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Digital adoption during COVID-19: Cross-country evidence from microdata

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The COVID-19 pandemic caused an unprecedented global economic downturn, affecting productivity, business dynamics, and digital technology adoption. Using a comprehensive commercial database from Spiceworks Ziff Davis, this study analyses the firm-level drivers of digitalisation during the pandemic across 20 European countries. The findings show that a considerable share of firms introduced new digital technologies during the COVID-19 crisis. Notably, firms that were larger, more digitalised, and more productive before the pandemic were more likely to introduce new digital technologies in 2020 and 2021. Additionally, firms with pre-existing complementary technologies had a higher likelihood of adopting digital applications that gained momentum during the pandemic (such as digital commerce, collaborative software, cloud, and analytics). These patterns may increase polarisation among the best-performing firms and the rest of the business population. Public policy can play a key role in fostering an inclusive digital transformation in the post-pandemic era.

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Executive Summary

The COVID-19 pandemic caused an unprecedented global economic downturn, affecting productivity, business dynamics, and digital technology adoption. This study utilises a comprehensive commercial database with information on digital products installs, Information Technologies (IT) expenditures and firm financials from Spiceworks Ziff Davis to analyse the digitalisation patterns during the COVID-19 pandemic across 20 European countries (Austria, Belgium, Czechia, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, the United Kingdom), focusing on the period between 2019 and 2021.

The analysis reveals that the pandemic has accelerated the introduction of digital technologies by firms, both in novel technology classes as well as in terms of upgrading existing ones. Indeed, a significant share of firms introduced new digital technologies during the pandemic, with the highest shares among firms introducing "IT Systems" (about 80%), followed by "Digital Sales" and "Digital Workplace" (about 50%). Almost all firms installing products related to "IT Systems" upgraded their technological base, while "Advanced Applications and Analytics" had the highest number of new adopters.

Pre-existing digital and productivity gaps among firms, as well as their characteristics, significantly influenced firms' ability to react to the crisis and, relatedly, to adopt new digital technologies. Indeed, firms that were more digital, more productive, and larger before COVID-19 were those increasing more significantly their digital technology installs during the pandemic.

In particular, pre-existing digital capabilities have been pivotal. In order to further analyse those, the study uses a novel methodology – leveraging network analysis – that uncovers the existing interdependencies and complementarities among digital technologies, and the potential sequentiality in their adoption. Based on this methodology, the analysis shows that the ex-ante presence of *supporting* technologies – those underpinning and enabling the deployment of more complex digital solutions – fostered the adoption of key applications during the pandemic, like "Analytics", "Cloud", "Digital Commerce", and "Collaborative Software". These applications experienced the highest growth in adoption among the firms analysed, with "Digital Commerce" diffusion almost doubling over the pandemic, followed by "Analytics", "Collaborative Software", and "Cloud" (increasing by about 50%). The analysis also suggests that during the pandemic key digital applications were more likely adopted in bundle rather than in isolation.

These findings have policy interest, indicating that the digital adoption dynamics during the COVID-19 pandemic may have increased polarisation between highly digital, top-performing firms and the rest of the business population. This underscores the role of policymakers in promoting an inclusive digital transformation in the post-pandemic era. A comprehensive policy mix affecting firms' incentives and capabilities and capturing synergies across different policy areas – including a focus on human capital, digital capabilities, digital infrastructure, framework conditions, and regulation – appears crucial in this respect.

1 Introduction

The COVID-19 pandemic triggered a major global economic downturn, unprecedented since World War II. During the crisis, large portions of economic activity were intermittently restricted over months to limit the spread of the virus, with consequences on both the demand and supply sides of the economy. Relatedly, the crisis caused a significant increase in economic uncertainty, with negative consequences for corporate investment, hirings, and durable goods consumption, as well as pressures on global value chains (GVCs), with relevant cost-push inflationary implications.

Business firms had to adapt to the unexpected COVID-19 shock and reorganise their production processes as well as their interaction with customers and suppliers. In turn, the changes induced by the crisis had relevant effects on, e.g., inter- and intra-sectoral reallocations, firm entry and exit, and worked as a catalyst for an acceleration in the adoption of digital technologies and of teleworking practices (Schwellnus, Haramboure and Samek, 2023[1]; Criscuolo et al., 2021[2]; OECD, 2021[3]).

Digital and communication technologies and the use of teleworking provided an unexpected source of resilience, avoiding the loss of GDP of magnitude estimated to be approximately 10 log points of GDP between Q1 and Q2 of 2020 in selected OECD nations (Eberly, Haskel and Mizen, 2021[4]). This underscores the crucial importance of digital transformation in bolstering resilience throughout the pandemic.

The aim of this paper is to discuss how digitalisation patterns have evolved over the COVID-19 pandemic at a level of granularity not yet explored in the literature, focusing in particular on the role of pre-crisis firm characteristics and discussing relevant implications for the post-pandemic recovery.

