristics and may instead be more directly linked to its adoption and utilisation.

Figure 4.14. Estimation of productivity regressions including complementary factors – Big data analysis



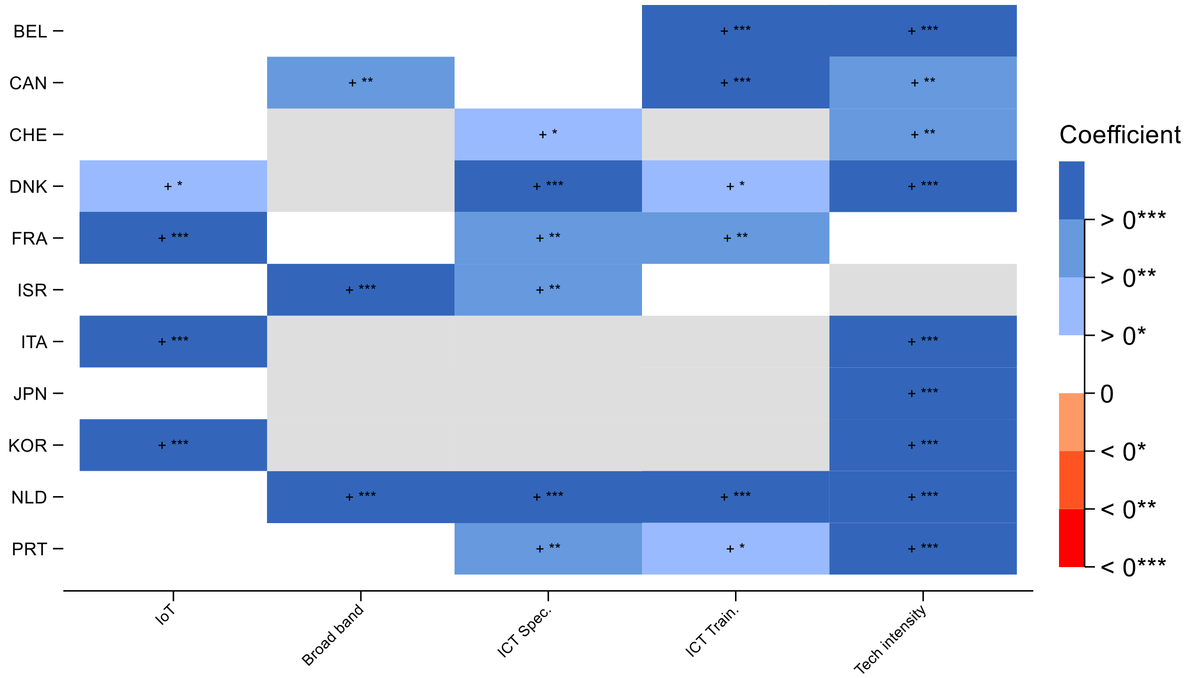
Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Germany and Korea. Although not reported, the model includes controls for firm size and age class, as well as sector and year fixed effects, where available. Regressions for Germany include a dummy equal to 1 if the firm has export activities. For further details, see Box 4.3. See Table A C.17 for the complete list of coefficients. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure 4.15 presents the regression results for the association of IoT adoption and complementary assets on firm productivity across countries. As with other advanced digital technologies, controlling for the presence of complementary assets again reveals that the use of IoT is not consistently associated with higher productivity.

The relationship between technology use and productivity varies across countries. A statistically significant productivity premium is observed in Denmark, France, Italy and Korea. This pattern underscores the role of complementary assets, which in some cases appear more strongly associated with productivity than the technology itself.

In line with previous results, the considered proxies for human and technological capital are generally positively and significantly associated with productivity levels, with some notable exceptions, as discussed above.

Figure 4.15. Estimation of extended productivity regressions including complementary factors – IoT

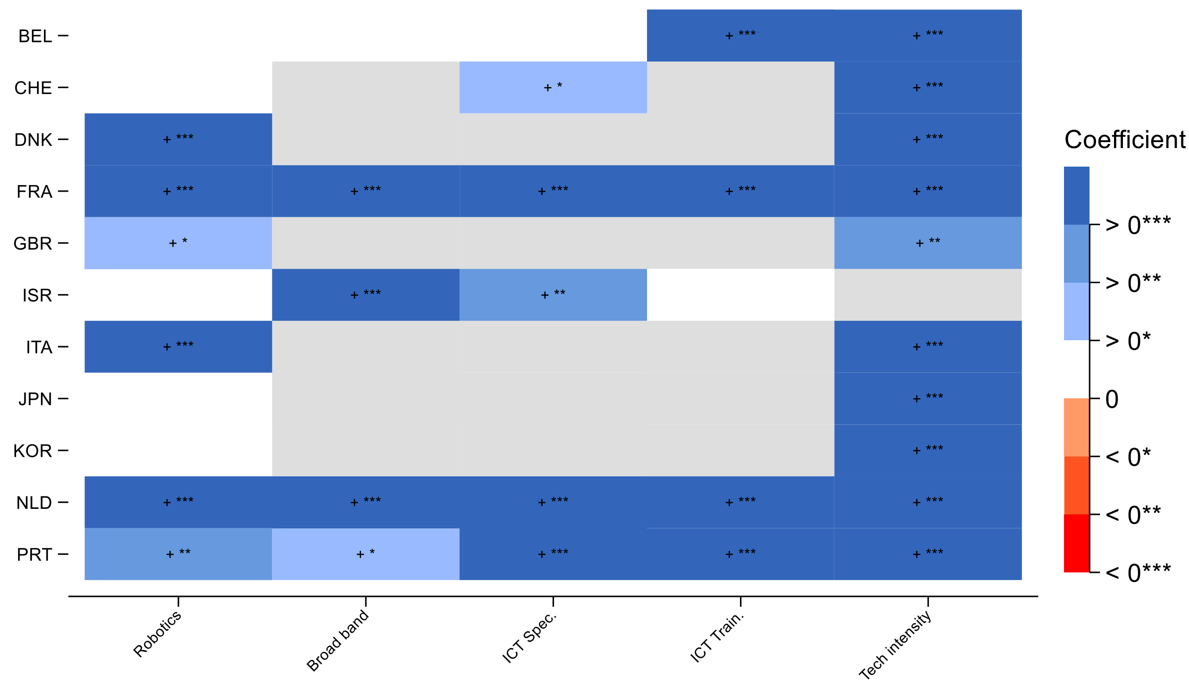


Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Canada and Korea. Although not reported, the model includes controls for firm size and age class, as well as sector and year fixed effects, where available. For further details, see Box 4.3. See Table A C.18 for the complete list of coefficients. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure 4.16 presents the regression results for the impact of the use of robots and related complementary assets on firm productivity across countries. Accounting for the role of complementary assets again reduces the magnitude of the productivity advantages associated with using robots.

However, despite this reduction, premia remain statistically significant in six of the eight countries where they were initially observed (see Figure 4.12). For Belgium, Japan, and Korea the previously identified premium is no longer present.

Figure 4.16. Estimation of productivity regressions including complementary factors – Robotics

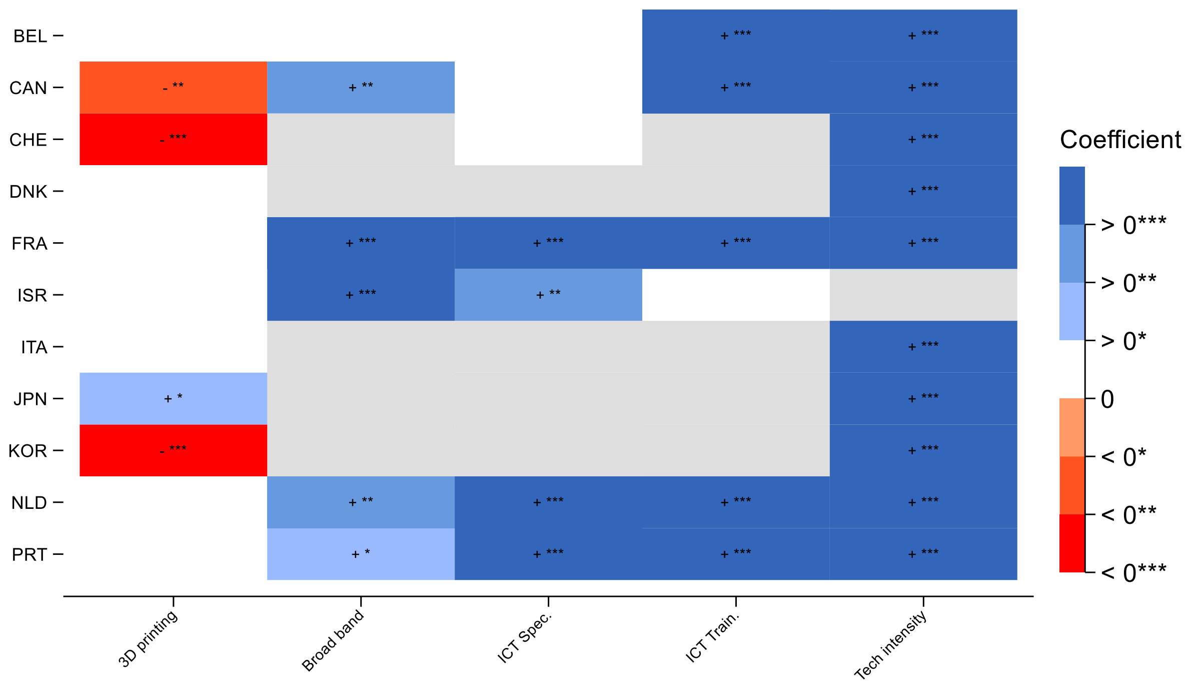


Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Korea. Although not reported, the model includes controls for firm size and age class, as well as sector and year fixed effects, where available. For further details, see Box 4.3. See Table A C.19 for the complete list of coefficients. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure 4.17 presents the regression results for the coefficients of 3D printing use and complementary assets, highlighting their association with firm-level productivity across countries. The results indicate that, after controlling for proxies for firms' human and technological capital, a positive and statistically significant association between the use of 3D printing and productivity is now observed only in Japan – down from Japan and Italy in the previous analysis (see Figure 4.12). Moreover, the magnitude of the productivity advantages for 3D printing users in Japan declined considerably, becoming only weakly significant. By contrast, the adoption of 3D printing is now even associated with a small productivity penalty in Canada, Switzerland and Korea. The relationship between these proxies and productivity is consistently positive across countries.

Overall, these findings suggest that the use of 3D printing does not yield consistent productivity gains. However, they highlight the importance of complementary assets, which consistently show a strong and positive association with productivity advantages.

Figure 4.17. Estimation of productivity regressions including complementary factors – 3D printing



Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Canada and Korea. Although not reported, the model includes controls for firm size and age classes, as well as sector and year fixed effects, where available. For further details, see Box 4.3. See Table A C.20 for the complete list of coefficients. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

The findings discussed in this stylised fact highlight the crucial role of human and technological capital, not only as key assets complementary to adoption but also as important for firms' productivity advantages. These complementary assets are indeed critical to driving firm-level productivity, corroborating the importance of accounting for these factors to mitigate selection bias.

Overall, the results on productivity premia associated with advanced digital technologies reveal a mixed pattern. For AI, IoT and 3D printing, the advantages, in many cases, disappear once accounting for the role of human and technological capital more broadly, whereas for big data analysis and robotics, the premia tend to remain significant, albeit notably reduced, in multiple countries.

Among the analysed complementary assets, firms' technological capital - in particular, firms' digital technology intensity - emerges as an influential factor, consistently associated with higher productivity levels across most countries.[16] In most cases, it also accounts for a substantial share of the observed decline in the productivity advantages of adopters of advanced digital technologies, underscoring the importance of firms' pre-existing digital capabilities in boosting productivity.

Box 4.5. Management education and qualifications: evidence from the United Kingdom

While the MES 2023 survey for the United Kingdom lacks information on ICT specialists and training, it provides data on managerial human capital. Specifically, it captures the proportion of managers with a recognised management qualification and the proportion with a university degree or equivalent. Both variables are collected in brackets (e.g. none, fewer than 20%, 20-49%, etc.) and are used as categorical variables in the analysis. This box provides insights into the role of these management skills in the adoption of AI and robotics, as well as their influence on productivity. The adoption and productivity regressions use the econometric strategies outlined in Box 4.1 and Box 4.3, respectively.

