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

Preliminary work – please do not circulate further

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

[1] OECD Directorate for Science, Technology and Innovation

Keywords: Artificial Intelligence, Advanced digital technologies, Technology diffusion, Productivity.

JEL codes: J24; O33

Restricted Use - À usage restreint

Disclaimer

This document, as well as any data and any map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

Restricted Use - À usage restreint

Acknowledgements

The views expressed in this paper are those of the authors and do not necessarily reflect those of the OECD or its Member countries. The analysis would not have been possible without the valuable contribution of participants in the distributed microdata collection. These include Michel Dumont, Chantal Kegels (Belgium); Howard Bilodeau, Aisha Khalid, Mark Uhrbach (Canada); Frederic Warzynski (Denmark); Christina Palmou, Jaan Masso (Estonia); Luca Fontanelli (Germany); Iulia Siedschlag, Juan Duran Vanegas (Ireland); Gilad Be'ery, Matan Goldman, Eliav Orenbuch, Daniel Roash (Israel); Stefano Costa, Giulio Perani (Italy); Yuya Ikeda (Japan); Jaehan Cho, Hanhin Kim (Korea); Michael Polder, Christiaan Visser, Stef Weijers (Netherlands); Mathias Beck, Tatiana Bielakova, Johannes Dahlke, Martin Wörter, Dmitry Plekhanov (Switzerland); Oliver Schnabel, Rabiya Nasir, Christina Palmou (United Kingdom). Additional information on respective affiliations is reported in Table A B.1. The authors would also like to thank Nils Adriansson, Emanuel Alijaj, Manuel Betin, Stijn Broecke, Chiara Criscuolo, Luca Fontanelli, Peter Gal, Alexander Hijzen, Katharina Laengle, Guy Lalanne, Jens Lundsgaard, Lionel Nesta, Christina Palmou, Jerry Sheehan, Elena Verdolini, Frederic Warzynski, Delegates to the OECD Committee on Industry, Innovation and Entrepreneurship, Working Party on Industry Analysis, Working Party on Digital Economics, Measurement, and Analysis for useful discussions or comments at different stages of the project. Access to French data used in this work was made possible within a secure environment provided by CASD – Centre d'accès sécurisé aux données (Ref.10.34724/CASD). Research results are based on analysis of strictly controlled Research Microdata Files provided by the Central Statistics Office (CSO) of Ireland. The CSO does not take any responsibility for the views expressed or the outputs generated from this research. This analysis contributes to the MapProdIGIS project, financed under Work Programme Horizon Europe – 2021-2022 Horizontal support expenditure for Horizon Europe and Euratom Programmes under grant no. LC-01965484.

Co-funded by the European Union

Abstract

This paper analyses the use by firms of AI, big data analysis, internet of things, robotics and 3D printing across 15 OECD countries. It documents seven stylised 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 firm's digitalisation – emerge as critical enablers. Adopters tend to be more productive than other firms, 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 in fact 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.

Restricted Use - À usage restreint

Table of contents

Disclaimer 3

Acknowledgements 4

Abstract 5

Executive summary 9

1 Introduction 11

2 Existing literature on advanced digital technologies: a brief overview 15
- Characteristics of adopters of advanced digital technologies 16
- Advanced digital technologies, productivity and other firm-level outcomes 17
- Key insights and gaps 18

3 Data and methodology 19
- Firm-level surveys across countries 19
- Digital Diffuse: a distributed microdata project 20

4 Seven stylised facts about advanced digital technologies and firms 21
- Stylised fact 1: There are significant interdependencies among digital technologies and more advanced technologies tend to build on enabling ones 21
- Stylised fact 2: The diffusion of advanced digital technologies exhibits significant sectoral heterogeneity 24
- Stylised fact 3: Larger firms are more likely to adopt advanced digital technologies 30
- Stylised fact 4: Human and technological capital are key for the adoption of advanced digital technologies 33
- Stylised fact 5: Education and technical occupations appear critical for the adoption of advanced digital technologies 36
- Stylised fact 6: Adopters of advanced digital technologies tend to be more productive than other firms 39
- Stylised fact 7: Human and technological capital are associated with higher productivity, explaining part of the productivity premia of adopters 42

Restricted Use - À usage restreint

5 Concluding remarks 50

References 2

Annex A. Additional information on data and methodology 10

Annex B. Technology definitions and survey coverage 14

Annex C. Regression tables and supplementary figures 20

FIGURES

Figure 1.1. Aggregate trends in technology adoption 12
Figure 4.1. Typical network of technology co-occurrences: Switzerland (2019) 22
Figure 4.2. Centrality of technologies 23
Figure 4.3. Relative adoption rates of AI by industry and country – different years 25
Figure 4.4. Relative adoption rates of big data analysis by industry and country – different years 26
Figure 4.5. Relative adoption rates of IoT by industry and country – different years 27
Figure 4.6. Relative adoption rates of robotics by industry and country – different years 28
Figure 4.7. Relative adoption rates of 3D printing by industry and country – different years 29
Figure 4.8. Adoption regression coefficients for size class dummies 31
Figure 4.9. Regression results on adoption of advanced digital technologies, human and technological capital 35
Figure 4.10. Adoption regression coefficients for tertiary education 37
Figure 4.11. Adoption regression coefficients for technical occupations measures 38
Figure 4.12. Estimation results of the baseline productivity regressions 41
Figure 4.13. Estimation of productivity regressions including complementary factors – AI 43
Figure 4.14. Estimation of productivity regressions including complementary factors – Big data analysis 45
Figure 4.15. Estimation of extended productivity regressions including complementary factors – IoT 46
Figure 4.16. Estimation of productivity regressions including complementary factors – Robotics 47
Figure 4.17. Estimation of productivity regressions including complementary factors – 3D printing 48

Figure A C.1. Conditional probabilities of technology use in Switzerland, 2019 33
Figure A C.2. Centrality of technologies in the ICT sector relative to other sectors 34
Figure A C.3. Centrality of technologies in the manufacturing sector relative to other sectors 35
Figure A C.4. Adoption regression age class coefficients 36

TABLES

Table A B.1. List of contributors to the *Digital Diffuse* project 17
Table A B.2. Technology coverage by country 18
Table A C.1. Baseline adoption regressions – AI 21
Table A C.2. Baseline adoption regressions – Big data analysis 21
Table A C.3. Baseline adoption regressions – Internet of things 22
Table A C.4. Baseline adoption regressions – Robotics 22
Table A C.5. Baseline adoption regressions – 3D printing 23
Table A C.6. Extended adoption regressions – AI 24
Table A C.7. Extended adoption regressions – Big data analysis 24
Table A C.8. Extended adoption regressions – Internet of things 25
Table A C.9. Extended adoption regressions – Robotics 25
Table A C.10. Extended adoption regressions – 3D printing 26
Table A C.11. Baseline productivity regressions – AI 26
Table A C.12. Baseline productivity regressions – Big data analysis 27
Table A C.13. Baseline productivity regressions – Internet of things 28

Restricted Use - À usage restreint

Table A C.14. Baseline productivity regressions - Robotics 28
Table A C.15. Baseline productivity regressions – 3D printing 29
Table A C.16. Extended productivity regressions – AI 29
Table A C.17. Extended productivity regressions – Big data analysis 30
Table A C.18. Extended productivity regressions – Internet of things 31
Table A C.19. Extended productivity regressions – Robotics 31
Table A C.20. Extended productivity regressions – 3D printing 32

Restricted Use - À usage restreint

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 who have access to the underlying 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 between 4% and 10%, while big data analysis and IoT are more widespread among firms at around 25%. This broad technological scope highlights relevant interdependencies and the technology-specific patterns and drivers of diffusion, as well as its heterogeneous impacts 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. Based on cross-country evidence from 15 countries, 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, where 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 enablers are often observed to be 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 & scientific services, IoT displaying more widespread adoption across sectors, and robotics and 3D printing being particularly relevant to manufacturing & 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. Human capital – in the form of ICT skills and training – as well as technological capital – proxied by the use of other digital technologies and digital infrastructure – are key for the adoption of advanced digital technologies. For AI, five out of the six countries in which ICT skills data is available show a positive association of AI adoption with ICT skills; two out 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 0.24, 0.53 and 0.15 percentage points, respectively.

Restricted Use - À usage restreint

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 premium for adopters ranges between 7.7% in France and 31% in Belgium. These productivity premia are stronger in large firms.
7. Part of the observed productivity premia can be attributed to differences in human and technological capital. These factors themselves are in fact 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 out of nine countries retain a significant AI-related productivity premium.

These results bring 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 relevant complementarities and path dependency 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 current analysis suggests that productivity gains are currently more pronounced for technologies such as big data analytics, 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.

For Official Use

Restricted Use - À usage restreint

1 Introduction

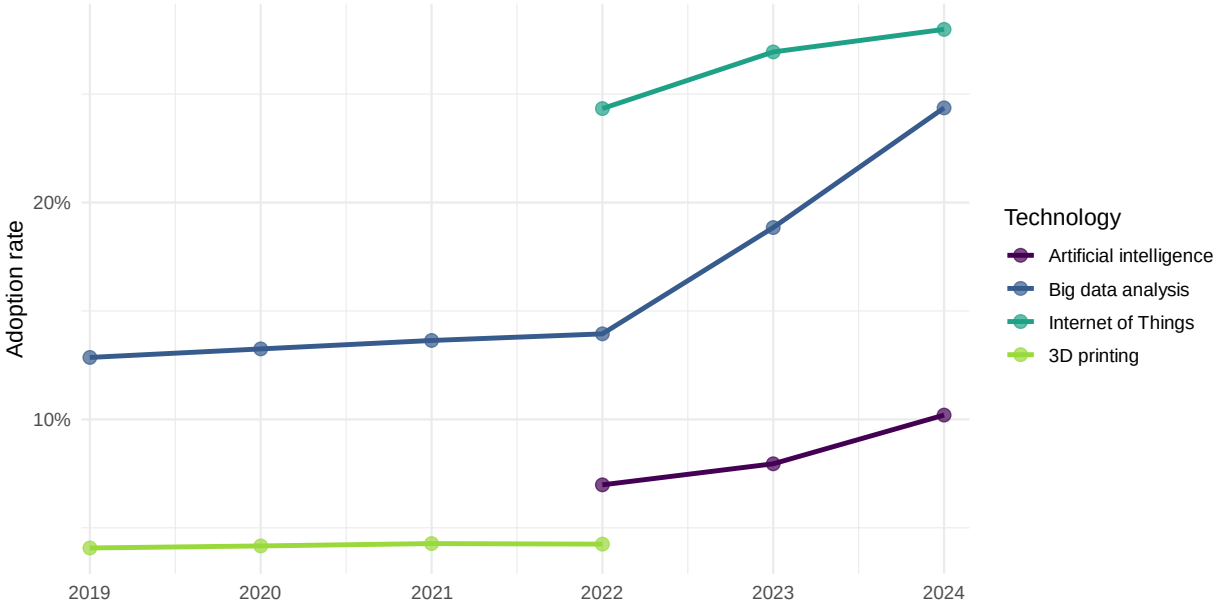
The diffusion of advanced digital technologies across firms has been a topic of high interest for policymakers, given their potential to transform economies and improve economic and social outcomes. Technologies such as AI have the potential to boost productivity by increasing efficiency, fostering innovation 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 how technology use is linked with 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, the 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.

Restricted Use - À usage restreint

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, across 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.

For Official Use

Restricted Use - À usage restreint

Due to the synergies between these technologies, their joint transformative potential is often highlighted in policy, 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 occupational measures, of technological capital, further analysing technological interdependencies, as well as 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 instead allow zooming in on the human capital drivers of technology adoption. These data sources 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 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. Advanced technologies show considerable variation between technologies and sectors. 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 & 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 & 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 as well as for other firm characteristics, notably the age of firms, which possibly suggests relevant scale advantages in the adoption of advanced digital technologies.

Restricted Use - À usage restreint

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 by 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 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, as well as 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 for 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 of both specialised competences to develop tailor-made solutions and of critical thinking to understand when and how to use effectively generative AI (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.

Restricted Use - À usage restreint

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 by Bartelsman, Hagsten and Polder (2018[35]) and Bartelsman, van Leeuwen and Polder (2016[36]), which analyses 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 on this topic). Further discussion of some analyses contributing to these streams of research is provided below, highlighting key findings and research gaps.

Restricted Use - À usage restreint

Characteristics of adopters of advanced digital technologies

Several firm characteristics are associated with a higher likelihood of adoption of advanced digital technologies. The most common characteristic positively related to the use of advanced digital technologies is firm size. Analyses focusing on different advanced digital technologies, the evidence suggest 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, economies of scale or network externalities that may lead to higher adoption by larger firms.

The relationship between firm age and the use of advanced digital technologies is less clear when 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 been shown to also 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 in fact often already more digitalised, suggesting that prior digitalisation is an important enabler of adoption of 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 for successful technology adoption (Gulzar, Naqvi and Smolander, 2025[46]).

A relevant role of other firm characteristics for 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

For Official Use

Restricted Use - À usage restreint

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, even possibly 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 for 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 which 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 recent 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 ones. 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]) only for big data, while Espinoza et al. (2020[69]), Bettiol et al. (2023[66]) find a positive relationship for IoT. Cirillo et al. (2022[70]) find positive effects for each 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 for 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 a firm's 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 from investments in AI, such as growth in sales, employment and market valuations. DeStefano, Kneller and Timmis (2023[79]) find positive effects from 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 technological 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. Relevantly, 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 different countries. Furthermore, many studies rely on aggregated information, such as on the sector level and focus on a single technology. Additionally, many studies focus only on either the determinants of technology adoption or the productivity implications of adoption.

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.

For Official Use

Restricted Use - À usage restreint

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 discusses 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 as well as the metadata reported in Annex A and Annex B, respectively.

Official ICT surveys are 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 certain 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 including 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 at 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.

Restricted Use - À usage restreint

Digital Diffuse: a distributed microdata project

This section discusses the distributed microdata approach used. The evidence is based on representative firm-level data, which are sourced from official firm-level surveys containing information on the use of ICTs from across 15 countries. For countries where balance sheet data and/or LEED are available, additional evidence leverages these additional 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 cooperation with experts from each country. This strategy effectively deals with challenges regarding 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 a weighted and unweighted form conditional on the availability of sampling (probability) weights, or of a business register upon which these can be calculated. The Digital Diffuse program can run flexibly on different data sources but requires the presence of 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 or PhD degrees. 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, the share of workers in an ICT technical occupation and the share of workers 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 for the present analysis related information is only used to assess their role as enablers of the use of the abovementioned advanced digital technologies. Relevantly for the current analysis, the code allows to investigate the role of ICT skills (proxied by the presence of ICT specialists and the training for non-ICT specialists) and digital infrastructure (ultra-fast broadband connection), which is information often directly available in firm-level surveys.