Leveraging unique cross-country data on digital products installs by firms linked to IT expenditures and firm financials, the evidence uncovered in the analysis suggests that the adoption of digital technologies has rapidly accelerated during the pandemic. Indeed, a significant share of the firms analysed introduced new digital technologies over the crisis, with the highest shares among firms introducing “IT Systems” (about 80%), followed by “Digital Sales” and “Digital Workplace” (about 50%). Almost all firms installing products related to “IT Systems” upgraded their technological base, while “Advanced Applications and Analytics” had the highest number of new adopters. However, pre-existing gaps have played an important role in firms’ ability to react to the crisis. Indeed, firms that were more productive, larger, and more digital before COVID-19 were those increasing more their use of digital technologies in the aftermath of the pandemic shock. Notably, firms with higher pre-pandemic digitalisation levels (as proxied by a novel digitalisation index computed for the analysis) were overall better equipped to introduce new digital products over the crisis. Additionally, firms that already had complementary technologies in place before COVID-19 had higher likelihoods of adopting (for the first time) digital applications that gained momentum during the pandemic, such as “Analytics”, “Cloud”, “Digital Commerce”, and “Collaborative Software” (“Digital Commerce” diffusion almost doubled over the pandemic while “Analytics”, “Collaborative Software”, and “Cloud” increased by about 50%). These patterns may reinforce winner-takes-most dynamics and increase the polarisation among the best-performing firms and the rest of the business population, a phenomenon already documented before the crisis. In this context, public policy can play a key role to boost an inclusive digital transformation in the post-pandemic era.

A broad policy mix affecting firms’ incentives and capabilities, and capturing synergies across policy areas, is key to foster an inclusive digital transformation, even more so after the COVID-19 crisis. Such mix may include both demand-side measures raising awareness about new technologies and developing absorptive capacity, and supply-side measures – fostering competition and reducing barriers to the entry of new firms, providing relevant credit tools, improving knowledge production and sharing, strengthening the foundation of digital infrastructure and skills, and addressing the new regulatory challenges of the digital economy. These policies may allow digital technology diffusion and its returns to be more widespread across firms and sectors, ensuring an inclusive digital transformation in the aftermath of COVID-19.

The remainder of the work is organised as follows. Section 2 reviews the background literature on how the COVID-19 pandemic has affected digital technology adoption and diffusion by firms. Section 3 describes the data and methodology. Section 4 focuses on the results of the empirical analysis, while Section 5 concludes discussing the main takeaways and policy implications.

2 Background literature

Digitalisation has been profoundly changing how businesses operate and compete in today's global economy. Continual improvements in information and communication technologies (ICTs) and in new advanced digital technologies – such as artificial intelligence (AI) – are influencing firms' production processes, channels of interaction with customers and suppliers, organisational structures, as well as demand for skills. For example, the progress in communication technologies has allowed companies to gain greater access to international markets and to reorganise their production within GVCs. Growing real-time communication across devices has been easing remote control of production, for example via the Internet of Things (DeStefano, De Backer and Moussiegt, 2017[5]). More recently, developments in AI are allowing firms to scale up internal operations and leverage the potential of big data for decision making (Agrawal, Gans and Goldfarb, 2022[6]).

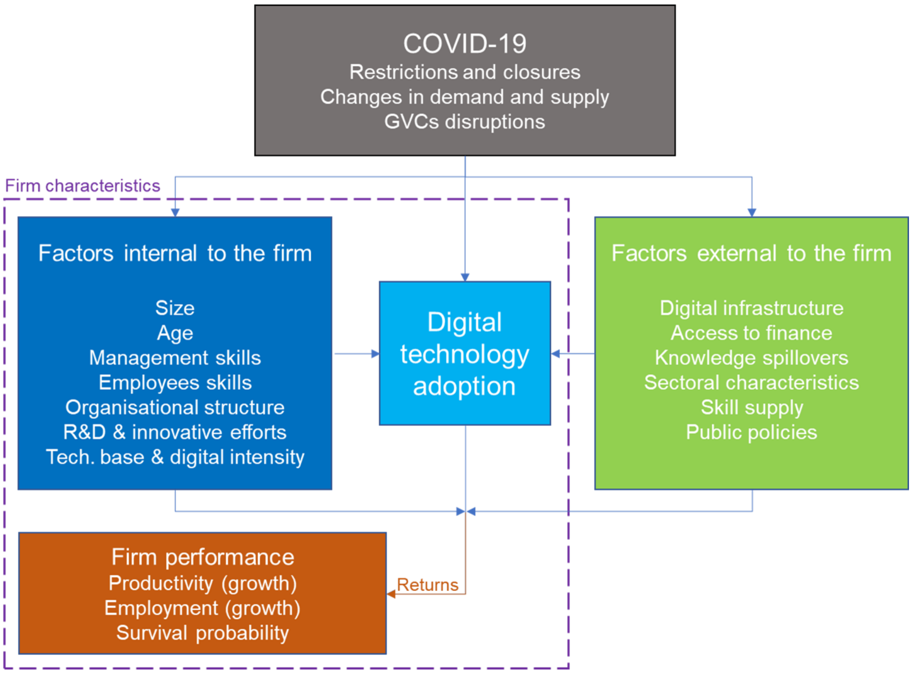
Nonetheless, a large body of literature has documented wide heterogeneity in the adoption and diffusion of digital technologies across firms, as well as in returns to adoption. This may be due, e.g., to different degrees of firms' absorptive capacity and digital capabilities, as well as to economies of scale and network externalities typical of the use of certain digital technologies [see for example Calvino et al., (2022[7]) focusing on Italy].

During the pandemic, digital technologies have been crucial in allowing companies to continue producing and selling, and people to continue working. Yet, the extent to which pre-existing digital and productivity gaps have interacted with the pandemic shock in shaping digital technology diffusion patterns is still under debate. This is particularly true if one is interested in cross-country empirical evidence on a wide range of digital technologies. To tackle these issues, the next subsection presents a framework to analyse the factors influencing digital technology adoption (and its returns) in relation to the disruptions caused by the COVID-19. Later, Subsection 2.2 reviews existing evidence about the diffusion of digital technologies, also including teleworking, during the pandemic.