Adoption

The results suggest that managers' formal qualifications are not associated with the adoption of either technology. However, managers' university-level education does appear to play a role. For AI, a weak positive association is found: firms where over 80% of managers hold a degree are four percentage points more likely to adopt AI, though this result is only statistically significant at the 10% level. For robotics, the association is stronger and more robust. Firms with 20-49% or more of their managers holding a university degree are around four percentage points more likely to adopt robotics, with this link being consistent across all higher education brackets.

Productivity

The baseline results, shown in Figure 4.13, indicate no productivity premium for AI adoption, while robotics users are, on average, 21% more productive than non-users in the same sector and size class. Including the variables for managers' qualifications and education does not substantially alter these findings. The productivity premium for robotics users remains statistically significant at 18%, while the lack of a premium for AI adoption also persists. Furthermore, management skills themselves are strongly correlated with firm productivity. Firms where over 80% of managers hold a recognised management qualification are 50% more productive than those where none of the managers hold such a qualification. A significant, positive association is also found for managers' university education, with a productivity premium of up to 31% for firms in the highest bracket.

This suggests that, while a highly skilled management team may increase the likelihood of adopting certain technologies like robotics and is associated with higher productivity, it does not appear to be the key factor in explaining productivity gains after adoption in the UK context.

5 Concluding remarks

This paper provides a comprehensive analysis of advanced digital technology diffusion in the age of AI, leveraging official, representative microdata across 15 OECD Member countries. The analysis in this paper has identified seven stylised facts regarding the key characteristics of the adopters of AI, big data analysis, IoT, robotics and 3D printing, the role of policy-relevant enablers of technology diffusion, and the links between the use of advanced digital technologies and productivity.

The analysis reveals some key insights into the patterns and determinants of advanced technology adoption: advanced technologies tend to be adopted together and often build on foundational enablers such as cloud computing, CRM and ERP systems, and fast broadband. This highlights both technological and organisational complementarities, a likely reason for the fact that technology diffusion varies considerably by sector and technology, with AI and big data analysis most prevalent in the ICT sector, robotics and 3D printing in manufacturing, and IoT comparatively more versatile. Adoption also rises with firm size, even after accounting for sectoral composition and firm age, which suggests meaningful scale advantages for firms integrating new technologies into processes. In line with previous findings, additional complementarities in the form of human and technological capital are also highly relevant for adoption as they are consistently associated with higher adoption. Further evidence from LEED on human capital indicates that education and technical occupations are important, as higher shares of graduates and technology-related roles tend to be linked to greater uptake of advanced technologies.

Building on the analysis of diffusion, this paper finds that adopters of advanced technologies are generally more productive than non-adopters, with the notable exception of 3D printing. As with the determinants of adoption, much of the productivity advantage is associated with human and technological capital. When these factors are taken into account, positive associations with firm productivity persist most clearly for big data analysis and, to a lesser extent, robotics, while, notably, AI shows a limited productivity premium over the period studied.

Because adoption depends on complementarities, effective strategies should combine investments in digital infrastructure such as fast broadband, foundational systems such as cloud and ERP or CRM, and skills development for both ICT specialists and non-ICT workers. Policies should take a comprehensive approach, taking technological complementarities and the potential of AI as a general-purpose technology into account. Moreover, policies should be sector-sensitive and address scale barriers faced by SMEs, while recognising the different diffusion drivers and economic impacts across technologies. Strengthening human capital and technological capital simultaneously, while co-operating internationally to establish an interoperable governance and policy environment for trustworthy AI, is central to accelerating responsible diffusion and realising productivity gains (see also OECD (2024[17]) and Lorenz, Perset and Berryhill (2023[94]) for further discussion).

While the current analysis is comprehensive in several respects, future work could extend the analytical scope in several directions. Future work may further zoom in on selected advanced technologies, examining their use patterns and links with firm-level or worker-level outcomes in greater detail, possibly establishing more causal links, as new cross-country data become available. In particular, ongoing work aims to focus on the role of AI, which has been growing in relevance, including with recent advancements in generative AI. More recent survey data may be better able to track the use of generative AI in firms by capturing recent trends and more comprehensively covering generative AI uses. They may more generally enable more detailed explorations of the patterns of use of different types of AI systems, their different uses across business functions, or the different development sources of the AI systems used (e.g. in-house development vs. acquisition from external providers). More recent data may also shed more light on the extent to which productivity returns to AI adoption are becoming more visible over time, even after accounting for the role of human and technological capital, or on their heterogeneity across different types of AI users. Finally, future work may further explore the links between AI use and other relevant economic and social outcomes based on micro-level data, including, for example, analysing the interrelations between different types of AI use and competition, focusing further on different actors in the AI value chain, exploring the role of AI innovation for innovation in other fields, and more broadly analysing the micro-economic drivers of AI-fuelled growth.

Endnotes

[1] For a further conceptual discussion about technology diffusion see Comin and Mestieri (2014[102]), who highlight that technology diffusion describes the accumulation of technology across adopters over time. In this paper, diffusion and adoption are often used interchangeably, with limited reference to their timing.

[2] See also Lane and Saint-Martin (2021[101]) for a review of the impact of AI on skill needs and the work environment.

[3] For a discussion of generative AI as a potential general-purpose technology, see Calvino, Haerle and Liu (2025[11]).

[4] For further information on the ICT survey used in France, see e.g. Insee (2023[103]).

[5] Eigenvector centrality (or eigen centrality henceforth) is a centrality measure commonly used in network analysis to assess the influence of a node in a connected network.

[6] Results for Germany are based on unweighted data and on a sectoral classification different from (and broader than) the one used for other countries.

[7] See Calvino et al. (2024[100]) for a related discussion in the context of a taxonomy of AI-intensive sectors.

[8] However, it may also be the case that due to its general-purpose nature, AI may showcase some embedding in manufacturing equipment that is not fully captured by the surveys due to limited awareness, despite reference in some questions to AI embedded in devices. For further discussion on the literature on embedded devices, see e.g. Zhang and Li (2023[98]) or Elahi et al. (2023[99]). Future work will also aim to further focus on the different purposes for which AI is used.

[9] Specifically, techies fall under ISCO-08 codes 133, 214, 215, 251, 252, 311, 313, 315, 351, and 352. Within this group, codes 133, 251, 252, 351 and 352 identify ICT techies, while codes 214, 215, 311, 313 and 315 denote non-ICT techies.

[10] Notably, the share of techies shows a statistically significant positive association with IoT in Portugal and 3D printing in Denmark when accounting for the firm's overall digital technology intensity (not shown in figure).

[11] Unreported results for Denmark and Portugal suggest that different types of technical occupations (ICT techies vs non-ICT techies) may be relevant for the adoption of different advanced digital technologies.

[12] Unreported descriptive statistics show that firms using advanced digital technologies tend to be more productive than their non-adopting counterparts. This pattern is particularly consistent for AI and big data analysis, where adopters exhibit higher productivity across most countries in the sample.

[13] Unreported analysis focusing on manufacturing and utilities, sectors that exhibit higher adoption rates of 3D printing, still suggests that – for most countries – adopters in this sector are not significantly more productive than other firms.

[14] Although noticeable productivity premia are observed for many advanced digital technologies, relevant differences in magnitude are observed across countries. Such differences could be driven by several factors, including differences in sectoral composition within broad sectors, technological maturity and diffusion levels. Countries with more advanced digital ecosystems and stronger AI integration within key industries may see greater productivity benefits. Additionally, differences in survey timing and AI definitions – such as the focus on machine learning in Japan – could partly explain the heterogeneity in estimated coefficients (see Annex B for further details).

[15] Germany was one of the countries for which a productivity premium was previously observed. However, data on the same set of complementary factors are not available. Unreported analysis suggests that once accounting for training, the presence of skilled employees, export status, financial constraints and innovation activity, the AI use coefficient is no longer statistically significant. See also Calvino and Fontanelli (2023[16]).

[16] Further unreported analysis for Israel, containing the share of other digital technologies adopted as a control, also shows a robust positive link between firm digitalisation and productivity.

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Annex A. Additional information on data and methodology

Balance sheets and LEED

Balance sheet data for Belgium is available from the Central Balance Sheet Office. This data source, which has been available since 1985, provides comprehensive coverage over all corporations and includes details on firm characteristics such as value added and intermediate inputs, essential for productivity proxies. The unit of analysis for these financial data is the enterprise. Employment is measured in headcounts and FTE.

Balance sheet data for Denmark is available from the FIRE dataset. This dataset provides detailed accounting information about the population of Danish firms and is available since 1992. It allows for the measurement of firm-level information such as revenue, value added, capital, material costs, employment, among others. Furthermore, LEED for the entire population of Danish workers are also available from the register-based Integrated Database for Labour Market Research (IDA). This dataset has been available since 1980 and contains rich worker-level information, such as formal education and a detailed description of workers' occupations.

For France, balance sheet data are provided by the annual structural statistics of companies (FARE), leveraging administrative tax data (see e.g. Insee & Ministère des Finances (DGFiP) (2021[95]) for further details). This dataset is available since 2008 and contains detailed information on the financial accounts of firms, which allows for the computation of additional proxies for productivity. FARE can be linked to the ICT survey.

Balance sheet data for the Netherlands is also available from the Statistics on Finances of Non-Financial Enterprise Groups (SFO) and covers the period from 2001 onwards. These data contain information on capital stock, value added, sales, and intermediate inputs. Annual LEED, covering the period from 2016 to 2022, include information on wages, hours worked, education level and type, gender and age, and can distinguish between part-time and full-time workers.

Balance sheet data for Portugal is available from the Integrated Business Accounts System (SCIE – *Sistema de Contas Integradas das Empresas*). The SCIE contains firm-level administrative financial data, including balance sheet and other account data. These are collected every year for the population of firms in the private sector, except for the financial sector, from 2006 to 2022, covering around 400 000 firms per year. LEED is available from the Personnel Records (QP – *Quadros de Pessoal*). The QP is a matched employer-employee database collected by the Portuguese Ministry of Labour, Solidarity and Social Security. It provides information on workers in all Portuguese firms, except for the public administration, regional and local, as well as public institutions; and employers or workers of domestic service. The data include information on workers' formal education, age, gender, occupation, monthly wage, hours of work and the type of labour contract, from 1985 to 2022, with information about around 3 million workers per year.

Description of the national ICT surveys

ICT surveys following Eurostat guidelines

For many European countries, the relevant data sources consist in national ICT surveys, which follow the guidelines provided by Eurostat through the Community Survey on ICT usage and e-commerce in enterprises and are gathered by national statistical offices annually. The surveys aim to collect and disseminate harmonised and comparable information on the use of ICT and e-commerce in enterprises at the European level. The data for these countries are thus generally based on common units of analysis and variable definitions, and they tend to overlap in terms of sectoral and size coverage. A main source of divergence between surveys may arise from the existence of optional questions that may be carried out only in some country-years. The countries included in the analysis whose data follow the Eurostat guidelines are Belgium, Denmark, Estonia, France, Ireland, Italy, the Netherlands and Portugal. Switzerland largely follows Eurostat guidelines in the implementation of its surveys. Survey weights are available for all countries with the exception of Ireland.

The Eurostat Community Survey on ICT usage and e-commerce in enterprises has been covering advanced digital technologies since 2014, with the latest survey implemented for 2024. Variables covered in all waves typically include the sector classification, the number of employees, turnover and the availability of fast broadband internet.

The survey uses the enterprise as the unit of analysis. The survey population generally comprises enterprises with 10 or more persons employed, with smaller firms (micro-enterprises) included on an optional basis. The sampling is rotating, except for enterprises with employment above a country-specific threshold, typically large firms, in which case all units are included. The survey includes probability weights for all countries.

Other firm-level surveys

The data for Canada are based on the 2023 Survey of Digital Technology and Internet Use (SDTIU), which is designed to measure the impact of digital technologies on the operations of Canadian enterprises. The data from this survey are used by government departments to develop policies and programmes that help improve Canada's innovation system and strengthen the overall economy. The SDTIU is sponsored by Innovation, Science and Economic Development Canada (ISED). Although survey weights are available, a significant share of firms that adopt advanced digital technologies lack information on turnover, particularly firms that adopt advanced digital technologies in certain sectors. The productivity regressions for Canada shown in this paper are therefore unweighted, and this should be taken into account when interpreting the results, e.g. by considering that large firms are more prevalent in unweighted samples.