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

For Official Use

Restricted Use - À usage restreint

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 present evidence based on summary statistics and regression analysis 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 for technology adoption and provides evidence on the co-occurrence patterns among different digital technologies. The analysis finally explores the relationship between technology adoption and firm-level productivity, and the role of relevant confounding factors. Whenever 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 in the harmonisation of the methodology, as discussed above, cross-country comparisons should be made with caution given differences in definitions and in 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 resulting productivity advantages. This section focuses on the extent to which digital technologies are interdependent, highlighting that they are often being 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 any 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 therefore are 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 around AI tend to be adopted together as well and form their own community. Specifically, in many countries, the adoption of the related technologies of AI and

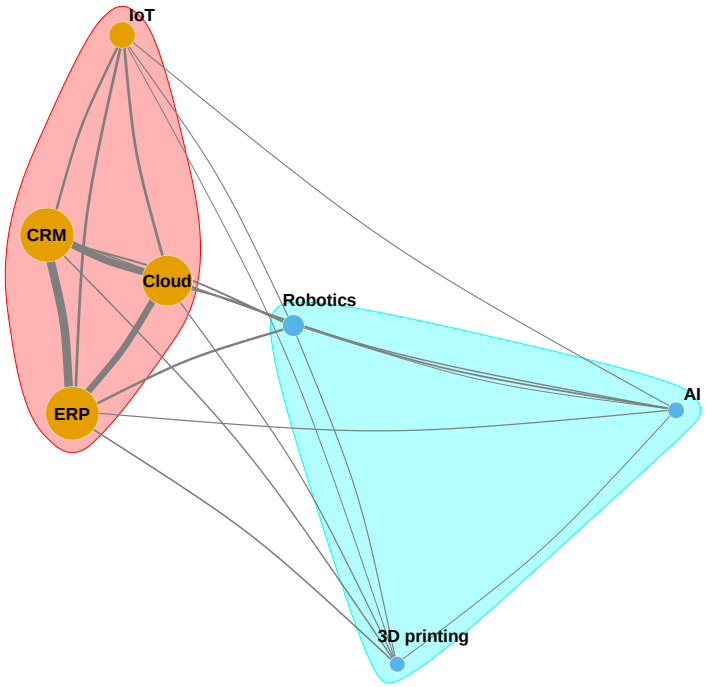
[1] See Calvino and Fontanelli (2023[16]) for a previous cross-country study that focuses on the diffusion and role of AI specifically.

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

big data analysis as well as other advanced technologies is often observed together when they are present in the same wave.

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 adoption across sectors.

Figure 4.1. Typical network of technology co-occurrences: Switzerland (2019)



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 ($\gamma = 1$).
Source: Authors' calculation based on microdata from the KOF Swiss Innovation and Digitalisation Survey.

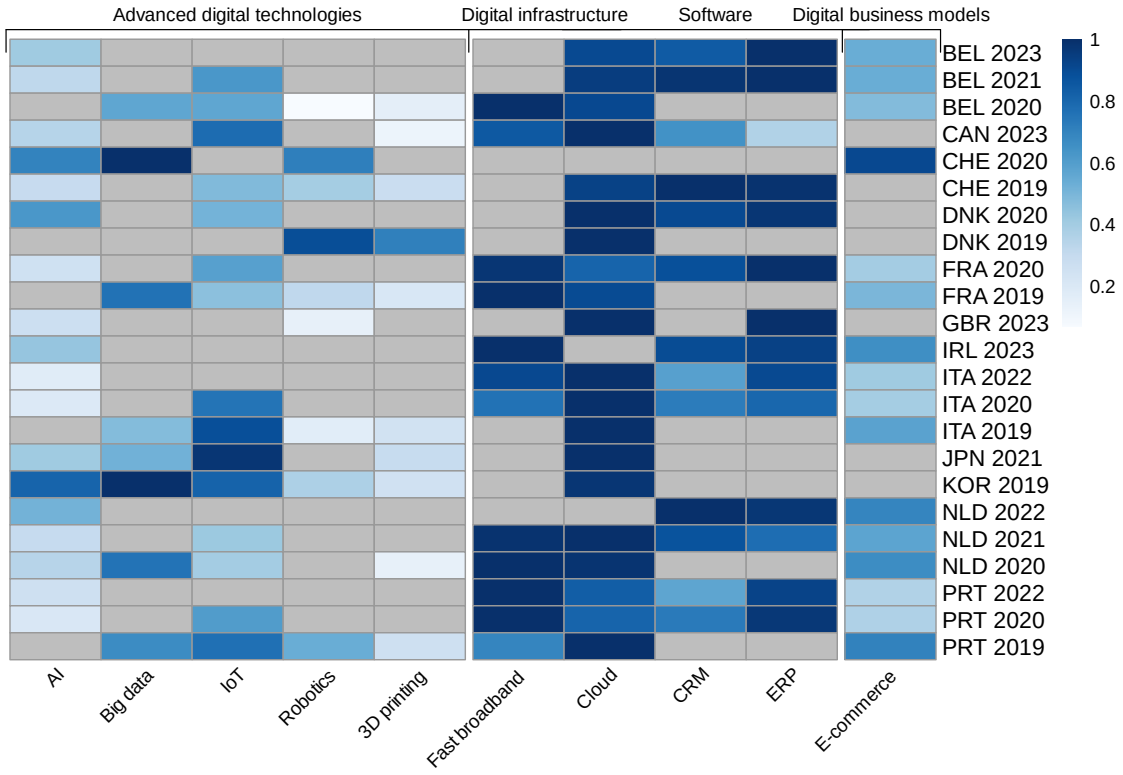
Moving to a cross-country picture, Figure 4.2 illustrates the eigenvector centrality[4] of technologies within the networks of technology co-occurrences from surveys across various countries and years, where every row represents an undirected network in a country-year, with the nodes given by the technologies and the edges defined by the observed number of co-occurrences between the 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 for more advanced digital technologies.

For Official Use

Restricted Use - À usage restreint

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 for 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 ways of 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 thus highlights the importance of both technological and organisational interdependencies in the diffusion of digital technologies.

Restricted Use - À usage restreint

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.[5] 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 required human skills in this sector.[6]

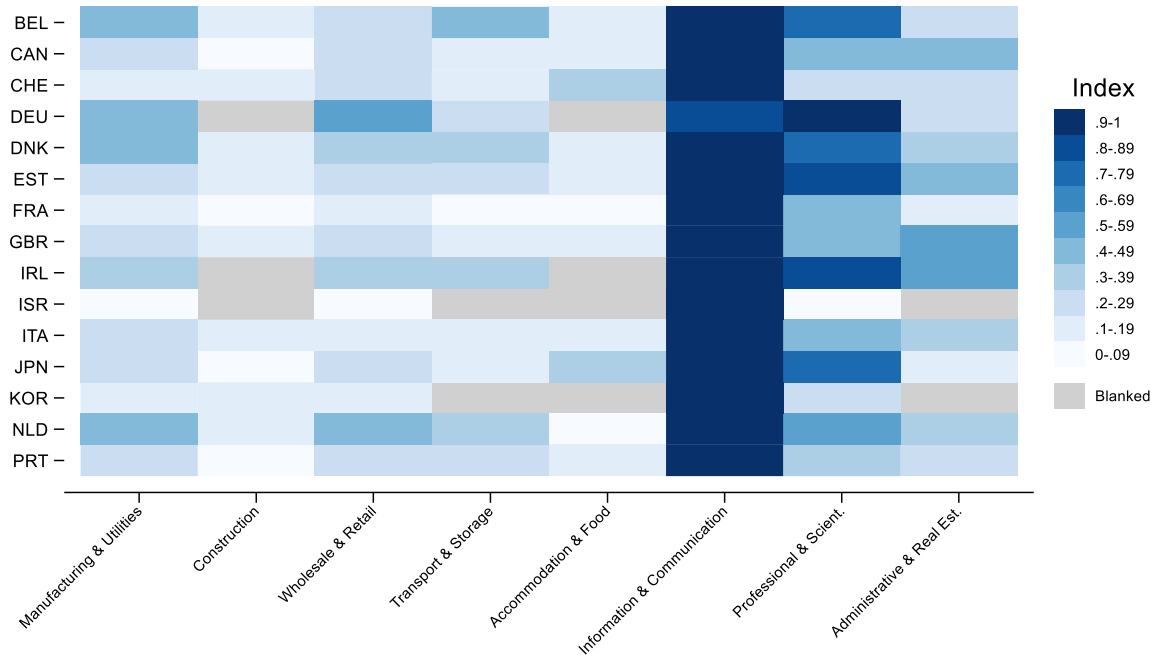
The professional & scientific activities sector also emerges as a significant adopter of AI in several countries. In contrast, manufacturing & utilities, the leading adopter of robotics and 3D printing, shows considerably lower AI adoption rates. This suggests that while AI may play an important role in optimising industrial processes, for instance, when embedded in advanced robotics, its adoption across firms in the manufacturing & utilities sector is not as deep as it is in service-oriented and knowledge-intensive sectors.[7]

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 or Portugal tend to show generally lower adoption rates, except in the ICT sector.

For Official Use

Restricted Use - À usage restreint

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.

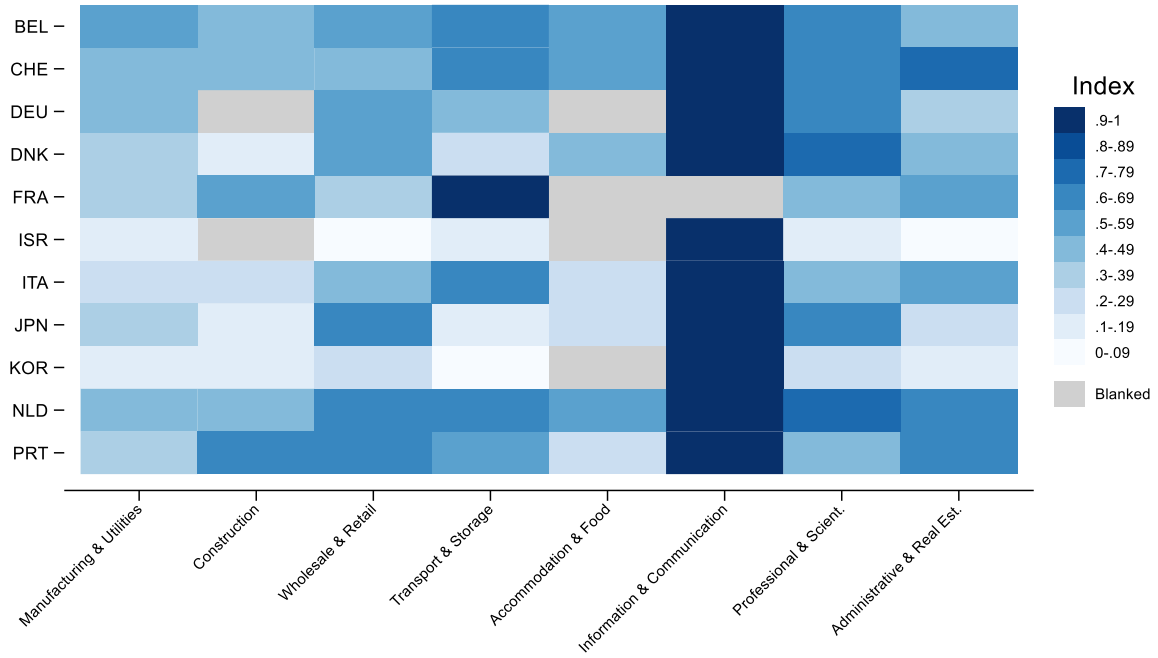
Figure 4.4 presents the relative adoption rates of big data analysis. The use of this technology follows a pattern similar to AI, with the ICT sector consistently reporting the highest adoption rates across most countries. This reflects the fundamental role of data analytics in digital services, where 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. Diffusion of big data analysis is also strong in the professional & scientific activities sector, which reports the second highest adoption rates for 7 out of the 11 countries analysed. In contrast, manufacturing & 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.

Restricted Use - À usage restreint

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.

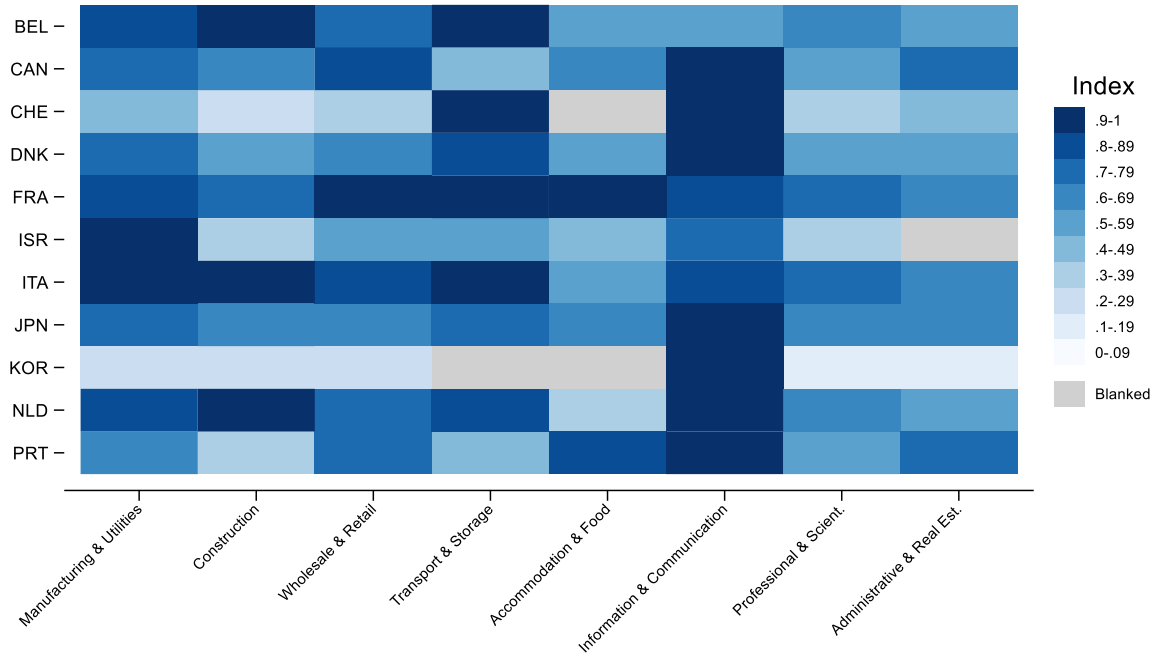
Figure 4.5 presents the relative adoption rates of IoT across countries and sectors. As with AI and big data analysis, the ICT sector generally presents the highest adoption rates. However, IoT exhibits a distinct, broader pattern compared to other advanced digital technologies. In fact, in countries such as Belgium, France, Israel and Italy, the construction, manufacturing & utilities and transport & storage sectors surpass the adoption rates found in the ICTs 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 & storage sector – are key drivers of its diffusion in these economies.