2.1. Firm characteristics and the digital transformation: a conceptual framework over the COVID-19 pandemic

The decision to adopt digital technologies and the ex-post returns to adoption may be influenced by several factors. Figure 1 shows a conceptual framework, which builds upon the work by Calvino et al. (2022[7]), aimed at disentangling the factors that may foster or hinder digital adoption by firms and its relation to firm performance (notably in terms of productivity returns), considering digital technology adoption as a mediating element. These factors can be grouped into those *internal* to firms and *external* ones. Internal factors refer to firm characteristics and firm capabilities. The former group includes, e.g., firm size and age, while firm capabilities include those related to human capital – such as the quality of workforce and management – and those related to technology – including other technologies already in use by the firm, complementary intangible assets such as R&D or intellectual property. External factors focus on, e.g., the availability of fast broadband infrastructure, technology spillovers arising at the sectoral or geographical level, access to finance, the quality of the education system and its ability to supply digital skills, and public policies aimed at fostering firm digital investments.[1]

Figure 1. Drivers and returns of digital adoption at the firm-level



Note: The figure focuses on the drivers and returns of digital technology adoption and how drivers interact with returns. The figure does not display, e.g., feedback loops from firm performance to factors internal to the firm and digital technology adoption.
Source: authors' elaboration based on Calvino et al. (2022[7]).

A number of studies have pointed out how larger and more productive firms, with better management and digital capabilities, are more likely to adopt digital technologies. For example, Calvino et al. (2022[7]), analysing the Italian context, find a positive role of, e.g., managerial skills and use of complementary technologies on the adoption of digital technologies. This is in line with other studies: for example, Bloom, Sadun and Van Reenen (2012[8]) find that subsidiaries of US multinationals in Europe use IT capital more efficiently than domestic firms, as a result of better management practices. Queiró (2016[9]) finds that manager education positively affects firm productivity, and this effect is channelled by improved use of new technologies. Acemoglu, Lelarge and Restrepo (2020[10]) and Deng, Plümpe and Stegmaier (2020[11]), focusing on robotics, find that adoption is highly skewed and mostly adopted by just few large firms. Calvino and Fontanelli (2023[12]),[2] focusing on AI, show that AI is more widely used across large firms[3] and that several complementary assets and skills are significantly linked to AI use. In turn, this evidence points to the fact that although adoption of some digital technologies – especially the most advanced ones – is relatively low and skewed towards larger firms, it may have a sequential hierarchical pattern, with more sophisticated technologies frequently adopted only after more basic applications [e.g., Zolas et al., (2020[13])]. Similarly, a large body of literature has documented the relevance of digital infrastructure (Calvino and Fontanelli, 2023[12]), access to finance (Bircan and De Haas, 2020[14]; Benfratello, Schiantarelli and Sembenelli, 2008[15]), as well as knowledge spillovers at the sectoral level (Malerba, 2002[16]) in enabling the diffusion of innovation and the adoption of digital technologies, and in fostering productivity (Akerman, Gaarder and Mogstad, 2015[17]; Bertschek and Niebel, 2016[18]).

A successful combination of firm characteristics and capabilities, low external barriers to competition and growth, together with, e.g., relevant digital skills in local labour markets, would not only positively affect digital technology adoption, but also returns to adoption and firm efficiency. Indeed, digital technologies such as software and other intangible assets are characterised by features such as scalability, synergies, non-rivalry and non-excludability (Haskel and Westlake, 2017[19]). These should allow firms to reduce costs of search, replication, transportation, tracking, and verification (Goldfarb and Tucker, 2019[20]) and thus improve processes, automate routine tasks, and reduce costs of interactions with suppliers and customers, possibly increasing firm productivity (Bartel, Casey and Kathryn, 2007[21]; Akerman, Gaarder and Mogstad, 2015[17]).

Nonetheless, several contributions have shown how returns to digital technology adoption are not homogeneous across firms. Indeed, digital technologies require absorptive capacity – i.e., the ability of firms to recognise the value of new information and technologies, assimilate and exploit them commercially (Cohen and Levinthal, 1990[22]) – to be effectively used. Also, digitalisation requires increasingly sophisticated complementary investments in knowledge and intangible assets. Intangibles are scalable at low cost and non-rival, creating scale economies that may reinforce the position of leading firms and likely unleash winner-takes-most dynamics (Berlingieri et al., 2020[23]; Andrews, Criscuolo and Gal, 2016[24]). For example, scalability allows firms to replicate innovations and business models across different locations and allows larger firms to benefit relatively more from digital technologies (Brynjolfsson and Hitt, 1998[25]). Also, intangibles are characterised by large sunk costs of development and low variable costs, which tend to favour the larger players on the market (De Ridder, 2022[26]; Bajgari, Criscuolo and Timmis, 2021[27]; Calligaris, Criscuolo and Marcolin, 2018[28]). In addition, the characteristics of digital technologies might reinforce the productivity advantage of the best-performing firms, especially when intangible assets, such as software, are proprietary (Bessen, 2020[29]).

Different likelihoods of digital adoption across firms, coupled with heterogeneous returns to adoption, might result in increased divergences among the leading firms and the rest of the business population. In the last decades, a widening productivity divergence has indeed been observed across advanced economies between “leaders” and “laggards” (Andrews, Criscuolo and Gal, 2016[24]). These divergences have been related to the digital transformation, especially because digital technologies have been exploited effectively only by few firms rather than most businesses (Berlingieri et al., 2020[23]).