The firm-level data source for Germany is the Mannheim Innovation Panel (MIP), which is gathered by the Leibniz Centre for European Economic Research (ZEW) as part of the Community Innovation Survey. The ZEW has been collecting data on innovation activities of the German enterprise sector since 1993 on an annual basis through a representative survey. The survey is based on a stratified random sample of firms with 5 or more employees in the manufacturing sector and business services, however, as weights are not included in the version upon which this analysis is based, the reported results for Germany are unweighted, and this should be taken into account when interpreting the results (see also above).

The data for Israel are based on the Survey on ICT Uses and Cyber Defence in Businesses, which examines firms' use of advanced digital technologies in 2020. This survey, conducted from July 2020 to March 2021, estimates business activity in 2020. The survey includes probability weights.

The data for Japan are collected by the Japanese National Innovation Survey (J-NIS) 2020 and 2022. These surveys provide information on the innovation activities of Japanese firms, focusing on technology use during the three-year periods from 2017 to 2019 and from 2019 to 2021, respectively. The data collection is biannual, and the surveys include probability weights.

The data for Korea are part of the Survey for Business Activities from Statistics Korea (KOSTAT). This survey asks establishments about their use of various digital technologies, including AI, big data analysis, cloud computing services, IoT, robotics and 3D printing. The survey covers all Korean firms with at least 50 full-time employees and a capital stock of at least KRW 300 million, regardless of their sector of activity. For firms with fewer than 50 employees, the sample includes those in wholesale and retail trade and other service industries with a turnover exceeding KRW 1 billion.

The data for Switzerland are sourced from the KOF Enterprise Panel, based on two waves of the Swiss innovation survey and one wave of the ICT survey (see also Beck, Plekhanov and Wörter (2020[96])).

The unit of analysis is the enterprise, specifically targeting enterprises with at least 5 full-time equivalents (FTEs). The surveys include probability weights. Questions referred to the previous year.

The data for the United Kingdom are sourced from the 2023 wave of the Management and Expectations Survey (MES), which is collected by the Office for National Statistics (ONS). The survey covers UK businesses with ten or more employees across the production and services sectors. Key sectors excluded from its scope are agriculture, forestry and fishing (SIC divisions 1-3), financial and insurance activities (SIC divisions 64-66), and public institutions in health and education. Probability weights are included in the survey.

Further description of the Digital Diffuse program

Before running the statistical and regression analyses, the program performs a series of basic data cleaning steps, including deflation and purchasing power adjustment of monetary variables, and the computation of weights, if they are not specified as an input and a business register is available. A labour productivity proxy is then computed as the ratio between turnover and employment, usually taken directly from the ICT survey. Conditional on data availability, further productivity proxies are also computed from balance sheet data.

The main set of summary statistics includes the shares of firms using each technology based on several sectoral aggregations, size and age classes, number of digital technologies used by firms and productivity quantiles.

Different sectoral aggregations (based on the ISIC Rev. 4 classification) are computed by the program, notably including at 2-digit, SNA A7 and SNA A38 levels.

Size and age are reported in terms of classes. The size class variable encompasses five categories (fewer than 10 persons engaged, between 10 and 19 persons engaged, between 20 and 49 persons engaged, between 50 and 249 persons engaged, and 250 or more persons engaged, plus a category for firms with missing information), whereas four classes are reported for firm age (less than 6 years old, between 6 and 10 years old, 11 years old or more, and a category for firms with missing information on age). Information on firms with fewer than 10 persons engaged is generally excluded from the analysis since it is not covered by many surveys, although used for robustness checks when available (see below). As a proxy for firm digital technology intensity, the code builds a variable counting the overall number of technologies used at the firm-level, conditional on data availability. The technology under scrutiny is excluded and the number is normalised when the number of technologies is used as an explanatory variable in regression analysis (see Box 4.1 for further details).

Firms are divided into productivity classes based on the quantiles of the productivity distribution, which are computed at the industry SNA A38 level in order to take into account sector level differences in productivity.

The analysis distinguishes six productivity classes: top 10%, between 90% and 60%, between 60% and 40%, between 40% and 10%, and bottom 10% of the productivity distribution.

The program also computes correlation tables year by year, average employment, turnover, productivity, and age based on several aggregations (e.g. use/non-use within sectors), generates tables reporting co-occurrences of pairs of technologies, and generates overall counts of non-missing observations at different levels of aggregation.

Beyond summary statistics, the Digital Diffuse program estimates two main series of regressions: adoption and productivity regressions.

The adoption regressions employ the use of each advanced digital technology (where available) as dependent variables in regression models including size and age classes as explanatory variables and, when available, other complementary factors (firm digital technology intensity, digital infrastructure, ICT skills), as well as industry or geographic fixed effects. If LEED are available, the program re-estimates all models with each measure of skills as an additional explanatory variable. Separate regressions are estimated, including different sets of industry fixed effects at available levels of sectoral aggregation (see above). Geographical fixed effects are also included as robustness (where available). The regressions are mainly linear probability models. However, the program also computes probit regressions for robustness purposes.

The productivity regressions include labour productivity as the dependent variable. Labour productivity is measured by turnover over employment and, where available, value added over employment. The adoption of advanced digital technologies are the main explanatory variables. Technology use variables are also interacted with size classes. These regressions also include a series of controls (size and age class, complementary factors – firm digital technology intensity, digital infrastructure, and ICT skills) and fixed effects (sectoral and geographic). As with the adoption regressions, where LEED are available, the program re-estimates all models with each measure of skills as an additional explanatory variable. Additional exploratory sets of productivity regressions are estimated by the program at the sectoral level. Robustness checks are also estimated excluding firms at the top 5% of the productivity distribution, lagging the explanatory variables and including as a regression the dependent variable in lagged form.

Another set of productivity regressions leveraging MFP measures estimated using the methods proposed by Ackerberg et al. (2015[97]) and Wooldridge (2009[93]) are implemented conditional on data availability. As with the labour productivity regressions described above, the adoption of advanced digital technologies is used as the main set of explanatory variables. Controls such as size and age class, complementary factors – firm digital technology intensity, digital infrastructure, and ICT skills, and sectoral fixed effects are included. As with the previous set of regressions, where LEED are available, the program re-estimates all models with each measure of skills as an additional explanatory variable.

Annex B. Technology definitions and survey coverage

This section provides detailed information on the coverage of the relevant technologies for this paper. Additionally, definitions are provided for the latest available year in which the technology was surveyed.

Definitions for surveys following Eurostat guidelines

AI

AI is defined as “systems that use technologies such as text mining, computer vision, speech recognition, natural language generation, machine learning, deep learning to gather and/or use data to predict, recommend or decide, with varying levels of autonomy, the best action to achieve specific goals. Artificial intelligence systems can be purely software based, e.g. chatbots and business virtual assistants based on natural language processing; face recognition systems based on computer vision or speech recognition systems; machine translation software; data analysis based on machine learning; or embedded in devices, e.g. autonomous robots for warehouse automation or production assembly works; autonomous drones for production surveillance or parcel handling.”

AI was surveyed in 2021, 2023 and 2024. The questions referred to the reference year and included information on the type of AI used, such as text mining, and the purpose of the technology, such as use of AI for marketing or sales. Optional questions include information on how AI was acquired and the reasons for not adopting it.

Big data analysis

Big data analysis refers to the use of technologies, techniques or software tools such as data or text mining, machine learning, etc. for analysing big data extracted from the enterprise's own data sources or other data sources.

Big data analysis was surveyed in 2016, 2018 and 2020, although all questions were optional for countries to implement in 2016 and 2018. Questions referred to the previous year. The information collected is related to data sources, methods and the use of an external provider to perform the analysis.

Cloud computing services

Cloud computing services refer to “ICT services that are used over the internet to access software, computing power, storage capacity, etc., where the services have all of the following characteristics: are delivered from servers of service providers; can be easily scaled up or down (e.g. number of users or change of storage capacity); can be used on-demand by the user, at least after the initial set up (without human interaction with the service provider); are paid for, either per user, by capacity used, or they are pre-paid. Cloud computing may include connections via Virtual Private Networks (VPN).”

The use of cloud computing services was surveyed in 2014, 2015, 2016, 2017, 2018, 2020, 2021 and 2023, although all questions were optional for countries to implement in 2015 and 2017. Questions referred to the reference year and also asked about the types of services bought.

IoT

IoT refers to interconnected devices or systems, often called “smart” devices or “smart” systems. They collect and exchange data and can be monitored or remotely controlled via the internet, through software on any kind of computers, smartphones or through interfaces like wall-mounted controls.

IoT was surveyed in 2020 and 2021. However, in 2020, implementation was optional for all questions. Information referred to the reference year and included information on the type of devices used and purpose of the technology.

CRM

CRM is defined as “software for managing information about customers (e.g. relations or transactions)” that “facilitates communication with the customer and helps track customer interests, purchasing habits.”

CRM was surveyed in 2014, 2015, 2017, 2019, 2021 and 2023. The information referred to the reference year and included information on the purpose of the technology.

E-commerce

E-commerce refers to the sales of goods or services where “the order is placed via web sites, apps or EDI-type messages (EDI: Electronic Data interchange) by methods specifically designed for the purpose of receiving orders. The payment may be done online or offline. E-commerce does not include orders written in e-mail.”

E-commerce is the only technology to have been surveyed in all years. Information collected referred to the previous year. Enterprises were inquired regarding the importance of e-commerce sales in total sales and percentage breakdown of web sales value by type of customer relationship, such as B2C (business to customer), B2B (business to business) or B2G (business to public authorities).

ERP

ERP is defined as “software used to manage resources by sharing information among different functional areas (e.g. accounting, planning, production, marketing). ERP software can be off-the-shelf software, customised to the needs of the enterprise or self-created software.”

ERP was surveyed in 2014, 2015, 2017, 2019, 2021 and 2023. Information on usage referred to the reference year without sub-questions.

Robotics

Robotics refers to machines programmed to move and perform specific tasks automatically. There are two main types of robots:

1. Industrial Robots: These are automatically controlled, reprogrammable, multipurpose manipulators, programmable in three or more axes, which may be either fixed in place or mobile for use. Most industrial robots are based on a robotic arm and a series of links and joints with an end effector that carries out the task.
2. Service Robots: These have a degree of autonomy and can operate in complex and dynamic environments that may require interaction with persons, objects or other devices. They use wheels

or legs to achieve mobility and are often used in inspection, transport or maintenance tasks. Examples include autonomous guided vehicles, inspection and maintenance robots, and cleaning robots.

Robotics was surveyed in 2018, 2020 and 2022, although all questions were optional to be implemented by countries in 2018. Information referred to the reference year and inquired enterprises on the type of robotics used, the purpose and motives of the usage of robotics.

3D printing

3D printing or additive layer manufacturing refers to the use of special printers either by the enterprise itself or the use of 3D printing services provided by other enterprises for the creation of three-dimensional physical objects using digital technology.

3D printing was surveyed in 2018 and 2020. The questions referred to the previous year and included information on the ownership of the printers and the purpose of the technology.

Country-specific information for other surveys

Canada

AI refers to systems that display intelligent behaviour by gathering or using data to predict, recommend or decide, with varying levels of autonomy, the best action to achieve specific goals. AI-based systems can be purely software based or embedded in a device.

IoT: the interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data. Examples include smart televisions, Wi-Fi enabled security cameras, automatic car tracking adapter, Canary smart security system, Cisco's connective factory, Phillips hue smart bulbs and August smart locks.

Germany

AI: a method of information processing that allows computers to autonomously solve problems.

Big data analysis: systematic analysis of large amounts of data.

Israel

AI is a multidisciplinary field devoted to making machines intelligent; intelligence being the quality that enables an entity to function appropriately in its environment. Today, most applications in the field are based on the ability of machines and systems to interpret data, to learn and derive insights from said data, and to use these insights to perform tasks and achieve goals all in an adaptive process.