In contrast, lower adoption rates are observed in sectors such as administrative & real estate and professional & 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 is the only service-based sector where the diffusion of this technology is pervasive.

For Official Use

Restricted Use - À usage restreint

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



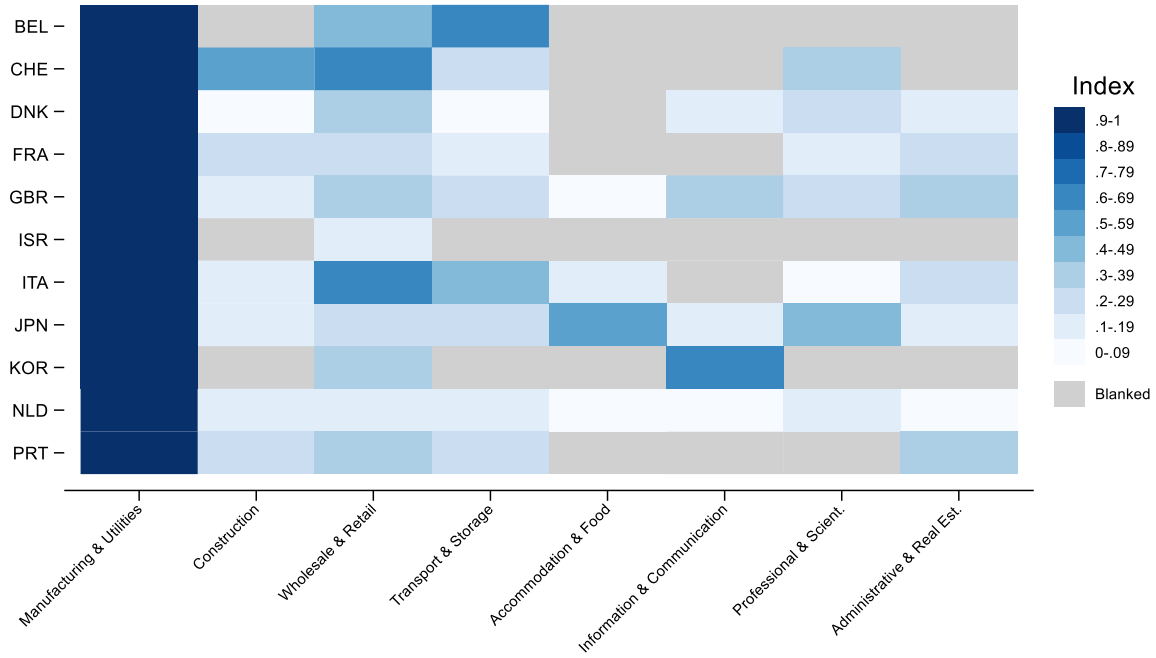
Note: This figure reports the relative adoption rates of IoT across sectors. Within each country, the adoption rates are normalised such that the sector with the highest rate is equal to one. Values are weighted for all countries except for Canada and Korea. Some cells are blanked for confidentiality 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.

Finally, 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 & utilities sector. This aligns with the relevance and the long-standing use of robots for automation in 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 & utilities, wholesale & retail reports the highest adoption rates in five of the nine countries analysed.

Restricted Use - À usage restreint

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



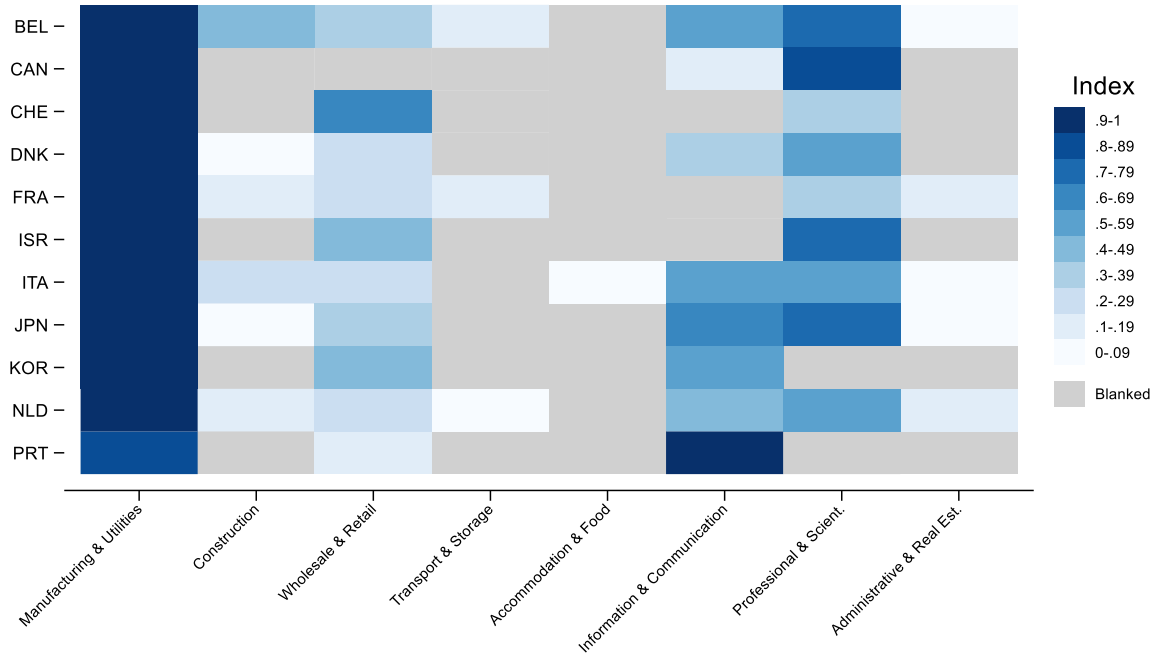
Note: This figure reports the relative adoption rates of robotics for Belgium (BEL), Switzerland (CHE), Denmark (DNK), France (FRA), the United Kingdom (GBR), Israel (ISR), Italy (ITA), Japan (JPN), Korea (KOR), the Netherlands (NLD) and Portugal (PRT) across sectors. Within each country, the adoption 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.

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 & utilities, followed by the professional & 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 on the application and impact of 3D printing). Notably, Portugal is the only country for which manufacturing & utilities does not have the highest adoption rate of 3D printing, where it is surpassed by the ICT sector.

The professional & 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 homogenous in others. These variations in patterns 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.

Restricted Use - À usage restreint

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 the sectoral applications. AI and big data analysis show broader adoption across service-oriented industries, particularly in ICT and professional & scientific sectors. IoT appears to be more versatile, with more widespread adoption across sectors. Robotics and 3D printing are particularly relevant to the manufacturing & 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 is displayed 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 towards 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 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.

Restricted Use - À usage restreint

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 to better understand 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 analysing 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 thanks to 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 with respect 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).

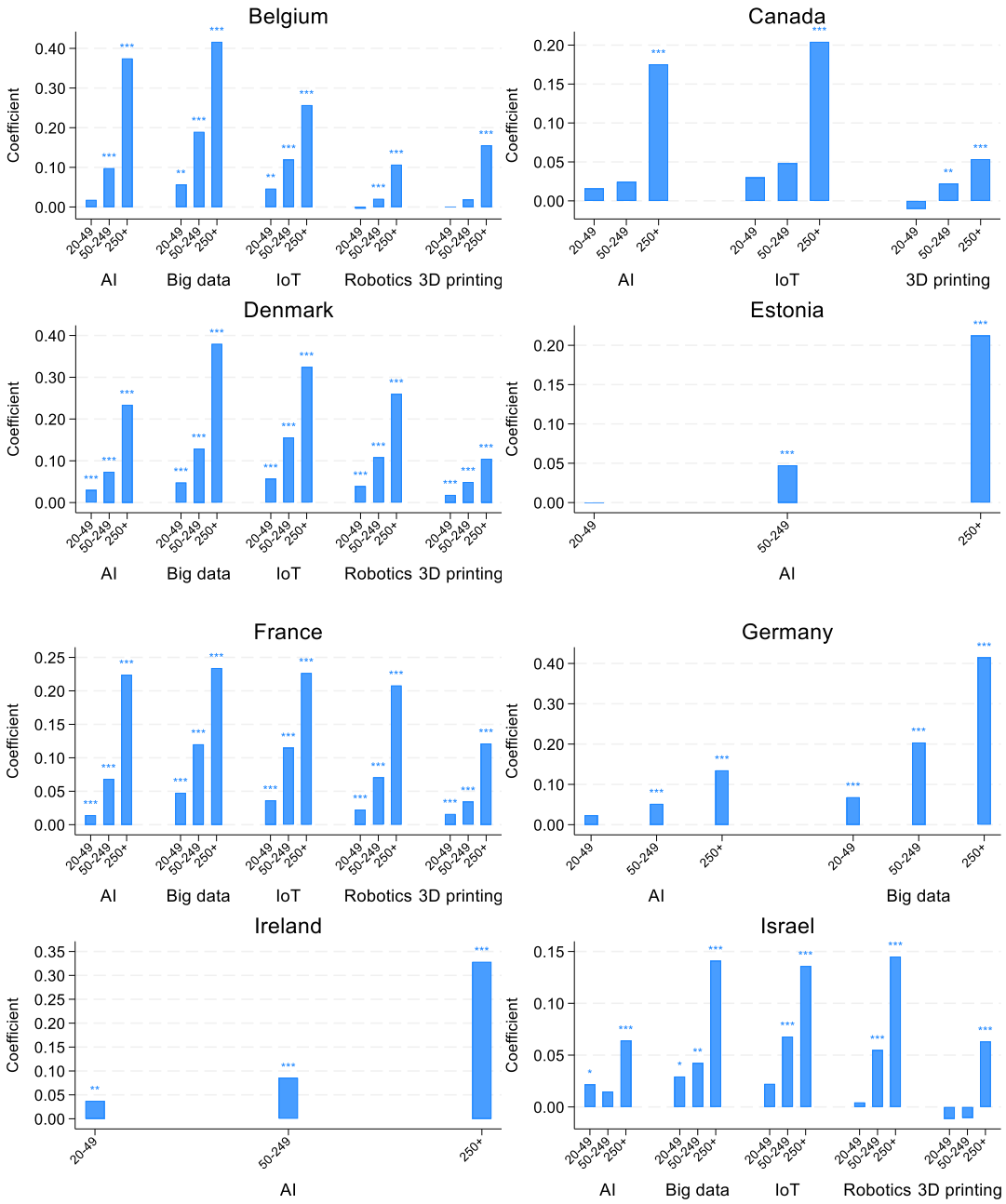
It is apparent that the likelihood of adoption increases monotonically with firm size for almost all technologies and countries considered. A coefficient of 0.4 – such as that observed for large Belgian firms (250 or more persons engaged) adopting AI or big data – indicates that being a large firm increases 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 a statistically significant coefficient.

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, suggesting that scale advantages may play a relevant role in their diffusion. By contrast, while Calvino and Fontanelli (2023[16]) and Zolas (2020[39]) identify a relevant association of firm age with technology adoption, a heterogenous picture emerges for the role of age across countries and technologies when firm size is taken into account, as shown in Figure A C.4 in Annex C.

For Official Use

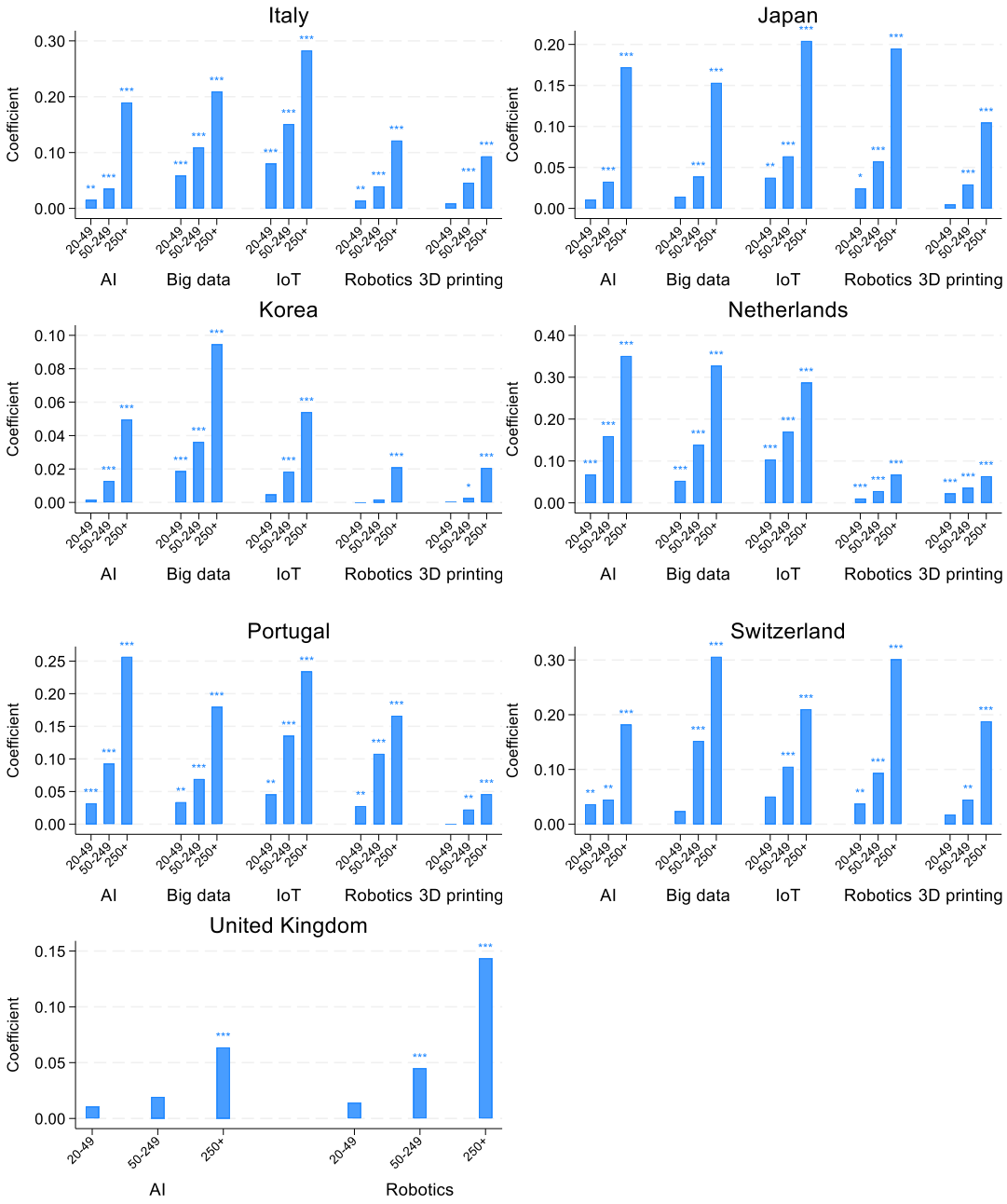
Restricted Use - À usage restreint

Figure 4.8. Adoption regression coefficients for size class dummies



For Official Use

Restricted Use - À usage restreint



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.