In this context, the developments and disruptions brought by the COVID-19 pandemic have affected both the adoption of digital technologies and their returns, possibly widening pre-existing divergences.[4] Indeed, changes in demand and supply related to restrictions and closures as well as shocks to GVCs may have interacted with pre-existing digital and productivity gaps, with ex-ante more digital and productive firms better able to cope with the pandemic shock.

2.2. Digital technologies and teleworking during the pandemic

During the pandemic, firms significantly accelerated their pace of digitalisation (Criscuolo, 2022[30]; Criscuolo et al., 2021[2]; OECD, 2021[3]). Indeed, the crisis shaped the business decisions of firms, potentially altering investment strategies and priorities in the long run. In particular, through the required sudden and far-reaching changes “imposed” on businesses to continue operating, the COVID-19 crisis resulted as a catalyst for an unexpected acceleration in the adoption of digital technologies and of remote working practices (see also Box 2.1).

For example, DeStefano and Timmis (forthcoming[31]) find that the COVID-19 led to a rapid diffusion of many digital technologies including e-commerce, online payments, general analytics and A/B testing. In particular, the authors find that e-commerce, a more basic technology, was adopted relatively more by small firms during the pandemic rather than larger firms. On the contrary, more productive firms with advanced software and cloud in place pre-pandemic were more likely to adopt A/B testing, a technology with a higher level of complexity. Overall, the authors find that COVID-19 led to a broad adoption of more basic technologies, while the diffusion of sophisticated technologies tended to be confined to a minority of advanced firms. Similarly, Ragoussis and Timmis (2023[32]) focusing on online technology diffusion induced by the COVID-19, using a database that comprises several millions of active websites and thousands of technologies, find that, over 2020, there was rapid adoption of e-commerce, online payments, and digital advertising technologies around the world. In particular, the authors find that the pandemic alone accounted for about a quarter of the overall increase in e-commerce or e-payments usage over the year 2020.

Riom and Valero (2020[33]) and Riom, Valero and Oliveira-Cunha (2021[34]), focusing on the United Kingdom, find that a significant share of firms invested in new technologies, management practices, and digital capabilities in response to the pandemic. The authors argue that new technologies related to sales and marketing, people management and remote working (e.g., collaboration software) were highly adopted, either alone or in “bundles” with other technologies including cloud, data analytics, and cyber security. Also, the authors stress that heterogeneous patterns of diffusion during COVID-19 might increase digital gaps in the future, especially considering that more digital firms seemed to be better able to adopt new technologies. In this respect, Teruel et al (2023[35]), focusing on firms’ reaction to COVID-19 in employment in EU countries, also confirm that more digitalised firms were those increasing more their use of digital technologies. For the US, Bloom, Davis and Zhestkova (2021[36]), document a strong increase in new patent applications related to technologies that have been supporting remote work since the beginning of the pandemic.

The trends observed are consistent with detailed surveys conducted by the European Investment Bank (EIB, 2022[37]; EIB, 2023[38]), broadly focusing on EU countries. These studies indicate that, over the pandemic, there was a marked rise in the percentage of EU companies integrating advanced digital technologies into their operations. Notably, the analysis shows that firms that were already highly digitalised before the pandemic increased their investments in digital technology at a greater rate than their less digitalised counterparts.

Box 2.1. Teleworking during the pandemic

The widespread uptake of telework (remote working) practices has been one of the major changes induced by the COVID-19 pandemic. Indeed, restrictions and closures implied a sudden shock for firms' activities, and remote working has been crucial to quickly adapt and ensure some degree of continuity in business operations.

As shown by Bloom et al. (2023[39]), the share of job postings reporting remote working for one or more days per week rose by more than three times in the US and by a factor of five (or more) in Australia, Canada, New Zealand, and the United Kingdom from 2019 to early 2023.[5] The authors also report that remote working practices tend to prevail in the Finance, Insurance, Information, and Communications sectors and are positively associated with, e.g., computer use, levels of education, and earnings. A number of earlier papers found similar results, even if there is yet no consensus on exact scale of this change (Brynjolfsson et al., 2022[40]). For example, Criscuolo et al. (2021[2]) find that, on average across 25 countries, the share of regular teleworkers – workers working from home at least once per week – rose from nearly 31% before the pandemic to almost 58% during the first wave. For the EU, e.g., Eurofound (2020[41]) documents that, during the pandemic, approximately 34% of the workforce in the European Union worked exclusively from home.[6] For the US, Brynjolfsson et al. (2020[42]) found that the share of the workforce working from home rose from around 15% before the pandemic to around 50%. Crescenzi, Giua and Rigo (2022[43]) find that roughly 12% of Italian workers worked remotely during the lockdown imposed in 2020, with larger and more productive firms being more likely to adopt remote working practices. OECD (2021[3]) reports overall similar increasing patterns and documents that the switch to remote working happened more in areas with larger shares of households with broadband connection (and within those, more for workers in larger firms and those living in cities).

The two main questions related to the rise of remote working practices are if those will be (i) long-lasting and if (ii) they will ensure the same (or higher) levels of productivity for firms.