Big data analysis refers to the use of techniques, technologies and software tools for analysing big data extracted from own enterprise's data sources or other data sources. Big data are generated from activities that are carried out electronically and from machine-to-machine communications (e.g. data produced from social media activities, from production processes, etc.). Big data typically have characteristics such as: (1) Significant volume referring to vast amounts of data generated over time. (2) Variety referring to the different formats of complex data, either structured or unstructured (e.g. text, video, images, voice, docs, sensor data, activity logs, click streams, coordinates, etc.). (3) Velocity referring to the high speed at which data are generated, becomes available and changes over time. (4) Reliability referring to the quality of the data and the effect it has on the information drawn from them.

IoT refers to the internet interconnection of computing devices embedded in machines, devices and everyday objects, enabling them to send and receive data and/or affect their operation, with or without human intervention.

Robotics: An industrial robot is an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications. A service robot is a machine that has a degree of autonomy and is able to operate in a complex and dynamic environment that may require interaction with persons, objects or other devices, excluding its use in industrial automation applications. Does not include software robots (internet "bots".)

Japan

AI: Machine learning is a technology or method that enables a computer to acquire knowledge from experience (data) and automatically perform tasks such as prediction, classification, clustering, and grouping. Machine learning can be broadly divided into “supervised learning” in which correct answer data (a collection of pairs of inputs and outputs (correct answers)) is given, and “unsupervised learning” in which case data (a mere collection of input cases) is given. Machine learning also includes such as “reinforcement learning,” which gives clues for learning with rewards (scores) instead of correct answer data. Machine learning can be considered as a field of AI.

Big data analysis refers to the use of techniques, technologies, and software tools for analysing big data extracted from internal and external data sources. "Big data" refers to the vast amounts of data generated in various types and formats that are collected through networks such as the Internet.

Korea

AI is a technology that mimics humans by learning, reasoning, perceiving, and understanding the natural language based on the computer programs.

Big data analysis: large volumes of digital data on a massive scale may include numerical, text and image data.

United Kingdom

AI is technology where computer programs or machines can learn from data and perform tasks usually done by humans. AI is currently used in a variety of ways, including: online product recommendations, facial recognition, self-driving vehicles, medical diagnostic tools, chatbots that interact in a conversational way and can answer complex questions.

Robotic equipment (or robots) is automatically controlled, reprogrammable, and multipurpose machines used in automated operations in industrial and service environments. Robots may be mobile, incorporated into stand-alone stations, or integrated into a production line. A robot may be part of a manufacturing cell or incorporated into another piece of equipment.

Industrial robots may perform operations such as: palletising, pick and place, machine tending, material handling, dispensing, welding, packing and repacking, and cleanroom.

Service robots are commonly used in businesses for such operations as cleaning, delivery, construction, inspection, and medical services such as dispensing or surgery.

Table A B.1. List of contributors to the *Digital Diffuse* project

Country	Contributor(s)	Institution(s)
BELGIUM	Michel Dumont, Chantal Kegels	Federal Planning Bureau
CANADA	Howard Bilodeau, Aisha Khalid, Mark Uhrbach	Statistics Canada (STATCAN)
DENMARK	Frederic Warzynski	FIND, Aarhus University
ESTONIA	Christina Palmou; Jaan Masso	Organisation for Economic Co-operation and Development (OECD); University of Tartu
FRANCE	Hélder Costa	OECD
GERMANY	Luca Fontanelli	University of Brescia
IRELAND	Iulia Siedschlag, Juan Duran Vanegas	Economic and Social Research Institute (ESRI)
ISRAEL	Gilad Be'ery; Matan Goldman, Eliav Orenbuch, Daniel Roash	Ministry of Economy and Industry; Central Bureau of Statistics (ICBS)
ITALY	Stefano Costa, Giulio Perani	Italian National Statistical Office (ISTAT)
JAPAN	Yuya Ikeda	National Institute of Science and Technology (NISTEP)
KOREA	Jaehan Cho, Hanhin Kim	Korea Institute for Industrial Economics and Trade (KIET)
NETHERLANDS	Michael Polder, Christiaan Visser, Stef Weijers	Statistics Netherlands (CBS)
PORTUGAL	Hélder Costa	OECD
SWITZERLAND	Mathias Beck, Tatiana Bielakova, Johannes Dahlke, Martin Wörter, Dmitry Plekhanov	Swiss Federal Institute of Technology (ETH)
UNITED KINGDOM	Oliver Schnabel, Rabiya Nasir; Christina Palmou	Office for National Statistics (ONS); OECD

Table A B.2. Technology coverage by country

Country	Technology	Years covered
Belgium	3D printing	2019
	AI	2020, 2022
	Big data analysis	2019
	IoT	2019-2020
	Robotics	2019
Canada	3D printing	2023
	AI	2023
	IoT	2023
Denmark	3D printing	2017-2019
	AI	2016-2018, 2020
	Big data analysis	2017-2018
	IoT	2020
	Robotics	2017-2019
Estonia	AI	2022-2023
France	3D printing	2019
	AI	2020, 2022
	Big data analysis	2019
	IoT	2019-2020
	Robotics	2019
Germany	AI	2018, 2020
	Big data analysis	2018
Ireland	AI	2023
Israel	3D printing	2020
	AI	2020
	Big data analysis	2020
	IoT	2020
	Robotics	2020
Italy	3D printing	2019
	AI	2020, 2022

	Big data analysis	2019
	IoT	2019-2020
	Robotics	2019
Japan	3D printing	2019, 2021
	AI	2019, 2021
	Big data analysis	2019, 2021
	IoT	2019, 2021
	Robotics	2021
Korea	3D printing	2017-2019
	AI	2017-2019
	Big data analysis	2017-2019
	IoT	2017-2019
	Robotics	2017-2019
Netherlands	3D printing	2017, 2019
	AI	2019-2021
	Big data analysis	2015-2017, 2019
	IoT	2019-2020
	Robotics	2017, 2019, 2021
Portugal	3D printing	2017, 2019
	AI	2020, 2022
	Big data analysis	2015, 2017, 2019
	IoT	2019, 2020
	Robotics	2017, 2019
Switzerland	3D printing	2018-2019
	AI	2018-2020
	Big data analysis	2018, 2020
	IoT	2019
	Robotics	2019-2020
United Kingdom	AI	2023
	Robotics	2023

Annex C. Regression tables and supplementary figures

Regression tables

Table A C.1. Baseline adoption regressions – AI

Variables	BEL	CAN	CHE	DEU	DNK	EST	FRA	GBR	IRL	ISR	ITA	JPN	KOR	NLD	PRT
Age: 6-10	0.0093	-0.0025	-0.0212		-0.0248**		0.0240**			0.0119		0.0162	-0.0166***	0.0209***	-0.0055
	(0.0251)	(0.0250)	(0.0551)		(0.0106)		(0.0097)			(0.0245)		(0.0183)	(0.0054)	(0.0070)	(0.0251)
Age: >10	0.0179	0.0020	-0.0227		-0.0412***		-0.0033			-0.0116		0.0226	-0.0175***	0.0012	-0.0041
	(0.0200)	(0.0205)	(0.0479)		(0.0089)		(0.0071)			(0.0160)		(0.0155)	(0.0049)	(0.0056)	(0.0228)
Size: 20-49	0.0182	0.0159	0.0365**	0.0234	0.0298***	0.0001	0.0142***	0.0105	0.0374**	0.0218*	0.0152**	0.0106	0.0015	0.0672***	0.0318***
	(0.0124)	(0.0209)	(0.0168)	(0.0094)	(0.0063)	(0.0099)	(0.0052)	(0.0165)	(0.0147)	(0.0128)	(0.0066)	(0.0073)	(0.0038)	(0.0045)	(0.0109)
Size: 50-249	0.0981***	0.0243	0.0448**	0.0518***	0.0737***	0.0474	0.0684***	0.0192	0.0855***	0.0147	0.0351***	0.0326***	0.0128***	0.1590***	0.0926***
	(0.0137)	(0.0174)	(0.0180)	(0.0092)	(0.0064)	(0.0104)	(0.0072)	(0.0160)	(0.0204)	(0.0133)	(0.0063)	(0.0064)	(0.0034)	(0.0055)	(0.0143)
Size: 250+	0.3748***	0.1753***	0.1820***	0.1350***	0.2339***	0.2125***	0.2241***	0.0636***	0.3285***	0.0641***	0.1897***	0.1720***	0.0496***	0.3508***	0.2566***
	(0.0176)	(0.0219)	(0.0236)	(0.0153)	(0.0108)	(0.0247)	(0.0097)	(0.0223)	(0.0317)	(0.0153)	(0.0082)	(0.0084)	(0.0041)	(0.0079)	(0.0168)
N	5375	3895	4248	6159	15804	5808	17757	11762	2017	1987	32497	20922	38629	30295	8465
R^2	0.140	0.077	0.121	0.068	0.149	0.137	0.096	0.061	0.185	0.244	0.038	0.069	0.065	0.115	0.092

Note: This table reports the main estimation results of the baseline adoption regression of AI using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany, Ireland and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.2. Baseline adoption regressions – Big data analysis

Variables	BEL	CHE	DEU	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
Age class: 6-10	0.1181**	0.2100**		-0.0347*	0.0513***	0.0064		0.0324	-0.0250***	-0.0140	0.0120
	(0.0520)	(0.0966)		(0.0196)	(0.0173)	(0.0306)		(0.0324)	(0.0067)	(0.0151)	(0.0327)
Age class: >10	0.0482	0.0946*		-0.0599***	0.0049	-0.0338		-0.0031	-0.0259***	-0.0530***	-0.0360
	(0.0403)	(0.0535)		(0.0160)	(0.0138)	(0.0215)		(0.0198)	(0.0060)	(0.0126)	(0.0285)
Size class: 20-49	0.0566**	0.0236	0.0684***	0.0480***	0.0476***	0.0294*	0.0585***	0.0142	0.0186***	0.0526***	0.0338**
	(0.0273)	(0.0316)	(0.0243)	(0.0115)	(0.0088)	(0.0156)	(0.0135)	(0.0088)	(0.0041)	(0.0090)	(0.0144)
Size class: 50-249	0.1897***	0.1520***	0.2039***	0.1292***	0.1202***	0.0424**	0.1091***	0.0387***	0.0362***	0.1385***	0.0693***
	(0.0274)	(0.0331)	(0.0262)	(0.0117)	(0.0107)	(0.0173)	(0.0155)	(0.0092)	(0.0034)	(0.0084)	(0.0135)
Size class: 250+	0.4166***	0.3060***	0.4149***	0.3800***	0.2341***	0.1410***	0.2090***	0.1532***	0.0946***	0.3273***	0.1798***
	(0.0314)	(0.0436)	(0.0397)	(0.0179)	(0.0120)	(0.0201)	(0.0114)	(0.0092)	(0.0045)	(0.0099)	(0.0152)

N	2179	2612	1380	7978	16459	1987	20034	20886	38629	33072	9675
R^2	0.102	0.117	0.171	0.109	0.067	0.198	0.066	0.048	0.082	0.065	0.043

Note: This table reports the main estimation results of the baseline adoption regression of big data analysis using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.3. Baseline adoption regressions – Internet of things

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
Age class: 6-10	0.0530	-0.0765	0.0256	-0.0392	0.0203	0.0665***		0.0127	-0.0146***	0.0026	0.0280
	(0.0381)	(0.0640)	(0.1020)	(0.0307)	(0.0181)	(0.0238)		(0.0505)	(0.0054)	(0.0111)	(0.0620)
Age class: >10	0.0250	-0.0103	0.0090	-0.0155	-0.0093	0.0526***		0.0369	-0.0087*	0.0137	0.0383
	(0.0306)	(0.0519)	(0.0798)	(0.0255)	(0.0151)	(0.0135)		(0.0427)	(0.0049)	(0.0093)	(0.0576)
Size class: 20-49	0.0465**	0.0298	0.0505	0.0570***	0.0364***	0.0224	0.0802***	0.0375**	0.0047	0.1034***	0.0455**
	(0.0197)	(0.0374)	(0.0334)	(0.0185)	(0.0086)	(0.0175)	(0.0138)	(0.0164)	(0.0042)	(0.0078)	(0.0196)
Size class: 50-249	0.1198***	0.0483	0.1050***	0.1556***	0.1150***	0.0679***	0.1509***	0.0635***	0.0184***	0.1698***	0.1353***
	(0.0190)	(0.0319)	(0.0359)	(0.0182)	(0.0103)	(0.0253)	(0.0126)	(0.0143)	(0.0039)	(0.0080)	(0.0204)
Size class: 250+	0.2570***	0.2042***	0.2100***	0.3247***	0.2267***	0.1360***	0.2829***	0.2043***	0.0540***	0.2870***	0.2340***
	(0.0214)	(0.0327)	(0.0491)	(0.0268)	(0.0120)	(0.0234)	(0.0118)	(0.0149)	(0.0046)	(0.0104)	(0.0255)
N	4813	3895	1601	4027	15990	1987	35586	20922	38629	20457	6902
R^2	0.045	0.043	0.120	0.070	0.060	0.070	0.055	0.028	0.045	0.071	0.077