For Official Use

Restricted Use - À usage restreint

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 technology. The results presented in this paper rely on a series of linear probability models, estimated using the following equation:

$$\text{Technology use}_{it} = \beta_0 + \beta_1 \text{SizeClass}_{it} + \beta_2 \text{AgeClass}_{it} + \delta_s + \gamma_t + \varepsilon_{it}$$

where $\text{Technology use}_{it}$ is a binary variable indicating whether firm *i* uses an advanced digital technology in year *t*. The equation is estimated separately for each technology. SizeClass_{it} and AgeClass_{it} represent fixed effects based on size and age classes, respectively. δ_s and γ_t capture sector and, upon availability, year fixed effects. Finally, ε_{it} denotes the usual 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 for the adoption of advanced digital technologies, specifically human and technological capital, the equation above is extended as follows:

$$\text{Technology use}_{it} = \beta_0 + \beta_1 \text{SizeClass}_{it} + \beta_2 \text{AgeClass}_{it} + \beta_3 X'_{it} + \delta_s + \gamma_t + \epsilon_{it}$$

where X'_{it} is a vector of binary variables that identify relevant factors. These include, upon data availability, 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 being covered: 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 for 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 providing the necessary tools and skills to identify use cases or leverage their potential, relevantly 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]), or 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 of 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.

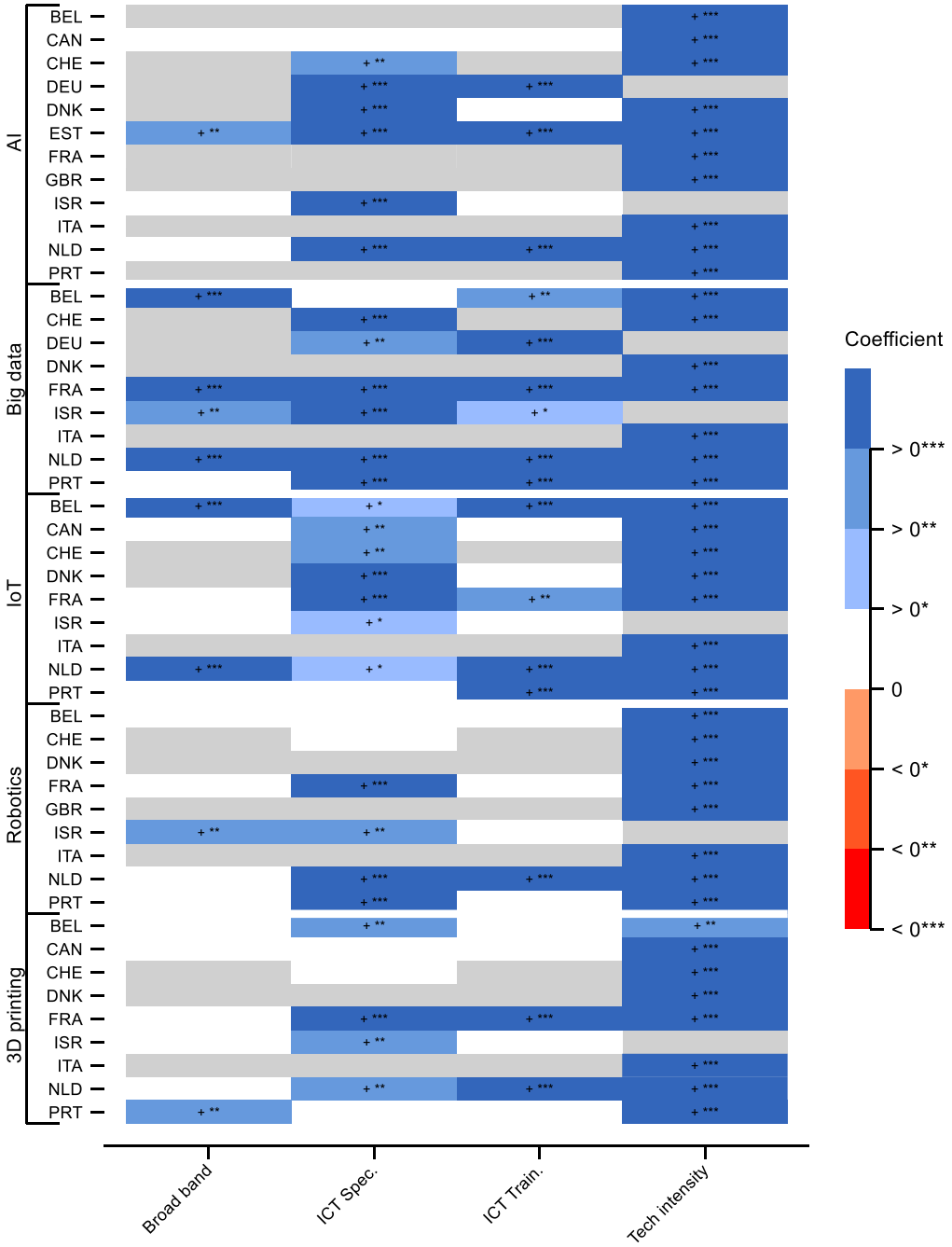
Figure 4.9 presents the sign and statistical significance of selected coefficients from adoption regressions across advanced digital technologies and countries, conditional on data availability. With respect to the role of human capital, the presence of ICT specialists and ICT training is widely associated 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 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 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, for the adoption of advanced digital technologies, suggesting the existence of relevant complementarities in adoption. 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.

Restricted Use - À usage restreint

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.

Restricted Use - À usage restreint

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: a first proxy is the share of a firm's workforce holding tertiary education qualifications, and the second one 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. (2024[90]), using the International Standard Classification of Occupations (ISCO-08).[8]

The use of information from LEED provides significantly more details 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 survey's 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.

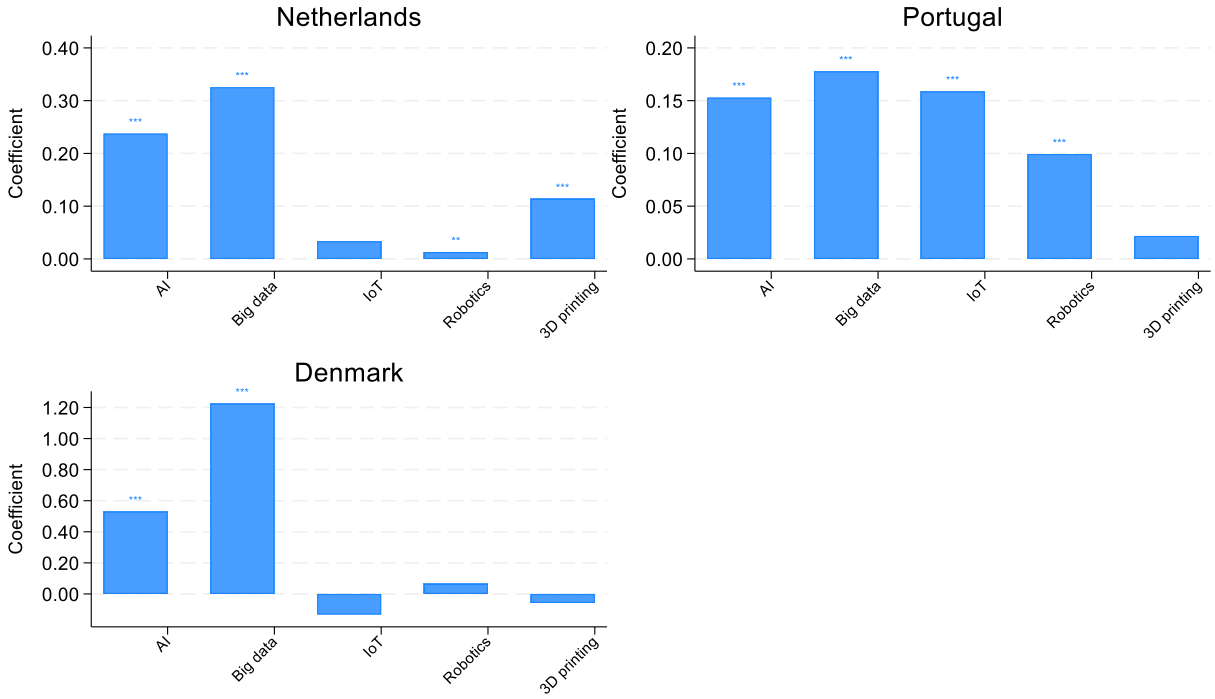
The results for Denmark also show a strong positive relationship for AI and big data - and it is even more pronounced in this case. A one percentage point increase in the tertiary education share is associated with a 0.5 percentage point higher likelihood of AI adoption and a 1.2 percentage point increase for big data analysis. 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 its human capital alone.

For Official Use

Restricted Use - À usage restreint

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.

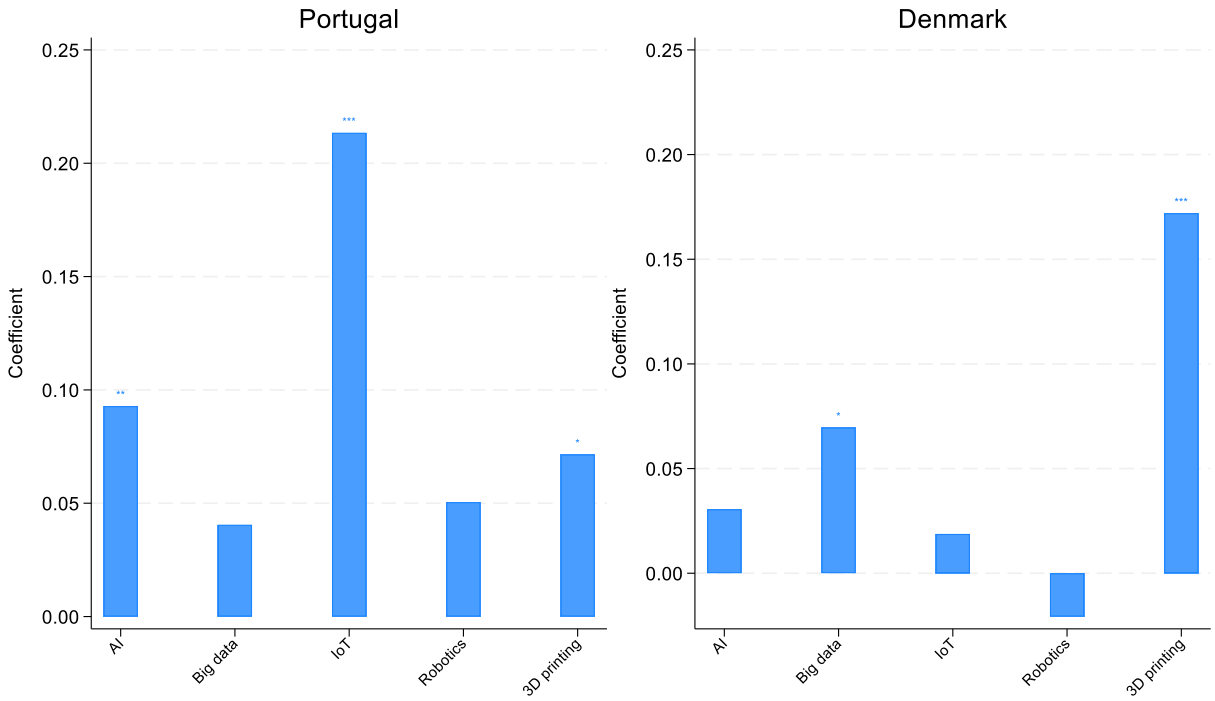
Further focusing on the role of occupational composition, Figure 4.11 presents the regression coefficients of the share of techies for the adoption of each advanced digital technology in Denmark and Portugal. In Portugal, the results suggest that technical skills are positively correlated with the adoption of AI, IoT and 3D printing, whereas in Denmark this is the case for big data analysis and 3D printing.[9] 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 quantitative effect.[10]

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

For Official Use

Restricted Use - À usage restreint

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.

Restricted Use - À usage restreint

Box 4.2. Spotlight on the role of human capital to adopt and develop AI

Adopting a similar methodology, Fontanelli et al. (2024[90]) 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 on 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, as well as 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, with this link being stronger for firms that develop their own AI systems.

Moreover, the role of ICT engineers is particularly relevant in fostering AI adoption in Wholesale & Retail, ICT business services and Professional, Scientific & 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 and non-technical higher intellectual occupation play an important role for 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 regressions 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.[11] 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 between 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).

Restricted Use - À usage restreint

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:

$$\log(\text{Productivity})_{it} = \beta_0 + \beta_1 \text{Technology use}_{it} + \beta_2 \text{SizeClass}_{it} + \beta_3 \text{AgeClass}_{it} + \delta_s + \gamma_t + \varepsilon_{it}$$

where $\log(\text{Productivity})_{it}$ is the logarithm of a firm's productivity, measured as the ratio of turnover to the number of persons engaged. The main explanatory variable, $\text{Technology use}_{it}$, 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. SizeClass_{it} and AgeClass_{it} represent fixed effects based on size and age classes, respectively. δ_s and γ_t capture sector and, upon availability, 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.