In general, there is a non-monotonic relationship between telework and productivity [as discussed, e.g., in Criscuolo et al. (2021[2])]. On the one hand, at lower levels, increased remote working is related to higher productivity because of costs savings for firms – for example, in terms of office space – as well as higher worker satisfaction and efficiency due, e.g., to reduced time for commuting. On the other hand, at higher levels, fewer face-to-face interactions on the workplace imply lower opportunities for, e.g., information sharing and learning on the job (especially for younger workers), reduced knowledge flows, limited managerial oversight, and team coordination – with overall negative implications for productivity. In turn, there seems to exist an optimal level of remote working at an intermediate level of intensity, that Behrens, Kichko and Thisse (2021[44]), Bloom, Mizen and Shivani (2021[45]) and Criscuolo et al. (2021[2]) find to lie between 1 and 3 days of remote work a week.

Several surveys conducted during the pandemic years have found positive expectations related to the continuation of remote working in the medium term. For example, for the United Kingdom, Riom and Valero (2020[33]) found that a considerable share of firms expected to maintain the process innovations – such as remote working – implemented during the pandemic [a result later confirmed from the follow-up survey presented in Oliveira-Cunha, Riom and Valero (2021[34])]. Criscuolo et al. (2021[2]) surveyed managers and employees about their expectations around working from home, finding positive expectations about the future use of remote working practices – which also aligns with evidence from Aksoy et al. (2022[46]) and Barrero et al. (2021[47]). In particular, Aksoy et al. (2022[46]) find that employers plan higher post-pandemic working from home levels in countries and regions with greater cumulative restrictions on commercial and social activities during the pandemic. Also, Bloom et al. (2023[39]) – in relation to the trends commented above – find that the share of job postings reporting remote working has not only increased, but that it is on a likely upward trajectory.

Even if results about the effect of remote working on productivity in the long-term are still mixed, possibly reflecting the role of other factors (e.g., management, skills, communications infrastructure) (Bloom, Mizen and Shivani, 2021[45]; Morikawa, 2021[48]), there is general consensus on the long-lasting nature of remote working practices, at least to some extent, following the pandemic. In turn, the observed trends and expectations on the persistent use of remote working may have a wide range of implications – e.g., for the future of organisations, the geography of work and cities, and innovation [see Criscuolo, (2022[30]) for additional discussion].

As a growing strand of the literature shows, pre-exiting levels of digitalisation not only seem to favour further digital efforts, but also the overall resilience of firms. Indeed, some contributions closely focus on returns to digital adoption during COVID-19 (see also Subsection 2.1), showing that ex-ante more digitalised firms were more resilient to the sudden shock implied by the pandemic, e.g., in terms of revenues, employment, productivity, firm dynamics, and innovative outcomes. Notably, while the role of ex-ante digitalisation for firm (performance) resilience is not the direct focus of this work, the review in Box 2.2 further highlights the role of digitalisation for economic outcomes during the pandemic, and how pre-existing digital and productivity gaps may have further increased over the crisis.

In summary, although some evidence already points to a rise in digital technology use during the COVID-19 pandemic, a closer analysis of the factors prompting this uptake appears relevant. Indeed, while a growing body of research has focused on the role of digitalisation for firm resilience over the pandemic, evidence about how ex-ante firm characteristics shaped digital efforts over the pandemic, especially in a cross-country perspective, across several digital technologies, comprehensively accounting for the interrelations and complementarities among different types of digital technologies, appears still limited.

In this context, subsequent sections will delve into how ex-ante digitalisation and particular firm characteristics (especially focusing on productivity) shaped digital diffusion trends during the pandemic – both focusing on more general technologies and on specific applications. The analysis will not only focus on overall patterns of digital transformation, but also account for the complex relations existing among different digital technologies. To shed light on these aspects, the following section will delve into the data and empirical setting employed in the subsequent analysis. Later sections discuss empirical findings, uncovered also thanks to a novel methodology identifying complementarities among digital technologies, and elaborate on their interpretation to provide policy implications.

Box 2.2. The returns to digital adoption over the COVID-19 pandemic: the role of digitalisation for firm resilience

Digital technologies are an important factor for resilience during a crisis. Research on previous recessions has shown that ICT-intensive firms were more resilient to economic shocks (Pierri and Timmer, 2022[49]) and were also more successful in introducing process innovation (Bertschek, Polder and Schulte, 2019[50]).

While the literature related to the effects of digitalisation during the COVID-19 pandemic is still emerging, there is overall consensus about the positive role of digitalisation on a range of economic outcomes.

Taking a macroeconomic perspective, Eberly, Haskel and Mizen (2021[4]) highlight how the so called "potential capital", i.e., the equipment that can be combined with labour working from home to produce output, significantly contributed to reduce the fall in GDP during the pandemic. This capital, together with the remote work it facilitated, contributed to saving about 10 log points of GDP between the first and second quarter of 2020 in a sample of OECD countries, highlighting the key role of the digital transformation for resilience during the pandemic.

Focusing on firm performance, Copestake, Estefania Flores and Furceri (2022[51])[7] and Delanote, Rudyk and Rückert (2022[52]) find that firms in industries that were more digitalised in the pre-crisis period experienced lower revenue losses following the COVID-19 recession. Similarly, Abidi, El Herradi and Sakha (2023[53]) focus on the Middle East and Central Asia region and find that, while the COVID-19 crisis has had a negative impact on firms' performance, companies that had invested in digital technologies before the crisis were significantly less affected. In particular, digitally-constrained firms in contact-intensive sectors experienced a larger decline in sales than the same companies in non-contact-intensive sectors. Relatedly, Trunschke et al. (2023[54]) show that firms with a higher pre-pandemic share of employees working from home performed better during the pandemic in terms of higher revenues and stock returns.[8] On the contrary, Costa et al. (2022[55]) argues that, in Italy, the hardest economic effects were experienced by firms with an elementary level of digitalisation and innovation. The latter result aligns with Calvino et al. (2022[7]), stressing that, in Italy, ex-ante digital firms were more likely to register an increase in revenues in 2020 relative to 2019. Overall, these results connect to the ones in Coad et al. (2023[56]), arguing that the crisis impacted negatively the growth of sales and value added of firms – especially for those at lower quantiles of the distribution.