Note: This table reports the main estimation results of the baseline adoption regression of internet of things using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.4. Baseline adoption regressions – Robotics

Variables	BEL	CHE	DNK	FRA	GBR	ISR	ITA	JPN	KOR	NLD	PRT
Age class: 6-10	0.0032	-0.0729	-0.0171	0.0298***		0.0229		0.0288	-0.0028	0.0004	0.0351
	(0.0124)	(0.0491)	(0.0111)	(0.0099)		(0.0199)		(0.0343)	(0.0033)	(0.0021)	(0.0264)
Age class: >10	0.0000	-0.0328	-0.0099	0.0152**		0.0007		0.0433**	-0.0036	0.0019	0.0084

	(0.0102)	(0.0417)	(0.0093)	(0.0077)		(0.0093)		(0.0184)	(0.0030)	(0.0018)	(0.0204)
Size class: 20-49	-0.0046	0.0374**	0.0391***	0.0225***	0.0139	0.0044	0.0137**	0.0243*	-0.0002	0.0104***	0.0277**
	(0.0064)	(0.0174)	(0.0077)	(0.0057)	(0.0089)	(0.0105)	(0.0066)	(0.0127)	(0.0013)	(0.0016)	(0.0128)
Size class: 50-249	0.0209***	0.0934***	0.1084***	0.0708***	0.0449***	0.0548***	0.0395***	0.0572***	0.0017	0.0281***	0.1078***
	(0.0074)	(0.0173)	(0.0080)	(0.0068)	(0.0104)	(0.0160)	(0.0071)	(0.0127)	(0.0014)	(0.0018)	(0.0140)
Size class: 250+	0.1068***	0.3010***	0.2602***	0.2080***	0.1434***	0.1450***	0.1216***	0.1949***	0.0209***	0.0669***	0.1661***
	(0.0115)	(0.0313)	(0.0126)	(0.0092)	(0.0168)	(0.0208)	(0.0074)	(0.0127)	(0.0021)	(0.0031)	(0.0139)
N	4840	4266	11845	16459	12015	2019	20034	10495	38629	61708	6391
R^2	0.041	0.142	0.200	0.146	0.075	0.134	0.033	0.100	0.015	0.103	0.134

Note: This table reports the main estimation results of the baseline adoption regression of robotics using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.5. Baseline adoption regressions – 3D printing

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
Age class: 6-10	0.0424*	-0.0166	0.0635*	0.0031	0.0028	0.0140		0.0045	-0.0052	0.0152***	0.0013
	(0.0224)	(0.0135)	(0.0382)	(0.0084)	(0.0063)	(0.0179)		(0.0087)	(0.0033)	(0.0058)	(0.0288)
Age class: >10	0.0143	-0.0114	0.0724***	-0.0017	-0.0003	0.0155		0.0122*	-0.0038	0.0104**	-0.0063
	(0.0135)	(0.0142)	(0.0226)	(0.0067)	(0.0053)	(0.0149)		(0.0066)	(0.0030)	(0.0042)	(0.0275)
Size class: 20-49	0.0006	-0.0102	0.0174	0.0183***	0.0160***	-0.0114	0.0088	0.0047	0.0002	0.0222***	0.0000
	(0.0134)	(0.0102)	(0.0157)	(0.0061)	(0.0041)	(0.0153)	(0.0066)	(0.0054)	(0.0014)	(0.0043)	(0.0086)
Size class: 50-249	0.0190	0.0221**	0.0448**	0.0493***	0.0346***	-0.0105	0.0459***	0.0292***	0.0024*	0.0357***	0.0224**
	(0.0139)	(0.0107)	(0.0174)	(0.0066)	(0.0051)	(0.0150)	(0.0082)	(0.0053)	(0.0014)	(0.0043)	(0.0102)
Size class: 250+	0.1555***	0.0535***	0.1880***	0.1048***	0.1212***	0.0632***	0.0933***	0.1046***	0.0206***	0.0636***	0.0459***
	(0.0203)	(0.0132)	(0.0397)	(0.0102)	(0.0074)	(0.0243)	(0.0083)	(0.0060)	(0.0020)	(0.0064)	(0.0093)
N	2179	3895	2950	11845	16459	2019	20034	20911	38629	17838	6391
R^2	0.134	0.135	0.156	0.175	0.142	0.103	0.123	0.074	0.016	0.085	0.077

Note: This table reports the main estimation results of the baseline adoption regression of 3D printing using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.6. Extended adoption regressions – AI

Variables	BEL	CAN	CHE	DEU	DNK	EST	FRA	GBR	ISR	ITA	NLD	PRT
Broad band		-0.0119				0.0370**			0.0072		-0.0043	
		(0.0139)				(0.0156)			(0.0138)		(0.0044)	
Exporter				0.0401***								
				(0.0116)								
ICT Spec.		0.0021	0.0472**	0.0557***	0.1327***	0.0940***			0.0547***		0.0496***	
		(0.0203)	(0.0187)	(0.0201)	(0.0235)	(0.0285)			(0.0212)		(0.0066)	
ICT Train.		0.0127		0.0331***	-0.0002	0.1070***			0.0453		0.0575***	
		(0.0240)		(0.0093)	(0.0213)	(0.0248)			(0.0404)		(0.0067)	
Tech intensity	0.6325***	0.5497***	0.1820***		0.9002***	0.1322***	0.5005***	0.1713***		0.3097***	0.7546***	0.4223***
	(0.0393)	(0.0676)	(0.0384)		(0.0634)	(0.0431)	(0.0295)	(0.0246)		(0.0228)	(0.0197)	(0.0480)
N	5375	3895	3806	4129	4027	2743	17757	11762	1987	32497	30272	8465
R^2	0.207	0.199	0.139	0.083	0.266	0.199	0.146	0.083	0.260	0.065	0.236	0.129

Note: This table reports the main estimation results of the extended adoption regression of AI using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.7. Extended adoption regressions – Big data analysis

Variables	BEL	CHE	DEU	DNK	FRA	ISR	ITA	NLD	PRT
Broad band	0.1069***				0.0247***	0.0471**		0.0460***	0.0104
	(0.0325)				(0.0092)	(0.0194)		(0.0081)	(0.0137)
Exporter			0.1030***						
			(0.0306)						
ICT Spec.	0.0408	0.1120***	0.1319**		0.0882***	0.0663***		0.1119***	0.0866***
	(0.0257)	(0.0345)	(0.0544)		(0.0134)	(0.0249)		(0.0096)	(0.0215)
ICT Train.	0.0608**		0.0851***		0.0485***	0.0932*		0.0926***	0.0718***
	(0.0301)		(0.0247)		(0.0122)	(0.0495)		(0.0097)	(0.0206)
Tech intensity	1.0351***	0.4320***		0.7194***	0.6705***		0.4997***	0.9242***	0.8334***
	(0.1151)	(0.0760)		(0.0558)	(0.0550)		(0.0532)	(0.0309)	(0.0968)
N	2179	2429	989	7978	16459	1987	20034	33072	9563

R^2	0.178	0.183	0.194	0.138	0.100	0.235	0.093	0.158	0.113

Note: This table reports the main estimation results of the extended adoption regression of big data analysis using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.8. Extended adoption regressions – Internet of things

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	NLD	PRT
Broad band	0.1172***	0.0467			-0.0124	0.0114		0.0202***	0.0294
	(0.0431)	(0.0299)			(0.0084)	(0.0211)		(0.0064)	(0.0296)
ICT Spec.	0.0515*	0.0846**	0.0782**	0.1152***	0.0391***	0.0559*		0.0165*	0.0693
	(0.0276)	(0.0383)	(0.0323)	(0.0233)	(0.0146)	(0.0291)		(0.0097)	(0.0426)
ICT Train.	0.0962***	0.0126		0.0368	0.0403**	0.0409		0.0640***	0.1375***
	(0.0328)	(0.0391)		(0.0262)	(0.0161)	(0.0476)		(0.0099)	(0.0402)
Tech intensity	0.7723***	0.8798***	0.4010***	0.5776***	0.5972***		0.9543***	0.5152***	0.7736***
	(0.1273)	(0.0933)	(0.0786)	(0.0658)	(0.0575)		(0.0486)	(0.0266)	(0.1545)
N	2179	3895	1385	4027	7305	1987	35586	20457	3083
R^2	0.109	0.163	0.195	0.130	0.087	0.079	0.103	0.123	0.160

Note: This table reports the main estimation results of the extended adoption regression of internet of things using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.9. Extended adoption regressions – Robotics

Variables	BEL	CHE	DNK	FRA	GBR	ISR	ITA	NLD	PRT
Broad band	-0.0024			-0.0051		0.0239**		0.0017	0.0072
	(0.0073)			(0.0058)		(0.0107)		(0.0019)	(0.0124)
ICT Spec.	0.0063	-0.0095		0.0255***		0.0482**		0.0109***	0.0640***
	(0.0077)	(0.0168)		(0.0076)		(0.0188)		(0.0025)	(0.0203)
ICT Train.	0.0126			0.0082		0.0251		0.0163***	0.0292
	(0.0118)			(0.0074)		(0.0299)		(0.0028)	(0.0191)

Tech intensity	0.1595***	0.2210***	0.2708***	0.1811***	0.0947***		0.1676***	0.0847***	0.3738***
	(0.0410)	(0.0448)	(0.0393)	(0.0321)	(0.0153)		(0.0296)	(0.0078)	(0.0899)
N	2179	3844	11845	16459	12015	2019	20034	53056	6262
R^2	0.074	0.161	0.205	0.151	0.089	0.147	0.042	0.119	0.167

Note: This table reports the main estimation results of the extended adoption regression of robotics using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.10. Extended adoption regressions – 3D printing

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	NLD	PRT
Broad band	0.0099	-0.0051			-0.0021	-0.0161		0.0009	0.0279**
	(0.0135)	(0.0100)			(0.0041)	(0.0102)		(0.0037)	(0.0115)
ICT Spec.	0.0255**	0.0116	0.0082		0.0317***	0.0620**		0.0150**	0.0067
	(0.0125)	(0.0118)	(0.0183)		(0.0068)	(0.0278)		(0.0062)	(0.0150)
ICT Train.	0.0253	-0.0127			0.0238***	0.0009		0.0203***	0.0078
	(0.0178)	(0.0155)			(0.0063)	(0.0320)		(0.0062)	(0.0109)
Tech intensity	0.1260**	0.1151***	0.1890***	0.3092***	0.1871***		0.2108***	0.1978***	0.1681***
	(0.0517)	(0.0330)	(0.0435)	(0.0302)	(0.0256)		(0.0323)	(0.0191)	(0.0527)
N	2179	3895	2709	11845	16459	2019	20034	17838	6262
R^2	0.146	0.153	0.176	0.186	0.157	0.114	0.133	0.104	0.088

Note: This table reports the main estimation results of the extended adoption regression of 3D printing using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.1 for further details on the econometric strategy.