As robustness checks, the same equation is re-estimated using the ratio of value added to number of persons engaged in logarithmic form as 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 on firm productivity, the equation above is extended as follows:

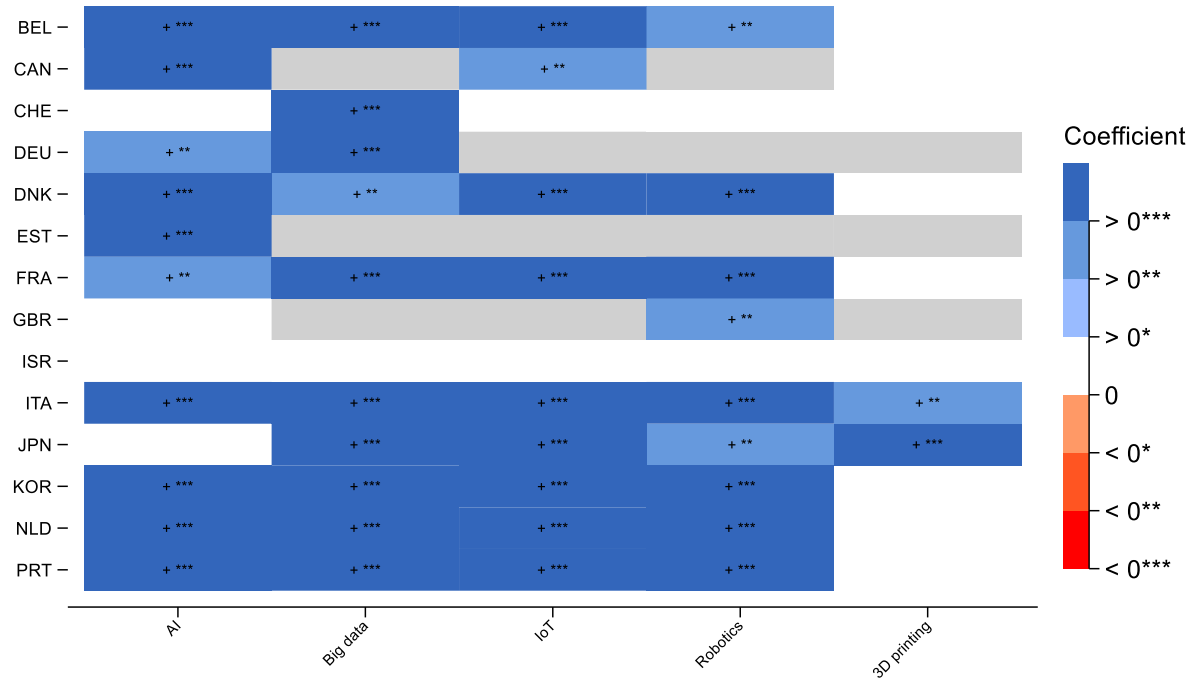
$$\log(\text{Productivity})_{it} = \beta_0 + \beta_1 \text{Technology use}_{it} + \beta_2 \text{SizeClass}_{it} + \beta_3 \text{AgeClass}_{it} + \beta_4 X'_{it} + \delta_s + \gamma_t + \varepsilon_{it}$$

where $\boldsymbol{X'_{it}}$ is a vector of binary variables that identify additional relevant factors, notably related to human and technological capital. These include, upon data availability, 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 variables definitions).

For Official Use

Restricted Use - À usage restreint

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 relationship between AI adoption and the proxy of labour productivity analysed. Relevant exceptions appear to be Japan, where however AI adoption is proxied by machine learning, which only represents a subset of AI technologies, Israel, Switzerland and the United Kingdom. The productivity advantage of AI adopters is estimated to range between 7.7% in France and 31% in Belgium, highlighting relevant cross-country variation. These results align with those discussed more at 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 among the large 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 out of the 11 countries analysed, with premia of adopters of IoT 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. These findings overall suggest that firms leveraging IoT technologies tend to be, on average, more productive than their non-adopting counterparts.

Restricted Use - À usage restreint

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%.[12] However, no such significant relationship is identified in the other countries analysed, suggesting a different role for 3D printing compared to other advanced digital technologies.[13]

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 abovementioned 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 out of 12 countries for AI; 7 out of 9 for big data analysis; 6 out of 10 for the internet of things; and 7 out 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 to be overall more productive than other firms.

Unreported results using value added per employee as an alternative productivity measure for 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 lose their statistical significance.

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. Relevantly, 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 for 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 to 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 into the productivity regression (see Box 4.3 for details on the econometric strategy).

By accounting for these assets, this section aims at better understanding 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 – 4.16 present the regression results for each advanced digital technology. The overall findings indicate that proxies of both human and technological capital are strongly associated with higher productivity levels across the countries and technologies considered. Moreover, when controlling for these

For Official Use

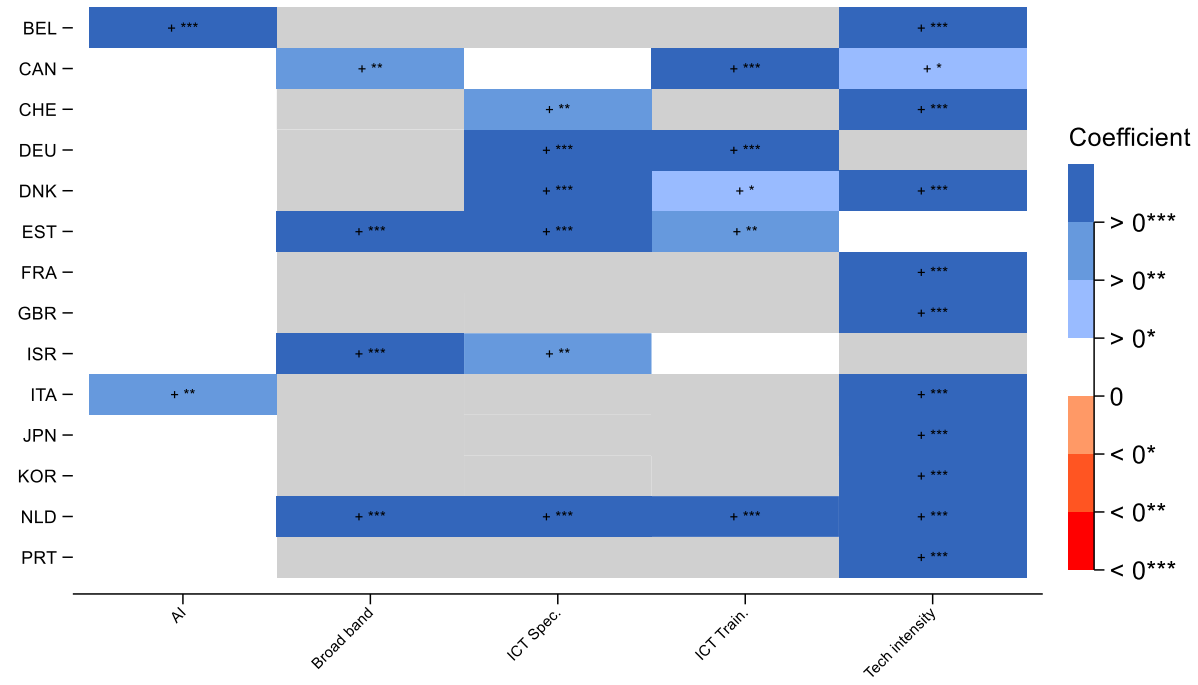
Restricted Use - À usage restreint

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 for firm productivity across countries. For European countries following Eurostat guidelines, the surveys that included 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[14] countries that exhibit a productivity premium 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. This overall 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[91]) 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 2017-21 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 2-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[92]) 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 for 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.

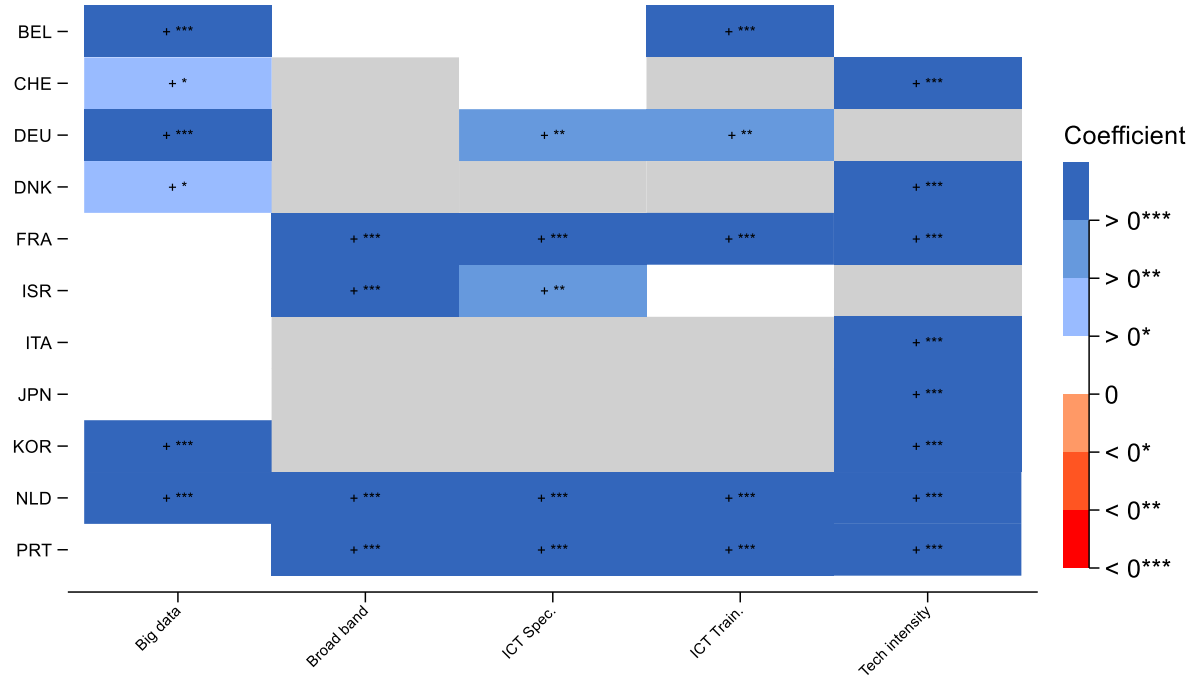
While the productivity premia of firms leveraging big data analysis significantly decline in magnitude, they remain positive and statistically significance in many countries. However, in France, Italy, Japan and Portugal – one of the two countries where all complementary asset variables are available – the productivity premia disappear.

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.

For Official Use

Restricted Use - À usage restreint

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



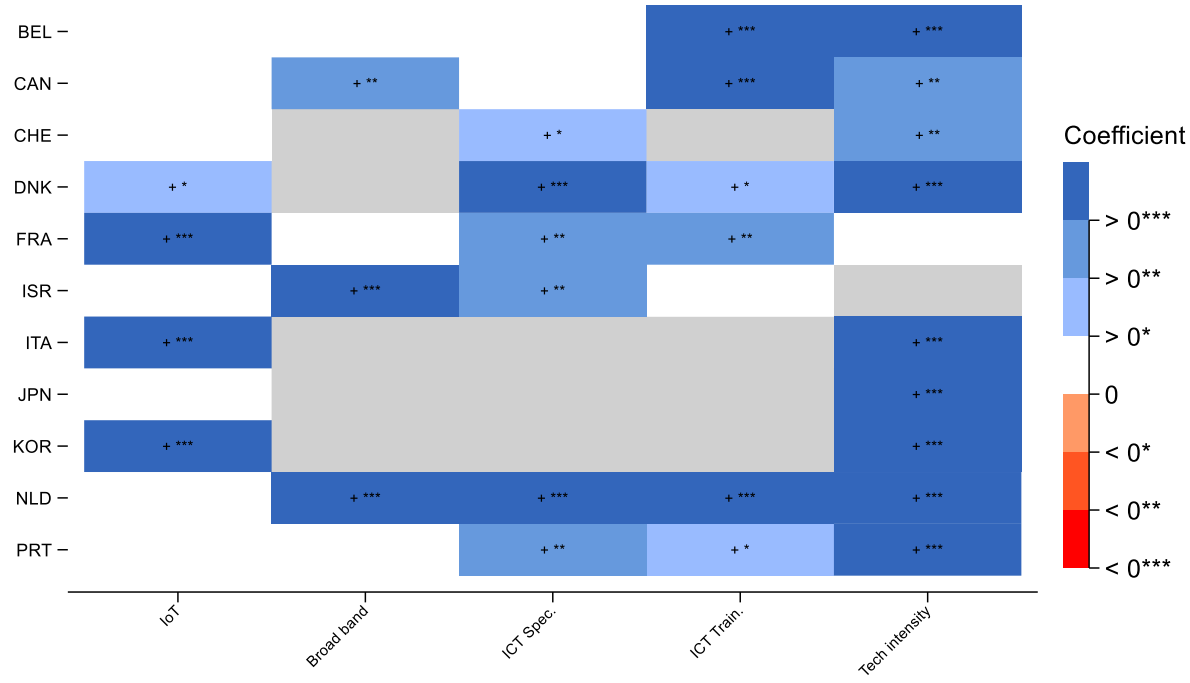
Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over 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 impact 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 in observed in Denmark, France, Italy and Korea. This pattern underscores the role of complementary assets, which in some cases appear more significant than the technology itself.

In line with previous results, the considered proxies of 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.

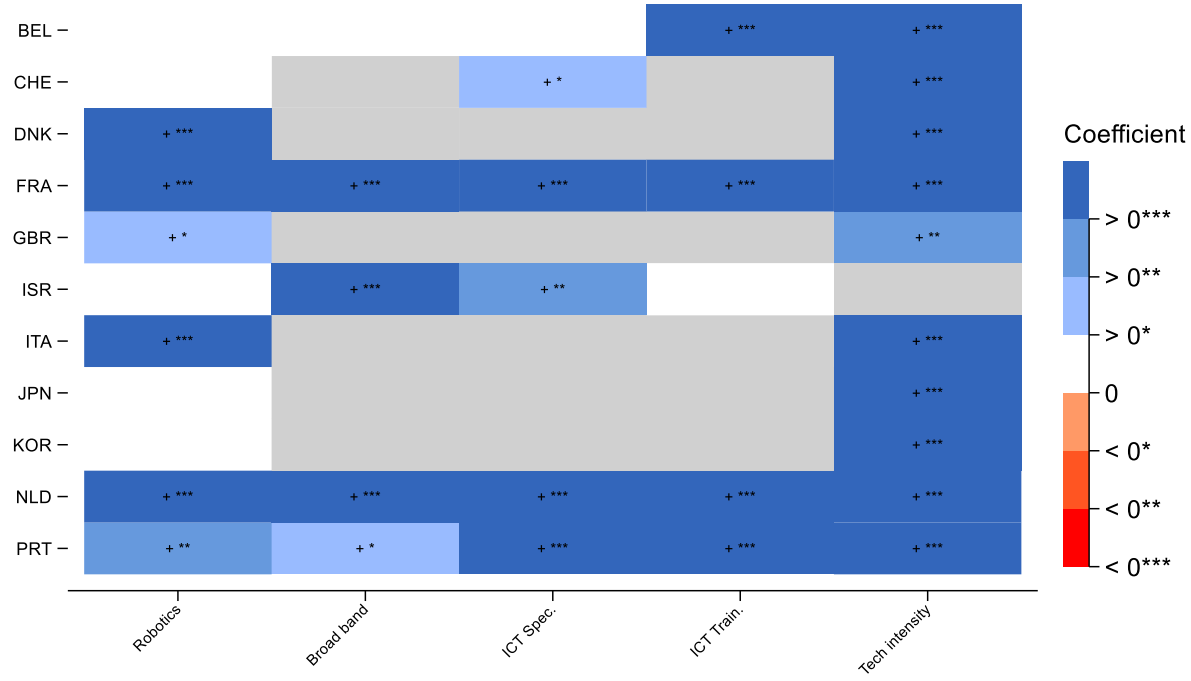
Figure 4.16 presents the regression results for the impact of the use of robots and related complementary assets on firm productivity across countries. Accounting for the role of complementary assets reduces again the magnitude of the productivity premia associated with using robots.