Specifically focusing on the banking sector, Dadoukis, Fiaschetti and Fusi (2021[57]) study banks' market and accounting performance during COVID-19, showing that high-IT adopters performed better in terms of market returns, Tobin's q, and lending. In addition, higher pre-crisis IT investments were associated with more loans issued as support measures.

Focusing on Total Factor Productivity (TFP), Jaumotte et al. (2023[58]) show that firms that were ex-ante more digital resulted more resilient to the crisis. In particular, focusing on the evolution of within-firm TFP, the authors argue that TFP growth in 2021 was relatively larger for the ex-ante more digital-intensive firms. In a similar vein, Borowiecki, Giovannelli and Høj (2023[59]) find that firms that were more ICT-intensive before the pandemic experienced a smaller decline in labour productivity growth, as compared to less ICT-intensive firms in the same 2-digit level sector. This result also aligns with Oliveira-Cunha, Riom and Valero (2021[34]), that find that firms which adopted digital technologies before the crisis showed higher resilience.[9] Finally, regarding firm exit, Muzi et al. (2023[60]) find negative relationships of firm exit with digitalisation and innovation.

Focusing on employment, Oikonomou, Pierri and Timmer (2023[61]) study the role of IT as a mitigating factor for the COVID-19 shock in the US. In particular, the authors analyse the interplay between the sudden decline in mobility and unemployment at the local level, as mediated by firms' adoption of IT before the pandemic. Interestingly, the authors find that in low-IT adoption states the drop in mobility was associated to a higher rise in unemployment during the pandemic. Conversely, unemployment probability resulted lower in areas where IT was adopted more intensely by firms before the pandemic.[10] These findings are in line to the ones in Ben Yahmed, Berlingieri and Brüll, (2022[62]) – which focus on the German case – and show that digitalisation has improved the employment resilience of regions to the pandemic shock.[11] Similarly, evidence from Tereul et al. (2022[63]) shows that firms in highly digitalised sectors were less likely to reduce the number of employees, and evidence for Australia, New Zealand and the United Kingdom (Andrews, Charlton and Moore, 2021[64]) also seems to suggest that tech savvy firm were more resilient to the crisis.[12]

Lastly, focusing on innovative outcomes, Trunschke et al. (2023[54]) find that, during the pandemic, highly digitalised firms did not reduce their innovation activities as strongly as less digitalised firms. In other words, firms' pre-existing digital capabilities were beneficial for innovation activities during the COVID-19 pandemic.

Overall, the evidence points to a positive role of digitalisation in the aftermath of the COVID-19 crisis. More able to react to the sudden shock implied by the pandemic, ex-ante more digitalised firms were more resilient regarding revenues, employment, and innovative outcomes.

3 Data and methodology

This section presents the data and methodology employed to investigate the patterns of digital technology diffusion across firms during the pandemic. Subsection 3.1 focuses on the data and variables used in the analysis, while Subsection 3.2 describes the empirical approach.

3.1. Data and key variables

The commercial database used for the analysis comes from the Spiceworks Ziff Davis Aberdeen Group (formerly known as Harte Hanks). The database collects unique detailed information at the establishment level on IT usage – including both technology totals (such as the number of PCs, servers, and storage capacity) – as well as information on the digital products used (e.g., name of product, functionality, first date of adoption). This is a unique feature of this data source, which allows an unprecedented level of detail to investigate digital technology installs. In addition, the database also reports basic financials and related information (e.g., employment, turnover, sector, country, region, and presence of IT staff) as well as estimates of IT budget spending for software, hardware, and related ICT categories. Information is collected both through survey-based inquiries and web-scraping techniques, and – as typical for several commercial data sources [see, e.g., Bajgar et al. (2020[65])] – tends to overrepresent larger firms with respect to the overall business population.

The database has been extensively used for economic analysis by a number of empirical papers. A first set of research works has mainly relied on information about technology totals (e.g., number of PCs) and IT budget to derive proxies of digitalisation at the firm and establishment levels. For example, among the first papers relying on the database Bresnahan, Brynjolfsson and Hitt (2002[66]) studied complementarities among IT, workplace reorganisation, and innovation. Similarly, Brynjolfsson and Hitt (2003[67]) focused on the effects of computerisation for productivity and output growth. Both papers derived measures of IT usage through information on the PC stocks available in the database. More recently, Bloom, Sadun and Van Reenen (2012[8]) have relied on information about IT intensity (computer per worker) in relation to management practices to investigate productivity figures of multinational enterprises operating across the US and European countries. A related index has been used by De Stefano, Kneller and Timmis (2018[68]) to study the effects of heterogeneous types of ICT on firm performance in presence of new ADSL broadband technology. Similarly, Ahnert et al. (2021[69]) have used the same index to study the relation among digitalisation in the banking sector and entrepreneurship. Lastly, focusing on the pandemic period, Oikonomou, Pierri and Timmer (2023[61]) have studied the labour market implications of information technology (IT) during the COVID-19 crisis in the US, using information on IT budget per employee. A second set of contributions has used information about digital products and software contained in the database. For example, Bloom, Garicano and Sadun (2014[70]) and the above-mentioned work by De Stefano, Kneller, and Timmis (2018[68]) to have relied on information about Enterprise Resource Planning (ERP) to study organisational adaptation to new management software and determinants of adoption, respectively. DeStefano, De Backer and Moussiegt (2017[5]), studying the determinants of digital technology use by companies, relied on both information about technology totals (e.g., PCs and Pentium PCs) and digital software (such as database management applications, innovation software, security, and groupware software). More recently, Cao and Iansiti (2022[71]) have derived information on Cloud use exploiting the detailed functionality classification available in the database (e.g., information on the hardware and software components of Cloud – “Infrastructure as a Service” and “Platform as a Service”).

