OECD Science, Technology and Industry Working Papers

This publication contributes to the OECD's Artificial Intelligence in Work, Innovation, Productivity and Skills (AI-WIPS) programme, which provides policymakers with new evidence and analysis to keep abreast of the fast-evolving changes in AI capabilities and diffusion and their implications for the world of work. The programme aims to help ensure that adoption of AI in the world of work is effective, beneficial to all, people-centred and accepted by the population at large. AI-WIPS is supported by the German Federal Ministry of Labour and Social Affairs (BMAS) and will complement the work of the German AI Observatory in the Ministry's Policy Lab Digital, Work & Society. For more information, visit https://oecd.ai/work-innovation-productivity-skills and https://denkfabrik-bmas.de/.

Federal Ministry
of Labour and Social Affairs

Note to Delegations:

This document is also available on O.N.E under the reference code:

DSTI/CIIE/(2022)16/FINAL

Acknowledgements

This analysis would not have been possible without the valuable contribution of participants in the *AI diffuse* project, namely Michel Dumont, Chantal Kegels (Belgium); Frederic Warzynski (Denmark); Iulia Siedschlag, Weijie Yan (Ireland); Gilad Be'ery, Matan Goldman, Eliav Orenbuch, Daniel Roash (Israel); Stefano Costa, Giulio Perani (Italy); Yuya Ikeda (Japan); Jaehan Cho, Hanhin Kim (Korea); Natália Barbosa (Portugal); Mathias Beck, Johannes Dahlke, Martin Wörter, Dmitry Plekhanov (Switzerland). Additional information on respective affiliations is reported in Table A B.1 in the Appendix. The authors would like to thank Chiara Criscuolo, who contributed significantly with several insights and provided guidance throughout the project, Antonio Ughi for excellent research assistance and support in the collection of metadata, Kezban Akkurt, Stijn Broecke, Hélène Dernis, Kenta Ikeuchi, Hanna-Mari Kilpelainen, Guy Lalanne, Francesco Manaresi, Luca Marcolin, Dirk Pilat, Lea Samek, Andrew Wyckoff, participants to the Working Party on Industry Analysis, the Committee on Industry, Innovation and Entrepreneurship, the AI-WIPS 2nd international conference (session on AI, productivity and diffusion) for insightful comments, suggestions or discussions. 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). This work contributes to the OECD programme on AI in Work, Innovation, Productivity and Skills (AI-WIPS), supported by the German Federal Ministry of Labour and Social Affairs (BMAS).

Abstract

This report analyses the use of artificial intelligence (AI) in firms across 11 countries. Based on harmonised statistical code (*AI diffuse*) applied to official firm-level surveys, it finds that the use of AI is prevalent in ICT and Professional Services and more widespread across large – and to some extent across young – firms. AI users tend to be more productive, especially the largest ones. Complementary assets, including ICT skills, high-speed digital infrastructure, and the use of other digital technologies, which are significantly related to the use of AI, appear to play a critical role in the productivity advantages of AI users.

Authors: Flavio Calvino (OECD) and Luca Fontanelli (University of Brescia)

Keywords: Artificial Intelligence, Technology adoption, Productivity

Résumé

Ce rapport examine l'utilisation de l'intelligence artificielle (IA) au sein des entreprises dans 11 pays. Il se fonde sur l’application d'un code statistique harmonisé (*AI diffuse*) appliqué aux enquêtes officielles menées auprès des entreprises. Les résultats montrent que l'utilisation de l'IA est prépondérante dans les entreprises liées aux TIC et dans les services professionnels. L’IA est plus répandue dans les grandes entreprises - et, dans une certaine mesure, dans les jeunes entreprises. Les utilisateurs de l'IA ont tendance à être plus productifs, notamment dans les plus grandes entreprises. Les actifs complémentaires, en particulier les compétences en TIC, l'infrastructure numérique à haut débit et l'utilisation d'autres technologies numériques, toutes significativement liés à l'utilisation de l'IA, semblent jouer un rôle crucial dans la productivité des utilisateurs de l'IA.

Kurzfassung

Dieser Bericht analysiert den Einsatz von Künstlicher Intelligenz (KI) in Unternehmen in 11 Ländern. Auf der Grundlage eines harmonisierten statistischen Codes (*AI diffuse*), der auf amtlich erhobenen Daten auf Unternehmensebene angewandt wurde, wird festgestellt, dass der Einsatz von KI in den Bereichen Informations- und Kommunikationstechnologie (IKT) und freiberufliche Dienstleistungen weit verbreitet und in großen - und bis zu einem gewissen Grad auch in jungen - Unternehmen weiter verbreitet ist. KI-Nutzer sind tendenziell produktiver, insbesondere die größten Unternehmen. Komplementäre Faktoren wie IKT-Kenntnisse, eine schnelle digitale Infrastruktur und der Einsatz anderer digitaler Technologien, die in signifikantem Zusammenhang mit dem Einsatz von KI stehen, scheinen eine entscheidende Rolle bei den Produktivitätsvorteilen der KI-Nutzer zu spielen.

Executive Summary

AI has a strong potential to affect radically and widely the economic landscape, with relevant implications for several economic and social outcomes. Little empirical work has however comprehensively analysed its patterns of diffusion across firms, especially at the international level.

This work draws a portrait of AI adopters across countries, focusing on their characteristics, the role of complementary assets – such as intangibles and digital infrastructure –, and the existing links between AI use and productivity.

It pioneers a distributed microdata approach that uses a common statistical code developed by the OECD – in the context of the *AI diffuse* project – and executed in a decentralised manner on official firm-level surveys. The analysis, based on data across 11 countries, highlights a series of stylised facts.

- AI is more widely used across large firms. This may be relevantly related to the more considerable endowments or capabilities to use intangibles and other complementary assets needed to fully leverage the potential of AI.
- Shares of AI users appear to some extent higher across younger firms. Start-ups indeed often bring to the market more radical innovations, especially when new technological paradigms emerge.
- Shares of AI adoption are consistently higher in ICT and Professional Services, suggesting that AI use is not yet equally spread across all sectors. Considering that AI is at relatively early stages of diffusion, this suggests its full potential as a general-purpose technology is yet to fully materialise.
- Several complementary assets are significantly linked to AI use. These notably include intangibles, such as ICT skills and training, firm-level digital capabilities, as well as digital infrastructure. More general skills and innovative activities appear also positively linked to AI use.
- AI users tend to be on average more productive than other firms. These productivity premia tend to originate from large firms, but do not seem to reflect the use of AI alone. In fact, the above mentioned complementary assets appear to play a critical role in the productivity advantages of AI users.

A polarised adoption, mainly by larger and more productive firms, combined with a role of AI strengthening their advantages, may imply that in the future existing gaps between leaders and the rest of the firm population may widen, with relevant implications for social outcomes. Policy makers can play a key role in this context, supporting an inclusive digital transformation.

A broad policy mix affecting incentives and capabilities would be needed to boost technology diffusion in the age of AI. This would include both demand-side measures raising awareness about new technologies and developing absorptive capacity, and supply-side measures fostering competition, providing relevant credit tools, improving knowledge production and sharing, and strengthening the foundation of digital infrastructure and skills. Such policies may allow AI use and its returns to be more widespread across firms and sectors, ensuring an inclusive digital transformation in the age of AI.

Synthèse

L'IA possède un fort potentiel pour transformer radicalement et largement les économies, avec des répercussions économiques et sociétales. Toutefois, peu de travaux empiriques ont analysé de manière exhaustive ses modes de diffusion au sein des entreprises, en particulier au niveau international.

Ce travail brosse un portrait des adoptants de l'IA dans différents pays, tout particulièrement sur leurs caractéristiques, le rôle des actifs complémentaires - tels que les actifs immatériels et l'infrastructure numérique - et les liens entre l'utilisation de l'IA et la productivité.

Il se fonde sur une approche pionnière de microdonnées distribuées, élaborée à partir d' un code statistique unique développé par l'OCDE - dans le contexte du projet *AI diffuse* - exécuté de manière décentralisée sur des données d'enquêtes officielles au niveau de l'entreprise menées dans les pays. L'analyse des données issues de 11 pays met en évidence une série de faits stylisés.

- L'IA est plus répandue dans les grandes entreprises, notamment en raison de leurs plus fortes dotations ou capacités d'utilisation des actifs incorporels et d'autres actifs complémentaires, nécessaires à une pleine exploitation du potentiel de l'IA.
- La proportion d'utilisateurs de l'IA semble, dans une certaine mesure, plus importante au sein des jeunes entreprises. En effet, ces dernières introduisent souvent des innovations plus radicales sur le marché, particulièrement lorsque de nouveaux paradigmes technologiques surviennent.
- Les pourcentages d'adoption de l'IA dans les entreprises sont systématiquement plus élevés dans les secteurs liés aux TIC et les services professionnels, suggérant ainsi que l'utilisation de l'IA n'est pas encore répartie de façon homogène dans tous les secteurs. Étant donné la précocité du stade de diffusion de l'IA, son potentiel en tant que technologie à usage général ne serait pas encore pleinement exploité.
- Plusieurs actifs complémentaires sont significativement liés à l'utilisation de l'IA. Il s'agit notamment d'actifs incorporels, tels que les compétences et la formation en matière de TIC, les capacités numériques au sein de l'entreprise, ainsi que l'infrastructure numérique. Les compétences plus générales et les activités innovantes semblent également positivement corrélées avec l'utilisation de l'IA.
- Les entreprises utilisant l'IA seraient plus productives que les autres, en moyenne. Ces primes de productivité seraient plus marquées dans les grandes entreprises, mais elles ne semblent pas refléter uniquement l'utilisation de l'IA. En fait, les actifs complémentaires mentionnés ci-dessus semblent jouer un rôle crucial dans les avantages de productivité des utilisateurs d'IA.

Une adoption principalement polarisée par des entreprises plus grandes et plus productives, combinée au renforcement de leurs avantages grâce à l'IA, pourrait davantage creuser les écarts existants entre les chefs de file et le reste des entreprises, avec des implications au niveau sociétal. Les décideurs politiques peuvent jouer un rôle majeur dans ce contexte, en soutenant une transformation numérique inclusive.

Un large éventail de mesures touchant aux incitations et aux capacités serait nécessaire pour stimuler la diffusion des technologies à l'ère de l'IA. Il s'agirait à la fois de mesures axées sur la demande, afin de sensibiliser les entreprises aux nouvelles technologies et développer la capacité d'absorption, et de mesures axées sur l'offre, visant à encourager la concurrence, fournir des outils de crédit appropriés, améliorer la production des connaissances et leur partage, et renforcer les bases en termes d’infrastructure et de compétences numériques. De telles politiques pourraient permettre une plus grande étendue de l'utilisation de l'IA et de ses bénéfices dans les entreprises et les secteurs, garantissant alors une transformation numérique inclusive à l'ère de l'IA.

Zusammenfassung

Die künstliche Intelligenz (KI) hat ein großes Potenzial, die wirtschaftliche Landschaft radikal und weitreichend zu verändern, was sich auf verschiedene wirtschaftliche und soziale Ergebnisse auswirken wird. Es gibt jedoch nur wenige empirische Arbeiten, die die Verbreitungsmuster von KI in Unternehmen, insbesondere auf internationaler Ebene, umfassend analysiert haben.

Diese Arbeit zeichnet ein Porträt der KI-Anwender in den verschiedenen Ländern und konzentriert sich dabei auf ihre Merkmale, die Rolle ergänzender Vermögenswerte - wie immaterielle Güter und digitale Infrastruktur - und die bestehenden Verbindungen zwischen KI-Einsatz und Produktivität.

Sie leistet Pionierarbeit mit einem verteilten Mikrodatenansatz, der einen gemeinsamen statistischen Code verwendet, der von der OECD - im Rahmen des *AI Diffuse*-Projekts - entwickelt und dezentral auf der Grundlage amtlich erhobener Daten auf Unternehmensebene durchgeführt wurde. Die Analyse, die auf Daten aus 11 Ländern basiert, zeigt eine Reihe von stilisierten Fakten auf.

- KI wird in großen Unternehmen in größerem Umfang eingesetzt. Dies könnte damit zusammenhängen, dass sie über umfangreichere Mittel oder Fähigkeiten zur Nutzung immaterieller und anderer komplementärer Vermögenswerte verfügen, die erforderlich sind, um das Potenzial der KI voll auszuschöpfen.
- Der Anteil der KI-Nutzer scheint in jüngeren Unternehmen bis zu einem gewissen Grad höher zu sein. Start-ups bringen in der Tat oft radikalere Innovationen auf den Markt, insbesondere wenn neue technologische Paradigmen auftauchen.
- Der Anteil der KI-Nutzung ist in der Branche der Informations- und Kommunikationstechnolgie (IKT) und bei den freiberuflichen Dienstleistungen durchweg höher, was darauf hindeutet, dass die KI noch nicht in allen Sektoren gleich stark verbreitet ist. In Anbetracht der Tatsache, dass sich die KI in einem relativ frühen Stadium der Verbreitung befindet, deutet dies darauf hin, dass sich ihr Potenzial als Allzwecktechnologie erst noch voll entfalten muss.
- Mehrere komplementäre Vermögenswerte sind in erheblichem Maße mit dem Einsatz von KI verbunden. Dazu gehören insbesondere immaterielle Güter wie IKT-Kenntnisse und -Schulungen, digitale Fähigkeiten auf Unternehmensebene sowie die digitale Infrastruktur. Allgemeinere Fähigkeiten und innovative Aktivitäten scheinen ebenfalls positiv mit dem Einsatz von KI verbunden zu sein.
- KI-Nutzer sind im Durchschnitt produktiver als andere Unternehmen. Diese Produktivitätsvorteile stammen in der Regel von großen Unternehmen, scheinen aber nicht allein auf den Einsatz von KI zurückzuführen zu sein. Vielmehr scheinen die oben erwähnten komplementären Vermögenswerte eine entscheidende Rolle für die Produktivitätsvorteile der KI-Nutzer zu spielen.

Eine polarisierte Übernahme, hauptsächlich durch größere und produktivere Unternehmen, in Verbindung mit einer Rolle der KI, die deren Vorteile verstärkt, kann bedeuten, dass sich in Zukunft die bestehenden Unterschiede zwischen den führenden Unternehmen und dem Rest der Unternehmenspopulation vergrößern, was sich auf die sozialen Ergebnisse auswirkt. Politische Entscheidungsträger können in

diesem Zusammenhang eine Schlüsselrolle spielen, indem sie eine integrative digitale Transformation unterstützen.

Um die Technologieverbreitung im Zeitalter der KI voranzutreiben, wäre ein breiter Politikmix erforderlich, der Anreize und Fähigkeiten beeinflusst. Dazu gehören sowohl Maßnahmen auf der Nachfrageseite, die das Bewusstsein für neue Technologien schärfen und die Absorptionsfähigkeit entwickeln, als auch Maßnahmen auf der Angebotsseite, die den Wettbewerb fördern, relevante Kreditinstrumente bereitstellen, die Wissensproduktion und den Wissensaustausch verbessern und die Grundlage der digitalen Infrastruktur und der Fähigkeiten stärken. Derartige Maßnahmen könnten es ermöglichen, dass die Nutzung von KI und ihre Erträge in Unternehmen und Sektoren weiter verbreitet werden, um einen integrativen digitalen Wandel im Zeitalter der KI zu gewährleisten.

Table of contents

FIGURES

TABLES

1 Introduction

Artificial intelligence (AI) is rapidly reshaping economies and societies. AI-driven products and services are already a crucial part of most people's routines, whether they realise it or not. AI brings tremendous opportunities to productivity and wellbeing but also risks to human rights and democratic values.

Relevantly, AI is often considered as a general-purpose technology (GPT), whose applications can potentially bring significant improvements to adopters. It is already changing the demand for skills and may play an important role to tackle societal challenges, such as those related to health and climate change.

While the role of AI is at the centre of the economic and policy debate, little empirical work has so far comprehensively analysed its patterns of diffusion across firms, especially at the international level. Limited cross-country evidence indeed exists on the characteristics of AI adopters, the factors driving AI diffusion, and the extent to which AI use by firms has been so far related to their productivity.

This is however crucial to better understand how to fully leverage the potential of the digital transformation and what are its implications for the economy. In particular, at a moment in which the diffusion of innovation stalls and policy makers face the need to reignite growth, better understanding the role of different factors fostering AI adoption and the extent to which AI diffusion may relate to widening gaps between most productive firms and the rest is of clear policy relevance.

In this context, the analysis aims at drawing a portrait of AI adopters across countries, focusing on their characteristics, the role of complementary assets – such as intangibles[1] or digital infrastructure –, and the existing links between AI use and productivity.

It does so by pioneering a distributed microdata approach that uses a common statistical code developed by the OECD – in the context of the *AI diffuse* project – and executed in a decentralised manner on official firm-level surveys, which contain information on AI use by firms. This has been possible thanks to the cooperation of researchers and experts in several institutions across 11 countries, whose contribution has been essential (see Table A B.1).

The analysis highlights a series of stylised facts. First, AI is more widely used across large firms. Scale advantages may be related to several factors, such as fixed costs of adoption, larger amount of data to leverage AI applications, lower financing constraints, and – relevantly – more considerable endowments of (or capabilities to use) intangibles and other complementary assets, needed to fully leverage the potential of AI.

Second, shares of AI users also appear – at least to some extent – higher across younger firms. Start-ups indeed often bring to the market more radical innovations, especially when new technological paradigms, such as the one based on AI, emerge.

Third, shares of AI adoption are consistently higher in ICT and Professional Services, suggesting that AI use is not yet equally spread across all sectors. Considering that AI is at relatively early stages of diffusion, this suggests that its full potential as a general-purpose technology is yet to fully materialise. In particular, at the moment its applications appear yet more widespread across selected services sectors that generally represent a small portion of economic activities.

Fourth, several complementary assets are significantly linked to AI use. These notably include a series of intangibles, such as ICT skills and training, firm-level digital capabilities, proxied using several digital technologies, as well as digital infrastructure. More general skills and innovative activities, which may also increase firm absorptive capacity, appear also positively linked to AI use.

Fifth, AI users tend to be on average more productive than other firms, with shares of AI use generally higher among the most productive firms. These productivity premia tend to originate from large firms but do not seem to reflect the use of AI alone. Complementary assets appear to play a key role, with productivity advantages likely related, at least to a certain extent, to the selection of more digital and competitive firms into AI use. Indeed, productivity premia significantly reduce or disappear when accounting for the role of complementary assets, notably those related to the digital transformation.

This suggests that some firms – likely larger, with higher digital capabilities, and already more productive – may be those currently exploiting more intensively AI technologies. Initial evidence seems also to highlight that some more direct effects of AI on productivity may start emerging for firms that develop their own AI algorithms, likely endowed with higher digital capabilities and complementary assets.

A polarised adoption, mainly by leading firms, combined with a role of AI strengthening their advantages, may imply that in the future existing gaps between leaders and the rest of the firm population may widen, with relevant implications for social outcomes. This is particularly relevant also considering the current context, in which gaps between firms have been likely strengthening even further over the COVID-19 pandemic.

Policy makers can play a key role in this context, supporting an inclusive digital transformation. A broad policy mix affecting incentives and capabilities, capturing synergies across different policy areas, would be needed to boost technology diffusion in the age of AI. This would include both demand-side measures raising awareness about new technologies and developing absorptive capacity, and supply-side measures fostering competition, providing relevant credit tools, improving knowledge production and sharing, and strengthening the foundation of digital infrastructure and skills.

Such policies may allow AI use and its returns to be more widespread, not only across firms – fostering technology diffusion and its returns beyond leaders –, but also across sectors – strengthening the potential of the diffusion of AI applications beyond the ICT sector. These are likely to bring double dividends for several economic and social outcomes, ensuring an inclusive digital transformation in the age of AI.

This study is a first proof of concept highlighting the potential of the data collected in the context of the *AI diffuse* project. Future work may expand its scope, both in terms of country coverage and in terms of analysis, possibly focusing on broader sets of advanced digital technologies beyond AI. This is complementary to other OECD work that has studied the diffusion of AI across firms. This includes the analysis by Calvino et al. (2022[1]) , which focuses on similar questions combining different sources of big data matched with firm financials for the UK, and the ongoing OECD-BCG-Insead survey on AI in business.

The rest of the analysis is organised as follows. Section 2 discusses the related literature, summarising empirical evidence from different data sources. Section 3 discusses the underlying data and the methodology used to analyse those across different countries. Section 4 investigates the link between AI use, firm characteristics, and factors complementary to AI use, while Section 5 focuses on the AI-productivity link. Section 6 discusses the implications of the main findings, draws some final remarks, and points to possible next steps for future analysis.

2 Existing evidence on AI use by firms

Analysing the diffusion and role of AI in the economy is particularly relevant for several reasons. AI-driven products and services are already a crucial part of most people's routines, whether they realise it or not. AI is changing the demand for skills and may play an important role to tackle societal challenges, such as those related to health and climate change.

Relevantly, AI is often considered as a general-purpose technology (GPT), also considering its potential for applicability across several domains and its rapid advances over time. AI appears therefore different from other innovations, which may be instead directed at a more specific domain or feature, such as a product, process or organisational aspect. These characteristics, together with the extent to which AI may be interlinked with other technologies or complementary assets, may also make AI adopters different from innovators in other domains.

The literature analysing the use of AI by firms is however at its early stages, given that advances in AI technologies are relatively recent and that it is particularly challenging to comprehensively investigate the adoption and implications of AI for businesses, given the current data availability.

Existing studies on AI use by firms are mainly based on three data sources: i) firm-level surveys; ii) job posting data with information on AI skills demand; and iii) information contained in intellectual property (IP) records, in particular patents. Most of these studies are country-specific and largely rely on data for the United States.

This section discusses the existing literature on AI use by firms by summarising the empirical evidence emerging from firm-level surveys, job posting, and IP data, finally highlighting the main takeaways emerging from these three streams of research.

2.1. Evidence from firm-level surveys

Firm-level surveys, in particular ICT surveys carried out by National Statistical Offices, recently started to include information on the use of AI technologies by samples of firms in a specific country-year. The variables describing the use of AI technologies are generally binary: firms are indeed asked whether they use, or not, AI technologies, generally without relevant information about the timing of first adoption.

ICT surveys have been so far mainly used to investigate the link between AI use and firm characteristics, such as firm size, age, sector of activity and productivity, from a country-specific perspective.[2]

The most recent evidence about the diffusion of AI technologies and the characteristics of AI users from the United States is based on the technology module of the Annual Business Survey (ABS) survey. In 2018 the use of AI technologies was still relatively rare in the US (6.6%) and more likely in larger and more digitalised firms Zolas et al. (2020[2]). In the 2019 wave of the ABS survey, AI users are also asked the reasons why AI has been adopted, and Acemoglu et al. (2022[3]) show that the main purposes for AI adoption by firms are the improvement of processes quality and reliability, the update of obsolete ones and the automation of production. Furthermore, the relation between labour productivity and AI use is found to be not statistically significant, possibly pointing to the fact that AI effects may take longer time to materialise.

AI technologies in Germany are characterised by a similar state of diffusion, as it emerges from the findings of the German 2018 Community Innovation Survey (CIS). As in the US case, the use of AI technologies appears still limited (5.8%), more likely in larger firms and concentrated in few sectors of activity (ICT and consulting) (Rammer, Fernández and Czarnitzki, 2022[4]). AI use tends to be correlated with process innovation activities, especially when related to cost reduction, and sales from product innovations. Czarnitzki, Fernández and Rammer (2022[5]) employ the same data source to investigate the link between AI use and (multi factor) productivity and find a positive and significant effect.

Finally, Cho et al. (2022[6]) study AI users in 2018 using the Survey for Business Activities from Statistics Korea (KOSTAT) and find overall similar results vis-á-vis other contributions in terms of diffusion, with only 9% of Korean firms using AI technologies. Furthermore, the use of AI is significantly linked with the use of other digital technologies, suggesting the possible existence of complementarities between AI use and the digital infrastructure and capabilities of firms.

Notwithstanding the many advantages linked to being an official data source, ICT surveys often cannot be used to estimate the intensity of AI use and investments. Furthermore, in most cases it is challenging to build panels of data relying on such surveys. Other contributions to the literature that employ alternative more granular sources of data are further discussed below.

2.2. Evidence from online job posting data

One of the most used data sources to study AI is information on skills demand from online job vacancy data: In particular, many authors have used Burning Glass Technology (BGT) data (now Lightcast) as this source provides information on job postings and their requirements in terms of skills, including AI-related ones. Relevantly for the present analysis, these data have been employed to build firm-level indices of AI investment and demand, often focusing on the US. As discussed by Calvino et al. (2022[1]), although very rich in several respects, this data source only allows capturing the extent to which AI diffusion is related to the presence of AI-related skills in job postings.

Given the potential for substitutability vis-á-vis workers, the effects of AI on the labour market is one of the most explored topics in this research stream. In this respect, Acemoglu et al. (2022[7]) use BGT data to estimate the exposure of skills to AI at the establishment level, suggesting that AI exposure is associated with lower hirings. However, no link is found with the dynamics of employment and wages at the sector and occupation level, suggesting that the effects of AI technologies on labour markets may yet have to materialise.

Notwithstanding the absence of significant effects on labour markets, the demand of AI skills by firms has been rapidly growing over the past decade. Squicciarini and Nachtigall (2021[8]) rely on BGT data to track firms hiring AI workers in 5 countries (Canada, Singapore, the United Kingdom, and the United States) between 2012 and 2018. The authors show that AI labour demand, as well as the number of AI skills per posting, increased in all countries considered. ICTs, financial/insurance, and consulting services are the sectors in which AI demand is mostly concentrated.

Similarly, Alekseeva et al. (2021[9]) use AI online job vacancy data in 2010-2019 from BGT to build a proxy of AI demand by firms in the United States, which is found to steeply increase in the time span analysed, in line with the evidence of Squicciarini and Nachtigall (2021[8]). They also study the demand of AI skills by firms, focusing on its predictors: their analysis highlights that large firms, as well as those with high cash holdings and high R&D investments, demand more AI skills. Furthermore, AI skills are demanded by firms with higher wages and provide a positive wage premium, which is particularly high for IT professionals and managers.