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 disappears.

For Official Use

Restricted Use - À usage restreint

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



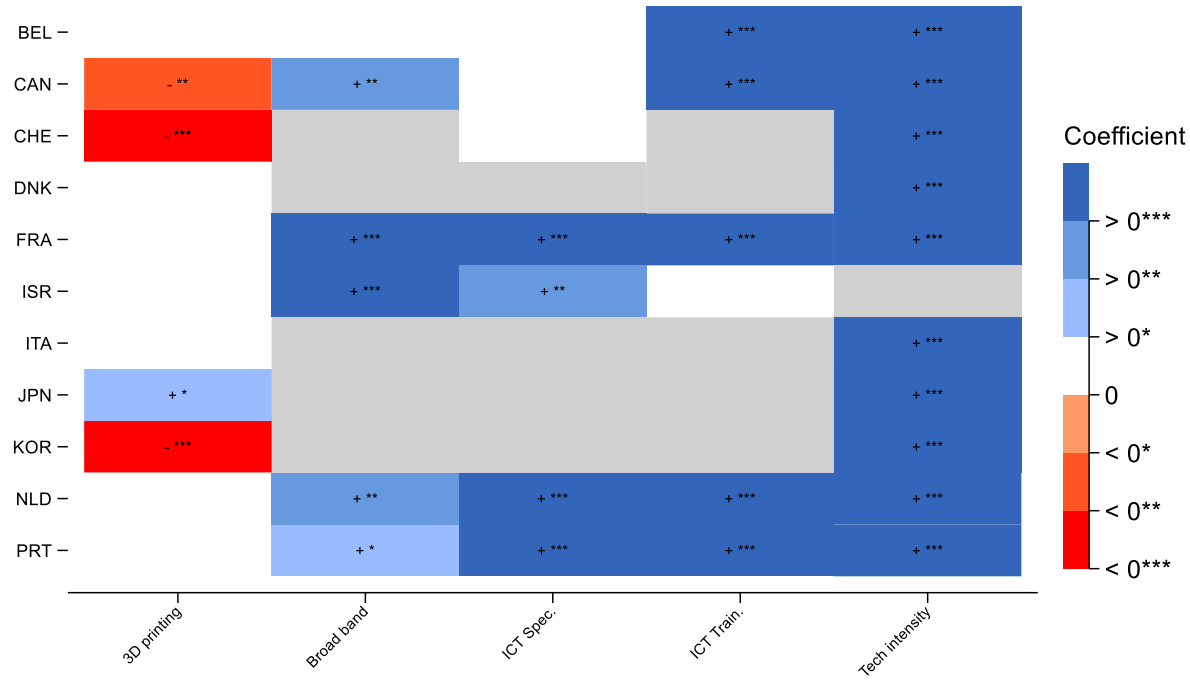
Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over 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 of 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 premia 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 the abovementioned proxies of firms' human and technological capital 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.

Restricted Use - À usage restreint

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 critical for firm's productivity advantages. These complementary assets result indeed critical in driving firm-level productivity, corroborating the importance of accounting for these factors to mitigate selection bias.

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

Among the analysed complementary assets, firms' technological capital, in particular firm digital technology intensity emerges as a particularly influential factor, consistently associated with higher productivity levels across most countries.[15] In most cases, it also accounts for a substantial share of the observed decline in the productivity premia of adopters of advanced digital technologies, underscoring the importance of firms' pre-existing digital capabilities in boosting productivity.

For Official Use

Restricted Use - À usage restreint

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 on 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 4.14, 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 with none. A significant, positive association is also found for managers' university education, with the productivity premium rising 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 higher productivity, it does not appear to be the key factor in explaining productivity gains after adoption in the UK context.

For Official Use

Restricted Use - À usage restreint

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 in 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, 3D printing and robotics in manufacturing, and IoT comparatively 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. In parallel to the determinants of adoption, much of the productivity premium 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]) or Lorenz, Perset and Berryhill (2023[93]) 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 at zooming in 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 more recent trends and more comprehensively covering generative AI uses. They

For Official Use

Restricted Use - À usage restreint

may more generally enable more detailed explorations of the patterns of use of different types of AI systems, their different use purposes across business functions, or the different sources of development 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 e.g. the interrelations between different types of AI use and competition, further focus on different actors in the AI value chain, explore the role of AI innovation for innovation in other fields, or more broadly analyse the micro-economic drivers of AI-fuelled growth.

For Official Use

Restricted Use - À usage restreint

[1] For further conceptual discussion about technology diffusion see Comin and Mestieri (2014[98]), 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[97]) 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] 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.

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

[6] See Calvino et al. (2024[96]) for a related discussion in the context of a taxonomy of AI-intensive sectors.

[7] 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[94]) or Elahi et al. (2023[95]). Future work will also aim at further focusing on the different purposes for which AI is used.

[8] 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.

[9] 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).

[10] 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.

[11] 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.

[12] 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.

[13] 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

For Official Use

Restricted Use - À usage restreint

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).

[14] 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 not anymore statistically significant. See also Calvino and Fontanelli (2023[16]).

[15] 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.

For Official Use

Restricted Use - À usage restreint

References

Abowd, J. et al. (2007), *Technology and the Demand for Skill:An Analysis of Within and Between Firm Differences*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w13043. [43]

Acemoglu, D. et al. (2022), *Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w30659. [21]

Ackerberg, D., K. Caves and G. Frazer (2015), "Identification Properties of Recent Production Function Estimators", *Econometrica*, Vol. 83/6, pp. 2411-2451, https://doi.org/10.3982/ecta13408. [93]

Agrawal, A., J. Gans and A. Goldfarb (eds.) (2019), *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics*, University of Chicago Press, https://doi.org/doi:10.7208/9780226613475-003. [60]

Amador, J. and C. Silva (2025), "The impact of ICT adoption on productivity: evidence from Portuguese firm-level data", *Empirica*, https://doi.org/10.1007/s10663-025-09652-4. [20]

Andres, R., T. Niebel and R. Sack (2025), "Big data and firm-level productivity – A cross-country comparison", *Information Economics and Policy*, Vol. 71, p. 101147, https://doi.org/10.1016/j.infoecopol.2025.101147. [68]

Babina, T. et al. (2024), "Artificial intelligence, firm growth, and product innovation", *Journal of Financial Economics*, Vol. 151, p. 103745, https://doi.org/10.1016/j.jfineco.2023.103745. [78]

Barbosa, N. and A. Faria (2022), "Digital Adoption and Productivity: Understanding Micro Drivers of the Aggregate Effect", *GEE Papers*, No. 162, Gabinete de Estratégia e Estudos, Ministério da Economia, https://EconPapers.repec.org/RePEc:mde:wpaper:0162. [73]

Bartel, A., C. Ichniowski and K. Shaw (2007), "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills", *The Quarterly Journal of Economics*, Vol. 122/4, pp. 1721-1758, https://doi.org/10.1162/qjec.2007.122.4.1721. [19]

Bartelsman, E., E. Hagsten and M. Polder (2018), "Micro Moments Database for cross-country analysis of ICT, innovation, and economic outcomes", *Journal of Economics & Management Strategy*, Vol. 27/3, pp. 626-648, https://doi.org/10.1111/jems.12256. [35]

Bartelsman, E., G. van Leeuwen and M. Polder (2016), "CDM Using a Cross-country Micro Moments Database", *Economics of Innovation and New Technology*, Vol. 26/1-2, pp. 168- [36]

182, https://doi.org/10.1080/10438599.2016.1202517.

Basu, S. et al. (eds.) (2025), *Similarities and Differences in the Adoption of General Purpose Technologies*, University of Chicago Press, https://doi.org/10.7208/chicago/9780226839097-006. [58]

Berisha, B., E. Mëziu and I. Shabani (2022), "Big Data Analytics in Cloud Computing: An Overview", *Journal of Cloud Computing*, Vol. 11/1, https://doi.org/10.1186/s13677-022-00301-w. [83]

Bettiol, M. et al. (2023), "Is this Time Different? How Industry 4.0 Affects Firms' Labor Productivity", *Small Business Economics*, Vol. 62/4, pp. 1449-1467, https://doi.org/10.1007/s11187-023-00825-8. [66]

Biagi, F. (2013), "ICT and Productivity: A Review of the Literature", *Institute for Prospective Technological Studies Digital Economy Working Paper*, No. 2013/09, European Commission, Joint Research Centre (JRC), https://doi.org/10.2788/32940. [37]

Bisio, L. et al. (2025), "Technological adoption and firm resilience: Understanding the impact of new digital technologies", *LEM Papers Series*, No. 21, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies. [81]

Bloom, N., R. Sadun and J. Reenen (2012), "Americans Do IT Better: US Multinationals and the Productivity Miracle", *American Economic Review*, Vol. 102/1, pp. 167-201, https://doi.org/10.1257/aer.102.1.167. [75]

Borgonovi, F. et al. (2023), "Emerging trends in AI skill demand across 14 OECD countries", *OECD Artificial Intelligence Papers*, No. 2, OECD Publishing, Paris, https://doi.org/10.1787/7c691b9a-en. [47]

Börner, K. et al. (2020), "Mapping the Co-evolution of Artificial Intelligence, Robotics, and the Internet of Things over 20 Years (1998-2017)", *PLoS ONE*, Vol. 15/12, p. e0242984, https://doi.org/10.1371/journal.pone.0242984. [14]

Bresnahan, T., E. Brynjolfsson and L. Hitt (2002), "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence", *The Quarterly Journal of Economics*, Vol. 117/1, pp. 339-376, https://doi.org/10.1162/003355302753399526. [18]

Brynjolfsson, E., W. Jin and K. McElheran (2021), "The Power of Prediction: Predictive Analytics, Workplace Complements, and Business Performance", *Business Economics*, Vol. 56/4, pp. 217-239, https://doi.org/10.1057/s11369-021-00224-5. [74]

Brynjolfsson, E. and P. Milgrom (2013), "Complementarity in Organizations", in Gibbons, R. and J. Roberts (eds.), *The Handbook of Organizational Economics*, Princeton University Press, Princeton, https://doi.org/10.1515/9781400845354-003. [87]

Brynjolfsson, E., D. Rock and C. Syverson (2021), "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies", *American Economic Journal: Macroeconomics*, Vol. 13/1, pp. 333-372, https://doi.org/10.1257/mac.20180386. [56]

Brynjolfsson, E., D. Rock and C. Syverson (2017), *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w24001. [57]

Caldarola, B. and L. Fontanelli (2025), "Scaling Up to the Cloud: Cloud Technology Use and Growth Rates in Small and Large Firms", https://doi.org/10.48550/arXiv.2409.17035. [80]

Calvino, F., C. Criscuolo and A. Ughi (2024), "Digital adoption during COVID-19: Cross-country evidence from microdata", *OECD Science, Technology and Industry Working Papers*, No. 2024/03, OECD Publishing, Paris, https://doi.org/10.1787/f63ca261-en. [52]

Calvino, F., A. Dechezleprêtre and D. Haerle (2025), "How can the digital transformation affect the net-zero transition?: A conceptual framework for the "twin" transition", *OECD Science, Technology and Industry Working Papers*, No. 2025/17, OECD Publishing, Paris, https://doi.org/10.1787/4ee71f6d-en. [6]

Calvino, F. et al. (2024), "A Sectoral Taxonomy of AI Intensity", *OECD Artificial Intelligence Papers*, No. 30, OECD Publishing, Paris, https://doi.org/10.1787/1f6377b5-en. [96]

Calvino, F. et al. (2022), "Closing the Italian digital gap: The role of skills, intangibles and policies", *OECD Science, Technology and Industry Policy Papers*, No. 126, OECD Publishing, Paris, https://doi.org/10.1787/e33c281e-en. [40]

Calvino, F. and L. Fontanelli (2024), *AI Users Are Not All Alike: The Characteristics of French Firms Buying and Developing AI*, CESifo Working Paper No. 11466, https://hdl.handle.net/10419/308362. [51]

Calvino, F. and L. Fontanelli (2023), "A Portrait of AI adopters Across Countries: Firm characteristics, Assets' Complementarities and Productivity", *OECD Science, Technology and Industry Working Papers*, No. 2023/02, OECD Publishing, Paris, https://doi.org/10.1787/0fb79bb9-en. [16]

Calvino, F., D. Haerle and S. Liu (2025), "Is generative AI a General Purpose Technology?: Implications for productivity and policy", *OECD Artificial Intelligence Papers*, No. 40, OECD Publishing, Paris, https://doi.org/10.1787/704e2d12-en. [11]

Calvino, F., J. Reijerink and L. Samek (2025), "The effects of generative AI on productivity, innovation and entrepreneurship", *OECD Artificial Intelligence Papers*, No. 39, OECD Publishing, Paris, https://doi.org/10.1787/b21df222-en. [12]

Calvino, F. et al. (2022), "Identifying and Characterising AI Adopters: A Novel Approach Based on Big Data", *OECD Science, Technology and Industry Working Papers*, No. 2022/06, OECD Publishing, Paris, https://doi.org/10.1787/154981d7-en. [41]

Cerqueira, C., F. Alexandre and M. Portela (2023), "Digitalization: the edge of first movers", *NIPE Working Papers*, No. 11, Universidade do Minho. Núcleo de Investigação em Políticas Económicas (NIPE). [42]

Cette, G., S. Nevoux and L. Py (2022), "The impact of ICTs and digitalization on productivity and labor share: evidence from French firms", *Economics of Innovation and New Technology*, Vol. 31/8, pp. 669-692, https://doi.org/10.1080/10438599.2020.1849967. [23]

Chatterji, A. et al. (2025), "How people use ChatGPT", *National Bureau of Economic Research*, No. 34255. [7]

Cho, J. et al. (2023), "What's driving the diffusion of next-generation digital technologies?", *Technovation*, Vol. 119, p. 102477, https://doi.org/10.1016/j.technovation.2022.102477. [22]

Ciccone, F., A. Bacciaglia and A. Ceruti (2023), "Optimization with Artificial Intelligence in Additive Manufacturing: A Systematic Review", *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 45/6, https://doi.org/10.1007/s40430-023-04200-2. [29]