Overall, the database has been extensively used by the literature to derive information on ICT technologies and digital software and study a variety of research topics, ranging from the productivity effects of ICT, labour market outcomes in time of crisis, and the organisational adaptation to new digital technologies.

The current analysis uses data for the years 2019, 2020,[13] and 2021 for 20 countries in Europe. Countries included in the analysis are Austria, Belgium, Czechia, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, the United Kingdom. In particular, the study builds on a balanced panel[14] of 937 757 establishments[15] with information on digital products (see Table A A.2 in the Annex, reporting information on the main establishment characteristics).[16]

The analysis considers information on technological products installed at the establishment level.[17] The database groups related digital products into functionalities.[18] Based on this information, the analysis further considers digital “applications” (for similar functionalities) and broad “classes” (for related applications). In particular, relevant technology classes are “IT Systems” (including, e.g., the application “IT Architecture”), “Advanced Applications and Analytics” (including, e.g., “Machine Learning” and “Analytics”), “Business/Industry software” (e.g., “Enterprise Resource Planning” and “Business Management”), “Digital Sales” (e.g., “Digital Commerce”, “Marketing and Advertising”) and “Digital Workplace” (e.g., “Cloud” and “Collaborative Software”) (see Table A A.1 in Annex for additional details).

Information on classes and applications are used in a complementary way to explore digitalisation patterns over the COVID-19 pandemic (Section 4). Notably, the analysis in Subsection 4.1 relies on digital classes, while Subsection 4.2 focuses on digital applications that were key during the pandemic. The methodological framework described in the next subsection provides further context for these analyses.

The analysis also exploits information on digital functionalities to derive a digitalisation index, aimed at capturing the relative digital complexity of each firm.[19] This complements information about IT budget spending reported in the database (see Table A A.2 in the Annex for further details).

Table 1. Digital technology classes, applications, and functionalities

Digital class	Digital application	Digital functionality (e.g.)
Advanced Applications and Analytics	Analytics	Web Analytics
		Marketing Analytics
	A/B Testing	A/B Testing
	Machine Learning	Machine Learning
	Big Data	Big Data
	Production printer	Production printer
Digital Sales	Digital Commerce	Payment Processing, E-commerce platform, Retail software, E-Commerce Platform/Software
	CRM & Sales software	CRM, Sales Performance Management
	Customer Service	Contact Centre Management, Customer Feedback Management
	Marketing and Advertising	Email Marketing
Digital Workplace	Cloud	Infrastructure as a Service (IaaS), Platform as a Service (PaaS)
	Collaborative Software	Collaboration software, Project management, Document management
	Publishing and Design software	Graphic Design, CAD/CAM, Design & Publishing Software
	Suites and SaaS	Software as a Service (SaaS), Office Suites
Industry/Business software	Industry software	Manufacturing software, Sustainability software
	Business Intelligence	Business Intelligence
	Human Capital	Human Resources Management

	Management	
	ERP & Business Management	Enterprise resource planning, Business Process Management, Enterprise Application Integration, Enterprise Management
	Financial Management	Enterprise Asset Management
	Supply Chain Management	Supply Chain Management
IT Systems	IT Architecture	PCs, Servers, Printers
	IT Development	Frameworks & Libraries, Programming Languages
	Web Architecture	Website Builders
	Data Management	Data Integration, Data Management
	IT Security	Anti-Virus, Data Loss Prevention Software, Disaster Recovery, Email Security

Note: Further information on technologies is available in Table A A.1 in the Annex.
Source: authors' elaboration on the Spiceworks database.

3.2. Empirical approach

The empirical analysis carried out in Section 4 aims to study the role of different firm-level factors influencing the introduction of new digital products during the pandemic (in either 2020 or 2021), based on firm characteristics in 2019. A linear probability model (LPM) is employed to study the likelihood of such introduction as a function of various firm attributes measured before the pandemic.[20] The specification of the empirical model is:

$$PI_i = \beta_0 + \beta X_{i,2019} + FE_{industry \times country} + \varepsilon_i,$$

Equation 1

where PI_i is a dummy equal to 1 if plant i has introduced a new digital product during COVID-19 (2020 or 2021), in a given digital class or digital application (see Table 1). In particular, the analysis in Subsection 4.1 focuses on the introduction of new digital products according to the five broad digital classes "IT Systems", "Advanced Applications and Analytics", "Business/Industry software", "Digital Sales" and "Digital Workplace". Subsection 4.2 focuses on the first adoption over the pandemic of four specific digital applications ("Cloud", "Analytics", "Digital Commerce", "Collaborative Software").