BGT data have also been employed to study the effects of AI investments on firm size. In this context, Babina et al. (2020[10]) use US data on online job postings from BGT and from Cognism Inc., which provide information on individual job histories, to build firm-level measures of AI investments based on AI-related skills at the employee level. AI investments are more likely in ex-ante larger firms with higher cash holdings and R&D investments, in line with Alekseeva et al. (2021[9]). Furthermore, they have a positive effect on the size growth of US listed firms. This effect is stronger for larger firms and may be thus linked to increasing industry concentration. No effect on the growth of sales per worker and of total factor productivity (TFP) is however found.

BGT data are not the only source of job posting used in the literature. Bäck et al. (2022[11]) employ AI job posting data from Finland between 2013 and 2019 from Oikotie Oy, a Finnish company managing an online postings website. They show that AI adoption is positively correlated with (labour) productivity for large firms, notably when following a sufficiently long time lag, supporting the existence of J-curves in the relation between AI and the dynamics of productivity.

2.3. Evidence from Intellectual Property data

Another relevant data source to study AI diffusion are intellectual property records, and in particular patenting activity by firms. Indeed, in the US the two most important purposes for AI adoption by firms are the improvement of process quality and reliability and the update of obsolete ones (Acemoglu et al., 2022[3]), purposes that are closely connected to innovation (and thus patenting, see also Agrawal, McHale and Oettl (2018[12])). However, studies using patents as a proxy of innovation may tend to capture firms developing (rather than using) new AI technologies.

Patent data have been used to investigate the relation between AI adoption and firm productivity. By employing an event study design based on the year of AI patent applications, a positive effect of AI innovations is found for employment and sales per worker of US firm, but a negative one for value-added per worker (Alderucci et al., 2020[13]). In a related study that matches cross-country AI patents with firm-level balance sheet data from Orbis, a positive effect of AI innovations on labour productivity is found for SMEs and service firms, but no link is found for large firms (Damioli, Van Roy and Vertesy, 2021[14]). This finding may to some extent depend on the age of AI adopters. Webb et al. (2018[15]) show indeed that AI patents tend to be filed by firms started in the 2000-2015 period relative to the 1970–1989 one, suggesting that AI technologies may be related to the activity of new companies.

Patent data have also been employed to study the relation between AI innovations and technological knowledge. The trajectory of AI technologies is found to be relevantly based on previous ICT knowledge by Santarelli, Staccioli and Vivarelli (2022[16]) who also link AI patents to firm financials. Furthermore, AI patentees exhibit a high sectoral concentration in high-tech services, as opposed to robot-related innovations that tend to be patented by manufacturing firms. AI patents production appears also concentrated at the country level (see Baruffaldi et al. (2020[17]) or DiBiaggio et al. (2022[18])). Similarly, being an AI innovator is more likely if the firm developed past innovations in AI or a related technology fields (e.g., ICT) (Igna and Venturini, 2022[19]). Finally, Iori, Martinelli and Mina (2021[20]) suggest that government-funded AI patents had a significant impact in the early stages of AI development, with private actors taking over a more relevant role in later stages.

AI-related patents have also been employed to estimate the exposure of occupations and sectors to AI. Webb (2019[21]) maps the information from AI-, robot-, and software-related patents into the task and occupation classification from the O*NET database to estimate their AI exposure. Exposure to AI is larger for high-skilled occupations and tasks, whereas the one to robots and software is larger for low- and medium-skilled ones. AI exposure is also studied by Felten, Raj and Seamans (2021[22]), who link information on AI-related skills with O*NET occupations to build a measure of AI exposure. Most AI-exposed occupations are high skilled (also see Webb (2019[21])) and the most exposed sectors are the service ones.

AI patents have been further combined with trademarks data by Dernis et al. (2021[23]) to study the origin of AI technologies, goods, and services. These appear to be produced either by start-ups or large incumbents, mostly from the ICT sector and mainly located in the US, Japan, Korea, and the People's Republic of China. Trademarks are also employed by Nakazato and Squicciarini (2021[24]). They use data from the European Union Intellectual Property Office (EUIPO), the Japan Patent Office (JPO) and the USPTO over the period 2009-18 and show that AI-related goods are not limited to the business-to-business markets but are also diffused in consumer goods industries.

One of the few analyses that at our knowledge combines several data sources to study AI use by firms is the work by Calvino et al. (2022[1]), which is complementary to this paper and builds upon the two analyses mentioned above. The authors focus on the United Kingdom and combine data on intellectual property records, website information,[3] online job postings, and firm-level financials. They show that a significant share of AI adopters are active in ICT and professional services. Adopters tend to be highly productive and larger than other firms, while young adopters tend to hire AI workers more intensively. Human capital appears to play an important role, not only for AI adoption but also for its returns. Significant heterogeneity also emerges when distinguishing between different groups of AI adopters (firms carrying out AI innovation, those with an AI core business, and those demanding AI talent).

2.4. Wrapping up the existing evidence on AI use by firms

Overall, the literature studying AI use by firms highlights how rates of AI adoption are still limited in several advanced countries, suggesting that AI diffusion across firms is still at a relatively early phase, although demand for AI jobs appears consistently rising.

Furthermore, the literature has suggested the existence of an association between AI use and firm size, characterised by both selection of larger firms into AI and a positive effect of AI on firm size. The selection of larger firms into AI may be driven by the high fixed cost related to AI adoption (Brynjolfsson, Rock and Syverson, 2021[25]), related for example to the necessity of high computing power and large datasets for running AI algorithms. Accordingly, smaller firms may result more constrained in their possibilities to leverage AI technologies, as these tend to be more financially constrained (Hadlock and Pierce, 2010[26]) and less digitalised (Zolas et al., 2020[2]). In this respect, Bessen et al. (2022[27]) have shown that venture capital funding is more accessible when firms can rely on proprietary training data.

A positive effect of AI on firm size have been found in Babina et al. (2020[10]), focusing on the United States. This effect has been found to be larger in ex-ante larger firms. Accordingly, the diffusion of AI technologies may strengthen existing trends in industry concentration (Bajgar, Criscuolo and Timmis, 2021[28]) by reinforcing winner-take-most dynamics (Korinek and Stiglitz, 2017[29]; Tambe et al., 2020[30]) and increasing further barriers to entry for new firms, that are linked to digital-intensity and intangible investments (Calvino and Criscuolo, 2019[31]; Calvino, Criscuolo and Verlhac, 2020[32]).

Conversely, the findings of the literature investigating the relation between firm productivity and AI use are largely inconclusive. This evidence may seem at first sight to clash against studies finding a positive relation between ICT/digitalisation and firm productivity (see for example Gal et al. (2019[33]); Borowiecki et al., (2021[34]); Brynjolfsson, Jin and McElhera (2021[35])). Given the early phase of AI diffusion, the absence of a relation may be consistent with the existence of a J-curve in productivity following the adoption of AI technologies by firms (Brynjolfsson, Rock and Syverson, 2021[25]). According to this theory, it may be too early to witness an effect of AI on productivity given that the complementary investments in intangibles (see also Box 1 below) may take time to materialise (Brynjolfsson, Rock and Syverson, 2017[36]). Furthermore, AI is still developing and is not yet standardised, possibly requiring more and different intangibles for its returns to fully materialise.

AI technologies may indeed affect firm productivity through several channels. They can increase the quality of predictions and possibly automate workers' tasks, thus reducing operating costs and the uncertainty of decision-making (Agrawal, Gans and Goldfarb, 2018[37]). They have the potential to reshape R&D processes, increasing their speed and scope, and may be able to generate product and process innovations in unexplored ways (Cockburn, Henderson and Stern, 2018[38]), also by learning consumer preferences and recombining existing knowledge into new knowledge and breakthrough technologies (Agrawal, McHale and Oettl, 2018[12]).

Box 1. Zooming in on intangibles: what they are and why they matter

In recent decades, the relevance of intangibles for innovation and firm performance, and more broadly for economic growth, has soared (De Ridder (2019[39]); Corrado et al. (2022[40])). Investments in knowledge-based capital and the digital transformation have led to a significant rise of the so-called intangible economy (Haskel and Westlake, 2017[41]). But what are intangibles?

A key distinction among firms' assets is between those that have a tangible or intangible nature. Tangible capital (or investment) has physical substance and can therefore be touched and seen. Instances of tangible assets are machinery, buildings, or computers owned by a firm. Conversely, intangibles cannot be seen or touched as they do not have a physical nature, they tend instead to be knowledge based. Examples of intangible assets are patents, trademarks, software, databases, branding, employer-provided training or firm-specific human capital (see Corrado et al. (2009[42]; 2021[43])).

The distinction between tangible and intangible capital is key to understand whether and how technologies spread across firms, as these are characterised by tangible and intangibles components that have different degrees of complementarity. Relevantly, the characteristics of the capital stock are likely to drive technology diffusion – by affecting firms' absorptive capacity and willingness to invest in a new technology – and determine the ability of firms to successfully capture returns after adoption.

In fact, digital technologies need relevant complementary intangible investments to be effectively implemented by firms in their activity. ICT or other specialised skills and capabilities, changes in business processes, development or implementation of new software, collection of large and meaningful databases are examples of complementary investments. These may take time but appear key to successfully capture the gains of digital technologies, especially when they have a general-purpose potential such as AI (Brynjolfsson, Rock and Syverson, 2017[36]).

From a micro-economic perspective, the effect of AI on productivity potentially depends on whether additional sales are generated, on the AI-employment nexus, and on the reduction of costs. Evidence of a positive effect of AI on firm size has been recorded (Babina et al., 2020[10]). Concerning employment, it is not easy to disentangle the potential effects of AI on labour markets, as new skills will be required and others will become obsolete (Acemoglu and Restrepo, 2019[44]). So far, the net effect is unclear (Acemoglu et al., 2022[7]). Finally, theoretical studies support the cost-reduction channel as a potential effect of AI (Acemoglu and Restrepo, 2019[44]; Hsieh and Rossi-Hansberg, 2019[45]; De Ridder, 2019[39]), but to our knowledge there are no empirical contributions directly exploring this hypothesis.

Most of the existing literature has studied the diffusion of AI technologies and the characteristics of AI adopters in a single country. The generalisation of existing findings is therefore limited by the fact that most of extant contributions are country-specific and focus on the US mainly.

In this context, this work studies the diffusion of AI among firms by taking a cross-country perspective. It aims indeed at providing an international overview of the most relevant stylised facts on the characteristics of AI users and the link between AI use and productivity.

Furthermore, the relation between AI use and complementary assets (e.g., digital skills, capabilities, and infrastructure) has not yet been explored in depth by the extant literature. However, this association is key, because the link between firm characteristics, such as size and productivity, and AI may stem from the availability of complementary assets. In this respect, the ex-ante diffusion of complementary assets to firms could be relevant for the adoption of AI, possibly informing about which policies can be better suited to foster the diffusion of advanced digital technologies. This is an important feature of the present study.

Analysing the use of AI by firms across countries is very challenging, given the limited amount of existing information and the accessibility requirements of several data sources. The next section focuses on the methodology that was developed to overcome the existing challenges and presents information about the data used in this study.

3 Data and methodology

This section discusses the data and methodology employed to investigate the use of AI technologies by firms across countries.

Section 3.1 starts by discussing the underlying data employed in this work. These data are sourced from confidential official firm-level surveys including information on the use of ICTs, notably AI, from 11 countries (Belgium, Denmark, France, Germany, Ireland, Israel, Italy, Japan, Korea, Portugal, and Switzerland).

The data are separately analysed by means of a common statistical procedure (*AI diffuse*) based on a distributed micro-data approach, that is discussed in Section 3.2.[4] Such an approach is for the first time applied to analyse the role of advanced digital technologies. It builds upon the OECD experience in distributed microdata analysis to study the micro-drivers of economic performance (*DynEmp, MultiProd, MicroBeRD*) and on earlier work by Bartelsman, Hagsten and Polder (2018[46]) analysing previous waves of ICTs and focusing for instance on the role of e-commerce.

3.1. Firm-level surveys across countries

This section discusses the different sources of data used in this study. The cross-country perspective adopted in this work is indeed based on the analysis of highly representative firm-level surveys from 11 countries: Belgium, Denmark, France, Germany, Ireland, Israel, Italy, Japan, Korea, Portugal, and Switzerland.

The common features of these sources are their representativeness, as they are based on official data generally collected by National Statistical Offices,[5] the presence of information about the use by businesses of digital technologies – notably including AI – together with firm characteristics and outcomes – notably including employment and turnover.[6] Information on technology use is generally binary (i.e., firms are asked whether they use a technology or not).[7]

Although the statistical treatments have been harmonised as much as possible (see the next subsection for additional details) differences across countries still exist in terms of time, sectoral, and size coverage, the presence of sampling weights, and the availability and definition of the relevant variables, as well as on the exact survey questions. Key features of the different sources are briefly summarised below, with additional comprehensive information on metadata reported in the Appendix.[8]

Concerning European countries, which are widely covered in this study, most data sources consist in national ICT surveys, which follow the guidelines provided by Eurostat (Community Survey on ICT usage and e-commerce in enterprises) and are gathered by National Statistical Offices. These are the sources for Belgium, Denmark, France, Ireland, Italy, and Portugal. Data for these countries are thus generally based on common variables' definitions and overlap in terms of sectoral and size coverage. Sectors covered include manufacturing, utilities, construction, wholesale and retail trade, transportation and storage, accommodation and food service activities, ICT (including repair of computers and communication equipment), real estate activities, and professional and scientific services. The data comprehensively cover firms with 10 or more persons employed.[9] However, the availability of relevant variables related to technologies and skills may vary substantially across countries and years. Furthermore, at the time of writing, information on AI use is available for different time periods: 2018 in France, 2020 in Belgium, Italy, Portugal, and Ireland, and 2016, 2017, 2018 and 2020 in Denmark.[10]

The firm-level data source for Germany is instead the Mannheim Innovation Panel (MIP), gathered by the Centre for European Economic Research (ZEW) as part of the Community Innovation Survey. Information on AI is available for 2018. The survey also covers firms with less than 10 persons engaged. Weights are not available in the version used for the current analysis, which covers 21 groups of sectors.[11]

Data for Japan are collected by the 2020 Japanese National Innovation Survey and concern information on innovation activities of Japanese firms, which are asked in 2020 about technology use between 2017 and 2019. This survey covers firms with more than 10 persons employed and includes weights. The sectoral coverage is slightly broader than the ones provided by the Eurostat surveys.[12] While the Japanese survey does not include specific questions on AI use, the cross-country analysis takes advantage of questions related to the use of Machine Learning, which is one of the most important fields of application of AI algorithms and will be thus employed as the proxy of AI in the analysis.

Data for Korea are part of the Survey for Business Activities from Statistics Korea (KOSTAT), wherein establishments are asked about the use of several digital technologies, notably including AI, in 2019. All Korean firms with more than 50 persons engaged and KRW 300 million of capital stock are part of this survey, independently from their sector of activity. Among firms with less than 50 persons engaged, the sample covers firms in wholesale and retail trade and other service industries with turnover above a given threshold, which amounts to one billion KRW. Given the comprehensive nature of the data, weights are not present in this survey.

Data for Israel are based on the Survey on ICT Uses and Cyber Defence in Businesses, which asks firms about their use of AI over 2020-2021. The data cover firms with at least 10 persons employed, and the sectoral coverage is comparable to those of European countries mentioned above.[13] The survey also includes probability weights.

Data for Switzerland are sourced from the KOF Enterprise Panel.[14] Information on the use of AI is available in three waves of the firm-level surveys, which include questions related to innovation activities and digitalisation of Swiss firms between 2018 and 2020. The surveys cover firms with at least 5 persons employed. The sectoral coverage overlaps with the one of other European countries and weights are also available.

3.2. *AI diffuse*: a distributed microdata project

This report presents a series of stylised facts on the diffusion of AI across firms. The evidence is based on confidential and highly representative firm-level data, that are sourced from official firm-level surveys containing information on the use of ICTs from across 11 countries (see Section 3.1 above).

These data are collected and analysed in the context of the OECD *AI diffuse* distributed micro-data project, that is led by the OECD Directorate for Science, Technology and Innovation with the pivotal contribution of researchers and experts from a large set of OECD countries. Their contribution has been extremely valuable for the current analysis. The full list of participants is reported in Table A B.1 in the Appendix.

This project pioneers the use of a common statistical code developed by the OECD *AI diffuse* team (see Box 2 “The *AI diffuse* program” for additional details). First, the code is run in a decentralised manner on the country-specific surveys by national experts from statistical offices, academia, or other institutions. Then, the country-specific output of the *AI diffuse* program is 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.[15]

The *AI diffuse* project aims at providing an international and comprehensive outlook about the diffusion of digital technologies, notably including AI, and its implications based on country-specific highly representative firm-level data. It does so by relying on statistical outputs which, despite coming from different sources, are as much as possible harmonised and at the same time jointly representative of a large group of developed economies.

The output of the *AI diffuse* program can be used to focus on a number of policy-relevant issues on firm technological adoption. It allows to analyse the determinants of firm-level use of digital technologies by identifying possible complementarities between digital technologies, skills, and digital infrastructure at the firm level, to study the relation between the use of digital technologies and firm characteristics, and the firm-level link between technology use and relevant economic outcomes, notably productivity. This paper exploits part of the *AI diffuse* output, focusing mainly on the use of AI, which is the main technology use variable of interest.

The program generates counts and shares of technology users and a wide set of summary statistics computed at different levels of aggregation (size class, age class, industry, number of other digital technologies, quantiles of the productivity distribution), relevantly distinguishing technology users from other firms.

The program also performs a series of distributed firm-level regressions, estimating two main sets of models. First, it focuses on factors associated with technology use by firms, including their characteristics in terms of size and age classes and, when available, other complementary factors such as several proxies related to firm digitalisation, digital infrastructure, and ICT skills. Second, it focuses on the relation between firm labour productivity and technology use, sequentially including relevant interactions and firm-level confounding factors, such as complementary assets, industry, size, and age classes.[16] Additional information on the output computed by the program is available in Box 2 below.

Box 2. The AI diffuse program

The AI 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 probability weights, or of a business register upon which these can be calculated.

The AI 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 year of observation.

The code has been designed to analyse the use by firms of advanced digital technologies (i.e., artificial intelligence, big data analysis, internet of things, machine learning, and 3-D printing) and of other digital tools or technologies (i.e., cloud computing services, customer relationship management software, e-commerce, enterprise resource planning software, robots). Conditional on data availability, the code also allows to distinguish AI users in firms sourcing AI externally (AI buyers) from firms developing their own AI (AI developers) and investigates the role of ICT skills (ICT specialists and training for non-ICT specialists), and digital infrastructure (ultra-fast broadband connection).

Before running the statistical and regression analyses, the program performs a series of basic data cleaning steps, including deflation and PPP 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.

The main set of summary statistics includes the shares of users of AI (and of other technologies, when available) 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, at 2-digit, SNA A7, SNA A38 levels, and using the classification proposed by Table A B.5 in the Appendix.

Size and age are reported in terms of classes. The size class variable encompasses 5 categories (less 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 4 classes are reported for firm age (less than 6 years old, between 6 and 10 years old, 11 or more years old, and a category for firms with missing age). Information on firms with less than 10 persons engaged is generally excluded from the analyses, although used for robustness checks when available (see below).

As a proxy of firm digitalisation, 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 such number is normalised when the number of technologies is used as an explanatory variable in regression analysis.

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

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

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

Adoption regressions employ the use of AI or of other digital technologies (upon availability) as dependent variables in regression models including as explanatory variables size and age classes and, when available, other complementary factors (firm digitalisation, digital infrastructure, and ICT skills), as well as industry or geographic fixed effects. Separate regressions are estimated, including different sets of industry fixed effects at all available levels of sectoral aggregation (see above). Geographical fixed effects are also included as robustness (upon availability). Regressions are mainly linear probability models. However, the program also computes logit regressions for robustness purposes.

Productivity regressions include labour productivity as dependent variable and the use of AI or of other digital technologies (upon availability) as 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 digitalisation, digital infrastructure, and ICT skills) and fixed effects (sectoral and geographic). Robustness checks are also estimated excluding firms at the top 5% of the productivity distribution.

Furthermore, additional exploratory sets of productivity regressions are estimated by the program at the sectoral level, and by employing quantile regression designs. Exploratory IV productivity regressions are also estimated using Leave-One-Out shares and market shares of technology-specific users as instrumental variables.

Finally, the program estimates a series of basic adoption and productivity regressions including firms with less than 10 persons employed, when the data include those firms.

4 AI use across countries: firm characteristics and assets' complementarity

This section investigates the link between AI use, firm characteristics, and factors complementary to AI use. It provides for the first time an international outlook on AI adoption based on firm-level data analysed in a harmonised way. The analysis reports figures for each country separately, noting differences in weighting and period of analysis due to data availability, and emphasises the main stylised facts that emerge.

The discussion is organised in three subsections. First, the analysis presents descriptively the shares of AI users focusing separately on different groups of firms, based on their size, age, sector of activity, and number of technologies used. Second, the descriptive analysis is extended by further taking into account the role of unobserved factors – such as sectoral characteristics – via regressions that estimate the firm-level determinants of using AI. Finally, the regression analysis explores the role of firm-level factors complementary to AI use, such as ICT skills, digitalisation, innovation activity, and export.

4.1. Descriptive evidence about AI use

This section focuses on the main characteristics of firms using artificial intelligence. It does so by reporting and discussing the shares of AI users across countries; distinguishing firms in different size and age classes, by industries, and number of other digital technologies used.

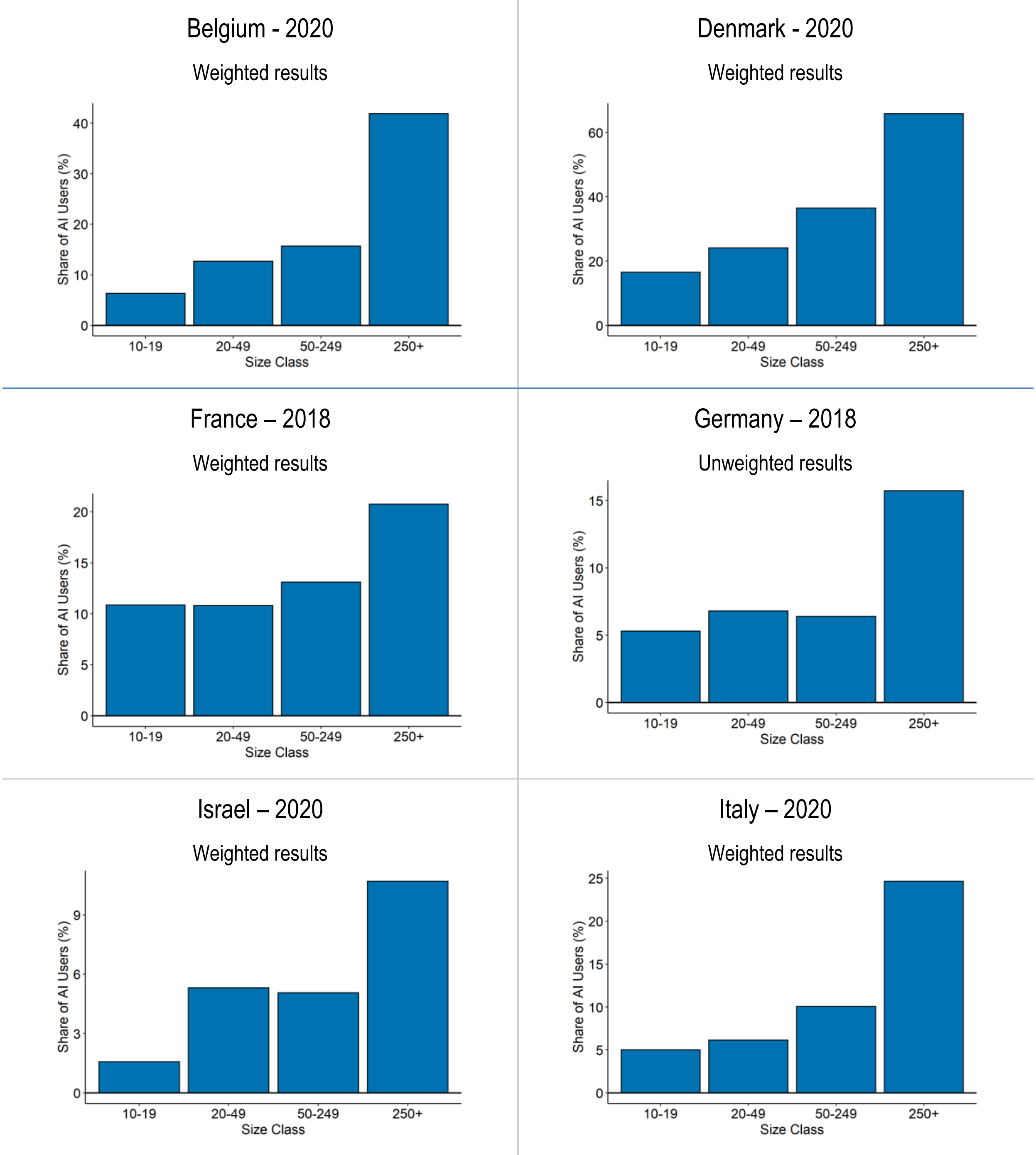
The shares of AI users by size class are reported in Figure 1. In all countries considered, the share of AI users is highest in the largest size class, i.e., for firms with more than 250 persons engaged. The share of AI users in the largest size class is generally twice as large as the share of AI users for the second-ranked one. This suggests the existence of scale advantages possibly due to high fixed costs in AI adoption, and is in line with the existing country-specific literature (see Alekseeva et al. (2021[9]); Babina et al. (2020[10])).