Cirillo, V. et al. (2023), "The Adoption of Digital Technologies: Investment, Skills, Work Organisation", *Structural Change and Economic Dynamics*, Vol. 66, pp. 89-105, https://doi.org/10.1016/j.strueco.2023.04.011. [33]

Cirillo, V. et al. (2022), "New Digital Technologies and Firm Performance in the Italian Economy", *Industry and Innovation*, Vol. 30/1, pp. 159-188, https://doi.org/10.1080/13662716.2022.2055999. [70]

Cockburn, I., R. Henderson and S. Stern (2019), "The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis", in Agrawal, A., J. Gans and A. Goldfarb (eds.), *The Economics of Artificial Intelligence: An Agenda*, University of Chicago Press, Chicago, https://doi.org/10.7208/9780226613475-006. [59]

Comin, D. and M. Mestieri (2014), "Technology Diffusion: Measurement, Causes, and Consequences", in *Handbook of Economic Growth*, Elsevier, https://doi.org/10.1016/b978-0-444-53540-5.00002-1. [98]

Conti, R., M. de Matos and G. Valentini (2024), "Big Data Analytics, Firm Size, and Performance", *Strategy Science*, Vol. 9/2, pp. 135-151, https://doi.org/10.1287/stsc.2022.0007. [67]

Crafts, N. (2021), "Artificial Intelligence as a General-purpose Technology: A Historical Perspective", *Oxford Review of Economic Policy*, Vol. 37/3, pp. 521-536, https://doi.org/10.1093/oxrep/grab012. [61]

Czarnitzki, D., G. Fernández and C. Rammer (2023), "Artificial Intelligence and Firm-level Productivity", *Journal of Economic Behavior & Organization*, Vol. 211, pp. 188-205, https://doi.org/10.1016/j.jebo.2023.05.008. [72]

Dahlke, J. et al. (2024), "Epidemic Effects in the Diffusion of Emerging Digital Technologies: Evidence from Artificial Intelligence Adoption", *Research Policy*, Vol. 53/2, p. 104917, https://doi.org/10.1016/j.respol.2023.104917. [54]

Damioli, G., V. Van Roy and D. Vertesy (2021), "The Impact of Artificial Intelligence on Labor Productivity", *Eurasian Business Review*, Vol. 11/1, pp. 1-25, https://doi.org/10.1007/s40821-020-00172-8. [71]

DeStefano, T., R. Kneller and J. Timmis (2023), "Cloud Computing and Firm Growth", *Review of Economics and Statistics*, pp. 1-47, https://doi.org/10.1162/rest_a_01393. [79]

Draca, M., R. Sadun and J. Van Reenen (2009), "Productivity and ICTs: A Review of the Evidence", in *The Oxford Handbook of Information and Communication Technologies*, Oxford University Press, https://doi.org/10.1093/oxfordhb/9780199548798.003.0005. [38]

Elahi, M. et al. (2023), "A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment", *Discover Artificial Intelligence*, Vol. 3/1, https://doi.org/10.1007/s44163-023-00089-x. [95]

Espinoza, H. et al. (2020), "Estimating the impact of the Internet of Things on productivity in [69]

Europe", *Heliyon*, Vol. 6/5, p. e03935, https://doi.org/10.1016/j.heliyon.2020.e03935.

European Commission (2021), *Advanced technologies for industry – Final report – Report on technology trends and technology adoption*, Publications Office, https://doi.org/10.2826/321124. [15]

Filippucci, F. et al. (2024), "The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges", *OECD Artificial Intelligence Papers*, No. 15, OECD Publishing, Paris, https://doi.org/10.1787/8d900037-en. [10]

Filippucci, F. et al. (2025), "Macroeconomic productivity gains from Artificial Intelligence in G7 economies", *OECD Artificial Intelligence Papers*, No. 41, OECD Publishing, Paris, https://doi.org/10.1787/a5319ab5-en. [3]

Filippucci, F., P. Gal and M. Schief (2024), "Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence", *OECD Artificial Intelligence Papers*, No. 29, OECD Publishing, Paris, https://doi.org/10.1787/b524a072-en. [2]

Fontanelli, L. et al. (2024), *The Role of Human Capital for AI Adoption: Evidence from French Firms*, Elsevier BV, https://doi.org/10.2139/ssrn.5010602. [90]

Gal, P. et al. (2019), "Digitalisation and productivity: In search of the holy grail – Firm-level empirical evidence from EU countries", *OECD Economics Department Working Papers*, No. 1533, OECD Publishing, Paris, https://doi.org/10.1787/5080f4b6-en. [64]

Gandomi, A., F. Chen and L. Abualigah (2023), "Big Data Analytics Using Artificial Intelligence", *Electronics*, Vol. 12/4, p. 957, https://doi.org/10.3390/electronics12040957. [31]

Goh, G., S. Sing and W. Yeong (2020), "A review on machine learning in 3D printing: applications, potential, and challenges", *Artificial Intelligence Review*, Vol. 54/1, pp. 63-94, https://doi.org/10.1007/s10462-020-09876-9. [28]

Goundar, S. (ed.) (2021), *How Artificial Intelligence is Transforming the ERP systems*, Information Age Publishing. [85]

Green, A. (2024), "Artificial intelligence and the changing demand for skills in the labour market", *OECD Artificial Intelligence Papers*, No. 14, OECD Publishing, Paris, https://doi.org/10.1787/88684e36-en. [48]

Gulzar, M., B. Naqvi and K. Smolander (2025), "Technology Change Adoption in Organizations: Drivers, Challenges, and Success Enablers", in *Lecture Notes in Business Information Processing, Software Business*, Springer Nature Switzerland, Cham, https://doi.org/10.1007/978-3-031-85849-9_32. [46]

Haller, S. and I. Siedschlag (2011), "Determinants of ICT adoption: evidence from firm-level data", *Applied Economics*, Vol. 43/26, pp. 3775-3788, https://doi.org/10.1080/00036841003724411. [44]

Harrigan, J., A. Reshef and F. Toubal (2023), "Techies and firm level productivity", No. 31341, National Bureau of Economic Research. [89]

Harrigan, J., A. Reshef and F. Toubal (2021), "The March of the Techies: Job Polarization Within and Between Firms", *Research Policy*, Vol. 50/7, p. 104008, https://doi.org/10.1016/j.respol.2020.104008. [88]

Himeur, Y. et al. (2022), "AI-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives", *Artificial Intelligence Review*, Vol. 56/6, pp. 4929-5021, https://doi.org/10.1007/s10462-022-10286-2. [32]

Klinger, J., J. Mateos-Garcia and K. Stathoulopoulos (2018), *Deep learning, deep change? Mapping the development of the Artificial Intelligence General Purpose Technology*, https://arxiv.org/abs/1808.06355. [62]

Koch, M., I. Manuylov and M. Smolka (2021), "Robots and firms", *The Economic Journal*, Vol. 131/638, pp. 2553-2584, https://doi.org/10.1093/ej/ueab009. [53]

Kroemer, O., S. Niekum and G. Konidaris (2021), "A review of robot learning for manipulation: Challenges, representations, and algorithms", *Journal of Machine Learning Research*, Vol. 22/30, pp. 1-82, http://jmlr.org/papers/v22/19-804.html. [26]

Lane, M. (2024), "Who will be the workers most affected by AI?: A closer look at the impact of AI on women, low-skilled workers and other groups", *OECD Artificial Intelligence Papers*, No. 26, OECD Publishing, Paris, https://doi.org/10.1787/14dc6f89-en. [49]

Lane, M. and A. Saint-Martin (2021), "The impact of Artificial Intelligence on the labour market: What do we know so far?", *OECD Social, Employment and Migration Working Papers*, No. 256, OECD Publishing, Paris, https://doi.org/10.1787/7c895724-en. [97]

Lane, M., M. Williams and S. Broecke (2023), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", *OECD Social, Employment and Migration Working Papers*, No. 288, OECD Publishing, Paris, https://doi.org/10.1787/ea0a0fe1-en. [50]

Ledro, C., A. Nosella and I. Dalla Pozza (2023), "Integration of AI in CRM: Challenges and guidelines", *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 9/4, p. 100151, https://doi.org/10.1016/j.joitmc.2023.100151. [84]

Liu, Z. et al. (2022), "Robot learning towards smart robotic manufacturing: A review", *Robotics and Computer-Integrated Manufacturing*, Vol. 77, p. 102360, https://doi.org/10.1016/j.rcim.2022.102360. [27]

Mammadov, H. et al. (2024), "Adoption of Artificial Intelligence in Small and Medium-Sized Enterprises in Spain: The Role of Competences and Skills", *Amfiteatru Economic*, Vol. 26/67, p. 848, https://doi.org/10.24818/ea/2024/67/848. [45]

McElheran, K. et al. (2024), "AI adoption in America: Who, what, and where", *Journal of Economics & Management Strategy*, Vol. 33/2, pp. 375-415, https://doi.org/10.1111/jems.12576. [34]

McElheran, K. et al. (2025), *The rise of industrial AI in America: Microfoundations of the Productivity J-curve(s)*, Elsevier BV, https://doi.org/10.2139/ssrn.5036270. [63]

Müller, O., M. Fay and J. vom Brocke (2018), "The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics", *Journal of Management Information Systems*, Vol. 35/2, pp. 488-509, https://doi.org/10.1080/07421222.2018.1451955. [65]

Niebel, T., F. Rasel and S. Viete (2018), "BIG data – BIG gains? Understanding the link between big data analytics and innovation", *Economics of Innovation and New Technology*, [77]

Vol. 28/3, pp. 296-316, https://doi.org/10.1080/10438599.2018.1493075.

OECD (2025), *Generative AI and the SME Workforce: New Survey Evidence*, OECD Publishing, Paris, https://doi.org/10.1787/2d08b99d-en. [8]

OECD (2025), *OECD ICT Access and Usage by Businesses database*. [9]

OECD (2024), *Fostering an inclusive digital transformation as AI spreads among firms*, OECD Publishing, Paris, https://doi.org/10.1787/5876200c-en. [17]

OECD (2024), *OECD Digital Economy Outlook 2024 (Volume 1): Embracing the Technology Frontier*, OECD Publishing, Paris, https://doi.org/10.1787/a1689dc5-en. [1]

OECD (2024), *OECD Digital Economy Outlook 2024 (Volume 2): Strengthening Connectivity, Innovation and Trust*, OECD Publishing, Paris, https://doi.org/10.1787/3adf705b-en. [4]

OECD (2024), "Review of relevance of the OECD Recommendation on ICTs and the Environment", *OECD Digital Economy Papers*, No. 370, OECD Publishing, Paris, https://doi.org/10.1787/216766c6-en. [5]

OECD (2023), "Putting AI to the test: How does the performance of GPT and 15-year-old students in PISA compare?", *OECD Education Spotlights*, No. 6, OECD Publishing, Paris, https://doi.org/10.1787/2c297e0b-en. [13]

OECD (2022), "Broadband networks of the future", *OECD Digital Economy Papers*, No. 327, OECD Publishing, Paris, https://doi.org/10.1787/755e2d0c-en. [82]

OECD (2017), *The Next Production Revolution: Implications for Governments and Business*, OECD Publishing, Paris, https://doi.org/10.1787/9789264271036-en. [86]

Oliveira, L. et al. (2021), "Artificial Intelligence and Cyber-Physical Systems: A Review and Perspectives for the Future in the Chemical Industry", *AI*, Vol. 2/3, pp. 429-443, https://doi.org/10.3390/ai2030027. [25]

Peres, R. et al. (2020), "Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook", *IEEE Access*, Vol. 8, pp. 220121-220139, https://doi.org/10.1109/access.2020.3042874. [30]

Radanliev, P. et al. (2020), "Artificial intelligence in cyber physical systems", *AI & SOCIETY*, Vol. 36/3, pp. 783-796, https://doi.org/10.1007/s00146-020-01049-0. [24]

Rammer, C., G. Fernández and D. Czarnitzki (2022), "Artificial intelligence and industrial innovation: Evidence from German firm-level data", *Research Policy*, Vol. 51/7, p. 104555, https://doi.org/10.1016/j.respol.2022.104555. [76]

Solow, R. (1987), "We'd Better Watch Out", *New York Review of Books*, Vol. 12, p. 36. [55]

Warzynski, F. (forthcoming), "AI adoption, productivity and labor composition: Evidence from Denmark". [91]

Wooldridge, J. (2009), "On estimating firm-level production functions using proxy variables to control for unobservables", *Economics Letters*, Vol. 104/3, pp. 112-114, https://doi.org/10.1016/j.econlet.2009.04.026. [92]

Zhang, Z. and J. Li (2023), "A Review of Artificial Intelligence in Embedded Systems", [94]

Micromachines, Vol. 14/5, p. 897, https://doi.org/10.3390/mi14050897.

Zolas, N. et al. (2020), *Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w28290. [39]

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. 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. Additionally, the ICT survey can also be linked with the *Déclaration annuelle de données sociales* (DADS). Among other employee-level characteristics, the DADS dataset contains employee-level information on occupation type, which can be aggregated to compute firm-level proxies for skills composition. DADS can be linked with balance sheet data and 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.

For Official Use

Restricted Use - À usage restreint

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. 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

Restricted Use - À usage restreint

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 Swiss Innovation and Digitalisation Survey, which has been collected biannually since 2019. The questions refer to the year of the survey. The unit of analysis is the enterprise, specifically targeting enterprises with at least 5 full-time equivalents (FTEs). The survey includes probability weights.

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.

For Official Use

Restricted Use - À usage restreint

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 (upon availability) 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 (upon availability). 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, upon availability, valued 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, upon availability of LEED, 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[93]) and Wooldridge (2009[92]) 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, upon availability of LEED, the program re-estimates all models with each measure of skills as an additional explanatory variable.

Restricted Use - À usage restreint

Annex B. Technology definitions and survey coverage

This section provides detailed information regarding the coverage of the relevant technologies for this paper. Additionally, definitions are provided from the latest available year in which the technology was surveyed. Some of the information currently reported may be further integrated or revised throughout the next steps of the project.

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 includes 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 the firm to not have adopted 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 your own enterprise's data sources or other data sources.

Big data analysis was surveyed in 2016, 2018 and 2020, although all questions were optional to be implemented by countries in 2016 and 2018. Questions referred to the previous year. The information collected is related to data sources, methods and the use to 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)."