Table A C.11. Baseline productivity regressions – AI

Variables	BEL	CAN	CHE	DEU	DNK	EST	FRA	GBR	ISR	ITA	JPN	KOR	NLD	PRT
AI	0.3098***	0.1819***	0.0383	0.0785**	0.1152***	0.1729***	0.0768**	0.0662	0.0656	0.1588***	0.1103	0.1760***	0.1653***	0.1966***
	(0.0560)	(0.0658)	(0.0421)	(0.0331)	(0.0306)	(0.0653)	(0.0336)	(0.0925)	(0.2190)	(0.0335)	(0.0766)	(0.0309)	(0.0222)	(0.0560)
Age class: 6-10	0.0357	0.3500***	0.1790		0.1081***		0.1583***		0.3380***		0.0911	-0.0235	0.1045**	-0.0213

	(0.1096)	(0.0900)	(0.1430)		(0.0321)		(0.0352)		(0.1210)		(0.1494)	(0.0295)	(0.0497)	(0.0962)
Age class: >10	0.0634	0.4943***	-0.0032		0.2070***		0.2651***		0.7140***		0.3488***	0.0482*	0.0795*	0.1567**
	(0.0963)	(0.0724)	(0.0902)		(0.0271)		(0.0302)		(0.1030)		(0.1276)	(0.0256)	(0.0476)	(0.0788)
Size class: 20-49	-0.0165	-0.0078	-0.0369	0.1280***	0.0831***	0.1402***	0.1507***	0.0763	0.0923	0.1397***	0.0174	-0.2130***	0.0652***	0.0863*
	(0.0501)	(0.0610)	(0.0337)	(0.0269)	(0.0183)	(0.0384)	(0.0179)	(0.0704)	(0.0748)	(0.0198)	(0.0366)	(0.0432)	(0.0225)	(0.0460)
Size class: 50-249	-0.1047**	0.1571***	0.0674*	0.2240***	0.1098***	0.2270***	0.2256***	0.1256*	0.1520**	0.2729***	0.1480***	-0.3950***	0.1404***	0.2988***
	(0.0527)	(0.0542)	(0.0373)	(0.0260)	(0.0177)	(0.0385)	(0.0223)	(0.0704)	(0.0763)	(0.0189)	(0.0338)	(0.0401)	(0.0219)	(0.0406)
Size class: 250+	0.1458**	0.1692**	0.1550**	0.4250***	0.1033***	0.3162***	0.3462***	0.0087	-0.0154	0.3245***	0.3680***	-0.2620***	0.0520**	0.1470*
	(0.0683)	(0.0698)	(0.0612)	(0.0348)	(0.0267)	(0.0561)	(0.0255)	(0.1070)	(0.0892)	(0.0207)	(0.0380)	(0.0413)	(0.0252)	(0.0833)
N	5336	3425	3934	6158	15598	5607	17701	11734	2019	32495	20501	38608	30024	8440
R^2	0.386	0.312	0.478	0.277	0.372	0.329	0.420	0.194	0.307	0.418	0.288	0.438	0.459	0.394

Note: This table reports the main estimation results of the baseline productivity regression results of AI. Each regression includes 2-digit NACE rev. 2 sector dummies, except for Israel where and SNA 38 fixed effects are used. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Canada, Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.12. Baseline productivity regressions – Big data analysis

Variables	BEL	CHE	DEU	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
Big data	0.2593***	0.1240***	0.2599***	0.0668**	0.0499***	-0.0170	0.0988***	0.2109***	0.2770***	0.1355***	0.1228***
	(0.0644)	(0.0432)	(0.0489)	(0.0303)	(0.0185)	(0.1780)	(0.0359)	(0.0542)	(0.0238)	(0.0184)	(0.0371)
Age class: 6-10	0.0433	0.1370		0.0967**	0.0177	0.3420***		0.0853	-0.0194	0.0547*	0.3249***
	(0.1607)	(0.1770)		(0.0435)	(0.0341)	(0.1190)		(0.1493)	(0.0294)	(0.0325)	(0.0737)
Age class: >10	0.2530*	-0.0415		0.1773***	0.1694***	0.7440***		0.3517***	0.0523**	0.0124	0.3384***
	(0.1496)	(0.1210)		(0.0360)	(0.0294)	(0.1030)		(0.1276)	(0.0255)	(0.0277)	(0.0671)
Size class: 20-49	0.0410	-0.0869**	0.1410***	0.0618**	0.1854***	0.0960	0.1462***	0.0160	-0.2180***	-0.0099	0.1520***
	(0.0682)	(0.0425)	(0.0529)	(0.0250)	(0.0164)	(0.0741)	(0.0271)	(0.0366)	(0.0432)	(0.0194)	(0.0327)
Size class: 50-249	-0.0585	0.0260	0.2099***	0.0798***	0.2729***	0.1750**	0.2686***	0.1434***	-0.4030***	0.0236	0.2975***
	(0.0647)	(0.0499)	(0.0533)	(0.0245)	(0.0200)	(0.0761)	(0.0336)	(0.0337)	(0.0401)	(0.0191)	(0.0322)
Size class: 250+	-0.0818	0.0622	0.4149***	0.0857**	0.3562***	0.0419	0.3369***	0.3548***	-0.2800***	-0.0529**	0.2122***
	(0.0843)	(0.0858)	(0.0751)	(0.0374)	(0.0213)	(0.0901)	(0.0281)	(0.0361)	(0.0413)	(0.0226)	(0.0780)
N	2128	2441	1380	7822	16445	1987	20034	20464	38608	32655	9660
R^2	0.367	0.491	0.303	0.386	0.408	0.358	0.442	0.290	0.439	0.404	0.416

Note This table reports the main estimation results of the baseline productivity regression results of big data analysis. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.13. Baseline productivity regressions – Internet of things

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
IoT	0.1247***	0.0934**	-0.0540	0.1486***	0.1207***	-0.0221	0.1664***	0.1397***	0.2250***	0.0924***	0.1616***
	(0.0413)	(0.0470)	(0.0841)	(0.0442)	(0.0198)	(0.1040)	(0.0193)	(0.0315)	(0.0234)	(0.0236)	(0.0437)
Age class: 6-10	-0.0177	0.3486***	0.2330	0.1344**	0.1107***	0.3430***		0.0905	-0.0231	0.0833*	0.1774
	(0.1063)	(0.0895)	(0.2380)	(0.0654)	(0.0363)	(0.1190)		(0.1499)	(0.0295)	(0.0490)	(0.1262)
Age class: >10	0.1395	0.4873***	0.0535	0.2727***	0.2385***	0.7460***		0.3447***	0.0471*	0.0171	0.2798**
	(0.0985)	(0.0723)	(0.1380)	(0.0576)	(0.0310)	(0.1020)		(0.1284)	(0.0256)	(0.0429)	(0.1155)
Size class: 20-49	0.0617	-0.0110	0.0670	0.1138***	0.2099***	0.0959	0.1342***	0.0151	-0.2140***	0.0439*	0.0882**
	(0.0470)	(0.0610)	(0.0552)	(0.0406)	(0.0174)	(0.0747)	(0.0200)	(0.0366)	(0.0432)	(0.0262)	(0.0443)
Size class: 50-249	-0.0041	0.1525***	0.0688	0.1298***	0.2548***	0.1760**	0.2596***	0.1447***	-0.3970***	0.1300***	0.3169***
	(0.0469)	(0.0543)	(0.0628)	(0.0391)	(0.0217)	(0.0768)	(0.0215)	(0.0335)	(0.0402)	(0.0234)	(0.0423)
Size class: 250+	0.1149*	0.1774**	0.2610***	0.0531	0.3530***	0.0425	0.2983***	0.3610***	-0.2660***	0.0856***	0.0507
	(0.0601)	(0.0697)	(0.0719)	(0.0555)	(0.0236)	(0.0893)	(0.0206)	(0.0356)	(0.0413)	(0.0286)	(0.1189)
N	4736	3425	1450	4001	15972	1987	35586	20500	38608	20276	6893
R^2	0.350	0.311	0.456	0.387	0.425	0.358	0.457	0.291	0.438	0.472	0.416

Note: This table reports the main estimation results of the baseline productivity regression results of internet of things. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Canada, Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.14. Baseline productivity regressions - Robotics

Variables	BEL	CHE	DNK	FRA	GBR	ISR	ITA	JPN	KOR	NLD	PRT
Robotics	0.2005**	0.0324	0.1345***	0.1289***	0.2091**	-0.1190	0.2103***	0.1435**	0.1350***	0.1559***	0.1916***
	(0.0872)	(0.0349)	(0.0250)	(0.0235)	(0.0869)	(0.1820)	(0.0531)	(0.0618)	(0.0329)	(0.0284)	(0.0532)
Age class: 6-10	0.0866	0.1880	0.0666*	0.0164		0.3450***		0.1116	-0.0261	0.0883***	0.2064**
	(0.1027)	(0.1410)	(0.0360)	(0.0341)		(0.1190)		(0.2627)	(0.0295)	(0.0307)	(0.1025)

Age class: >10	0.2092**	-0.0139	0.1689***	0.1677***		0.7450***		0.4124*	0.0456*	0.0654**	0.2231**
	(0.0902)	(0.0922)	(0.0305)	(0.0295)		(0.1020)		(0.2312)	(0.0256)	(0.0286)	(0.0960)
Size class: 20-49	0.0276	-0.0265	0.0556***	0.1849***	0.0694	0.0960	0.1491***	0.0766	-0.2130***	0.0407***	0.1547***
	(0.0469)	(0.0338)	(0.0205)	(0.0164)	(0.0697)	(0.0745)	(0.0273)	(0.0504)	(0.0432)	(0.0149)	(0.0402)
Size class: 50-249	0.0416	0.0686*	0.0753***	0.2698***	0.1208*	0.1810**	0.2711***	0.2086***	-0.3930***	0.1026***	0.3043***
	(0.0470)	(0.0382)	(0.0198)	(0.0200)	(0.0707)	(0.0779)	(0.0335)	(0.0491)	(0.0401)	(0.0146)	(0.0412)
Size class: 250+	0.1610***	0.2020***	0.0716**	0.3410***	0.0177	0.0569	0.3319***	0.2999***	-0.2570***	0.0345**	0.1706
	(0.0575)	(0.0404)	(0.0294)	(0.0215)	(0.1015)	(0.0951)	(0.0283)	(0.0593)	(0.0413)	(0.0167)	(0.1059)
N	4779	3932	11666	16445	11984	1987	20034	10263	38608	61025	6382
R^2	0.345	0.478	0.381	0.409	0.199	0.358	0.442	0.289	0.437	0.426	0.424

Note: This table reports the main estimation results of the baseline productivity regression results of robotics. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.15. Baseline productivity regressions – 3D printing

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
3D printing	0.0768	-0.1115	-0.0614	-0.0286	0.0297	0.1270	0.0849**	0.2025***	-0.0142	0.0190	0.0749
	(0.0878)	(0.1098)	(0.0429)	(0.0349)	(0.0329)	(0.1830)	(0.0360)	(0.0505)	(0.0346)	(0.0358)	(0.0731)
Age class: 6-10	0.0715	0.3441***	0.2020	0.0645*	0.0201	0.3400***		0.0876	-0.0266	0.0910*	0.2129**
	(0.1617)	(0.0899)	(0.1610)	(0.0360)	(0.0341)	(0.1190)		(0.1501)	(0.0295)	(0.0499)	(0.1029)
Age class: >10	0.2652*	0.4835***	0.0525	0.1671***	0.1697***	0.7430***		0.3486***	0.0450*	-0.0020	0.2252**
	(0.1508)	(0.0723)	(0.0994)	(0.0305)	(0.0294)	(0.1020)		(0.1277)	(0.0256)	(0.0435)	(0.0962)
Size class: 20-49	0.0559	-0.0110	0.0112	0.0610***	0.1873***	0.0969	0.1512***	0.0188	-0.2130***	0.0117	0.1600***
	(0.0678)	(0.0610)	(0.0396)	(0.0205)	(0.0164)	(0.0741)	(0.0273)	(0.0367)	(0.0432)	(0.0277)	(0.0402)
Size class: 50-249	-0.0107	0.1620***	0.1040**	0.0908***	0.2779***	0.1750**	0.2755***	0.1469***	-0.3930***	0.0586**	0.3233***
	(0.0630)	(0.0543)	(0.0449)	(0.0197)	(0.0200)	(0.0755)	(0.0338)	(0.0338)	(0.0401)	(0.0265)	(0.0405)
Size class: 250+	0.0116	0.2055***	0.2590***	0.1089***	0.3643***	0.0318	0.3496***	0.3667***	-0.2530***	0.0077	0.1991*
	(0.0787)	(0.0691)	(0.0473)	(0.0289)	(0.0213)	(0.0884)	(0.0279)	(0.0361)	(0.0413)	(0.0310)	(0.1056)
N	2128	3425	2711	11666	16445	1987	20034	20491	38608	17643	6382
R^2	0.360	0.310	0.438	0.379	0.407	0.358	0.441	0.289	0.437	0.422	0.422