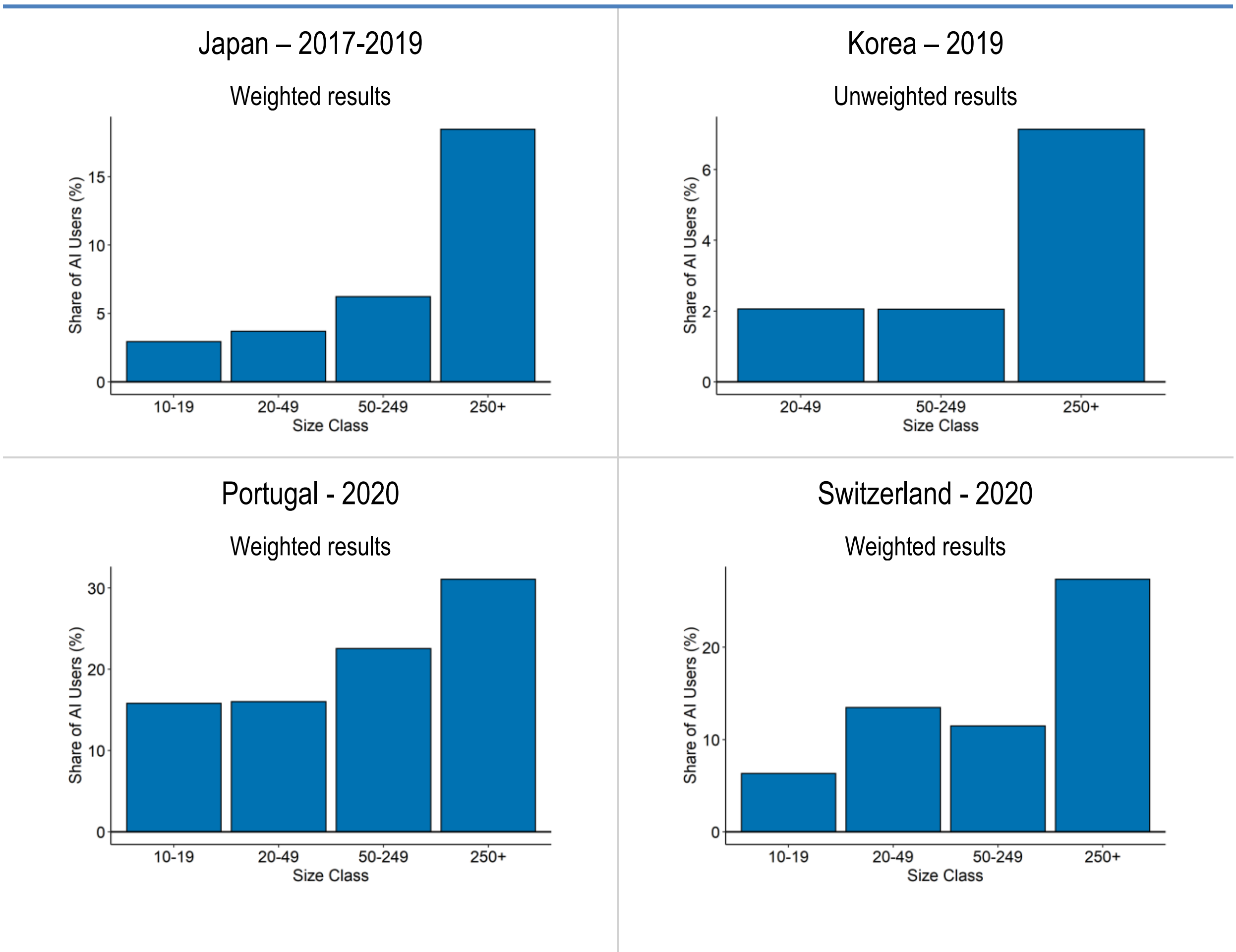
Their existence is likely related to complementary factors (see also Brynjolfsson et al. (2021[25]), Brynjolfsson et al. (2017[36])), whose relevance will be further discussed in the following subsections. These are indeed to a great extent intangibles and relate to both human capital (e.g., specialised ICT skills) and firm digitalisation (e.g., the availability of large datasets and software), which may be characterised by high fixed costs of acquisition.

The relations between AI use and size in Belgium, Switzerland, Denmark, France, Italy, Japan, Israel, and Portugal are all computed via a weighting procedure, although referring to different time periods, between 2018 and 2020. Shares of AI use tend to be highest in Denmark across all size classes considered. Focusing on the largest size class, adoption rates tend to be above 20% for Belgium, France, Italy, Portugal, and Switzerland, even though consistently lower than the shares of Denmark. Adoption rates tend instead to be lower in Japan, Korea, and Israel.[17] This evidence suggests the existence of relevant cross-country differences in terms of digitalisation, although cross-country comparisons should be taken with caution due to existing differences in time periods and definitions, as well as differences in sectoral compositions, which will be examined further in the following.[18]

Generally, the shares of AI users increase with firm size.[19] This is particularly the case for Belgium, Denmark, Italy, and Japan, in which larger size classes exhibit always higher shares of AI use than smaller ones. This highlights again the relevance of scale advantages.

Figure 1. Share of AI users by size class





Notes: This figure reports the share of AI user by size class for Belgium, Denmark, France, Germany, Israel, Italy, Japan, Korea, Portugal, and Switzerland. Size classes encompass 4 categories: between 10 and 19 persons employed, between 20 and 49 persons employed, between 50 and 249 persons employed, and 250 or more persons employed. Figures for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland are weighted. Figures for Germany and Korea are unweighted. In Korea the data for the smallest size class are unavailable due to confidentiality restrictions. Owing to methodological differences, figures may deviate from officially published national statistics.
Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France – Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea – Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

However, although overall increasing, this relation is heterogeneous across countries, possibly hinting at country specificities in the dynamics of AI diffusion.[20] In particular, in Switzerland, Israel, France, and Germany the relation between AI use and size class appears less monotonic. This may be due to the presence of waves of high-tech AI start-ups, whose employment may be lower than other firms. In this respect, the shares of AI users in lower size classes may be sometimes higher than the ones of larger size classes, because younger firms are on average smaller.

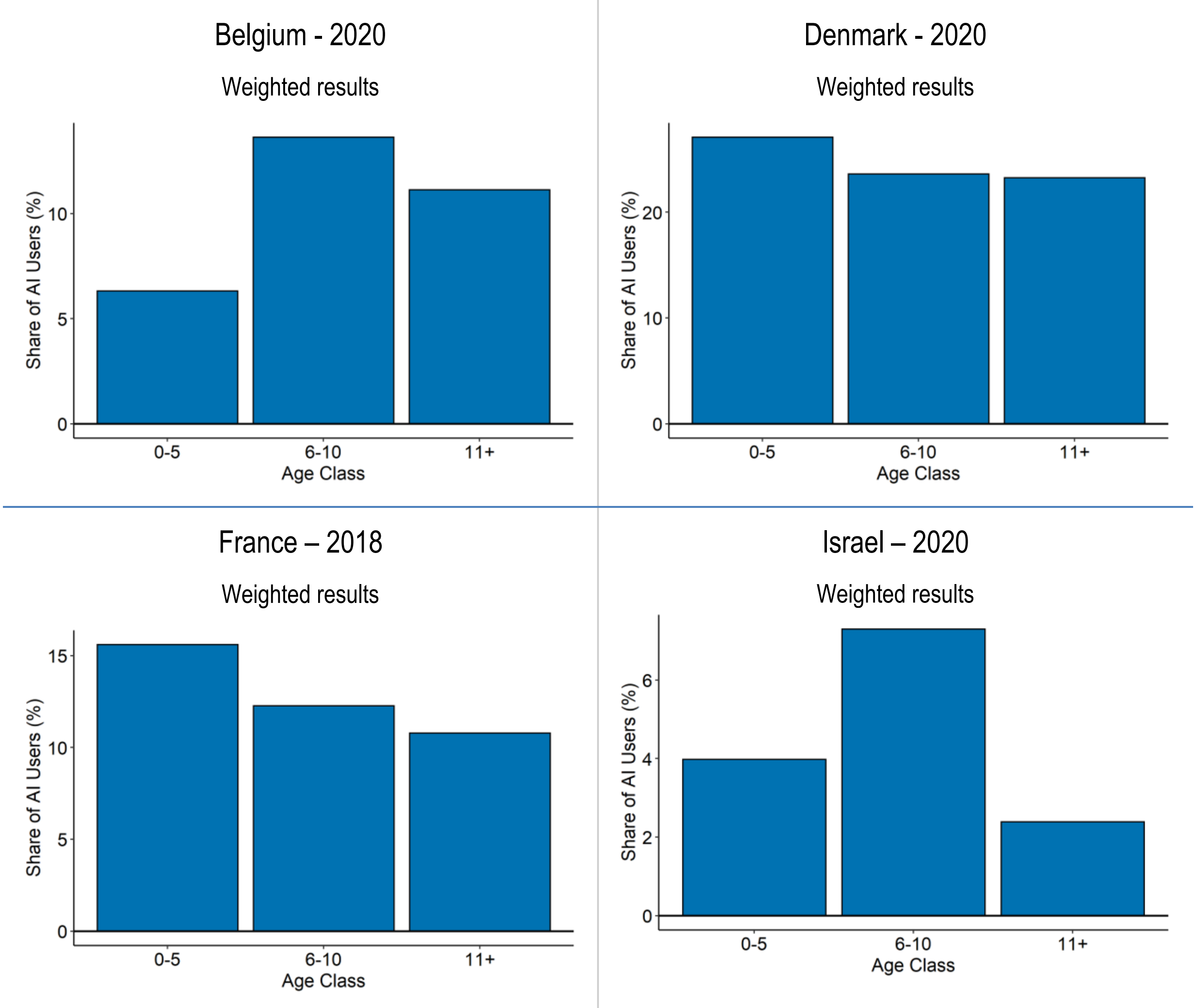
Figure 2 therefore focuses on the shares of AI users by age class, conditional on the availability of data. Comparing the youngest and oldest age class, the shares of AI use decrease with age in the case of Denmark, France, Korea, and Portugal. They are highest for the 6-10 years old age class in other cases.[21] However, French data refer to the year 2018 and Korean ones to 2019, differently from the other countries for which firms' age data are available and refer to more recent years (in particular, 2020 for Belgium, Israel and Japan).

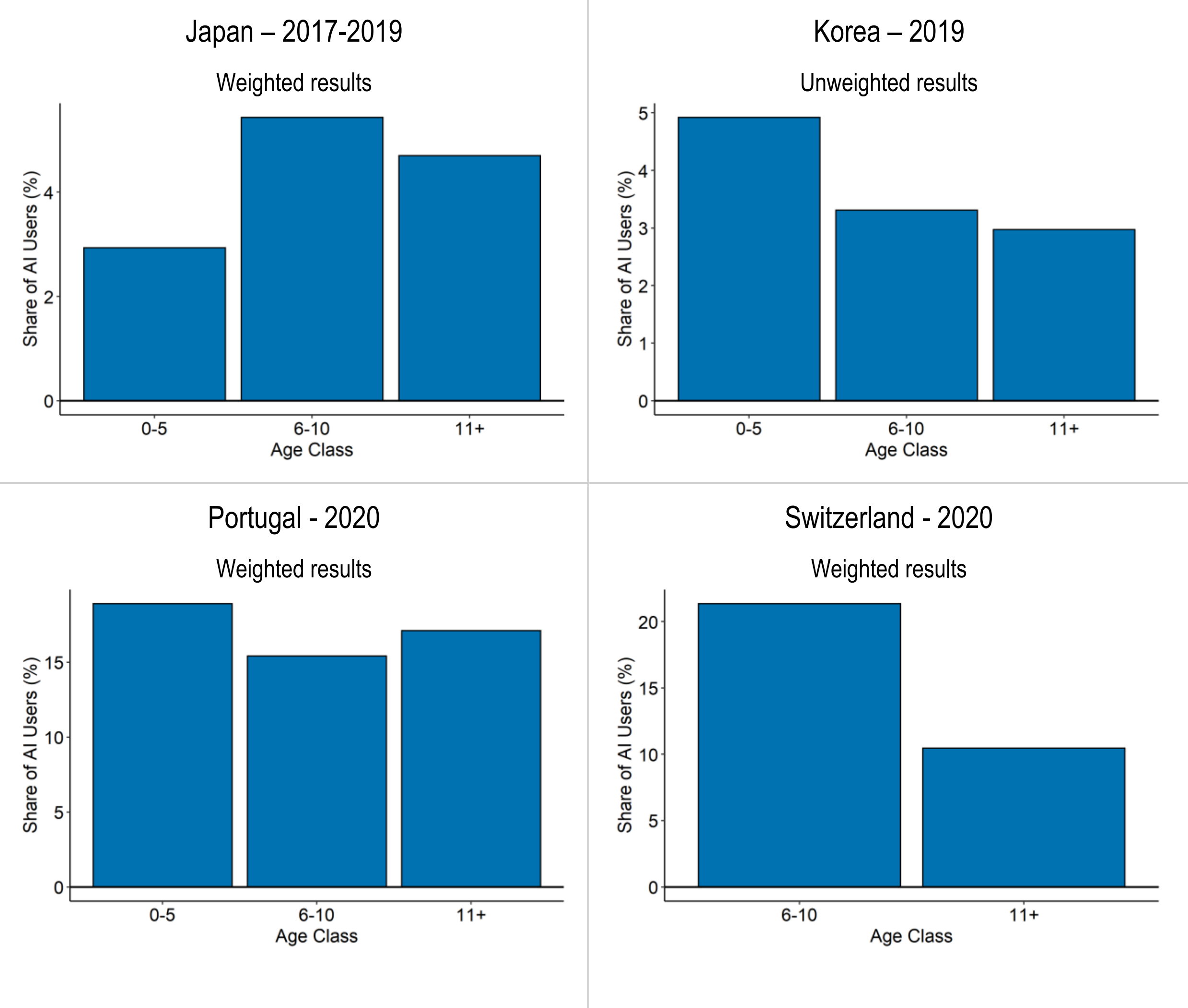
These findings may hint at the existence of waves of high-tech AI start-ups, especially in the earliest years of the past decade: such an interpretation would be indeed consistent with higher shares of young AI users in France in 2018 and Korea in 2019, which became older and switched to a higher age class later, as observed in Belgium, Israel and Japan, in more recent years. Evidence from Denmark may instead suggest the presence of more than one wave of AI start-ups,[22] while evidence from Portugal may possibly hint at a more recent wave.

Overall, this appears broadly in line with the timing of major improvements in AI technologies (see also Babina et al., 2020[4]). Indeed, since the early 2010s, breakthroughs in "machine learning" (ML), an AI subset that uses a statistical approach, have been significantly improving machines' ability to make predictions from historical data. In fact, the maturity of a ML modelling technique called "neural networks", along with large datasets and computing power, have been behind the expansion in AI development and its adoption (OECD, 2019[47]).[23] Accordingly, the adoption of AI technologies by firms for commercial purposes very likely surged after 2011, especially outside the US.

Beyond age and size, significant heterogeneity exists in the extent to which AI users are present in different sectors of the economy. This is shown in Figure 3, which reports the share of AI users by sector.[24]

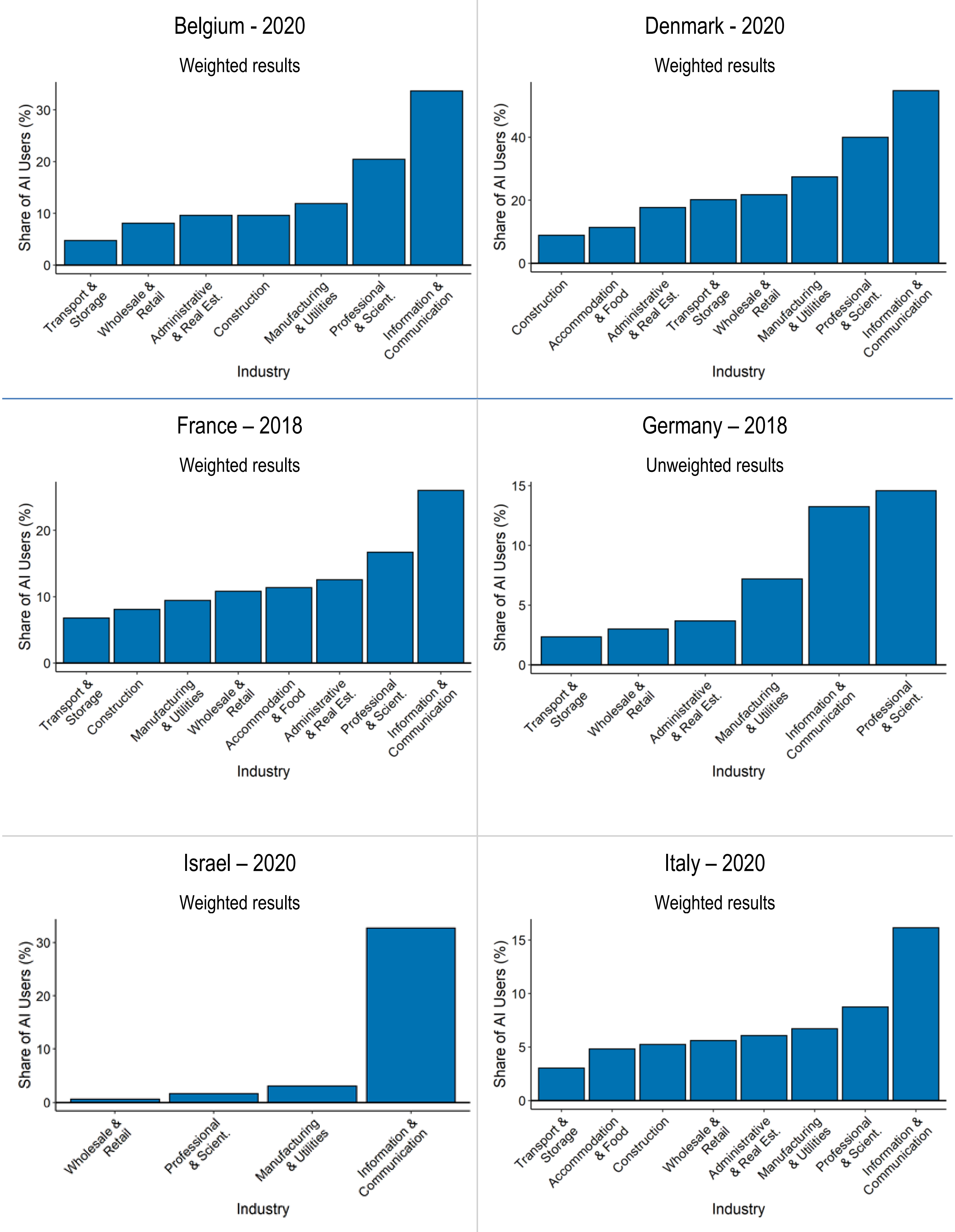
Figure 2. Share of AI users by age classes

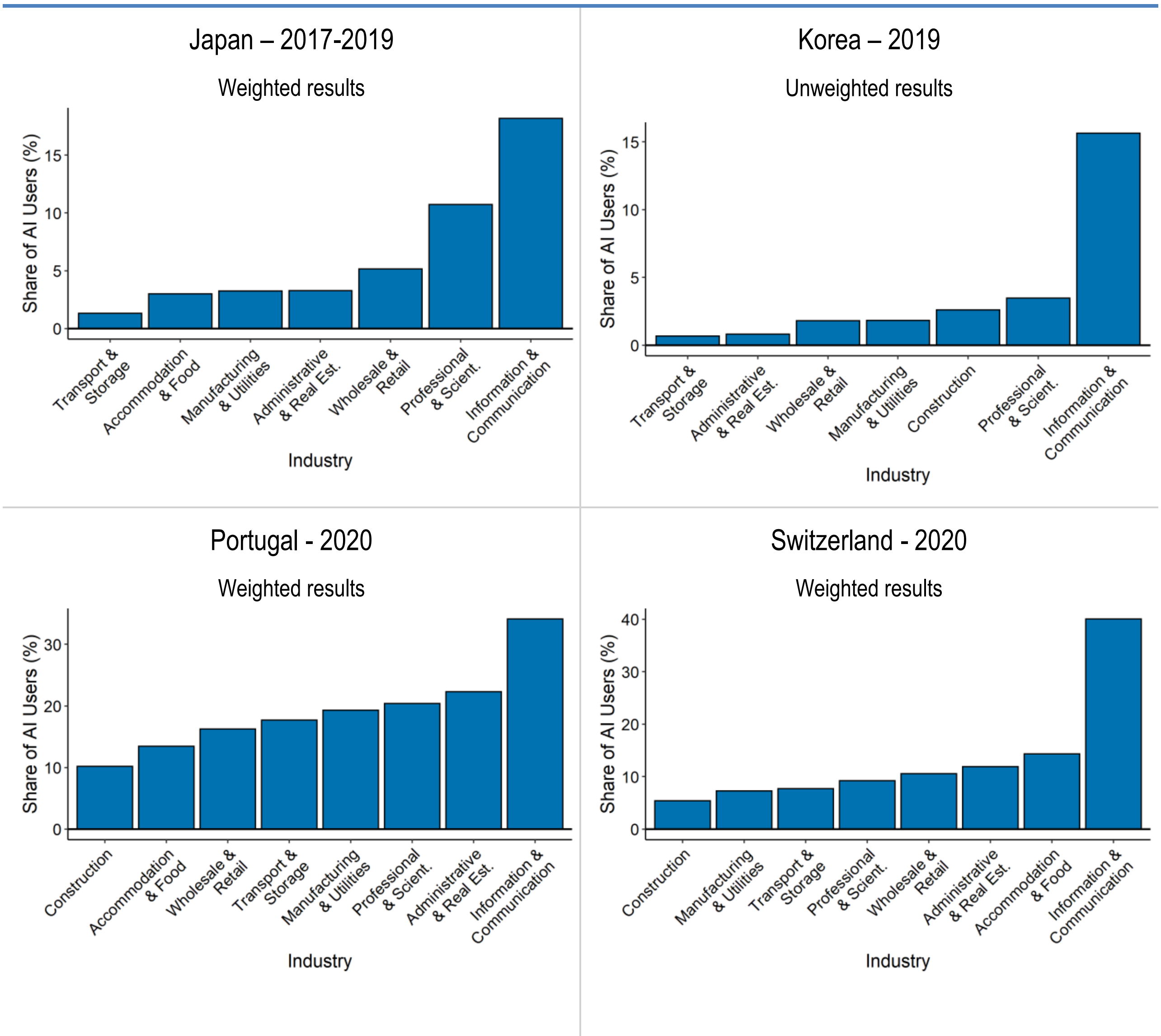




Notes: This figure reports the share of AI user by age class for Belgium, Denmark, France, Israel, Japan, Korea, Portugal, and Switzerland. Age classes encompass 3 categories: less than 6 years old, between 6 and 10 years old, and 11 or more years old. Figures for Belgium, Denmark, France, Israel, Japan, Portugal, and Switzerland are weighted. Figures for Korea are unweighted. In Switzerland the data for the youngest age class are unavailable due to confidentiality restrictions.
Sources: Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Israel - Survey on ICT uses and Cyber Defence in Businesses; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

Figure 3. Share of AI users by sector





Notes: This figure reports the share of AI user by broad sector for Belgium, Denmark, France, Germany, Israel, Italy, Japan, Korea, Portugal, and Switzerland (see Table A B.3 and Table A B.5. in the Appendix for further information on the sectoral classification). Shares have been sorted from the highest (right) to the lowest (left). Figures for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland are weighted. Figures for Germany and Korea are unweighted. In Germany the data for some industries are unavailable because not covered by the respective survey. In Belgium and Korea the share for the Accommodation & Food sector is unavailable due to confidentiality restrictions. In Israel, the shares for the Accommodation & Food, Administrative & Real Estate, Construction, and Transportation & Storage sectors have not been reported due to the small size of the cells. In Japan and Korea, sectors are based on conversions from national classifications. Owing to methodological differences, figures may deviate from officially published national statistics.
Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

The sectoral shares of AI users tend to be heterogeneous within and across countries. Across most countries, the ICT sector exhibits the highest shares of AI users.[25] This is probably not surprising considering the relatively early phase of AI diffusion – in this sense, AI does not appear to be a commodity yet – and the fact that the ICT sector is the one in which AI applications tend to originate.[26] This however also suggests that intangible assets play a central role for the use of AI, in particular the ones related to digitalisation.