For Official Use

Restricted Use - À usage restreint

The use of cloud computing services was surveyed in 2014, 2015, 2016, 2017, 2018, 2020, 2021 and 2023, although all questions were optional to be implemented by countries in 2015 and 2017. Questions referred to the reference year and further 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 for all questions implementation by countries was optional. Information referred to the reference year and included information on 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 refers to the reference year and includes 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 on total sales and percentage breakdown of web sales value by type of customer relationship, such as B2C (business to costumer), 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 manipulator programmable in three or more axes, which may be either fixed in place or mobile for use. Most of 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

Restricted Use - À usage restreint

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.

Restricted Use - À usage restreint

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)

Restricted Use - À usage restreint

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

For Official Use

Restricted Use - À usage restreint

	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

Restricted Use - À usage restreint

Annex C. Regression tables and supplementary figures

Regression tables

For Official Use

Restricted Use - À usage restreint

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
R2	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

R2	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
R2	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**

For Official Use

Restricted Use - À usage restreint

	(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
R2	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
R2	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.

Restricted Use - À usage restreint

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
R2	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
R2	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
R2	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)

Restricted Use - À usage restreint

N	2179	3844	11845	16459	12015	2019	20034	53056	6262
R2	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
R2	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)

For Official Use

Restricted Use - À usage restreint

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
R2	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
R2	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.

Restricted Use - À usage restreint

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
R2	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
R2	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
R2	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
R2	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

R2	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
R2	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
R2	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
R2	0.376	0.319	0.443	0.382	0.414	0.370	0.447	0.295	0.440	0.429	0.428

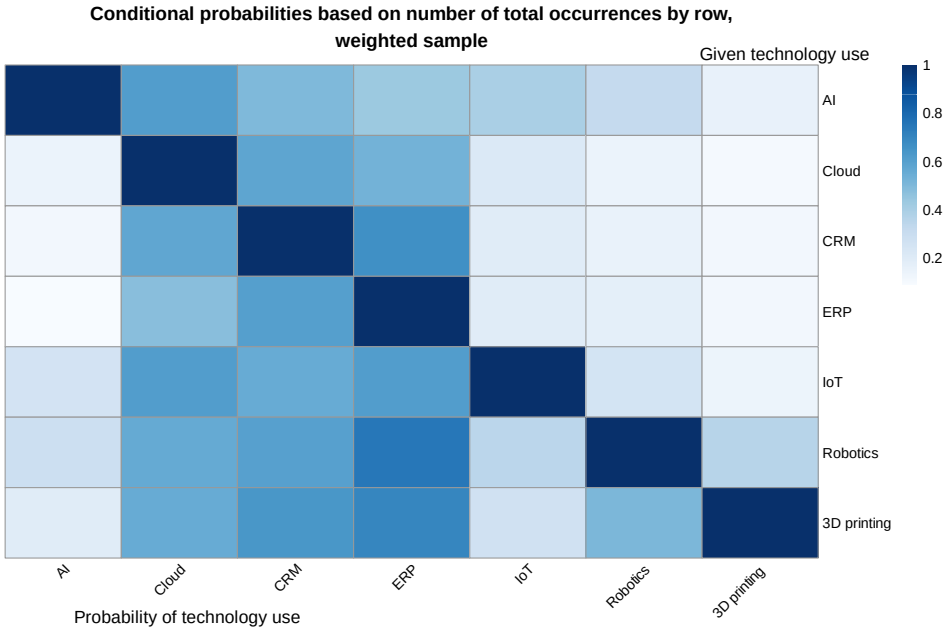
Note: This table reports the main estimation results of the extended productivity regression results of 3D printing. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available, as well as size and age dummies when available. 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.

For Official Use

Restricted Use - À usage restreint

Supplementary figures

Figure A C.1. Conditional probabilities of technology use in Switzerland, 2019

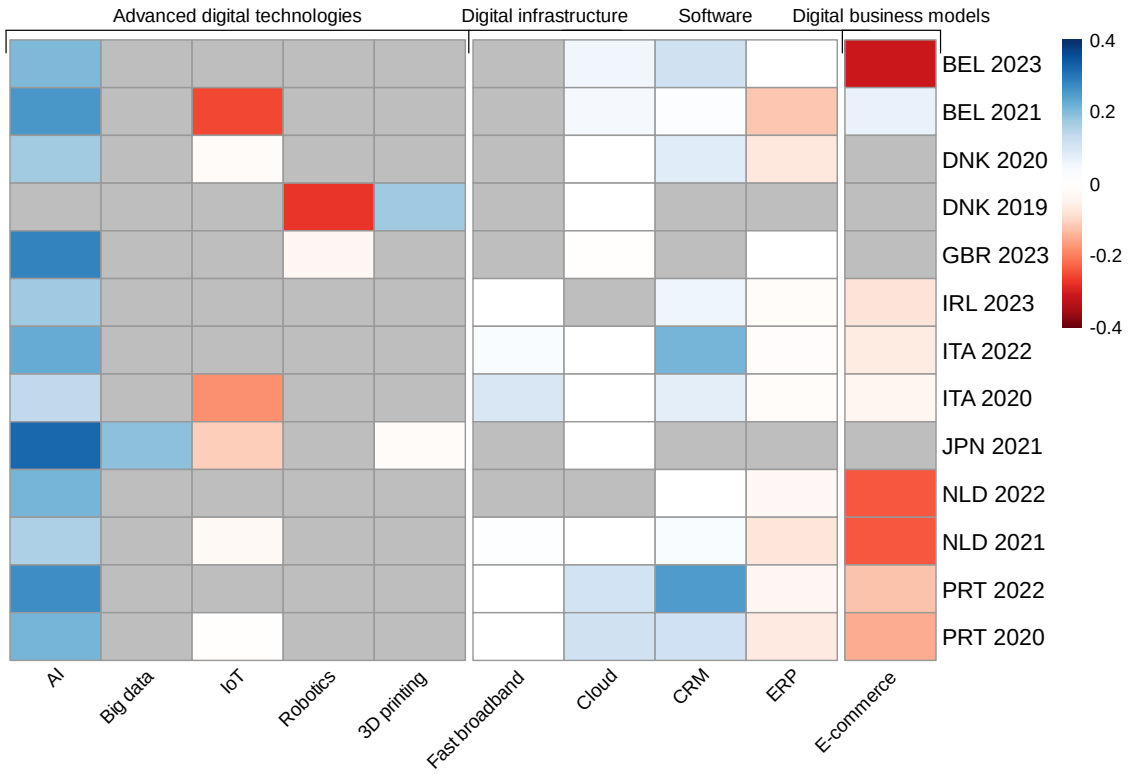


Note: Conditional probabilities of observing a technology (column), given that another technology is also observed in the network (row).
Source: Authors' calculations based on microdata from the KOF Swiss Innovation and Digitalisation Survey.

Restricted Use - À usage restreint

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



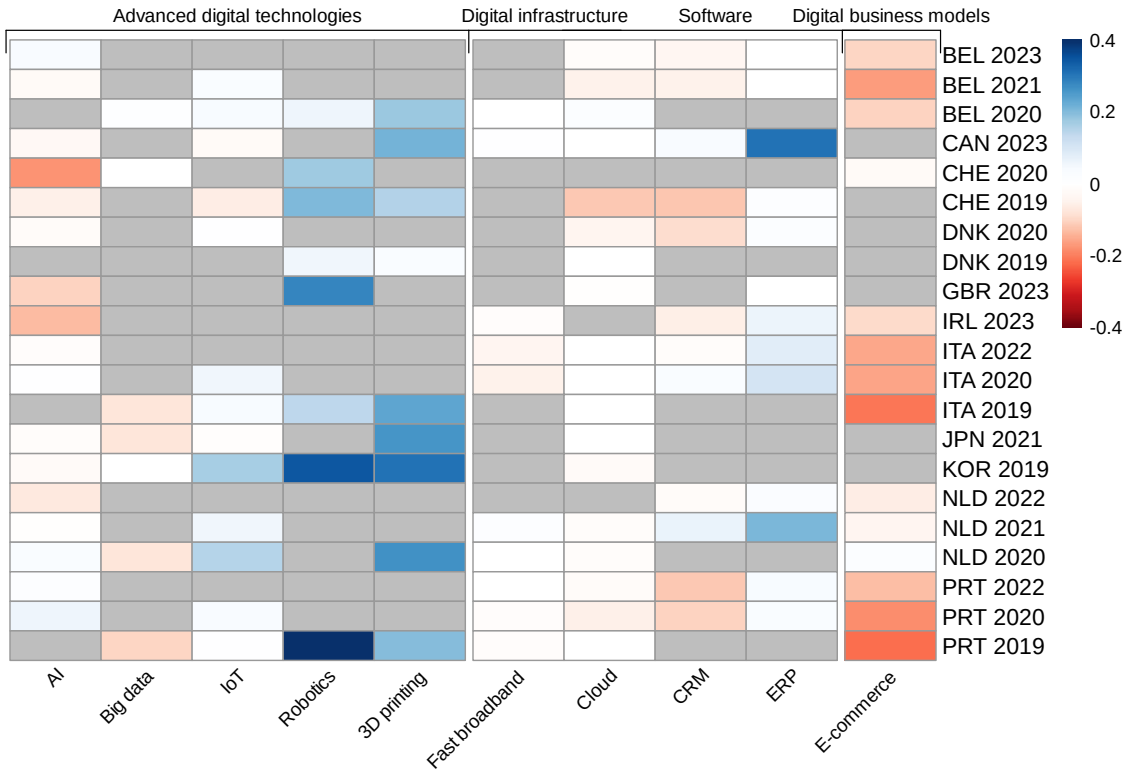
Note: The colour gradient represents the difference in eigen centrality between the ICT sector and the sector averages for each available technology (column) in the network of observed technology co-occurrences for each country-year (row). Positive values (in blue) indicate a more central position of 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.

For Official Use

Restricted Use - À usage restreint

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

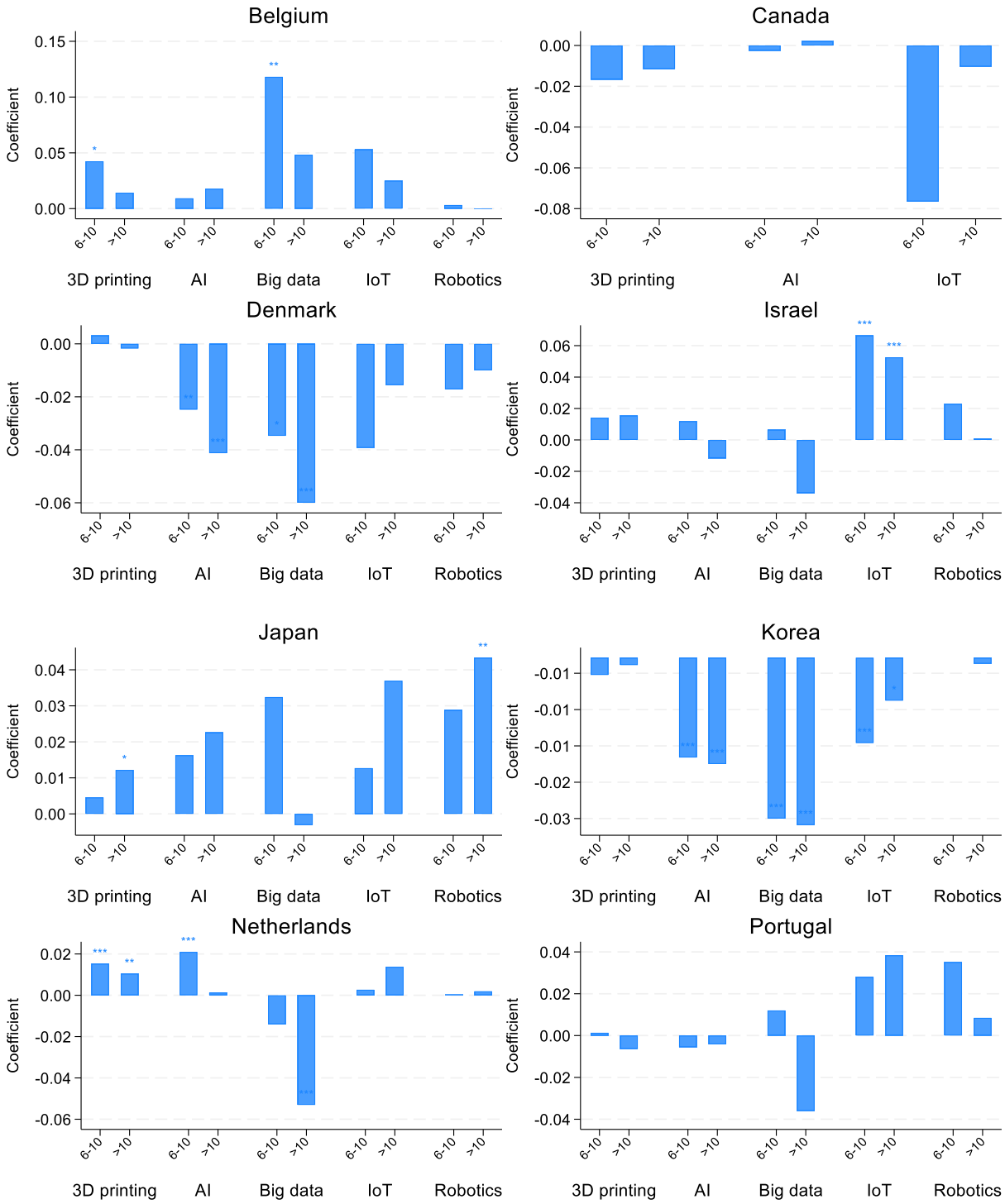
Difference in eigen centrality of technologies by country and survey year in the manufacturing & utilities sector compared to eigen centrality calculated across all available sectors



Note: The colour gradient represents the difference in eigen centrality between the manufacturing & 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.

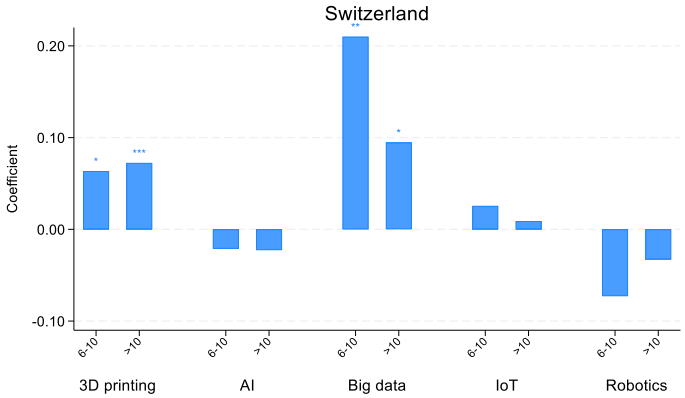
Restricted Use - À usage restreint

Figure A C.4. Adoption regression age class coefficients



For Official Use

Restricted Use - À usage restreint



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.

Restricted Use - À usage restreint