Note: This table reports the main estimation results of the baseline productivity regression results of 3D printing. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Canada, Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.16. Extended productivity regressions – AI

Variables	BEL	CAN	CHE	DEU	DNK	EST	FRA	GBR	ISR	ITA	JPN	KOR	NLD	PRT
AI	0.2014***	0.0571	-0.0248	0.0291	0.0239	0.0644	0.0040	0.0234	-0.0337	0.0700**	-0.0706	0.0162	0.0140	0.0742
	(0.0612)	(0.0707)	(0.0448)	(0.0377)	(0.0438)	(0.0848)	(0.0345)	(0.0967)	(0.2250)	(0.0330)	(0.0791)	(0.0348)	(0.0238)	(0.0556)
Broad band		0.1046**				0.2932***			0.2470***				0.0680***	
		(0.0442)				(0.0545)			(0.0738)				(0.0235)	
ICT Spec.		0.0705	0.0888**	0.1840***	0.1735***	0.2009***			0.2670**				0.1391***	
		(0.0495)	(0.0378)	(0.0463)	(0.0501)	(0.0725)			(0.1140)				(0.0252)	
ICT Train.		0.1555***		0.1289***	0.1358*	0.1647**			0.0551				0.1199***	
		(0.0542)		(0.0228)	(0.0824)	(0.0779)			(0.1700)				(0.0224)	
Tech intensity	0.8787***	0.2037*	0.3060***		0.5764***	0.1149	0.6643***	0.3090***		0.9746***	0.5499***	0.5250***	0.6224***	1.2717***
	(0.1608)	(0.1228)	(0.0792)		(0.1439)	(0.1229)	(0.0776)	(0.1175)		(0.0708)	(0.0726)	(0.0469)	(0.0733)	(0.1653)
Exporter				0.2960***										
				(0.0296)										
N	5336	3425	3535	4129	4001	2627	17701	11734	2019	32495	20501	38608	30001	8440
R^2	0.393	0.318	0.483	0.307	0.399	0.348	0.425	0.197	0.323	0.432	0.296	0.439	0.472	0.415

Note: This table reports the main estimation results of the extended productivity regression results of AI. Each regression includes 2-digit NACE rev. 2 sector dummies, except for Israel where and SNA 38 fixed effects are used. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Canada, Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.17. Extended productivity regressions – Big data analysis

Variables	BEL	CHE	DEU	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
Big data	0.1917***	0.0810*	0.2280***	0.0513*	0.0125	-0.1300	0.0524	0.0661	0.2080***	0.0690***	0.0304
	(0.0683)	(0.0436)	(0.0529)	(0.0306)	(0.0186)	(0.1760)	(0.0377)	(0.0552)	(0.0281)	(0.0193)	(0.0391)
Broad band	0.2176				0.0513***	0.2210***				0.0674***	0.0907***
	(0.3037)				(0.0173)	(0.0701)				(0.0178)	(0.0322)

ICT Spec.	0.0427	0.0610	0.1879**		0.1173***	0.2780**				0.1503***	0.2305***
	(0.0590)	(0.0472)	(0.0834)		(0.0235)	(0.1150)				(0.0218)	(0.0451)
ICT Train.	0.2422***		0.0934**		0.0904***	-0.0515				0.1265***	0.1045***
	(0.0752)		(0.0463)		(0.0216)	(0.1650)				(0.0204)	(0.0370)
Tech intensity	0.3769	0.2380***		0.3249***	0.5252***		0.8094***	0.4784***	0.2680***	0.2854***	0.5568***
	(0.2913)	(0.0857)		(0.1132)	(0.0992)		(0.1287)	(0.0778)	(0.0522)	(0.0728)	(0.1726)
Exporter			0.3610***								
			(0.0590)								
N	2128	2273	989	7822	16445	1987	20034	20464	38608	32655	9548
R^2	0.378	0.502	0.354	0.387	0.414	0.370	0.447	0.295	0.440	0.411	0.425

Note: This table reports the main estimation results of the extended productivity regression results of big data analysis. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.18. Extended productivity regressions – Internet of things

Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
IoT	0.0426	0.0003	-0.1210	0.0777*	0.1202***	-0.0633	0.1295***	0.0441	0.1310***	0.0163	-0.0293
	(0.0613)	(0.0493)	(0.0954)	(0.0454)	(0.0331)	(0.1080)	(0.0199)	(0.0333)	(0.0261)	(0.0246)	(0.0647)
Broad band	0.2176	0.1043**			0.0200	0.2160***				0.0652***	0.1067
	(0.3061)	(0.0443)			(0.0210)	(0.0715)				(0.0233)	(0.0660)
ICT Spec.	0.0413	0.0688	0.1080*	0.1715***	0.0877**	0.2730**				0.1445***	0.2013**
	(0.0592)	(0.0496)	(0.0641)	(0.0504)	(0.0347)	(0.1160)				(0.0328)	(0.0887)
ICT Train.	0.2364***	0.1538***		0.1411*	0.0954**	-0.0611				0.1100***	0.1172*
	(0.0756)	(0.0543)		(0.0829)	(0.0376)	(0.1680)				(0.0287)	(0.0635)
Tech intensity	0.7946***	0.2841**	0.3580**	0.4830***	0.1887		0.6957***	0.5637***	0.4020***	0.5203***	1.0477***
	(0.2777)	(0.1323)	(0.1670)	(0.1359)	(0.1233)		(0.0804)	(0.1016)	(0.0491)	(0.0809)	(0.2587)
N	2128	3425	1268	4001	7298	1987	35586	20500	38608	20276	3081
R^2	0.376	0.318	0.463	0.399	0.427	0.370	0.462	0.296	0.439	0.480	0.437

Note: This table reports the main estimation results of the extended productivity regression results of internet of things. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Canada, Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.19. Extended productivity regressions – Robotics

Variables	BEL	CHE	DNK	FRA	GBR	ISR	ITA	JPN	KOR	NLD	PRT
Robotics	0.0750	0.0085	0.1269***	0.1104***	0.1719*	-0.2030	0.1689***	0.0765	-0.0046	0.0898***	0.1111**
	(0.1779)	(0.0381)	(0.0253)	(0.0238)	(0.0877)	(0.1820)	(0.0541)	(0.0624)	(0.0337)	(0.0284)	(0.0555)
Broad band	0.2181			0.0508***		0.2200***				0.0796***	0.0747*
	(0.3053)			(0.0173)		(0.0723)				(0.0158)	(0.0391)
ICT Spec.	0.0414	0.0685*		0.1199***		0.2800**				0.1489***	0.1756***
	(0.0592)	(0.0368)		(0.0235)		(0.1180)				(0.0173)	(0.0573)
ICT Train.	0.2369***			0.0918***		-0.0584				0.1165***	0.1481***
	(0.0756)			(0.0216)		(0.1670)				(0.0161)	(0.0473)
Tech intensity	0.6987***	0.2910***	0.3237***	0.3412***	0.2358**		0.7235***	0.5508***	0.4980***	0.5096***	0.5391***
	(0.2434)	(0.0812)	(0.1018)	(0.0854)	(0.1085)		(0.1120)	(0.0880)	(0.0415)	(0.0481)	(0.1793)
N	2128	3564	11666	16445	11984	1987	20034	10263	38608	52454	6253
R^2	0.376	0.480	0.382	0.415	0.201	0.370	0.448	0.297	0.439	0.436	0.428

Note: This table reports the main estimation results of the extended productivity regression results of robotics. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Table A C.20. Extended productivity regressions – 3D printing

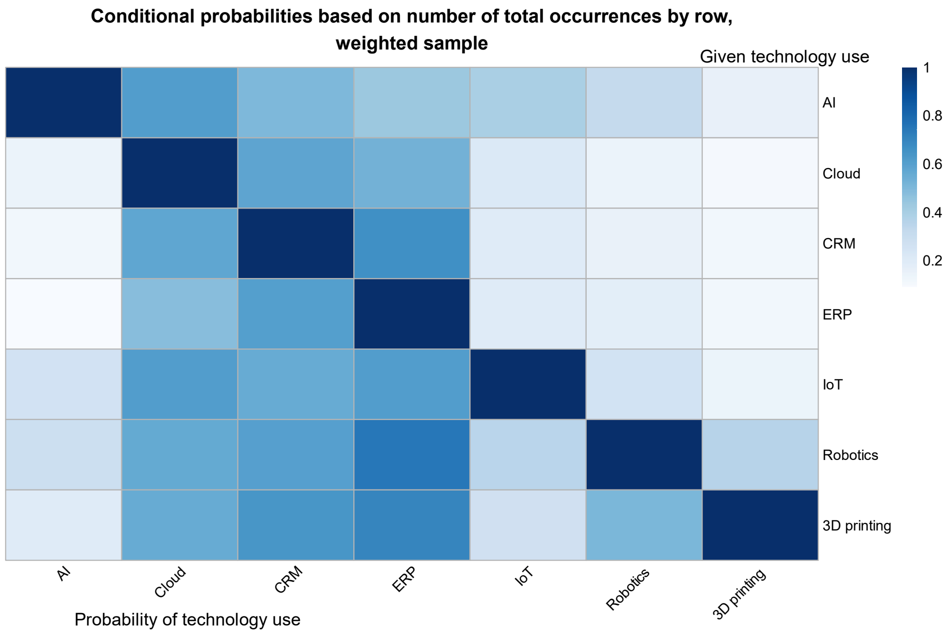
Variables	BEL	CAN	CHE	DNK	FRA	ISR	ITA	JPN	KOR	NLD	PRT
3D printing	0.0034	-0.2192**	-0.1250***	-0.0510	-0.0239	0.0957	0.0440	0.0928*	-0.1270***	-0.0455	0.0081
	(0.0876)	(0.1109)	(0.0475)	(0.0353)	(0.0337)	(0.1860)	(0.0366)	(0.0553)	(0.0357)	(0.0367)	(0.0739)
Broad band	0.2162	0.1066**			0.0502***	0.2160***				0.0580**	0.0761*
	(0.3053)	(0.0442)			(0.0173)	(0.0719)				(0.0243)	(0.0390)
ICT Spec.	0.0421	0.0670	0.0310		0.1185***	0.2640**				0.1358***	0.1752***
	(0.0591)	(0.0497)	(0.0431)		(0.0235)	(0.1180)				(0.0334)	(0.0573)
ICT Train.	0.2365***	0.1508***			0.0914***	-0.0637				0.1251***	0.1467***
	(0.0756)	(0.0539)			(0.0216)	(0.1660)				(0.0296)	(0.0472)
Tech intensity	0.7431***	0.2992***	0.4130***	0.5474***	0.4651***		0.7907***	0.4578***	0.5410***	0.3687***	0.6366***
	(0.2408)	(0.1089)	(0.1090)	(0.0956)	(0.0823)		(0.1163)	(0.0819)	(0.0403)	(0.0860)	(0.1742)
N	2128	3425	2505	11666	16445	1987	20034	20491	38608	17643	6253

R^2	0.376	0.319	0.443	0.382	0.414	0.370	0.447	0.295	0.440	0.429	0.428

Note: This table reports the main estimation results of the extended productivity regression results of 3D printing. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. All estimated regressions are weighted except for Canada, Germany and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Estimations based on country-specific firm-level surveys. See Annex A for details on the different sources. See Box 4.3 for further details on the econometric strategy.