The shares of AI users in non-ICT sectors tend to be lower and the gap between the ICT sectors and other sectors varies substantially across countries. Professional and Scientific services generally account for the second highest share of AI users across countries. The manufacturing sector tends instead to exhibit higher shares of AI users relatively to other sectors in countries for which more recent years are available (see e.g., Belgium, Denmark, Israel, Italy and Portugal vis-à-vis France, Japan, and Korea).[27]

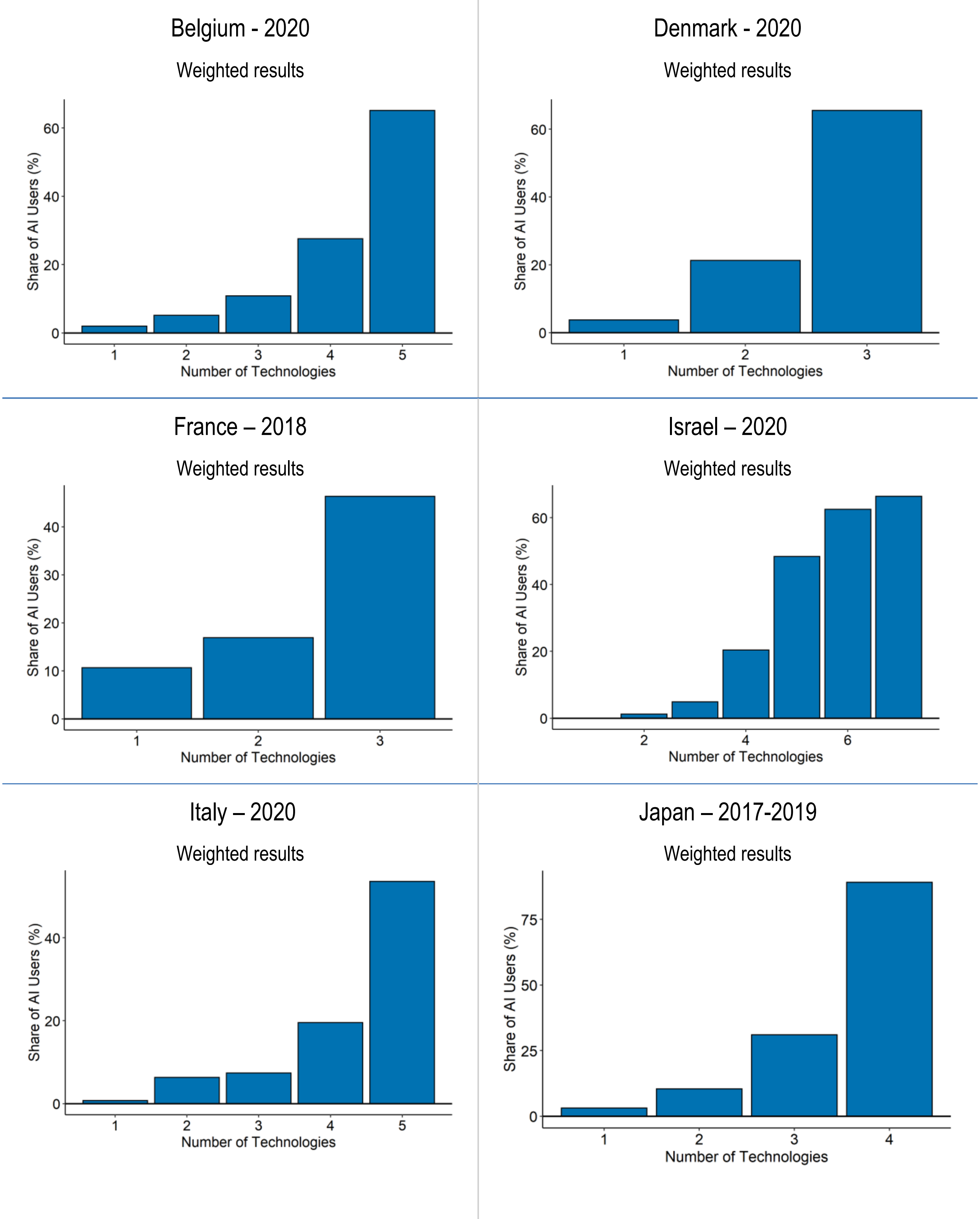
The shares of AI adoption of Israel and Switzerland are the most skewed towards the ICT sectors, whereas shares in Belgium, Denmark, France, Italy, and Portugal seem more homogeneous.[28] This may likely depend on pre-existing digitalisation gaps among sectors within countries. Furthermore, this may also reflect the GPT potential of AI, which may have already more evidently materialised in countries for which cross-sectoral diffusion is more homogeneous.

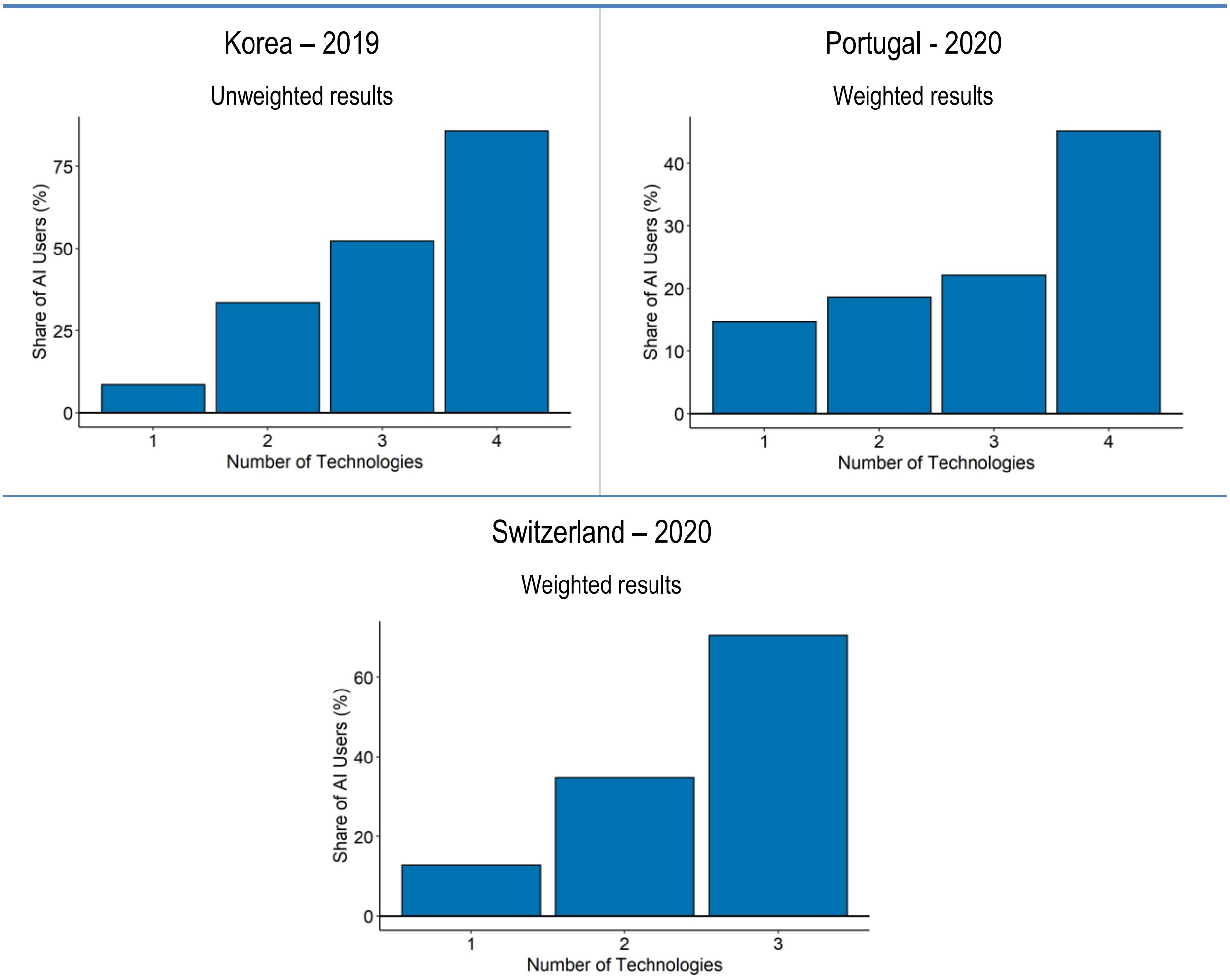
Observed differences among countries, which tend to be relevant in some cases, may also reflect pre-existing disparities in the overall state of digitalisation. For instance, comparing Italy and France, the shares of AI use in the former are lower across all sectors, notwithstanding the data are from one of the most recent years in the sample considered, in line with evidence on the Italian state of digitalisation (also see Calvino et al. (2022[48])). Conversely, the French sectoral shares are substantially higher, notwithstanding the fact that data refer to 2018.[29]

After considering differences across size, age, and sectors, the analysis provides a first outlook into the role of digitalisation for AI use. Indeed, higher shares of adoption among large firms, to some extent younger ones, and in the ICT sector, may likely reflect, at least to some extent, the role of other digital technologies or capabilities that may be required before getting to AI.

In this context, the shares of AI adoption by number of digital technologies used by firms (a proxy of digitalisation) are reported in Figure 4.[30] The number and nature of technologies vary consistently among countries depending on data availability. Accordingly, it would be misleading to make cross-country comparisons based on the exact number of technologies adopted. Notwithstanding, it is still interesting to focus on the relationship between adoption shares and the number of technologies used (a proxy of digitalisation).

Figure 4. Share of AI users by number of technologies





Notes: This figure reports the share of AI user by number of technologies employed by firms for Belgium, Denmark, France, Israel, Italy, Japan, Korea, Portugal, and Switzerland. The number and nature of digital technologies employed by firms may change across country (see Table A B.2. in the Appendix for further information on the number and type of technologies available for each country). Figures for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland are weighted. Figures for Korea are unweighted.
Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

Figure 4 shows that more digitalised firms are more likely to be AI users. Indeed, in each country considered, a higher number of technologies is associated with a higher share of AI users. This suggests the existence of complementarities between the overall digitalisation of firms and the adoption of AI, as also suggested in Brynjolfsson et al. (2021[35]). Indeed, before using AI, firms may indeed need to develop a series of complementary assets, for instance related to their internal business digital capabilities and to the acquisition of large datasets, to exploit AI-related applications. In this respect, the use of digital technologies by firms may help them cumulate the intangible complementary capital that eases adoption of more sophisticated digital technologies, such as AI.

4.2. Adoption regressions and firm characteristics

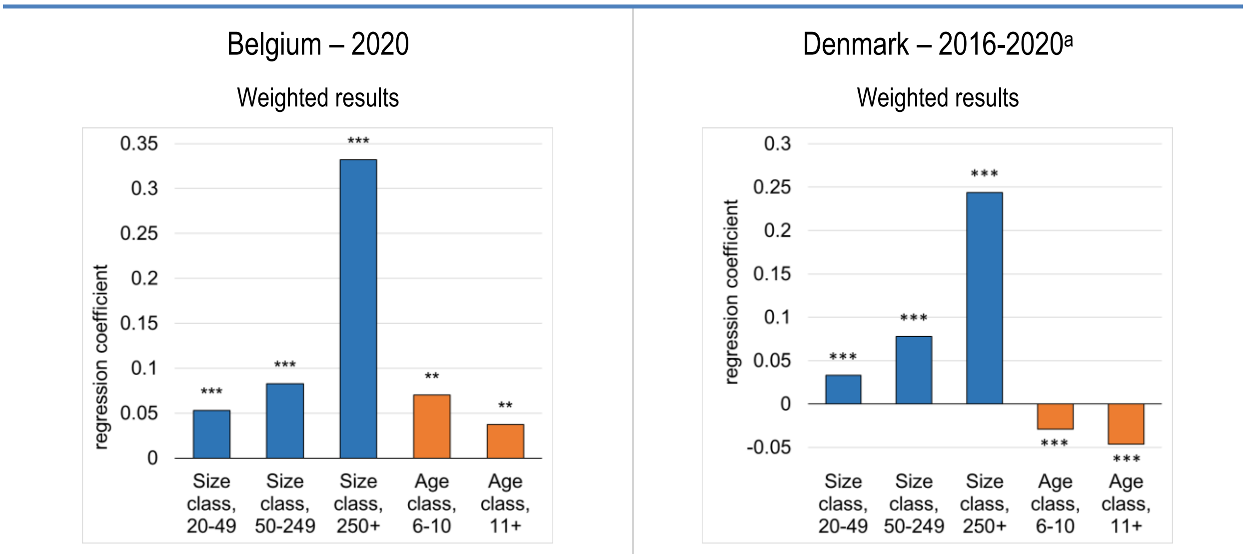
The previous subsection discussed a series of results based on the shares of AI users. In particular, it showed that AI users tend to be larger and, to some extent, younger than other firms. However, these descriptive findings may depend on the sectoral composition of countries. Indeed, the shares of AI users are not evenly distributed across sectors, with shares in the ICT sector being particularly high in most countries (see Figure 3). As the size and age of firms may be closely related to sectoral characteristics, the unconditional results reported in the previous subsection may be to some extent driven by these compositional effects. It is therefore useful to perform a regression analysis on the AI-size and age relation that can also control for sectoral heterogeneity.[31]

This subsection therefore reports the results of the estimation of a series of linear probability models (see Figure 5) that include AI use as dependent variable and size and age classes (upon availability) as the main explanatory variables. Relevantly, the regressions also control for 2-digit sector and year fixed effects (conditional on data availability).[32]

The estimation results relative to the size classes' coefficients confirm the evidence discussed in the previous section: larger firms are more likely to use AI.[33] Notwithstanding the additional controls, the coefficients associated to the largest size class are always positive and statistically significant, meaning that largest firms are significantly more likely to adopt AI with respect to the reference size class (10-19 persons engaged) and after taking into account the role of their age and sector of activity.

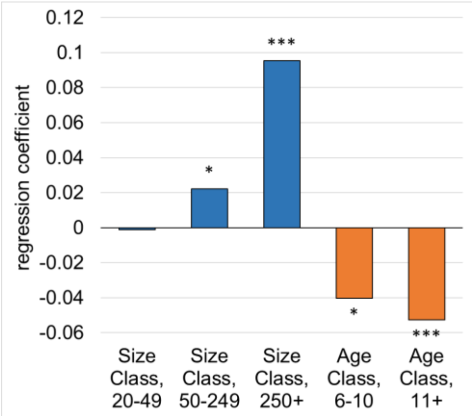
Furthermore, somewhat differently from descriptive results, regression analysis shows that the likelihood to use AI generally increases with size class. The non-monotonicity of the AI size relation highlighted in some cases in the previous subsection was therefore likely related to either sector-specific factors or to the age of firms.[34]

Figure 5. Estimation results for the baseline adoption regressions



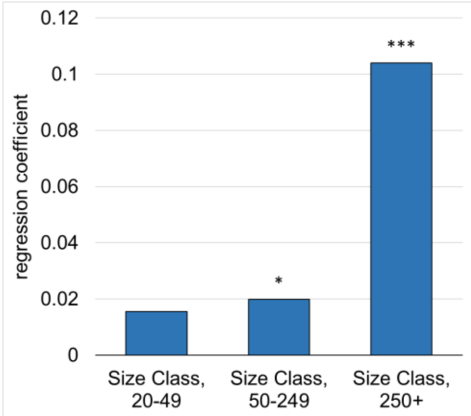
France – 2018

Weighted results



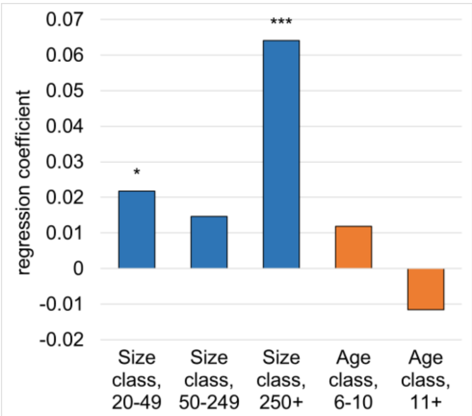
Germany – 2018

Unweighted results



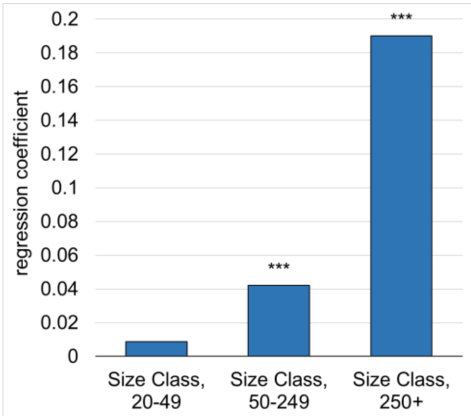
Israel – 2020

Weighted results



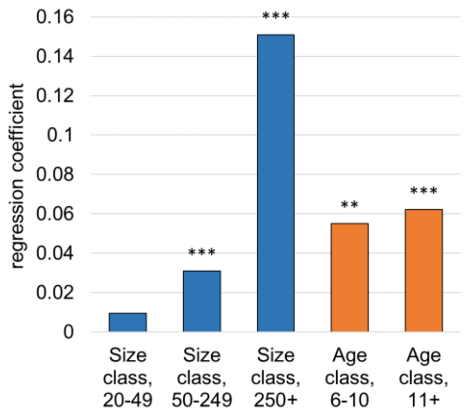
Italy - 2020

Weighted results



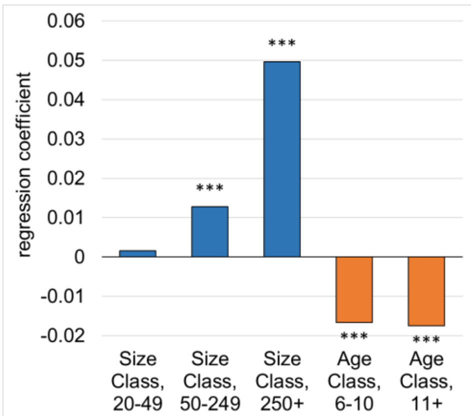
Japan – 2017-2019[a]

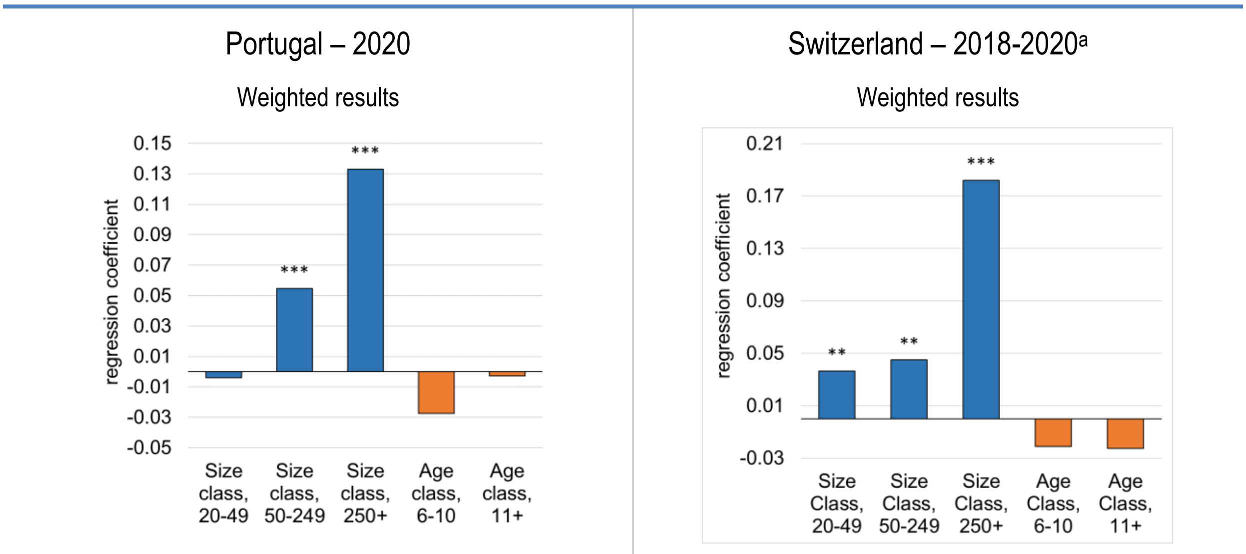
Weighted results



Korea – 2017-2019[a]

Unweighted results





Notes: This figure reports the main estimation results of the baseline adoption regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, Portugal, and Switzerland. The baseline adoption regression is a linear probability model that employs the AI use dummy as dependent variable and includes size and age classes as main independent variables. Each regression includes 2-digit sector and, upon availability, year fixed effects. Statistical significance based on robust standard errors is reported above bars: *** p<0.01, ** p<0.05, * p<0.1. Year fixed effects coefficients have not been reported for Denmark, Korea, and Switzerland. The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland, and are unweighted for Germany and Korea. [a]Results for Denmark, Korea, and Switzerland are based on more waves of yearly surveys. Results for Japan are based on a single wave referring to the years 2017-2019 (see Table A B.2 for additional information). See Table A A.1 for the complete list of regression coefficients, Table A B.2 for information on the variables, and Table A B.3 for additional details on the methodology.
Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

Finally, results related to age classes tend to confirm that older firms, conditional on size and sector, tend to be less likely to adopt AI. Indeed, coefficients related to older age classes are negative for most countries, and statistically significant in the case of Denmark, France, and Korea.[35] They are also negative, although not significant, in Israel, Portugal, and Switzerland, with signs consistent with the patterns reported in the previous subsection. Conversely, coefficients associated with older age classes are positive and significant in the case of Japan, where older firms appear more likely to use AI (conditional on size and sector).[36]

4.3. Factors complementary to AI use

After focusing on firm characteristics – notably age and size – taking into account the sectoral specificities of each country, this subsection discusses the role of factors complementary to AI use, and the extent to which they are related to AI adoption.

This is investigated by estimating a series of linear probability models that extend the previous ones by focusing on factors related to human capital, digital infrastructure, and market structure.[37]

Due to the use of surveys that encompass different country-specific questions, the set of complementary factors under consideration varies across countries (see Table A B.2 in Appendix for further details). However, this allows estimating the relation between AI use and a set of complementary factors that is broader than the one available in each country taken in isolation. The results are reported in Figure 6.

Overall, the evidence shows that complementary assets play a key role for AI use. In general, AI use is indeed more likely in presence of digital infrastructure and other digital capabilities (i.e., cloud computing services, use of other digital technologies, use of ultra-fast broadband connection), and in presence of higher ICT skills (proxied by the presence of ICT specialists and training).

Concerning the firm digital infrastructure, using cloud computing services is positively associated with AI in all regressions for which this information is available, suggesting a relevant complementarity between the two technologies also when additional factors are taken into account (as in the case of Denmark and Italy). Furthermore, the cloud variable is statistically significant in the majority of countries considered (Belgium, Denmark, Italy, Japan, Korea), losing significance in Switzerland and Israel only.[38]

The link between ultra-fast broadband connections and AI is also positive, but to some extent weaker than the AI-cloud relation.[39] Using ultra-fast broadband connections is indeed positively linked with AI use in all countries considered (Belgium, France, Israel, Italy, Portugal), although significant in Belgium and France only.

The joint evidence on the relation between AI, ultra-fast broadband connection and cloud computing services suggests that digital infrastructure is key for firms to use AI. AI algorithms may not always need high-speed broadband connections to be developed, trained, or applied to production processes. However, its presence may be crucial for the effective use of other digital technologies or complementary assets, for instance the frequent update of big datasets and the use of cloud computing services, wherein such datasets may be stored and further used for AI applications.

Human capital plays a crucial role for AI adoption. Indeed, the presence of ICT specialists is always positive and significantly correlated with the use of AI technologies (see the results for Denmark, France, Israel, and Switzerland). Despite remaining positive in all the countries for which data are available, the relation between AI use and ICT training may appear to some extent weaker, with estimated coefficients that tend to be lower and less significant than ones of ICT specialists.[40]

In Germany, the data allow further testing whether less specific sets of skills are relevant for the adoption of AI technologies.[41] Results show that training of employees is positively linked to AI use. However, after controlling for training and other confounding factors, educational attainments – proxied by the share of employees with a university degree – do not exhibit a statistically significant link with AI use.[42]

Overall, this evidence suggests that while generic skills are relevant, ICT skills constitute a necessary complementary asset to use AI algorithms. More in-depth ICT skills, as proxied by the presence of ICT specialists or ICT training, may be particularly relevant in this early stage of AI diffusion.

German data also help better understand the relation between AI, innovation, export activity, and financial resources.[43] German innovators are more likely to adopt AI technologies, suggesting a close link between technology adoption and previous innovation activities (see also Rammer et al. (2021[49])). Export by German firms is significantly linked to AI, suggesting that the availability of external markets, and therefore a larger market size, or facing international competition may foster AI adoption. Conversely, financial constraints are negatively associated to AI use, albeit not significantly.[44]

Figure 6. Estimation results of the extended adoption regressions

Notes: This figure reports the main estimation results of the extended version of the adoption regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, Portugal, and Switzerland. The adoption regression is a linear probability model that employs the AI use dummy as dependent variable and includes size and age classes, and other complementary factors as main independent variables. Complementary factors change across countries and mainly include ICT skills (ICT specialists and training for non-ICT specialists), digital infrastructure (use of ultra-fast broadband connection), digital capabilities (cloud computing use and number of other digital technologies). Each regression includes 2-digit sector and, upon availability, year fixed effects. Statistical significance based on robust standard errors is reported above bars: *** p<0.01, ** p<0.05, * p<0.1. Age class and year coefficients have not been reported for Denmark, Korea, and Switzerland. Age class coefficients have not been reported for Belgium, France, Israel, Japan, and Portugal. The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland, and are unweighted for Germany and Korea. [a]Results for Denmark, Korea, and Switzerland are based on more waves of yearly surveys. Results for Japan are based on a single wave referring to the years 2017-2019 (see Table A B.2 for additional information). See Table A A.2 for the complete list of coefficients, including the age class ones, Table A B.2 for information on the variables, and Table A B.3 for additional details on the methodology.

Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Additionally, the analysis further focuses on the role of firm digitalisation, extending the descriptive evidence reported above. Indeed, in Belgium, France, and Portugal, available estimations allow to further explore the link between AI use and overall digitalisation, proxied by the number of other digital technologies used by the firm, net of the use of AI.[45] The link between AI and other digital technologies is positive and significant, corroborating the unconditional findings of the previous subsection (see Figure 4).[46]

This suggests that firms take advantage of their existing internal digital capabilities to adopt AI. The use of other digital technologies by firms may indeed help firms develop the complementary assets that are needed to use AI. For instance, the presence of a CRM or an ERP infrastructure (see the case of France) may foster the collection of large amounts of data to be next used for training AI algorithms.

Finally, the results from adoption regressions accounting for the role of complementary assets show that the relation between size and AI use (see Sections 4.1 and 4.2) is at least partially driven by these. Despite remaining significant, the coefficients associated with larger size classes reported in Figure 5 tend indeed to lose part of their magnitude in Figure 6, when the additional controls related to complementary factors are added. This evidence suggests that scale advantages of AI use are at least partially related to the availability of such complementary assets.[47]

5 AI use and productivity

This section investigates the links between AI use and firm labour productivity.[48] The discussion is organised in two parts.

The first one provides descriptive evidence about the heterogeneity in AI adoption patterns across productivity classes (based on quantiles of the productivity distribution), providing a first descriptive outlook about the extent to which AI is used by firms with different productivity performance.

The second one further analyses the link between AI and productivity by presenting the results of regression analyses that account for relevant confounding factors, notably sectoral specificities. These regressions relate firm-level labour productivity to AI use, controlling for the role of firm size and age, and for sector-specific fixed effects. The analysis relevantly focuses on the size-specific links between productivity and AI, and on the possible origin of productivity differences between AI users and other firms, also including complementary factors in the productivity regressions.

5.1. Descriptive evidence: AI use by productivity classes

This section discusses the shares of AI users by productivity classes across countries. These allow to have a first descriptive glance at the link between AI use and labour productivity, by focusing on the patterns of AI use across firms that have a different position in the productivity distribution.

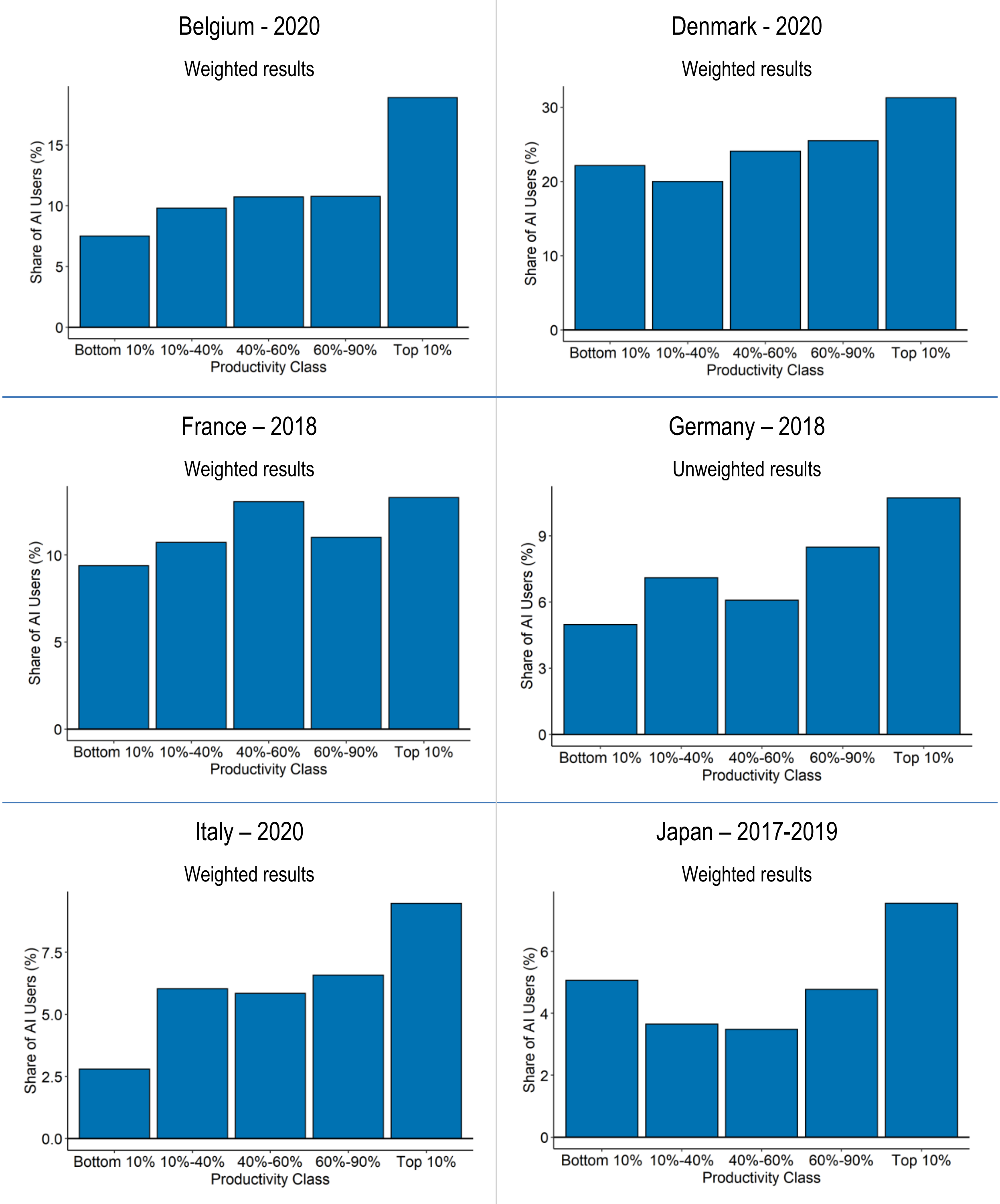
The analysis distinguishes six productivity classes based on the quantiles of the productivity distribution (see "The *AI diffuse* program" Box). These are computed within industries (based on the SNA A38 classification), to take into account cross-sectoral differences in productivity levels. Results are reported in Figure 7.[49]

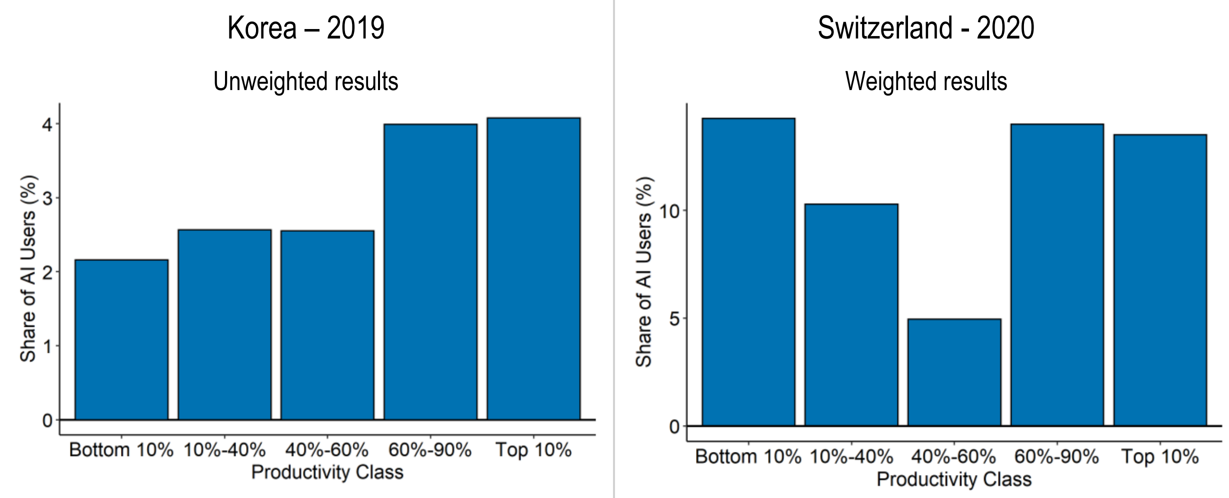
Overall, shares of firms using AI tend to be higher in classes associated with higher productivity and are generally highest across firms at the top 10 percent of the productivity distribution, suggesting the existence of a positive link between AI use and productivity. This is the case for all countries reported but Switzerland.

However, often shares of AI use do not monotonically increase with productivity quantiles (in particular for Switzerland and Japan),[50] pointing at possible cross-country differences in the patterns of adoption and use of AI. Higher shares of AI adoption in lower productivity quantiles might be related to a higher presence of AI start-ups, in line with the discussion in Section 4.1. Entrants in general tend to be on average less productive (Berlingieri et al., 2020[50]) and this may result in higher shares of AI users in lower productivity quantiles.[51]

Gaps in terms of AI use across productivity classes may likely reflect pre-existing differences between the top and the bottom of the productivity distribution (also see Andrews et al. (2016[51])). These appear more evident for some countries, such as Belgium or Italy, where there are larger relative differences in the shares of AI use at the top and at the bottom of the productivity distribution.

Figure 7. Share of AI users by productivity class





Notes: This figure reports the shares of AI users by productivity class for Belgium, Denmark, France, Germany, Italy, Japan, Korea, and Switzerland. Firms are divided in productivity classes based on quantiles of the productivity distribution. These are computed at the industry SNA A38 level to take into account sector-level differences in productivity levels. 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. Quantiles are weighted for Belgium, Denmark, France, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea.
Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Although to some extent descriptive, this evidence already provides relevant information about the relation between AI use and productivity, suggesting that AI use appears overall more prevalent across firms that have a leading position in terms of productivity.

The next subsection will further investigate this link by carrying out a more comprehensive regression analysis. It will estimate this relation conditional on other relevant factors, such as firm age, size, detailed sector of activity, and other relevant complementary assets for which information is available at the firm level. This may allow to better understand the origin of productivity premia of AI users. Although challenging with the data available – especially given the timing of the relevant variables and the lack of information about adoption timings – this may indeed provide an indication about the extent to which these premia are related to the use of AI itself or to other factors, hinting at possible selection of already more productive firms into AI use.

5.2. Evidence from productivity regressions

5.2.1. Baseline regressions and the role of firm characteristics

This subsection digs deeper into the link between AI and productivity, exploring it in a regression framework that relates labour productivity (dependent variable) to AI use, controlling for size and age classes, 2-digit sector and year fixed effects (upon availability).[52] These regressions provide a first-order characterisation of the AI-productivity link, accounting for the relevant potential confounding factors mentioned above.

Results are reported in Figure 8. AI use is positively linked with the productivity proxy considered in all cases reported. Furthermore, in most cases the AI-productivity relation is also statistically significant (Belgium, Denmark, France, Germany, Korea, and Italy).

Statistically significant estimated coefficients range between about 0.34 in Belgium to the 0.06 in France and ought to be interpreted as the average percentage difference in productivity between AI users and non-users.[53] The coefficients with highest estimated values (Belgium, Italy, and Korea) are one order of magnitude larger than the ones with lowest values (Denmark, France, and Germany).

Notably, results for Italy do not control for age due to data availability constraints, while results for Korea are unweighted and are more representative of larger firms, for which the AI-productivity relation is likely stronger (due to possible selection into AI use and to higher availability of complementary assets, see also Section 4.2). Conversely, both results from France and Denmark account for the role of firm age and exhibit similar values (about 0.09 and 0.06).

AI use coefficients are instead not statistically significant in Israel, Japan, and Switzerland.[54] Given the timing of the productivity proxy (2019), results for Israel can capture more significantly selection effects, possibly underestimating the AI-productivity relation. Results for Japan are based on Machine Learning,[55] which captures only one of the several applications of AI technologies. Concerning Switzerland unreported unweighted results highlight a positive productivity premium of AI users. This may suggest that productivity premia of larger AI users may to some extent be offset by smaller (likely younger) users, whose productivity is likely more similar to the one of non-users.

Focusing on other firm characteristics, the coefficients of the largest size and oldest age classes tend to be positive and significant across most regressions, suggesting that larger and older firms are on average more productive, in line with existing international evidence.[56]

Evidence from Section 4 has shown that AI use is more likely among larger firms. In the context of the link between AI and productivity, the existence of scale advantages in the use of AI discussed may enable the largest firms to better capture gains of AI diffusion. In this respect, it is useful to extend the productivity regression above by including an interaction term between AI and size classes, which help assess the size-class-specific link between AI and productivity.[57]

The estimation results of these regressions are reported in Figure 9. Focusing on the interaction term, the findings highlight that the relation between AI use and productivity is higher for larger firms and, in most of the countries considered (Denmark, France, Israel, Italy, Japan, and Korea), this is also statistically significant.

This evidence overall suggests that largest firms using AI are significantly more productive than smallest AI users and that the significant links between AI and productivity found in Figure 8 tend to originate from AI use in largest firms.

Furthermore, even though in Japan and Israel the AI-productivity link is on average not significant (see Figure 8), large firms using AI are significantly more productive, confirming that AI-productivity links may be specific to large firms in these initial stages of AI diffusion. Finally, in Switzerland the coefficients of the interaction between AI use and the size class 50-249 are very close to 10% significance.[58] In this sense, also evidence from Swiss regressions appears broadly in line with the general findings suggesting that the AI-productivity link in large firms is significant.

Largest AI users are instead not significantly more productive in Belgium and Germany. However, in Belgium the general AI coefficient remains positive and significant, highlighting that, despite the existence of scale advantages in AI use (see Section 4), productivity premia appear more widespread across different firms. Furthermore, unreported results for Germany show that very large AI users (with more than 500 persons employed) are significantly more productive than smallest ones.

Several robustness checks are carried out, including estimating the abovementioned regressions with additional geographic fixed effects (when available) or different sets of industry fixed effects – i.e., at the SNA A38 level. Overall, these additional analyses qualitatively confirm the main findings discussed above.

Furthermore, for one country (France) it is possible to further test the robustness of these findings when changing the productivity measure, using firm-level real value added instead of turnover, or when computing productivity in the following year (2019) to reduce possible simultaneity issues. Results confirm the existence of a productivity premium for the largest AI users, as discussed above.[59]

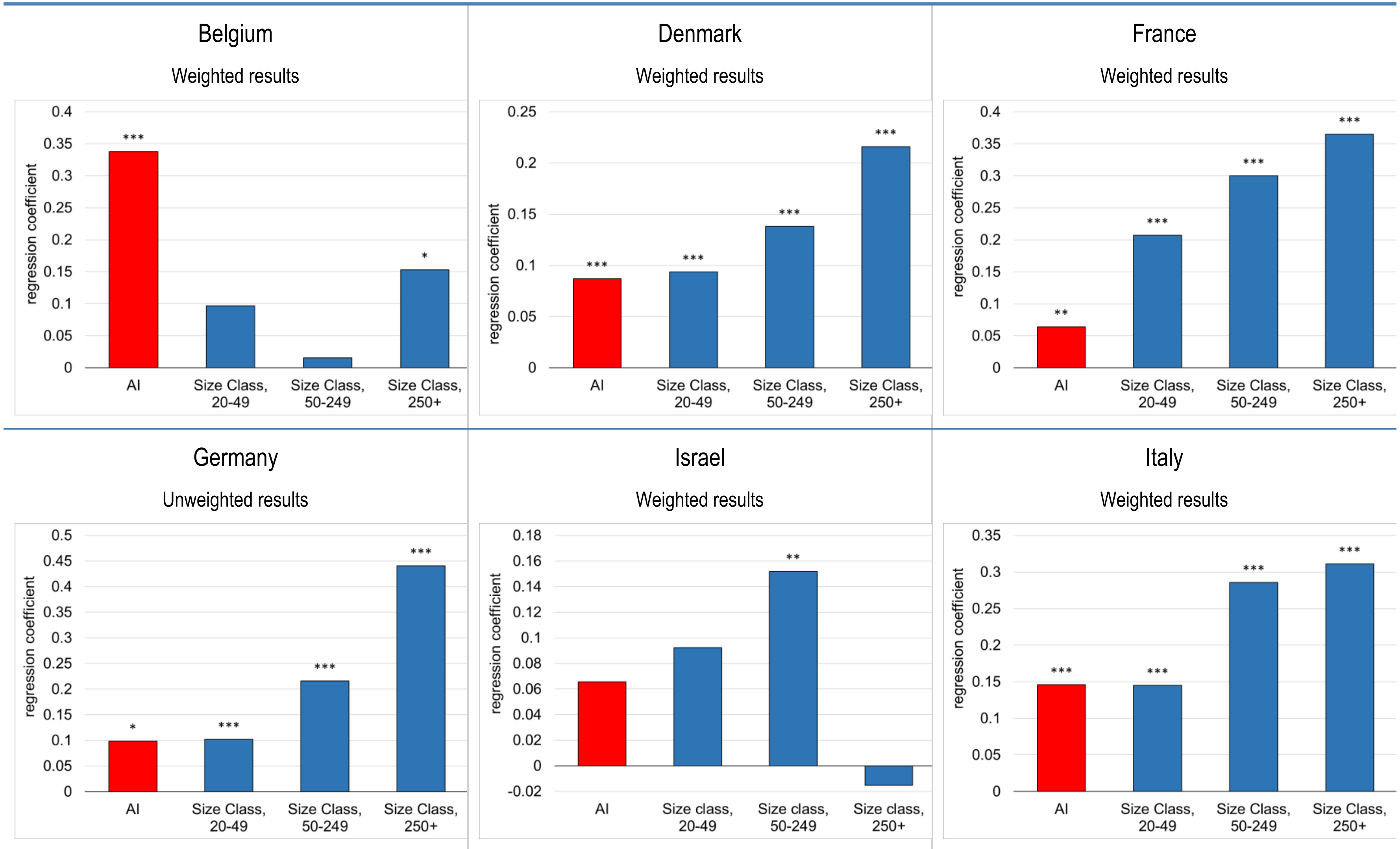
Overall, the evidence reported in this subsection suggests that a productivity premium of AI users is present in several countries and that this appears driven by the largest firms using AI.

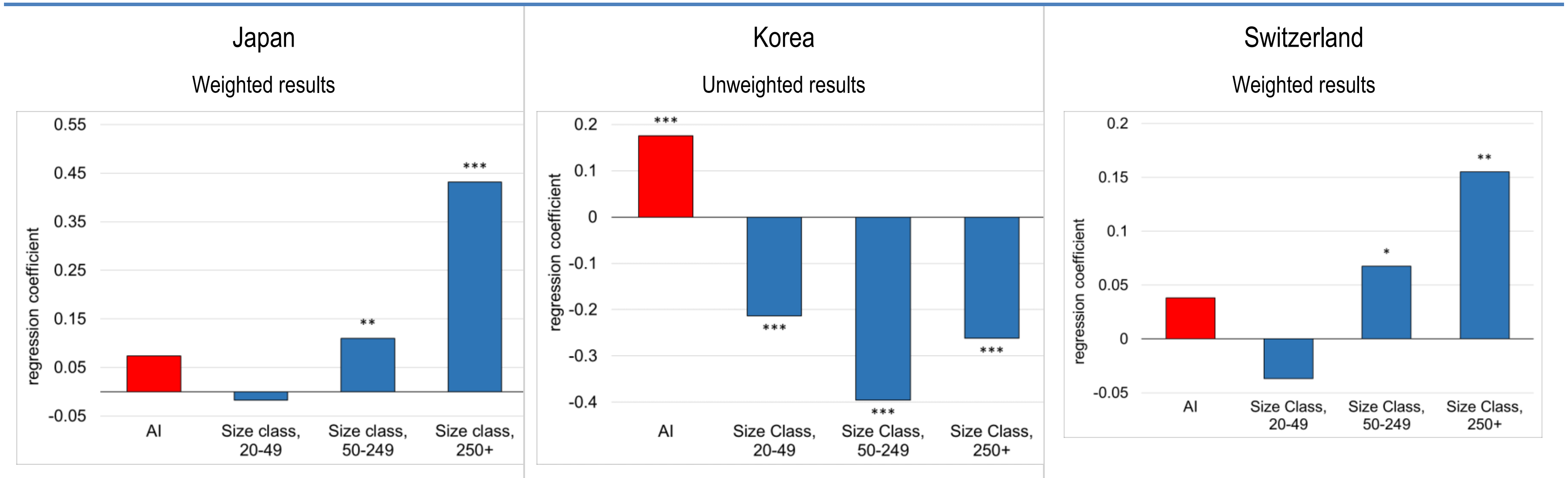
However, the regression analysis hereby reported does not allow to clearly distinguish between the productivity impact of AI and the presence of selection into AI use.[60]

In this sense, a positive link between AI and productivity may have two concomitant causes. First, the use of AI by firms may directly enhance their productivity, via the channels discussed in Section 3. Second, more productive firms may select into the use of AI. In this case, firms that were already on average more productive before adopting AI will be those in a better position to adopt, suggesting that AI productivity links may not stem from a causal impact of AI on productivity, but rather from pre-existing differences across firms.

In this context, the next subsection attempts to make a step further into exploring the origin of the AI-productivity links, conditional on the data available across countries.

Figure 8. Estimation results of the baseline productivity regressions

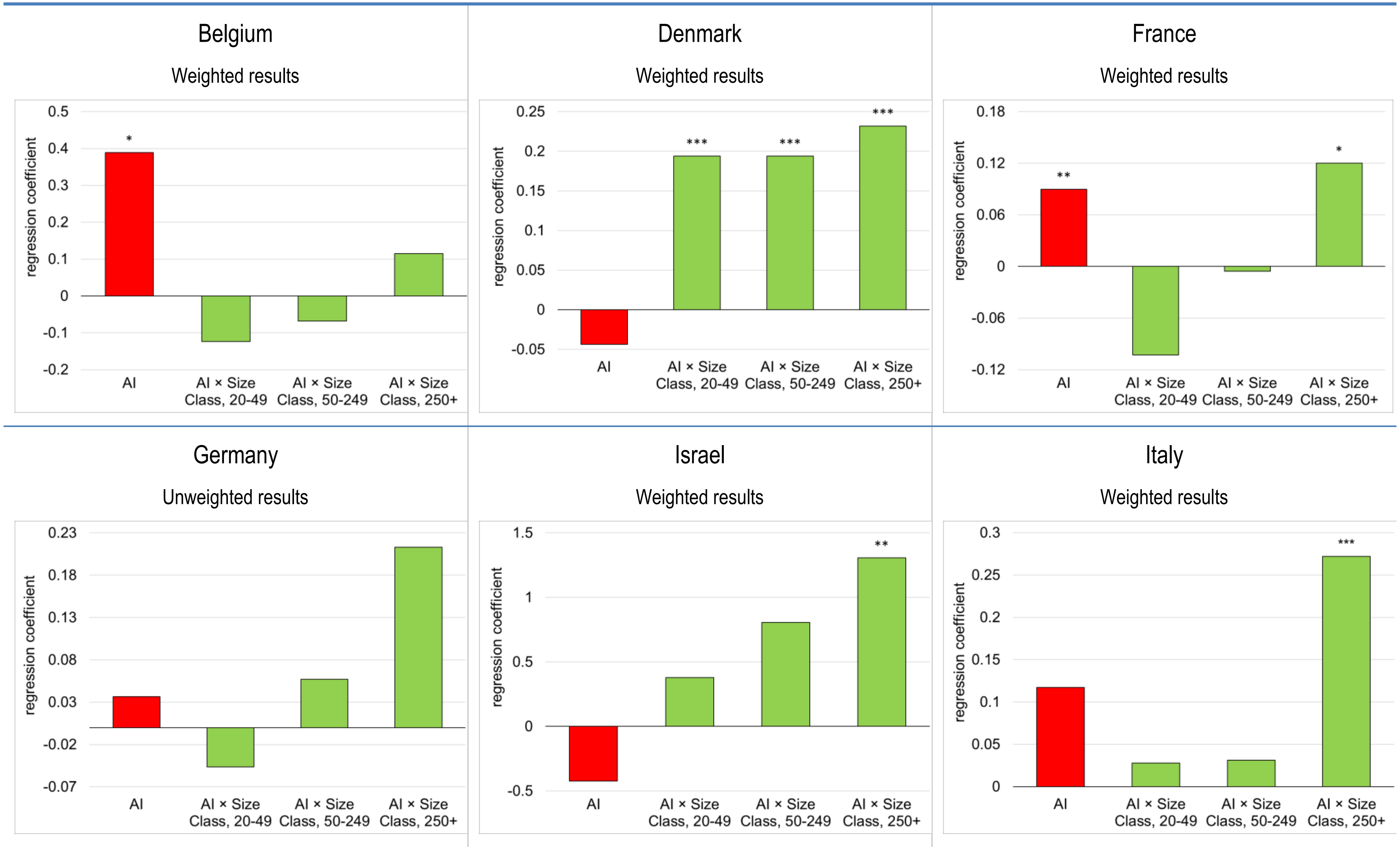


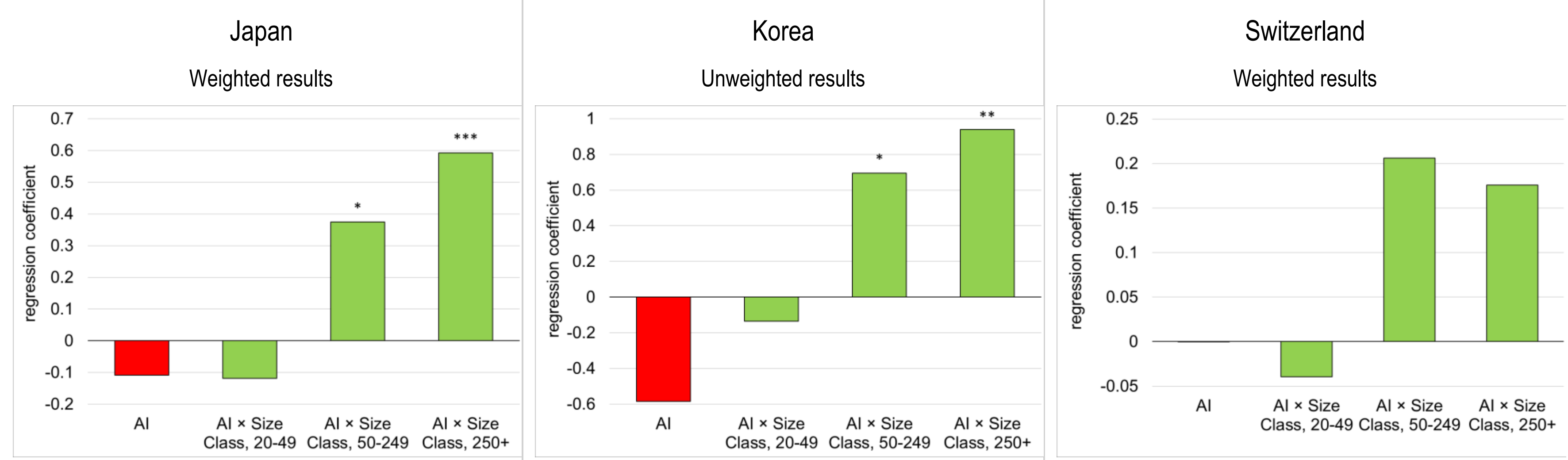


Notes: This figure reports the main estimation results of the baseline productivity regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, and Switzerland. The baseline productivity regression is an ordinary least square model that includes (log) labour productivity as dependent variable and AI use, size, and age classes as main explanatory variables. Each regression also controls for 2-digit sector and year fixed effects, upon availability. Statistical significance based on robust standard errors is reported above bars: *** p<0.01, ** p<0.05, * p<0.1. Age classes and year coefficients have not been reported for Denmark, Korea, and Switzerland. Age classes coefficients have not been reported for Belgium, France, Israel, and Japan Results are weighted for Belgium, Denmark, France, Israel, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea. See Table A A.3 for the complete list of coefficients, Table A B.2 for information on the variables, and Table A B.3 for additional details on the methodology.

Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Figure 9. Estimation from the productivity regressions including the interaction between AI and size





Notes: This figure reports the main estimation results of the productivity regression encompassing the AI-size interaction terms for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea,and Switzerland. This productivity regression is an ordinary least squares model that includes (log) labour productivity as dependent variable and AI use, size and age classes and the interaction terms between AI and size classes as main explanatory variables. Each regression controls for 2-digit sector and year fixed effects, upon availability. Statistical significance based on robust standard errors is reported above bars: *** p<0.01, ** p<0.05, * p<0.1. Size classes have not been reported in all country-specific plots. Age classes and year coefficients have not been reported for Denmark, Korea, and Switzerland. Age classes coefficients have not been reported for Belgium, France, Israel, and Japan. Results are weighted for Belgium, Denmark, France, Israel, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea. See Table A A.4 for the complete list of coefficients, Table A B.2 for information on the variables, and Table A B.3 for additional details on the methodology.
Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

5.2.2. The role of complementary assets

The previous subsection showed evidence of a positive and – in most cases – significant relation between AI and productivity, which seems predominantly driven by AI use in largest firms.