Supplementary figures

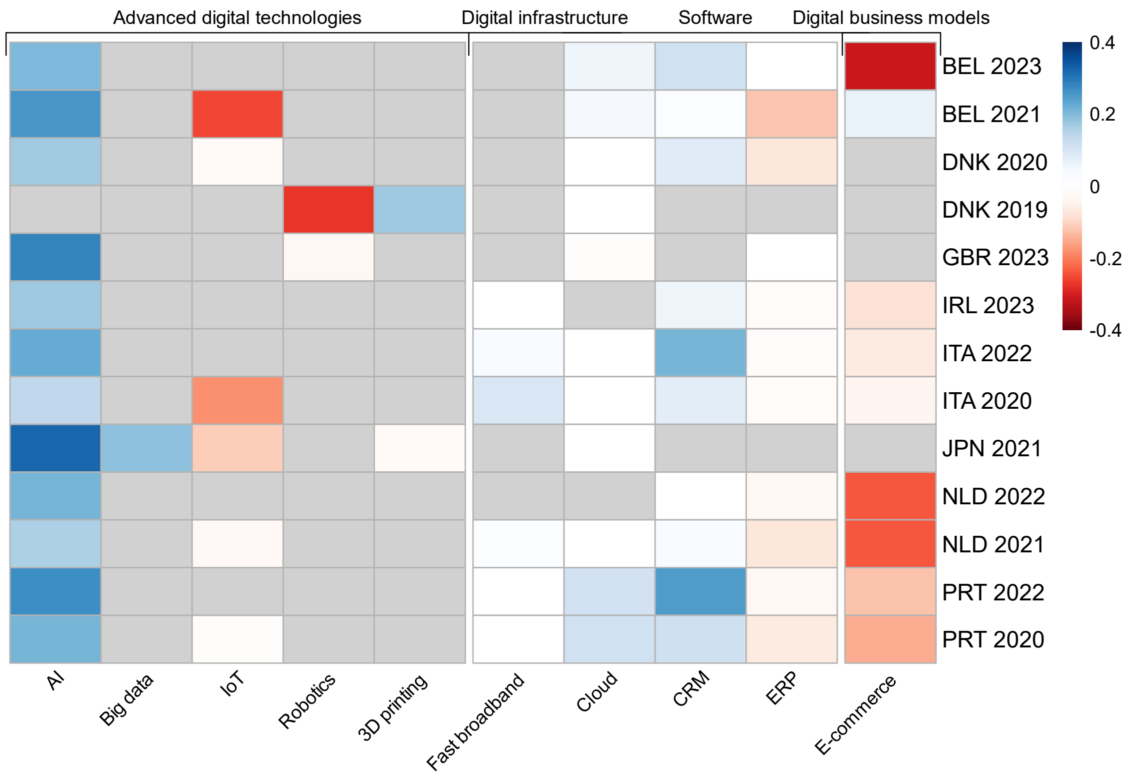
Figure A C.1. Conditional probabilities of technology use in Switzerland



Note: Conditional probabilities of observing a technology (column), given that another technology is also observed in the network (row). The data refer to the year 2019.
Source: Authors' calculations based on microdata from the KOF Enterprise Panel.

Figure A C.2. Centrality of technologies in the ICT sector relative to other sectors

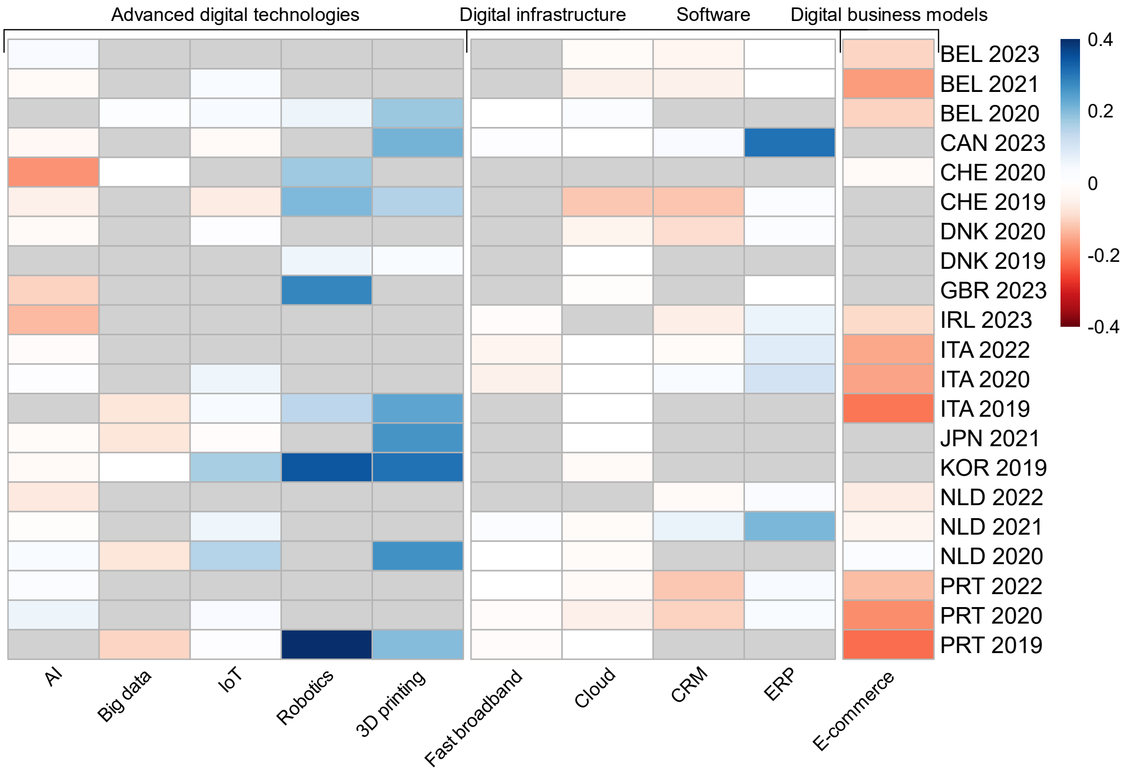
Difference in eigen centrality of technologies by country and survey year in the ICT sector compared to eigen centrality calculated across all available sectors



Note: The colour gradient represents the difference in eigen centrality between the ICT sector and the sector averages for each available technology (column) in the network of observed technology co-occurrences for each country-year (row). Positive values (in blue) indicate a more central position of the technology in the ICT sector compared to the overall network, while negative values (in red) represent a less central position. Greyed out cells correspond to technologies either not surveyed or not available in a given country-year. Networks with blanked co-occurrences due to confidentiality or a low number of available technologies are excluded.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

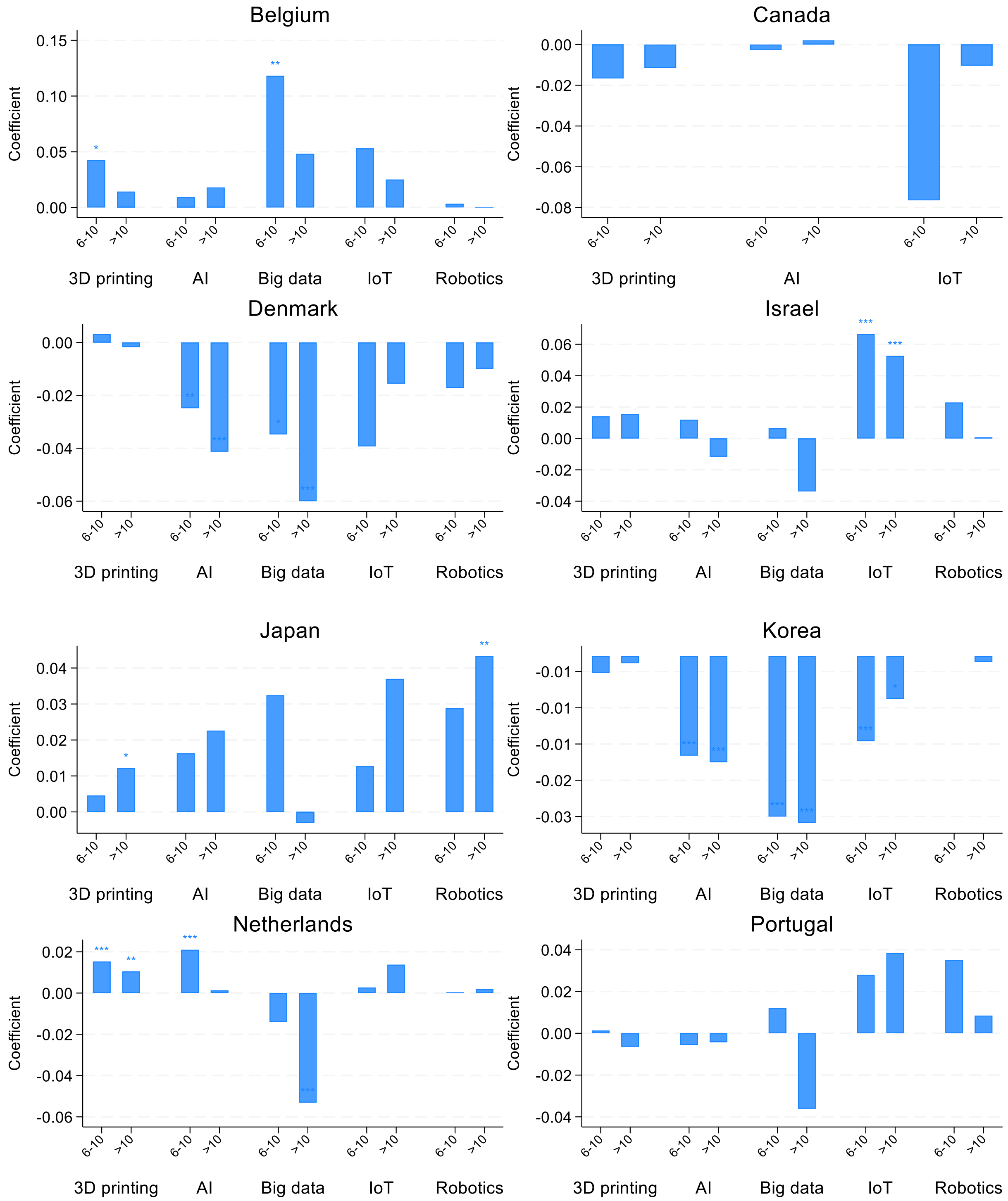
Figure A C.3. Centrality of technologies in the manufacturing sector relative to other sectors

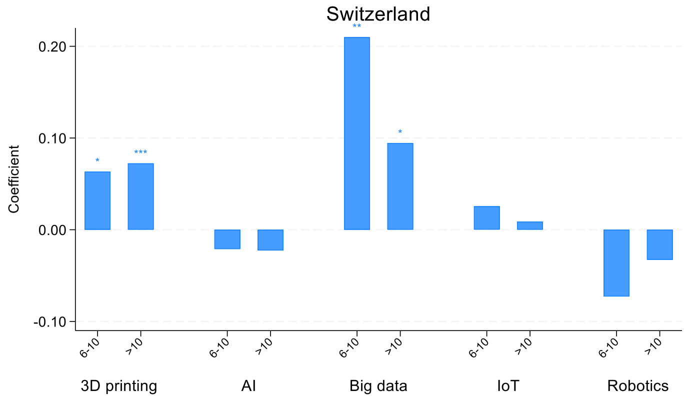
Difference in eigen centrality of technologies by country and survey year in the manufacturing and utilities sector compared to eigen centrality calculated across all available sectors



Note: The colour gradient represents the difference in eigen centrality between the manufacturing and utilities sector and the sector averages for each available technology (column) in the network of observed technology co-occurrences for each country-year (row). Positive values (in blue) indicate a more central position of the technology in the manufacturing sector compared to the overall network, while negative values (in red) represent a less central position. Greyed out cells correspond to technologies either not surveyed or not available in a given country-year. Networks with blanked co-occurrences due to confidentiality or a low number of available technologies are excluded.
Source: Elaborations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.

Figure A C.4. Adoption regression age class coefficients





Note: This figure reports the coefficients of age class dummies for Belgium, Canada, Denmark, France, Germany, Israel, Italy, Japan, Korea, the Netherlands, Portugal, and Switzerland. The adoption regression includes size classes and year dummies, when available. Each regression includes 2-digit NACE rev. 2 sector dummies. All estimated regressions are weighted except for Canada, Germany and Korea. See Annex B for the sample coverage years of each technology adoption regression. Statistical significance is denoted as follows: *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: Estimations based on country-specific firm-level surveys. See section 3 for details on the methodology and the Annex for details on the different sources.