However, AI use by firms is more likely in presence of a series of complementary assets (see Section 4), which may themselves generate productivity gains. In that case, the link between AI use by firms and productivity may depend on the selection of firms endowed with these assets into the use of AI, rather than on a causal impact of AI on productivity.

This section tries to make a step further taking this into account by discussing the results of a series of regressions that include several complementary factors as additional controls.[61] These are reported in Figure 10.[62]

Complementary assets confirm indeed to be significantly linked with productivity. Human capital (i.e., presence of ICT specialists and training for non-ICT employees), digital infrastructures (i.e., the use of ultra-fast broadband connection), and firms' digital capabilities (i.e., number of other digital technologies used by firms) are generally positively and significantly associated with productivity. Furthermore, in Germany, financially constrained firms are less productive, whereas exporters, firms employing skilled workers, and providing training to their employees are more productive.

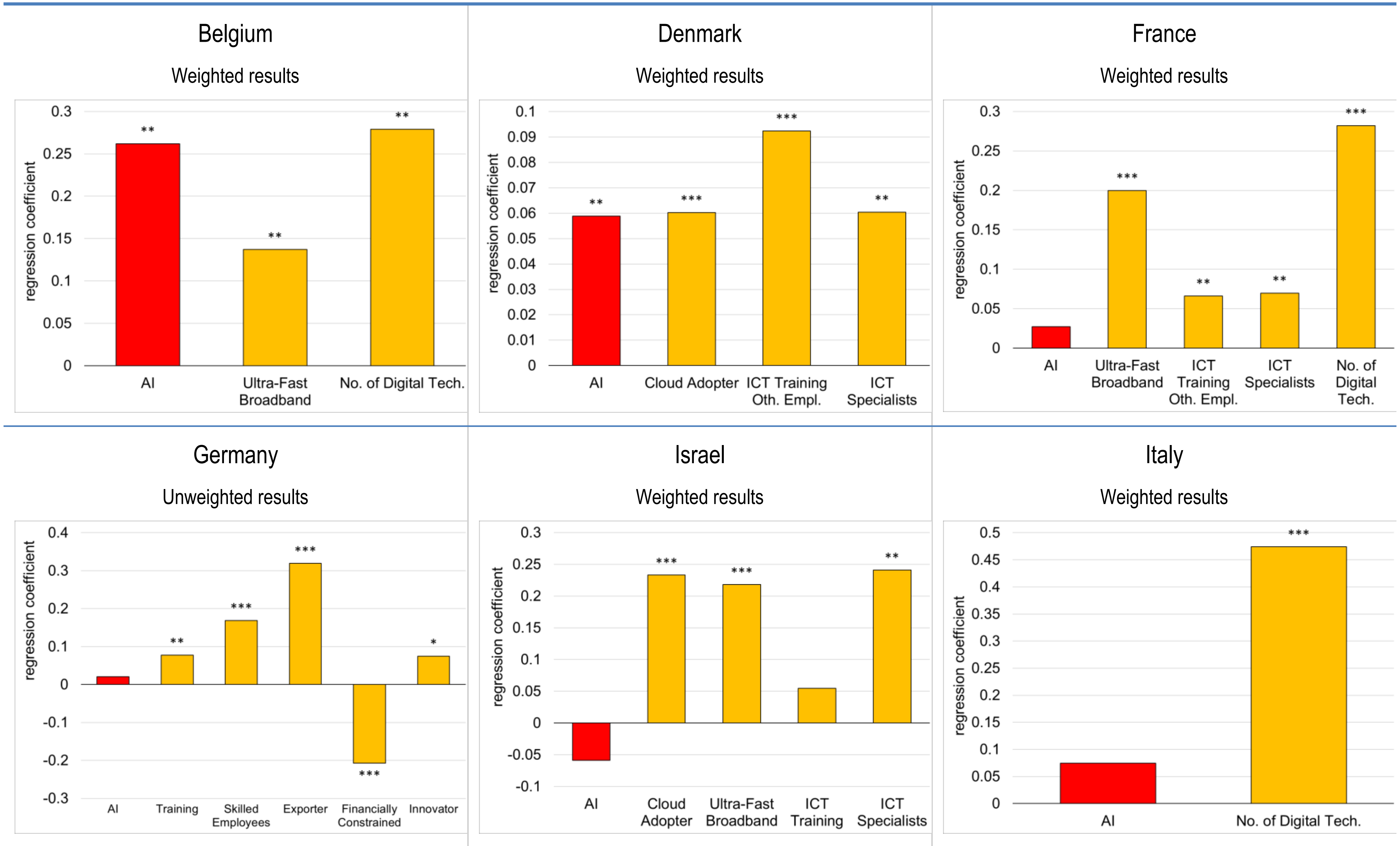
Most relevantly, when additional controls are applied, the coefficients of AI use generally decrease their magnitude and tend, in part or in total, to lose their significance. These findings suggest that the productivity premium of AI use does not seem to be driven by AI alone. It appears, at least in part, driven by the role of complementary assets, hinting at selection of already more productive firms into AI use.

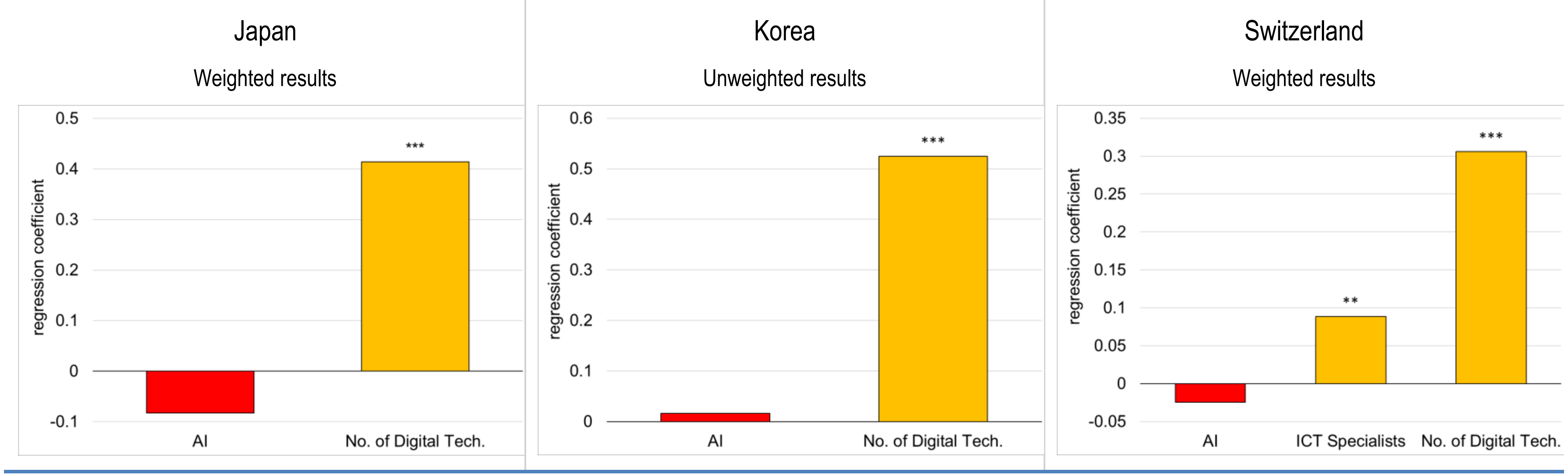
Indeed, the AI-productivity link in France, Germany, Italy, and Korea turns to be not significantly different from zero[63] (see Figure 8 for comparison). Accordingly, this highlights that in these countries the AI productivity premium is unlikely to be related to a causal effect of AI on productivity. Conversely, AI users in Belgium and Denmark remain significantly linked with productivity when complementary assets are included in the regressions. However, the presence of complementary factors as additional controls reduces the overall magnitude and level of significance of AI use coefficients also in these countries. This suggests that, although robust to the inclusion of relevant controls, also the productivity premium of Belgian and Danish AI users may be – at least partially – driven by selection.

A number of additional unreported robustness checks, encompassing additional geographic fixed effects (when available) and different sets of sectoral fixed effects, broadly confirm qualitatively the findings discussed in this section.

Further results from France, country for which the link with a time series of financial data was possible, confirm the evidence pointing to selection into AI use by more productive firms.[64] First, the significant link found for large French AI users discussed in the previous section disappears when regressions account for past productivity. Furthermore, using productivity in 2011 as dependent variable suggests that the relation between AI use and productivity was present well before AI technologies had potential to be exploited.

Figure 10. Estimation of the extended productivity regressions including complementary factors





Notes: This figure reports the main estimation results of the extended version of the productivity regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, and Switzerland. This productivity regression is an ordinary least squares model that includes (log) labour productivity as dependent variable and AI use, size and age classes and complementary assets as main explanatory variables. Each regression controls for 2-digit sector and year fixed effects, upon availability. Statistical significance based on robust standard errors is reported above bars: *** p<0.01, ** p<0.05, * p<0.1. Complementary assets change across countries and mainly include ICT skills (ICT specialists and training for non-ICT specialists), digital infrastructure (use of ultra-fast broadband connection), digital capabilities (cloud computing use and number of other digital technologies). Size class coefficients have not been reported in the plots. Age class and year coefficients have not been reported for Denmark, Korea, and Switzerland. Age class coefficients have not been reported for Belgium, France, Israel, and Japan. The results are weighted for Belgium, Denmark, France, Israel, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea. See Table A A.5 for the complete list of coefficients, Table A B.2 for information on the variables, and Table A B.3 for additional details on the methodology.

Sources: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea – Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Overall, this suggests that the productivity premium of AI users may not be driven by AI alone. Indeed, the evidence hints at the presence of some degree of selection into AI use by firms that may, at least in part, explain the AI productivity premium. Furthermore, it also suggests that the tendency of more productive firms to use AI may be likely related to complementary assets, especially those linked to the digital transformation, also considering that scale advantages reduce when controlling for these factors (see the discussion in Section 4.3).

The evidence presented does not however imply that AI has no direct effect on firm productivity. It can be that such an effect may just take time to fully materialise. Indeed, in early stages of diffusion the cost of complementary investments may offset productivity gains, generating J-curve dynamics of productivity over time (Brynjolfsson, Rock and Syverson, 2021[25]). Furthermore, it takes time for firms to develop and take advantage of the relevant complementary assets that may allow to exploit AI technologies most effectively (Brynjolfsson et al. (2017[36])).[65] Exploring differences across different types of AI users would be a promising avenue to further explore these issues.

In this respect, initial evidence based on French data shows that there are relevant differences between different types of AI users in their relationship with both complementary assets and productivity (Calvino and Fontanelli (2023[52])). Firms buying AI from external sources (AI buyers) rely significantly on ICT training for non-ICT employees only. Conversely, AI users developing their own AI (AI developers) depend on ICT specialists, suggesting that they rely on more in-depth ICT skills as opposed to AI buyers. Furthermore, AI developers – differently from AI buyers – appear significantly more productive even when initial productivity and complementary factors are controlled for. This suggests the existence of a positive AI-productivity link beyond selection for AI developers in France, highlighting that complementary factors may play a key role not only for AI adoption but also for realising productivity returns to AI use.[66]

6 Conclusions, policy discussion, and next steps

This work has explored the patterns of AI use in firms across different countries, focusing on their characteristics, the role of complementary assets – such as intangibles or digital infrastructure –, and the existing links between AI use and productivity.

It has done so by pioneering a distributed microdata approach based on a harmonised statistical code developed by the OECD – in the context of the *AI diffuse* project – and executed in a decentralised manner on official firm-level surveys. This has been possible thanks to the cooperation of researchers and experts in several institutions across 11 countries, whose contribution has been essential (see Table A B.1).

This section summarises and discusses the implications of the main findings of this analysis, which has uncovered novel stylised facts. It also provides some final remarks and points to the next steps for future analysis.

First, AI is more widely used across large firms. Scale advantages may be related to several factors, such as fixed costs of adoption, larger amount of data to leverage AI applications, lower financing constraints, and – relevantly – more considerable endowments of (or capabilities to use) intangibles and other complementary assets, needed to fully leverage the potential of AI.

Second, shares of AI users also appear – at least to some extent – higher across younger firms. Start-ups indeed often bring to the market more radical innovations, especially when new technological paradigms – such as the one based on AI – emerge.

Third, shares of AI adoption are consistently higher in ICT and Professional Services, suggesting that AI use is not yet equally spread across all sectors. Considering that AI is at relatively early stages of diffusion, this may suggest that its full potential as a general-purpose technology may yet have to fully materialise. In particular, at the moment its applications appear yet more widespread across selected services sectors that generally represent a small portion of economies.

Fourth, several complementary assets are significantly linked to AI use. These notably include a series of intangibles, such as ICT skills and training, firm-level digital capabilities, proxied using several digital technologies, as well as digital infrastructure. More general skills and innovative activities, which may also increase firm absorptive capacity, appear also relevantly linked to AI use.

Fifth, AI users tend to be on average more productive than other firms, with shares of AI use generally higher among the most productive firms. These productivity premia tend to originate from large firms but do not seem to reflect the use of AI alone. Complementary assets appear to play a key role, with productivity advantages likely related, at least to a certain extent, to the selection of more digital and competitive firms into AI use. Indeed, productivity premia significantly reduce or disappear when accounting for the role of complementary assets, notably those related to the digital transformation, which are positively related to firm productivity.

This suggests that some firms – likely larger, with higher digital capabilities, and already more productive – may be those currently exploiting more intensively AI technologies. Initial evidence seems also to highlight that some more direct effects of AI on productivity may start emerging for firms that develop their own AI algorithms, likely endowed with more digital capabilities and complementary assets.[67]

A polarised adoption, mainly by larger and more productive firms, combined with a role of AI strengthening their advantages, may imply that in the future existing gaps between leaders and the rest of the firm population may widen, with relevant implications for social outcomes. This is particularly relevant also considering the current context, in which gaps between firms have been likely strengthening even further over the COVID-19 pandemic.

Policy makers can play a key role in this context, supporting an inclusive digital transformation in the age of AI. Indeed, policies aimed at fostering technology diffusion – with particular attention to the complementary assets discussed above – would not only to boost AI adoption, but more broadly strengthen the inclusiveness of the digital transformation, enabling a more widespread diffusion of AI and its gains across the economy.[68]

Fostering firm capabilities and increasing their absorptive capacity is a crucial element of policies aimed at boosting digital technology diffusion and long-run economic growth.

Direct evidence from this study has highlighted the relevance of human capital, both generic but also and importantly related to digital and specialised ICT skills. In particular, firms' ability to fully take advantage of technological opportunities is intrinsically related to the skills of their workforce. High-quality education and training, not only generic but also – and relevantly – related to STEM, are crucial policy levers in this context, with long run effects that are likely to bring double dividends for several economic and social outcomes. More short-term interventions may also include financial incentives to training programs, aimed at upskilling workers at different levels.

Although not directly explored in this study due to lack of relevant information, improving managerial capabilities and organisational capital is similarly crucial to support the digital transformation in the age of AI, especially for smaller firms. Managers indeed play a key role not only in technology adoption decision, but also and importantly for creating the conditions that allow returns to adoption to fully materialise.[69]

The analysis has highlighted the key role of complementary digital technologies and digital infrastructure for AI adoption and productivity. Technological change is notably a cumulative process that is unlikely to happen abruptly and builds upon pre-existing expertise and knowledge base. Overall incentives or support to firm digitalisation, also aiming at overcoming the challenges of financing intangibles, may help strengthen the digital capabilities needed to take advantage of the most advanced technologies. Digital infrastructure is also key to allow these technologies to be fully operational: strengthening its foundations and reducing digital gaps may allow more firms to go digital. More in general, supporting research and innovation would also help increase the absorptive capacities of firms, fostering technology diffusion.

The analysis has finally discussed the existence of significant scale advantages in the use of AI, together with a relevant role of younger firms in its uptake, especially in some countries. Framework conditions oriented at reducing barriers to entry for new firms and barriers to growth for innovative ones, fostering competition, addressing the new regulatory issues of the digital economy (also related to the access and sharing of data), and improving knowledge production and sharing would be key policy levers in this context.

To sum up, a broad policy mix affecting incentives and capabilities, capturing synergies across different policy areas, would be needed to boost technology diffusion in the age of AI. This would include both demand-side measures raising awareness about new technologies and developing absorptive capacity, and supply-side measures fostering competition, providing relevant credit tools, improving knowledge production and sharing, and strengthening the foundation of digital infrastructure and skills.

Such policies may allow AI use and its returns to be more widespread not only across firms – fostering technology diffusion and its returns beyond leaders – but also across sectors, strengthening the potential of the diffusion of AI applications beyond the ICT sector. These are likely to bring double dividends for several economic and social outcomes, ensuring an inclusive digital transformation in the age of AI.

This study is a first proof of concept highlighting the potential of the data collected in the context of the *AI diffuse* project and is complementary to other OECD work that has studied the diffusion of AI across firms (notably see Calvino et al. (2022[1]) using different sources of big data focusing on the UK).

This line of work can be extended in several directions.

While broadening the coverage of the *AI diffuse* project, future work may aim at extending also the scope of analytical work to the diffusion of other advanced technologies – such as robots, 3-D printing, or internet of things – possibly focusing more closely on the extent to which technology adoption occurs in bundles, on their sequentiality or the relevant complementarities existing between different technologies. This may also shed further light on the differences between the characteristics of AI adopters and those of other advanced digital technologies.

Further analysis may also be oriented at exploiting the potential of firm-level surveys on technology adoption matched with other microeconomic information, such as the one available in firm-level balance sheets or linked employer employee data. This may allow refining the current analysis and further exploring the role of AI for other economic outcomes, such as labour, skills, or industry concentration, or the role of the complementarities existing between skills and digital technologies.

Future analysis may also focus on the role of other complementary assets not directly covered in this study, given data availability constraints, such as management skills and capabilities for AI diffusion. In this context, ongoing work is exploring the potential of online job posting data. Future analysis may focus more closely on specific groups of AI adopters, such as AI startups – for which also the timing of adoption may be more clearcut –, AI developers vs. AI buyers, AI-active firms target of an acquisition, digging deeper into their dynamics, also in relation with larger incumbents and with competition. Future work may also focus on the diffusion and role of digital technologies in the most recent years, as more data become available or using longitudinal commercial microdata that may allow to further explore patterns over the COVID-19 pandemic.

Finally, linking more directly the patterns of diffusion of advanced digital technologies – such as AI – with their potential to tackle societal challenges related to climate change, aiming at focusing more directly on the twin transition using microeconomic information on businesses, appears also particularly relevant for the next steps.

Endnotes

[1] See Box 1 in Section 2 for additional details about intangibles, including differences with respect to tangible assets, some examples, and key references.

[2] While this discussion reviews analyses specifically focusing on AI use by firms, other recent related contributions focus more broadly on the diffusion of other digital technologies (see e.g., Barbosa and Faria (2022[54]) focusing on several digital technologies in Portugal; DeStefano et al. (2020[55]) on cloud computing; DeStefano et al. (2023[64]) on broadband; Niebel et al. (2018[56]), Gierten et al (2021[62]) or Brynjolfsson et al. (2021[35]) on big data or predictive analytics).

[3] Additional work exploiting information on AI-related keywords reported in internet websites across four countries has been recently carried out by Dernis et al. (2023[60]).

[4] Results for Ireland are preliminary and instead based on initial data explorations. Productivity results for Portugal are also preliminary.

[5] These are therefore different in nature with respect to other commercial surveys.

[6] Relevant information on the timing of technology adoption is generally not available in this type of data.

[7] Additional information also including the questions related to AI use across countries is reported in the Appendix (Table A B.4).

[8] Discussion about AI measurement in AI use surveys is also available in Montagnier and Ek (2021[63]).

[9] For this reason, the cross-country analysis below will exclude information on firms below this threshold, even when provided by the data. Sampling weights are generally available in these data and allow computing weighted statistics.

[10] See Table A B.2 in the Appendix for further details on the timing of surveys and related technological variables.

[11] The MiP excludes some sectors present in surveys from other European countries (utilities, construction, sections 45 and 47 from wholesale and trade, accommodation and food, section 77 from administrative activities, section 951 from other service activities), while it includes the financial and insurance activities sector.

[12] As reported in the Appendix, it includes also “Agriculture, Forestry and Fishing” and “Mining and Quarrying” sectors.

[13] As reported in the Appendix, the original sectoral coverage is slightly different from the one of Eurostat surveys. The few sectors not included in Eurostat surveys have been excluded from the current analysis.

[14] This is based on two waves of the Swiss innovation survey and one wave of the ICT survey (see also Beck, Plekhanov and Wörter (2020[59])).

[15] Results for Ireland are preliminary and based on initial data explorations, which are conducted broadly in line with the type of analysis carried out by the *AI diffuse* program. Productivity results for Portugal are also preliminary. These results are not reported among the Figures or Tables, but their implications will be still commented throughout the analysis.

[16] The use of size and age classes rather than the respective continuous variables (see also Acemoglu et al. (2022[3])) has relevant advantages. First, the existence of fixed costs of adopting AI or economies of scale is likely to emerge more clearly when using size classes, due to possible threshold effects. Second, the use of size classes mitigates endogeneity issues relative to the use of continuous size in correlation with contemporaneous productivity. Third, the age of old firms may sometimes be imprecisely reported, and the use of age classes may mitigate this issue. Fourth, it makes the fixed effects structure compatible with the one adopted in adoption regressions. Robustness checks have been carried out for France and Germany employing the continuous version (in logs) of firm-level size. Those confirm the main results reported in the current analysis.

[17] However, the Japanese estimations are based on the use of Machine Learning by firms as a proxy of AI. As Machine Learning is only one of the types of AI applications, the shares of Japan may underestimate the overall rates of AI adoption. Evidence from Israel confirms existing findings on the digital gap with European countries (see Be'ery and Esperanza (2021[53])).

[18] Figure A A.1. in the Appendix further focuses on the shares of AI use by size in different years for Denmark and Switzerland, for which this information is available. The patterns of AI use by size over time are consistent with the figures reported in this section. Furthermore, shares of AI use have been increasing over time in both countries.

[19] Unreported preliminary results suggest this is also the case of Ireland.

[20] Unconditional figures, such as the ones reported in this subsection, may reflect cross-country differences for instance related to sectoral characteristics. The regression analysis in next subsection mitigates these by including sectoral fixed effects as additional controls. Cross-country differences in the definition of AI cannot instead be tackled by this approach. See the discussion above and Table A B.2 for additional information.

[21] In Switzerland, data for the youngest age class are unavailable due to confidentiality restrictions. Further insights about age are discussed in the next subsections, focusing on conditional correlations rather than unconditional shares of AI use. Further analysis on the unweighted shares of AI users in Japanese data suggests that the share of AI users in youngest firms (less than 10 years old) is not significantly different from the one of oldest firms (more than 10 years old).

[22] Unreported analysis shows indeed that in 2016 and 2017 the distribution of shares of AI use by age in Denmark is similar to the one of Israel and Japan, with the highest share of AI users in the 6-10 age class. The relation between shares of AI use and age class becomes monotonically decreasing in 2018.

Accordingly, this may be consistent with the presence of a first wave before 2016, and a second one in 2018.

[23] See also https://spectrum.ieee.org/history-of-ai or https://medium.com/neuralmagic/2012-a-breakthrough-year-for-deep-learning-2a31a6796e73 for further discussion about the breakthroughs in neural networks that occurred around 2012.

[24] The sectoral aggregation employed in Figure 3 is reported in Table A B.5 in the Appendix.

[25] The only exception is Germany, where the highest share of AI users can be found in the Professional and Scientific sector and whose results are however based on unweighted data and on a sectoral classification different from (and broader than) the one used for other countries. Still, the ICT sector in Germany is the second ranked in terms of AI users' share, in line with the overall evidence. The data do not allow to comprehensively investigate patterns of AI use in the Finance and Insurance sector, which is not available for most countries. Unreported analysis based on the few cases in which this is available however suggest that this may be another sector in which AI use is considerable.

[26] This may recall early patterns of diffusion of other digital technologies or tools, such as cloud computing.

[27] When different manufacturing sectors are considered separately, unreported analysis suggests that the shares of AI users tend to be higher in high-tech sectors (such as chemicals, pharmaceuticals, or computer and electronics).

[28] This is especially true in the case of Israel. The result of Israel may be due to the existence of a wide digital divide across different sectors, with a relevant role of high-tech start-ups driving the shares of AI users in the ICT sector.

[29] However, the comparison should be taken with caution since the definition of AI in France is different from other European countries, as detailed in Table A B.4 in the Appendix. Similar considerations would however apply if considering Portugal, for which data are more recent, instead of France.

[30] Digital technologies include, conditional on availability: AI, big data analysis, cloud computing services, customer relation management, enterprise resource planning, e-commerce, machine learning, robot, and 3-D printing. See Table A B.2 in the Appendix for further details on available technologies at the country level.

[31] In addition to the regression analysis commented below, unreported preliminary analysis, possible at the moment only for a subset of countries, also suggests that the descriptive patterns commented above do not appear to be driven by AI producers, a group of AI users that tends to be more concentrated in the ICT sector.

[32] The estimating equation is:

$$AI_{i,t} = a + b_1\, SizeClass_{i,t} + b_2\ AgeClass_{i,t} + FE_{i,t} + e_{i,t}$$

where *AI* is the AI use binary variable, *SizeClass* and *AgeClass* are fixed effects based on size and age classes, *FE* identifies sector and, upon availability, year fixed effects. Subscripts *i* identifies the firm and *t* the year. The timing of the variables included in the model is driven by data availability (see also Table A B.2 in the Appendix). Additional logit models, models including also geographic fixed effects and a different set of sector fixed effects (i.e., at SNA A38 level) have been estimated as robustness checks, qualitatively confirming the main findings reported.

33 Unreported preliminary results confirm this also in the case of Ireland.

34 The only exception is Israel, where the coefficients of size do not monotonically increase. However, the coefficients associated with smaller size classes are either weakly or not statistically significant.

35 Interestingly, the AI-age relation in France is driven by AI users developing their own AI technologies (AI developers), which appear significantly younger than other firms. Conversely, firms buying AI technologies from external sources (AI buyers) are not significantly younger. See Calvino and Fontanelli (2023[52]).

36 With respect to the descriptive statistics on the shares of AI users by age, results change more relevantly for Switzerland, Israel, and Japan. This is probably due to sectoral patterns in the use of AI technologies, as the AI-age link may indeed be driven by specific sectors, such as the ICT and Professional ones, within these countries.

37 In practice, additional variables related to such complementary factors are added to the previous model. The estimating equation therefore becomes:

$$AI_{i,t} = a + b_1\, SizeClass_{i,t} + b_2\, AgeClass_{i,t} + b_3\, ComplementaryAssets_{i,t} + FE_{i,t} + e_{i,t}$$

where *AI* is the AI use binary variable, *SizeClass* and *AgeClass* are fixed effects based on size and age classes, *ComplementaryAssets* are the binary variables that identify relevant complementary factors, *FE* identifies sector and, upon availability, year fixed effects. Subscripts *i* identifies the firm and *t* the year. A series of robustness checks (Logit models, additional fixed effects – geographic fixed effects – and different industry fixed effects (i.e., at SNA A38 level) generally confirms qualitatively the findings reported in this section.

38 In Israel and Switzerland, the link between AI and cloud computing services tends to lose its significance when also factors related to ICT skills are included in the regressions. As these have a positive and significant coefficient, it may be that cloud computing services are to some extent capturing underlying ICT skills within firms. However, this does not happen in Denmark, suggesting that the relation between technologies and ICT skills may change across countries. Unreported results for Portugal show also a positive and significant coefficient for the cloud computing variable (ICT skills controls are not available in this case).

39 The relative weakness of the link between AI and ultra-fast broadband may to some extent depend on the role played by ultra-fast broadband connections for other technologies, such as cloud, whose use is complementary to AI.

40 Additional evidence for France however suggests that ICT training for non-ICT employees is crucial for firms buying AI rather than developing their own algorithms in house (Calvino and Fontanelli, 2023[52]).

41 The variable “Training of Employees” equals 1 if the firm invests in employees’ training a part of personnel expenditure greater than the sector median, 0 otherwise. The variable “Skilled Employees” takes value 1 when at least 50% of employees have at least a university degree, 0 otherwise.

42 See also Calvino et al. (2022[1]) for additional evidence about tertiary education and AI use focusing on the United Kingdom.

43 The variable "Financially constrained" equals 1 when firms did not receive financial funds, despite they tried to obtain them, or did not ask them because pointless to do so. The dummy variable "Innovator" equals 1 when firms made a product or process innovation in the previous 3 years.

44The lack of significance may be related to the definition of the AI variable employed in this work, which cannot easily be related to financial constraints. These are indeed likely to bind firms at the time of adoption, rather than at the time of technology use.

45 The number of other digital technologies equals to the number of digital technologies (net of AI) employed by the firm and is normalised by the total number of technologies.

46 This evidence is in line with the findings of Cho et al. (2022[6]).

47 This appears in line with the hypothesis that proprietary ICT knowledge (e.g., data, software, and technologies) may be a key determinant of the advantages of larger companies, and may allow strengthening their position vis-à-vis competitors (see Bessen (2022[58])).

48 Productivity is proxied by the firm-level ratio between turnover and employment. The timing of the productivity variable slightly differs across countries, see the data section and Appendix for additional details.

49 Except for Germany and Korea, all figures are based on weighted productivity quantiles. The main findings for most countries are qualitatively confirmed when unreported analysis focuses on unweighted productivity quantiles.

50 Preliminary unreported figures suggest a similar pattern also for Israel. Preliminary unreported figures also highlight that shares of AI users tend to increase (non-monotonically) with productivity class also in Portugal.

51 Possibly, also timing of complementary investments and J-curve dynamics may play a role. Additional analysis may be needed to further investigate these hypotheses.

52 The estimated productivity equation is:

$$Log(Productivity)_{i,t} = a + b_1 AI_{i,t} + b_2\, SizeClass_{i,t} + b_3\, AgeClass_{i,t} + FE_{i,t} + e_{i,t}$$

where *Log(Producivity)* is the logarithm of labour productivity, *AI* is the AI use binary variable, *SizeClass* and *AgeClass* are fixed effects based on size and age classes, *FE* identifies sector and, upon availability, year fixed effects. Subscripts *i* identifies the firm and *t* the year. The timing of the variables included in the model is driven by data availability (see also Table A B.2 in the Appendix). A series of robustness checks encompassing additional geographic fixed effects and different sectoral fixed effects (i.e., SNA A38 level) broadly confirms the findings reported in this section.

53 For instance, this would imply that Belgian AI users are about 34% more productive of non-users, whereas the productivity gap between users and non-users in France amounts to 6.4%, conditional on other confounding factors.

54 A positive but not statistically significant coefficient is also evident in unreported preliminary results for Portugal.

55 See also Table A B.2 in the Appendix for additional information on the definitions.

56 The coefficients of age classes have not been reported in Figure 8 and can be found in the Appendix (Table A A.4). For Korea, the presence of a selected sample of small (in terms of employment) highly capitalised firms likely explains why the size coefficients are instead negative. Indeed, the reference size category (10-19) is likely to have significantly higher productivity.

57 This extended productivity equation reads as follows:

$$Log(Productivity)_{i,t} = a + b_1 AI_{i,t} + b_2\ SizeClass_{i,t} + b_3\ AI_{i,t} \times SizeClass_{i,t} + b_4\ AgeClass_{i,t} + FE_{i,t} + e_{i,t}$$

where *Log(Producivity)* is the logarithm of the labour productivity, *AI* is the AI use binary variable, *SizeClass* and *AgeClass* are fixed effects based on size and age classes, *AI*SizeClass* is the interaction term between *AI* and *SizeClass*, *FE* identifies sector and, upon availability, year fixed effects. Subscripts *i* identifies the firm and *t* the year. Robustness checks, which include additional geographic fixed effects and different industry fixed effects – i.e., SNA A38 –, provide results that are generally in line with the findings discussed in this section.

58 Qualitatively similar patterns also emerge in unreported preliminary results for Portugal, especially focusing on a sub-group of medium-sized firms.

59 Further details are discussed in Calvino and Fontanelli (2023[52]), that explore these issues linking ICT surveys with French balance sheet data. This approach may be further extended across countries in the next steps of the *AI diffuse* project, conditional on data availability.

60 This is due to data availability. Data on AI use do not include relevant information on the timing of adoption, and are available in separate cross-sections even in the few cases in which AI-related questions are present in more than one survey wave.

61 This section reports the estimation results of the following productivity equation:

$$Log(Productivity)_{i,t} = a + b_1 AI_{i,t} + b_2\ SizeClass_{i,t} + b_3\ AgeClass_{i,t} + b_4\ ComplementaryAssets_{i,t} + FE_{i,t} + e_{i,t}$$

where *Log(Producivity)* is the logarithm of labour productivity, *AI* is the AI use binary variable, *SizeClass* and *AgeClass* are fixed effects based on size and age classes, *ComplementaryAssets* are the relevant complementary factors (e.g., ICT skills, ultra-fast broadband connection, etc.), *FE* identifies sector and, upon availability, year fixed effects. Subscripts *i* identifies the firm and *t* the year. Unreported robustness checks, encompassing additional geographic fixed effects and different industry fixed effects (i.e., at the SNA A38 level), broadly confirm the findings discussed in this section.

62 Unreported preliminary results for Portugal also highlight qualitatively similar patterns.

63 Unreported preliminary results are in line with this evidence also in the case of Ireland.

64 These are further discussed in Calvino and Fontanelli (2023[52]).

65 In fact, firms may be still cumulating complementary assets, or experimenting AI procedures and learning about their best use. Limited early-stage direct effects could also be to some extent related to imitation by firms that do not have (yet) necessary complementary assets but started using the technology in response to a more generalised hype. It is not straightforward to examine this with the data available, given the

limited time coverage, the very recent inclusion of questions about AI in surveys across countries, and the limited relevant information of adoption timings.

[66] This may be in line with the analysis by Bessen (2022[58]) about the role of own-account software development for competitive advantage. Additional analysis may explore more in detail the differences between AI buyers and developers also in other countries.

[67] Further analysis, also based on data that will become available in the near future, may further qualify these findings.

[68] Policies fostering digital technology diffusion have been also discussed elsewhere, including Calvino and Criscuolo (2022[61]); Berlingieri et al. (2020[50])); Gal et al. (2019[57])) among others.

[69] See also further discussion in Calvino et al. (2022[48]) focusing on the case of Italy.

References

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. [3]

Acemoglu, D. et al. (2022), "Artificial Intelligence and Jobs: Evidence from Online Vacancies", *Journal of Labor Economics*, Vol. 40/S1, pp. S293-S340, https://doi.org/10.1086/718327. [7]

Acemoglu, D. and P. Restrepo (2019), "Automation and New Tasks: How Technology Displaces and Reinstates Labor", *Journal of Economic Perspectives*, Vol. 33/2, pp. 3-30, https://doi.org/10.1257/jep.33.2.3. [44]

Agrawal, A., J. Gans and A. Goldfarb (2018), *Prediction Machines: The Simple Economics of Artificial Intelligence*, Harvard Business Review Press. Cambridge, MA. [37]

Agrawal, A., J. McHale and A. Oettl (2018), *Finding Needles in Haystacks: Artificial Intelligence and Recombinant Growth*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w24541. [12]

Alderucci, D. et al. (2020), "Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata", https://www.aeaweb.org/conference/2020/preliminary/paper/Tz2HdRna. [13]

Alekseeva, L. et al. (2021), "The demand for AI skills in the labor market", *Labour Economics*, Vol. 71, p. 102002, https://doi.org/10.1016/j.labeco.2021.102002. [9]

Andrews, D., C. Criscuolo and P. Gal (2016), "The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy", *OECD Productivity Working Papers*, No. 5, OECD Publishing, Paris, https://doi.org/10.1787/63629cc9-en. [51]

Babina, T. et al. (2020), "Artificial Intelligence, Firm Growth, and Industry Concentration", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3651052. [10]

Bäck, A. et al. (2022), "Return of the Solow-paradox in AI? AI-adoption and firm productivity", *Papers in Innovation Studies, Lund University, CIRCLE-Centre for Innovation Research* 1. [11]

Bajgar, M., C. Criscuolo and J. Timmis (2021), "Intangibles and industry concentration: Supersize me", *OECD Science, Technology and Industry Working Papers* 12, https://doi.org/10.1787/ce813aa5-en. [28]

Barbosa, N. and A. Faria (2022), "Digital adoption and productivity: understanding micro [54] drivers of the aggregate effect", *GEE Paper 162*.

Bartelsman, E., E. Hagsten and M. Polder (2018), "Micro Moments Database for Cross-country ANalusis of ICT, Innovation and Economic Outcomes", *Journal of Economics & Management Strategy*, Vol. 27/3, pp. 626-648, https://doi.org/10.1111/jems.12256. [46]

Baruffaldi, S. et al. (2020), "Identifying and measuring developments in artificial intelligence: Making the impossible possible", *OECD Science, Technology and Industry Working Papers*, No. 2020/05, OECD Publishing, Paris, https://doi.org/10.1787/5f65ff7e-en. [17]

Beck, M., D. Plekhanov and M. Wörter (2020), "Analyse der Digitalisierung in der Schweizer Wirtschaft", *KOF Studies*, Vol. 153, https://doi.org/10.3929/ethz-b-000432882. [59]

Be'ery, G. and Esperanza (2021), "The Digital Gap of Israeli Business Sector: Highlights from the 1st ICT Usage Survey in International Comparison". [53]

Berlingieri, G. et al. (2020), "Laggard firms, technology diffusion and its structural and policy determinants", *OECD Science, Technology and Industry Policy Papers*, No. 86, OECD Publishing, Paris, https://doi.org/10.1787/281bd7a9-en. [50]

Bessen, J. (2022), *The New Goliaths*, Yale University Press, https://doi.org/10.12987/9780300265026. [58]

Bessen, J. et al. (2022), "The role of data for AI startup growth", *Research Policy*, Vol. 51/5, p. 104513, https://doi.org/10.1016/j.respol.2022.104513. [27]

Borowiecki, M. et al. (2021), "The impact of digitalisation on productivity: Firm-level evidence from the Netherlands", *OECD Economics Department Working Papers*, No. 1680, OECD Publishing, Paris, https://doi.org/10.1787/e800ee1d-en. [34]

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. [35]

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. [25]

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. [36]

Calvino, F. and C. Criscuolo (2019), "Business dynamics and digitalisation", *OECD Science, Technology and Industry Policy Papers* 62, https://doi.org/10.1787/6e0b011a-en. [31]

Calvino, F., C. Criscuolo and R. Verlhac (2020), "Declining business dynamism: Structural and policy determinants", *OECD Science, Technology and Industry Policy Papers* 94, https://doi.org/10.1787/77b92072-en. [32]

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*, https://doi.org/10.1787/e33c281e-en. [48]

Calvino, F. and L. Fontanelli (2023), "A portrait of AI adopters: evidence from France", [52] *https://www.nber.org/conferences/si-2022-it-and-digitization*.

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. [1]

Cho, J. et al. (2022), "What's driving the diffusion of next-generation digital technologies?", *Technovation*, p. 102477, https://doi.org/10.1016/j.technovation.2022.102477. [6]

Cockburn, I., R. Henderson and S. Stern (2018), *The Impact of Artificial Intelligence on Innovation*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w24449. [38]

Corrado, C. et al. (2021), "New evidence on intangibles, diffusion and productivity", *OECD Science, Technology and Industry Working Papers*, No. 2021/10, OECD Publishing, Paris, https://doi.org/10.1787/de0378f3-en. [43]

Corrado, C. et al. (2022), "Intangible Capital and Modern Economies", *Journal of Economic Perspectives*, Vol. 36/3, pp. 3-28, https://doi.org/10.1257/jep.36.3.3. [40]

Corrado, C., C. Hulten and D. Sichel (2009), "INTANGIBLE CAPITAL AND U.S. ECONOMIC GROWTH", *Review of Income and Wealth*, Vol. 55/3, pp. 661-685, https://doi.org/10.1111/j.1475-4991.2009.00343.x. [42]

Czarnitzki, D., G. Fernández and C. Rammer (2022), "Artificial Intelligence and Firm-Level Productivity", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4049824. [5]

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. [14]

De Ridder, M. (2019), "Market Power and Innovation in the Intangible Economy", *Discussion Papers, Centre for Macroeconomics (CFM)* 1907. [39]

Dernis, H. et al. (2023), "Identifying artificial intelligence actors using online data", *OECD Science, Technology and Industry Working Papers*, No. 2023/01, OECD Publishing, Paris, https://doi.org/10.1787/1f5307e7-en. [60]

Dernis, H. et al. (2021), "Who develops AI-related innovations, goods and services? A firm-level analysis", *OECD Science, Technology and Industry Policy Papers, No.121*, https://doi.org/10.1787/3e4aedd4-en. [23]

Destefano, T., R. Kneller and J. Timmis (2023), "The (fuzzy) digital divide: the effect of universal broadbnand on firm performance", *Journal of Economic Geography*, Vol. 23/1, pp. 139–177, https://doi.org/10.1093/jeg/lbac006. [64]

Destefano, T., R. Kneller and J. Timmis (2020), "Cloud computing and firm growth", *CESifo Working Paper Series 8306*. [55]

Dibiaggio, L., L. Nesta and M. Keita (2022), *Artificial Intelligence - Technologies and Key Players*, SKEMA Business School. [18]

Felten, E., M. Raj and R. Seamans (2021), "Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses", *Strategic Management* [22]

Journal, Vol. 42/12, pp. 2195-2217, https://doi.org/10.1002/smj.3286.

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* 1533, https://doi.org/10.1787/5080f4b6-en. [33]

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*, https://doi.org/10.1787/5080f4b6-en. [57]

Gierten, D. et al. (2021), "Firms going digital: tapping into the potential of data for innovation", *OECD Digital Economy Papers, No. 320*, https://doi.org/10.1787/ee8340c1-en. [62]

Hadlock, C. and J. Pierce (2010), "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index", *Review of Financial Studies*, Vol. 23/5, pp. 1909-1940, https://doi.org/10.1093/rfs/hhq009. [26]

Haskel, J. and S. Westlake (2017), *Capitalism without Capital*, Princeton University Press, https://doi.org/10.2307/j.ctvc77hhj. [41]

Hsieh, C. and E. Rossi-Hansberg (2019), *The Industrial Revolution in Services*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w25968. [45]

Igna, I. and F. Venturini (2022), "The determinants of AI innovation across European firms", *Papers in Innovation Studies, Lund University, CIRCLE - Centre for Innovation Research.*. [19]

Iori, M., A. Martinelli and A. Mina (2021), "The direction of technical change in AI and the trajectory effects of government funding", *LEM Papers Series, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy*. [20]

Korinek, A. and J. Stiglitz (2017), *Artificial Intelligence and Its Implications for Income Distribution and Unemployment*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w24174. [29]

Montagnier, P. and I. Ek (2021), "AI measurement in ICT usage surveys: A review", *OECD Digital Economy Papers, No. 308*, https://doi.org/10.1787/72cce754-en. [63]

Nakazato, S. and M. Squicciarini (2021), "Artificial intelligence companies, goods and services: a trademark-based analysis", *OECD Science, Technology and Industry Working Papers, No. 2021/06*, https://doi.org/10.1787/2db2d7f4-en. [24]

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*, Vol. 28/3, pp. 296-316, https://doi.org/10.1080/10438599.2018.1493075. [56]

OECD (2019), *Artificial Intelligence in Society*, OECD Publishing, Paris, https://doi.org/10.1787/eedfee77-en. [47]

Qureshi, Z. and C. Woo (eds.) (2022), *Gone Digital: Technology Diffusion in the Digital Era*, Brookings Institution Press. [61]

Rammer, C., D. Czarnitzki and G. Fernández (2021), "Artificial Intelligence and Industrial Innovation: Evidence From Firm-Level Data", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3829822. [49]

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. [4]

Santarelli, E., J. Staccioli and M. Vivarelli (2022), "Automation and related technologies: a mapping of the new knowledge base", *The Journal of Technology Transfer*, https://doi.org/10.1007/s10961-021-09914-w. [16]

Squicciarini, M. and H. Nachtigall (2021), "Demand for AI skills in jobs: Evidence from online job postings", *OECD Science, Technology and Industry Working Papers* 3, https://doi.org/10.1787/3ed32d94-en. [8]

Tambe, P. et al. (2020), *Digital Capital and Superstar Firms*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w28285. [30]

Webb, M. (2019), "The Impact of Artificial Intelligence on the Labor Market", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3482150. [21]

Webb, M. et al. (2018), *Some Facts of High-Tech Patenting*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w24793. [15]

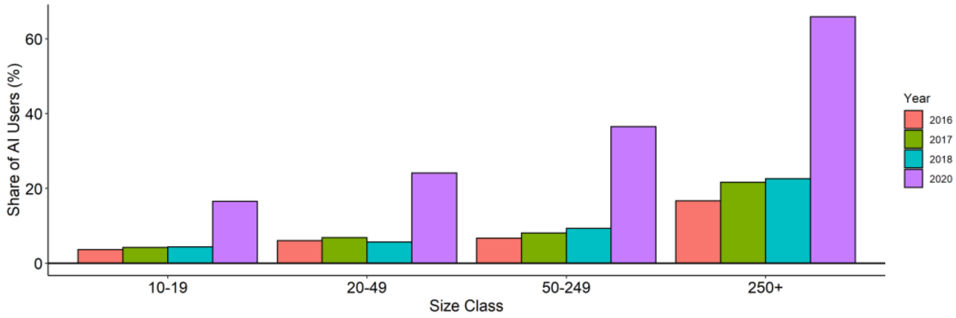
Zolas, N. et al. (2020), *Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w28290. [2]

Annex A. Additional figures and regression tables

Figure A A.1. Share of AI users by size class and year

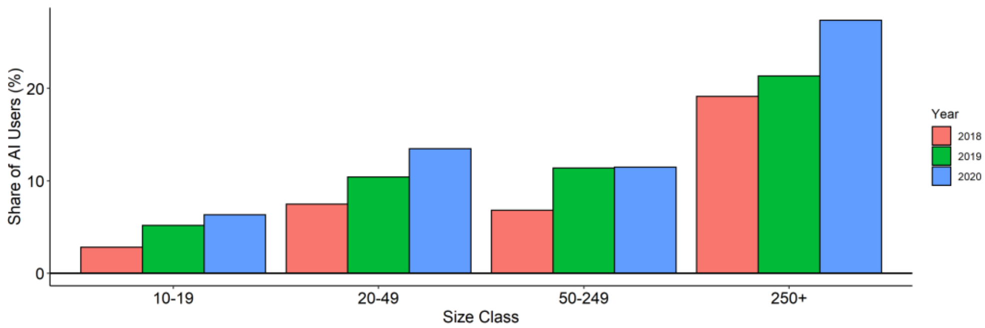
Denmark

Weighted results



Switzerland

Weighted results



Notes: This figure reports the share of AI users by size class over time for Denmark and Switzerland. Size classes encompass 4 categories: between 10 and 19 persons engaged, between 20 and 49 persons engaged, between 50 and 249 persons engaged, and 250 or more persons engaged. Results are weighted. Owing to methodological differences, figures may deviate from officially published national statistics.
Sources: Denmark - ICT Use in Enterprises; Switzerland - KOF Enterprise Panel.

Table A A.1. Estimation results for the baseline adoption regressions (cf. Figure 5)

	Belgium	Denmark	France	Germany	Israel	Italy	Japan	Korea	Portugal	Switzerland
Size class 20-49	0.0531***	0.0329***	-0.00122	0.0156	0.0218*	0.00887	0.00955	0.00158	-0.00404	0.0365**
	(0.0180)	(0.00651)	(0.0101)	(0.012)	(0.0128)	(0.0109)	(0.0112)	(0.00383)	(0.0222)	(0.0168)
Size class 50-249	0.0829***	0.0778***	0.0223*	0.0199*	0.0147	0.0420***	0.0309***	0.0128***	0.0546***	0.0448**
	(0.0186)	(0.00656)	(0.0118)	(0.0111)	(0.0133)	(0.0109)	(0.00944)	(0.00344)	(0.0211)	(0.0180)
Size class 250+	0.332***	0.244***	0.0953***	0.104***	0.0641***	0.190***	0.151***	0.0496***	0.133***	0.182***
	(0.0270)	(0.0110)	-0.0129	(0.0202)	(0.0153)	(0.0126)	(0.0117)	(0.00411)	(0.0240)	(0.0236)
Age class 6-10	0.0701**	-0.0291***	-0.0402*		0.0119		0.0550**	-0.0166***	-0.0274	-0.0212
	(0.0276)	(0.0106)	(0.0233)		(0.0245)		(0.0233)	(0.00545)	(0.0591)	(0.0551)
Age class 11+	0.0376**	-0.0461***	-0.0526***		-0.0116		0.0621***	-0.0175***	-0.00285	-0.0227
	(0.0172)	(0.00890)	(0.0204)		(0.0160)		(0.0185)	(0.00494)	(0.0536)	(0.0479)
Observations	2,628	15,960	8,981	3,054	1,987	15,557	10,854	38,629	3,772	4,248
R-squared	0.136	0.151	0.032	0.0489	0.244	0.032	0.077	0.065	0.041	0.121
Industry Fixed Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Eff.	No	Yes	No	No	No	No	No	Yes	No	Yes

Notes: This table reports the main estimation results of the baseline adoption regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, Portugal, and Switzerland. The baseline adoption regression is a linear probability model that employs the AI use dummy as dependent variable and includes size and age classes as main independent variables. Each regression includes 2-digit sector and, upon availability, year fixed effects. The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland, and are unweighted for Germany and Korea. Coefficients for variable "age = missing" are not reported for France, Israel, Japan, Korea, Portugal, and Switzerland. Regression constant is also not reported. Robust standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1.

Sources: AI diffuse elaborations based on: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

Table A A.2. Estimation results of the extended adoption regressions (cf. Figure 6)

	Belgium	Denmark	France	Germany	Israel	Italy	Japan	Korea	Portugal	Switzerland
Size class 20-49	0.0337*	0.0289***	-0.0132	0.0131	0.0132	0.00656	0.00501	-0.000548	-0.0199	0.0226
	(0.0173)	(0.00815)	(0.0101)	(0.0153)	(0.0134)	(0.0106)	(0.0108)	(0.00373)	(0.0220)	(0.0195)
Size class 50-249	0.0359*	0.0450***	-0.0138	-0.00571	-0.00490	0.0375***	0.0175*	0.00561*	0.0167	0.0286
	(0.0189)	(0.00894)	(0.0130)	(0.0139)	(0.0142)	(0.0109)	(0.00981)	(0.00329)	(0.0228)	(0.0232)
Size class 250+	0.216***	0.169***	0.0242	0.0949***	0.0157	0.181***	0.121***	0.0330***	0.0764***	0.109***
	(0.0293)	(0.0155)	(0.0170)	(0.0260)	(0.0229)	(0.0128)	(0.0131)	(0.00383)	(0.0273)	(0.0320)
Age class 6-10	0.0560**	-0.0190	-0.0412*		0.0103		0.0564**	-0.0150***	-0.0396	-0.108
	(0.0266)	(0.0129)	(0.0230)		(0.0248)		(0.0235)	(0.00527)	(0.0615)	(0.0792)
Age class 11+	0.0259	-0.0428***	-0.0515**		-0.0170		0.0584***	-0.0156***	-0.0162	-0.117*
	(0.0170)	(0.0108)	(0.0200)		(0.0165)		(0.0194)	(0.00477)	(0.0559)	(0.0708)
Ultra-Fast Broadband (>= 100 Mbits/sec)	0.0240*		0.0334**		0.00554	0.00528			0.0129	
	(0.0126)		(0.0144)		(0.0138)	(0.00905)			(0.0251)	
Cloud Adopter		0.0465***			0.0141	0.0319***	0.100***	0.223***		0.0257
		(0.00665)			(0.00922)	(0.00853)	(0.0156)	(0.0107)		(0.0186)
ICT Specialists		0.0986***	0.0390**		0.0530**					0.0780***
		(0.0136)	(0.0152)		(0.0215)					(0.0216)
ICT Training (for other employees)		0.0366**	0.0275**		0.0455					
		(0.0155)	(0.0126)		(0.0403)					
No. of Digital Tech	0.371***		0.0789***						0.156***	
	(0.0380)		(0.0178)						(0.0348)	
Exporter				0.0309**						
				(0.0150)						
Skilled Employees				0.0299						
				(0.0250)						
Training for Employees				0.0218*						
				(0.0118)						
Financially Constrained				-0.0215						
				(0.0327)						
Innovator				0.0450***						
				(0.0102)						
Observations	2,628	11,597	8,981	3,054	1,987	15,554	10,840	38,629	3,733	2,620
R-squared	0.206	0.188	0.043	0.271	0.261	0.036	0.116	0.146	0.057	0.120
Industry Fixed Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Eff.	No	Yes	No	No	No	No	No	Yes	No	Yes

Notes: This table reports the main estimation results of the extended version of the adoption regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, Portugal, and Switzerland. The adoption regression is a linear probability model that employs the AI use dummy as dependent variable and includes size and age classes, and other complementary factors as main independent variables. Complementary factors change across countries and mainly include ICT skills (ICT specialists and training), digital infrastructure (use of ultra-fast broadband connection), digital capabilities (cloud computing use and number of other digital technologies). Each regression includes 2-digit sector and, upon availability, year fixed effects. The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, Portugal, and Switzerland, and are unweighted for Germany and Korea. Coefficients for variable "age = missing" are not reported for France, Israel, Japan, Korea, Portugal, and Switzerland. Regression constant is also not reported. Robust standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1.

Sources: AI diffuse elaborations based on: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Portugal - Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE); Switzerland - KOF Enterprise Panel.

Table A A.3. Estimation results of the baseline productivity regressions (cf. Figure 8)

	Belgium	Denmark	France	Germany	Israel	Italy	Japan	Korea	Switzerland
AI Adoption	0.338***	0.0869***	0.0642**	0.0985*	0.0656	0.146***	0.0736	0.176***	0.0383
	(0.0980)	(0.0268)	(0.0301)	(0.0506)	(0.219)	(0.0491)	(0.128)	(0.0309)	(0.0421)
Size class 20-49	0.0966	0.0935***	0.207***	0.102***	0.0923	0.145***	-0.0171	-0.213***	-0.0369
	(0.0667)	(0.0161)	(0.0224)	(0.0374)	(0.0748)	(0.0275)	(0.0550)	(0.0432)	(0.0337)
Size class 50-249	0.0158	0.138***	0.300***	0.216***	0.152**	0.286***	0.110**	-0.395***	0.0674*
	(0.0721)	(0.0157)	(0.0279)	(0.0365)	(0.0763)	(0.0265)	(0.0454)	(0.0401)	(0.0373)
Size class 250+	0.153*	0.216***	0.365***	0.441***	-0.0154	0.311***	0.432***	-0.262***	0.155**
	(0.0924)	(0.0216)	(0.0349)	(0.0481)	(0.0892)	(0.0300)	(0.0471)	(0.0413)	(0.0612)
Age class 6-10	0.209*	0.0982***	0.103*		0.338***		0.000643	-0.0235	0.179
	(0.119)	(0.0267)	(0.0545)		(0.121)		(0.166)	(0.0295)	(0.143)
Age class 11+	0.0327	0.169***	0.184***		0.714***		0.231*	0.0482*	-0.00322
	(0.0943)	(0.0225)	(0.0495)		(0.103)		(0.137)	(0.0256)	(0.0902)
Observations	2,599	15,960	8,968	3,054	2,019	15,557	10,637	38,608	3,934
R-squared	0.369	0.401	0.375	0.271	0.307	0.485	0.395	0.438	0.478
Industry Fixed Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Eff.	No	Yes	No	No	No	No	No	Yes	Yes

Notes: This table reports the main estimation results of the baseline productivity regression for Belgium, Denmark, France, Germany, Israel, Italy, Japan, Korea, and Switzerland. The baseline productivity regression is an ordinary least square model that includes (log) labour productivity as dependent variable and AI use, size, and age classes as main independent variables. Each regression also controls for sector and, upon availability, year fixed effects. The estimated regressions include 2-digit sectoral fixed effects for Belgium, Denmark, France, Germany, Italy, Japan, Korea, and Switzerland, and SNA 38 fixed effects for Israel. The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea. Coefficients for variable "age = missing" are not reported for France, Israel, Japan, Korea, and Switzerland. Regression constant is also not reported. Robust standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1.
Sources: AI diffuse elaborations based on: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Table A A.4. Estimation from the productivity regressions including the interaction between AI and size (cf. Figure 9)

	Belgium	Denmark	France	Germany	Israel	Italy	Japan	Korea	Switzerland
AI Adoption	0.389*	-0.0438	0.0898**	0.0364	-0.422	0.117	-0.108	-0.584	-0.000291
	(0.230)	(0.0601)	(0.0453)	(0.0998)	(0.644)	(0.0775)	(0.157)	(0.413)	(0.0982)
Size class 20-49	0.109	0.0772***	0.218***	0.106***	0.0893	0.143***	-0.00957	-0.204***	-0.0309
	(0.0684)	(0.0163)	(0.0236)	(0.0391)	(0.0740)	(0.0283)	(0.0553)	(0.0433)	(0.0355)
Size class 50-249	0.0217	0.118***	0.300***	0.214***	0.128*	0.284***	0.0945**	-0.402***	0.0494
	(0.0759)	(0.0156)	(0.0296)	(0.0376)	(0.0759)	(0.0270)	(0.0464)	(0.0403)	(0.0390)
Size class 250+	0.0870	0.174***	0.338***	0.415***	-0.111	0.250***	0.353***	-0.281***	0.120
	(0.0953)	(0.0217)	(0.0404)	(0.051)	(0.0891)	(0.0314)	(0.0461)	(0.0415)	(0.0728)
AI × Size class 20-49	-0.124	0.194***	-0.103	-0.0466	0.378	0.0278	-0.119	-0.136	-0.0394
	(0.274)	(0.0740)	(0.0717)	(0.130)	(0.720)	(0.121)	(0.355)	(0.444)	(0.112)
AI × Size class 50-249	-0.0685	0.194***	-0.00567	0.0571	0.806	0.0314	0.375*	0.695*	0.206
	(0.251)	(0.0668)	(0.0773)	(0.147)	(0.694)	(0.109)	(0.196)	(0.415)	(0.126)
AI × Size class 250+	0.115	0.232***	0.120*	0.213	1.306**	0.272***	0.593***	0.939**	0.176
	(0.252)	(0.0702)	(0.0713)	(0.133)	(0.658)	(0.0910)	(0.166)	(0.416)	(0.134)
Age class 6-10	0.209*	0.0966***	0.104*		0.340***		0.00488	-0.0271	0.177
	(0.120)	(0.0266)	(0.0545)		(0.120)		(0.166)	(0.0294)	(0.142)
Age class 11+	0.0321	0.166***	0.184***		0.711***		0.238*	0.0446*	-0.0103
	(0.0948)	(0.0224)	(0.0494)		(0.103)		(0.136)	(0.0255)	(0.0899)
Observations	2,599	15,960	8,968	3,054	2,019	15,557	10,637	38,608	3,934
R-squared	0.370	0.402	0.375	0.271	0.310	0.486	0.397	0.439	0.480
Industry Fixed Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Eff.	No	Yes	No	No	No	No	No	Yes	Yes

Notes: This table reports the main estimation results of the productivity regression encompassing the AI-size interaction terms for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, and Switzerland. This productivity regression is an ordinary least squares model that includes (log) labour productivity as dependent variable and AI use, size and age classes and the interaction terms between AI and size classes as main independent variables. Each regression controls for 2-digit sector and, upon availability, year fixed effects. The estimated regressions include 2-digit sectoral fixed effects for Belgium, Denmark, France, Germany, Italy, Japan, Korea, and Switzerland, and SNA 38 fixed effects for Israel. The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea. All Coefficients for variable "age = missing" are not reported for France, Israel, Japan, Korea, and Switzerland. Regression constant is also not reported. Robust standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1.
Sources: AI diffuse elaborations based on: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Table A A.5. Estimation of the extended productivity regressions including the complementary factors (cf. Figure 10)

	Belgium	Denmark	France	Germany	Israel	Italy	Japan	Korea	Switzerland
AI Adoption	0.262**	0.0588**	0.0272	0.0205	-0.0590	0.0748	-0.0826	0.0162	-0.0248
	(0.102)	(0.0287)	(0.0298)	(0.0515)	(0.227)	(0.0482)	(0.130)	(0.0348)	(0.0448)
Size class 20-49	0.0773	0.0828***	0.167***	0.0255	0.0148	0.110***	-0.0233	-0.217***	-0.0454
	(0.0666)	(0.0187)	(0.0223)	(0.0477)	(0.0749)	(0.0282)	(0.0550)	(0.0432)	(0.0359)
Size class 50-249	-0.0219	0.0922***	0.188***	0.0953**	-0.00240	0.214***	0.0859*	-0.402***	0.00525
	(0.0736)	(0.0190)	(0.0292)	(0.0479)	(0.0792)	(0.0276)	(0.0458)	(0.0401)	(0.0419)
Size class 250+	0.0668	0.112***	0.150***	0.308***	-0.301***	0.175***	0.380***	-0.282***	0.0223
	(0.0982)	(0.0278)	(0.0413)	(0.0580)	(0.102)	(0.0332)	(0.0493)	(0.0413)	(0.0719)
Age class 6-10	0.198*	0.0935***	0.0972*		0.326***		-0.000842	-0.0202	0.0837
	(0.118)	(0.0314)	(0.0543)		(0.122)		(0.165)	(0.0294)	(0.160)
Age class 11+	0.0254	0.165***	0.183***		0.658***		0.223	0.0508**	-0.0620
	(0.0935)	(0.0264)	(0.0494)		(0.106)		(0.137)	(0.0256)	(0.0935)
Cloud Adopter					0.233***				
					(0.0601)				
Ultra-Fast Broadband (>= 100 Mbits/sec)	0.137**		0.200***		0.218***				
	(0.0554)		(0.0363)		(0.0734)				
No. of Digital Tech	0.279**		0.282***			0.474***	0.414***	0.525***	0.306***
	(0.123)		(0.0369)			(0.0515)	(0.0958)	(0.0469)	(0.0792)
ICT specialists		0.0604**	0.0699**		0.241**				0.0888**
		(0.0274)	(0.0328)		(0.113)				(0.0378)
ICT Training (for other employees)		0.0924***	0.0662**		0.0546				
		(0.0284)	(0.0276)		(0.172)				
Training for Employees				0.0777**					
				(0.0321)					
Skilled employees				0.169***					
				(0.0603)					
Financially constrained				-0.207***					
				(0.0760)					
Innovator				0.0750*					
				(0.0417)					
Exporter				0.319***					
				(0.0417)					

	Belgium	Denmark	France	Germany	Israel	Italy	Japan	Korea	Switzerland
Observations	2,599	11,597	8,968	1,991	2,019	15,557	10,637	38,608	3,535
R-squared	0.374	0.414	0.391	0.317	0.331	0.497	0.400	0.439	0.483
Industry Fixed Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Eff.	No	Yes	No	No	No	No	No	Yes	Yes

Notes: This table reports the main estimation results of the extended version of the productivity regression for Belgium, Denmark, France, Germany Israel, Italy, Japan, Korea, and Switzerland. This productivity regression is an ordinary least squares model that includes (log) labour productivity as dependent variable and AI use, size and age classes and complementary assets as main independent variables. Each regression controls for 2-digit sector and, upon availability, year fixed effects. The estimated regressions include 2-digit sectoral fixed effects for Belgium, Denmark, France, Germany, Italy, Japan, Korea, and Switzerland, and SNA 38 fixed effects for Israel. Complementary assets change on a country basis and mainly include ICT skills (ICT specialists and training), digital infrastructure (use of ultra-fast broadband connection), digital capabilities (cloud computing use and number of other digital technologies). The estimated regressions are weighted for Belgium, Denmark, France, Israel, Italy, Japan, and Switzerland, and are unweighted for Germany and Korea. Coefficients for variable "age = missing" are not reported for France, Israel, Japan, Korea, and Switzerland. Regression constant is also not reported. Robust standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1.

Sources: AI diffuse elaborations based on: Belgium - Survey on ICT and E-commerce in Enterprises; Denmark - ICT Use in Enterprises; France - Enquête sur les Technologies de l'information et de la communication et commerce électronique (TIC); Germany – Mannheim Innovation Panel; Israel - Survey on ICT uses and Cyber Defence in Businesses; Italy - Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese; Japan - Japanese National Innovation Survey; Korea - Survey on Business Activities; Switzerland - KOF Enterprise Panel.

Annex B. Additional information about metadata and methodology

Table A B.1. List of contributors to the *AI diffuse* project

Country	Contributor(s)	Institution(s)
BELGIUM	Michel Dumont, Chantal Kegels	Federal Planning Bureau
DENMARK	Frederic Warzynski	Aarhus School of Business and Social Sciences
FRANCE	Flavio Calvino	Organisation for Economic Cooperation and Development (OECD)
GERMANY	Luca Fontanelli	University of Brescia
IRELAND	Iulia Siedschlag, Weijie Yan	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)
PORTUGAL	Natália Barbosa	University of Minho
SWITZERLAND	Mathias Beck, Johannes Dahlke, Martin Wörter, Dmitry Plekhanov	Swiss Federal Institute of Technology (ETH)

Table A B.2. Metadata information: variables

Country	**BELGIUM**	**DENMARK**	**FRANCE**	**GERMANY**	**ISRAEL**	**ITALY**	**JAPAN**	**KOREA**	**PORTUGAL**	**SWITZERLAND**
Survey name	Survey ICT and e-commerce in enterprises	ICT Use in Enterprises	Technologies de l'information et de la communication et commerce électronique (TIC)	Mannheim Innovation Panel	Survey on ICT uses and cyber defense in businesses	Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese	Japanese National Innovation Survey 2020	Survey of Business activities	Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE)	KOF Enterprise Panel, years 2018-2020
Survey year (DOI)	2021	2017, 2018, 2019, 2021	2019 (https://doi.org/10.34724/CASD.49.251.V1)	2019	2020**	2021	2020	2018, 2019, 2020	2021	2019, 2020, 2021
AI use year*	2020	2016, 2017, 2018, 2020	2018	2018	2020**	2020	2017 to 2019	2017, 2018, 2019	2020	2018, 2019, 2020
Productivity year	2020	2016, 2017, 2018, 2020	2018	2018	2019	2020***	2019	2017, 2018, 2019	2020 (preliminary)	2018, 2019, 2020

Productivity measure	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment	Turnover/employment
Firm age	YES	YES	YES	NO	YES	NO	YES	YES	YES	YES
Cloud tech.	YES	YES****	NO	NO	YES	YES	YES	YES	YES	YES
Ultra-fast Broadband	YES	NO	YES	NO	YES	YES	NO	NO	YES	NO
ICT specialist	NO	YES	YES	YES	YES	NO	NO	NO	NO	YES
ICT training (for other employees)*****	NO	YES	YES	NO	YES	NO	NO	NO	NO	NO
Other variables	-	-	-	financial constraints training for employees export process innovations	-	-	-	-	-	-
Number of other tech. (last year)	6	4	3	0	8	5	4	5	4	3*****
Other technologies (last year)	cloud, CRM, e-commerce, ERP, IoT, ML	big data, cloud, ERP, IoT	e-commerce, ERP, CRM	-	3-D printing, robots, IoT, ERP, CRM, e-commerce, big data, cloud	IoT, cloud, CRM, e-commerce, ERP	3-D printing, IoT, big data, cloud	big data, cloud, IoT, robots, 3-D printing	cloud, CRM, ERP, IoT	big data, e-commerce, robots
Country	**BELGIUM**	**DENMARK**	**FRANCE**	**GERMANY**	**ISRAEL**	**ITALY**	**JAPAN**	**KOREA**	**PORTUGAL**	**SWITZERLAND**

Notes: *In most countries, surveys have been administered in the beginning of year *t*. Consequently, AI use can be assumed to largely reflect patterns in year *t-1*. **For Israel, the survey was administered between July 2020 and March 2021. ***For Italy, the productivity variable relies on 2019 data in case of missing employment in 2020. ****For Denmark, the cloud variable is not available in 2018. ***** For Israel, ICT training refers to firms providing any type of training to develop ICT related skills of the persons employed. For France and Denmark, ICT training refers to firms providing ICT training for other (non-ICT) employees. ******For the years 2019 and 2020, Switzerland has the following 8 technological variables available: 3-D printing, robots, IoT, ERP, CRM, e-commerce, big data, cloud.

Table A B.3. Metadata information: summary and regression details

Country	BELGIUM	DENMARK	FRANCE	GERMANY	ISRAEL	ITALY	JAPAN	KOREA	PORTUGAL	SWITZERLAND
Weighted results	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES
Deflated productivity	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Surveyed units	enterprises with 2 or more employees*	enterprises with at least 10 persons employed	enterprises with at least 10 persons employed	enterprises with at least 10 persons employed-	enterprises with at least 10 persons employed	enterprises with 10 or more persons employed	enterprises with 10 or more persons employed	Active corporations with at least 50 full-time employees and 300 million KRW or more capital stock.** Survey unit: Establishment	enterprises with 10 or more persons employed	enterprises with 5 or more employees*
Sectors included	NACE Rev. 2: C, D, E, F, G, H, I, J, L, M, N; 95.1	NACE Rev. 2: C, D, E, F, G, H, I, J, L, M, N; 95.1	NACE Rev. 2: C, D, E, F, G, H, I, J, L, N; 69-74; 95	NACE Rev. 2: 5-33, 35-39, 46, 49-53, 58-66, 69, 70.2, 71-74, 78-82	ISIC Rev. 4: B, C, D, E, F, G, H, I, J, M, L, N	NACE Rev. 2: C, D, E, F, G, H, I, J, L, M, N; 95.1	ISIC Rev. 4: A, B, C, D, E, F, G, H, I, J, K, L, M, N (sectors reported based on conversion from JSIC)	2-digit KSIC (Korean Standard Industrial Classification) converted to ISIC Rev. 4. All Industries.	NACE Rev. 2: C, D, E, F, G, H, I, J, L, M, N; 95.1	NACE Rev. 2: 10-27, 261-264, 2651, 266-268, 33, 325, 2652, 29-31, 321-324, 329, 35-39, 41-43, 45-47, 49-53, 55-56, 58-66, 68-74, 77, 79-82, 95-96

Notes: *micro firms (<10 employees) are excluded when computing summary statistics and regressions. **For Korea, the surveys also target enterprises in the 'Wholesale and Retail Trade" sectors, service industries and other service industries, with capital stock of 1 billion won or more even though they have 49 full-time employees or less.

Table A B.4. AI definitions across surveys and AI use questions

Country	Survey name	AI definition	AI use: survey question and options
BELGIUM*	Survey ICT and e-commerce in enterprises	Artificial intelligence refers to 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, etc.; or embedded in devices, e.g.: – autonomous robots for warehouse automation or production assembly works; – autonomous drones for production surveillance or parcel handling, etc.	Does your enterprise use any of the following Artificial Intelligence technologies? AI use is related to the selection of any of the following options: "a) Technologies performing analysis of written language (text mining), b) Technologies converting spoken language into machine-readable format (speech recognition), c) Technologies generating written or spoken language (natural language generation), d) Technologies identifying objects or persons based on images (image recognition, image processing), e) Machine learning (e.g. deep learning) for data analysis, f) Technologies automating different workflows or assisting in decision making (Artificial Intelligence based software robotic process automation, g) Technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, selfdriving vehicles, autonomous drones)".
DENMARK	ICT Use in Enterprises*	Artificial intelligence refers to 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, etc.; or embedded in devices, e.g.: – autonomous robots for warehouse automation or production assembly works; – autonomous drones for production surveillance or parcel handling, etc.***	Does your enterprise use any of the following Artificial Intelligence technologies? AI use is related to the selection of any of the following options: "a) Technologies performing analysis of written language (text mining), b) Technologies converting spoken language into machine-readable format (speech recognition), c) Technologies generating written or spoken language (natural language generation), d) Technologies identifying objects or persons based on images (image recognition, image processing), e) Machine learning (e.g. deep learning) for data analysis, f) Technologies automating different workflows or assisting in decision making (Artificial Intelligence based software robotic process automation, g) Technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, selfdriving vehicles, autonomous drones)".***
FRANCE	Technologies de l'information et de la communication et commerce électronique (TIC)	*L'intelligence artificielle désigne, sous un terme unique, l'ensemble des technologies visant à réaliser par l'informatique des tâches cognitives traditionnellement effectuées par l'humain : reconnaissance vocale, biométrie, reconnaissance d'images, aide à la décision, etc.*	*En 2018, votre entreprise a-t-elle eu recours à des logiciels et/ou des équipements intégrant des technologies d'intelligence artificielle?* AI use is related to the selection of any of the following options: *1) Ces logiciels et/ou équipements ont été développés principalement par les employés de votre entreprise (y compris ceux provenant de la maison-mère ou de filiales). 2) Ces logiciels et/ou équipements ont été développés principalement par un prestataire externe, pour répondre spécifiquement aux besoins de votre entreprise. 3) Ces logiciels et/ou équipements font partie d'offres "sur étagère" de fournisseurs.*
GERMANY	Mannheim Innovation Panel (MIP)	Artificial Intelligence (AI): a method of information processing that allows computers to autonomously solve problems.	Does your enterprise use Artificial Intelligence methods? *Yes/No option*
ISRAEL	Survey on ICT uses and cyber defense in businesses	Artificial Intelligence 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	Does your enterprise use AI technologies and/or services? *Yes/No option*

		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.	
ITALY*	Rilevazione sulle tecnologie dell'informazione e della comunicazione (ICT) nelle imprese	Artificial intelligence refers to 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, etc.; or embedded in devices, e.g.: – autonomous robots for warehouse automation or production assembly works; – autonomous drones for production surveillance or parcel handling, etc.	Does your enterprise use any of the following Artificial Intelligence technologies? AI use is related to the selection of any of the following options: “a) Technologies performing analysis of written language (text mining), b) Technologies converting spoken language into machine-readable format (speech recognition), c) Technologies generating written or spoken language (natural language generation), d) Technologies identifying objects or persons based on images (image recognition, image processing), e) Machine learning (e.g. deep learning) for data analysis, f) Technologies automating different workflows or assisting in decision making (Artificial Intelligence based software robotic process automation, g) Technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, selfdriving vehicles, autonomous drones)”.
JAPAN	Japanese National Innovation Survey 2020	Machine learning (AI) 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 artificial intelligence (AI).	Section “Usage of digitalisation (during the three years 2017 to 2019)” Please tick (✓) all boxes □ where they are applicable as the purpose of usage in each of the digitalisation [a] to [e]. However, if there is nothing applicable, please tick the box “Not used” only. AI use is related to the selection of Option [d] “Machine learning (AI)”, with any of the following purposes of usage: “Improving existing goods or services”, “Introducing new goods or services”, “Process automation or cost reduction”, ‘Data analysis and collection, or decision support”, “Others”.
KOREA	Survey of Business activities	AI is a technology that mimics humans by learning, reasoning, perceiving, and understanding the natural language based on the computer programs.	Do you utilize AI in your business? *Yes/No option*
PORTUGAL*	Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas (IUTICE)	Artificial intelligence refers to 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, etc.; or embedded in devices, e.g.: – autonomous robots for warehouse automation or production assembly works; – autonomous drones for production surveillance or parcel handling, etc.	Does your enterprise use any of the following Artificial Intelligence technologies? Options are: “a) Technologies performing analysis of written language (text mining), b) Technologies converting spoken language into machine-readable format (speech recognition), c) Technologies generating written or spoken language (natural language generation), d) Technologies identifying objects or persons based on images (image recognition, image processing), e) Machine learning (e.g. deep learning) for data analysis, f) Technologies automating different workflows or assisting in decision making (Artificial Intelligence based software robotic process automation, g) Technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, selfdriving vehicles, autonomous drones)”.
SWITZERLAND	KOF Enterprise Panel, years 2018-2019**	*L'intelligence artificielle (IA) se définit comme la capacité des machines et systèmes à acquérir et appliquer des connaissances et à se comporter de manière intelligente. Cette IA ou ces technologies basées sur le cognitif aident les ordinateurs et les humains à interagir, comprendre et apprendre afin qu'ils puissent accomplir une multitude de*	*Votre entreprise utilise-t-elle des systèmes basés sur l'intelligence artificielle?*** *Oui/Non* option

		tâches cognitives qui requièrent normalement l'intelligence humaine, comme la perception visuelle, la reconnaissance vocale, la prise de décision, la traduction inter-langues et la capacité à déplacer et manipuler des objets en conséquence. Les systèmes intelligents exploitent une combinaison d'analyse de big data, d'informatique en nuage, de communication M2M et d'Internet des objets.	

Notes: *The reported definition is the one used in the "General outline of the survey" of the "Community Survey on ICT usage and e-commerce in enterprises" (2021) (in "Module F"). **The definition of AI is not available in the 2020 questionnaire. **For Switzerland, the AI use question is homogeneous across surveys. ***For Denmark, the AI definitions and AI use questions in the 2017, 2018, 2019 surveys are broadly similar to those in the 2021 survey, although more focused on artificial intelligence and machine learning.

Table A B.5. "TIC" sectoral classification

Group of sectors	Sector code (ISIC rev.4)
Manufacturing & Utilities	10-39
Construction	41-43
Wholesale & Retail	45-47
Transport & Storage	49-53
Accommodation & Food	55-56
Information & Communication	58-63, 951
Professional & Scientific Activities	69-75
Administrative & Real Estate	68; 77-82