$X_{i,2019}$ is a vector of firm characteristics in 2019; based on the analysis in Section 2.1, relevant characteristics include firm ex-ante productivity,[21] digitalisation (proxied by a digitalisation index, by the number of complementary technologies, or by IT intensity)[22], size classes, age classes, human capital,[23] and firm structure (multi-plant domestic firm or multinational enterprise) (see also Table A A.2 in Annex).

Lastly, $FE_{industry \times country}$ are country-industry fixed effects, accounting for unobserved heterogeneity across NACE 2-digit sectors and countries (see above); ε_i symbolises an idiosyncratic error term.

4 Digital diffusion during the pandemic: cross-country evidence

This section examines the factors that influenced digital diffusion during the pandemic. The discussion is organised into two subsections. First, Subsection 4.1 explores the relationship between the introduction of new digital tools during the pandemic and pre-existing levels of digitalisation, productivity, size, and other firm characteristics. It focuses on broad technology classes ("IT Systems", "Digital Workplace", "Digital Sales", "Business/Industry software", and "Advanced Applications and Analytics"). Second, Subsection 4.2 focuses on the digital applications that diffused the most over the crisis, like "Cloud", "Analytics", "Digital Commerce", and "Collaborative Software". This latter subsection also analyses the role of pre-existing complementary supporting technologies on first adoption during COVID-19, as well as the role of digital bundles.

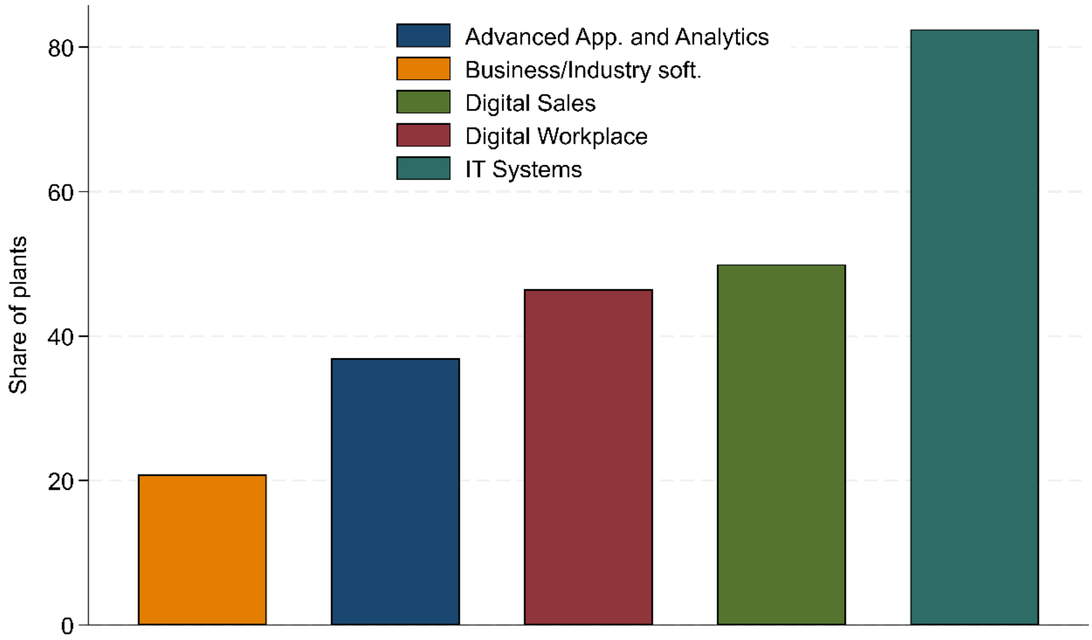
4.1. General patterns of digitalisation over the COVID-19 pandemic

As a first step, the analysis focuses on the shares of firms introducing new digital technologies during the pandemic. These are reported in Figure 2, according to the five broad technology classes: "IT Systems", "Advanced Applications and Analytics", "Business/Industry software", "Digital Sales" and "Digital Workplace".

The figure highlights that a significant share of firms introduced new digital technologies during the pandemic, with the highest shares introducing "IT Systems", followed by "Digital Sales" and "Digital Workplace". The diffusion of these technologies may be attributed to several interrelated factors. First, the widespread shift towards remote working may have required robust "IT Systems" to ensure operational business functions, internal and external communications, and online presence. New IT tools may have been indeed fundamental for companies to maintain their operations in the face of lockdowns and social distancing measures. Second, with physical stores either closed or operating at limited capacity due to health regulations, most businesses needed to pivot to online platforms to reach their customers, possibly driving the rapid diffusion of "Digital Sales" solutions. Similarly, digitalising the workplace – e.g., with the introduction of new collaborative software – likely became vital in ensuring that teams could interact, work and perform operations remotely (Brotherhood and Jerbashian, 2023[72]).

Figure 2. Share of firms introducing new digital products during the pandemic

Share by technology class



Note: The figure displays the share of plants introducing new digital products (at least one product) during the pandemic, by digital technology class (see Table 1 and Table A A.1 in Annex for additional details on the technology classification used). The figure reports results for the overall sample. Similar rankings are obtained focusing on specific countries or macro-sectors.
Source: authors' elaborations on Spiceworks data.

On the one hand, incentives to introduce those new technologies may have been stronger for firms that were less digital before the pandemic, as their limited use of digital technologies represented a threat for their survival in the aftermath of the COVID-19 shock. On the other hand, adopting digital technologies and introducing teleworking may have been easier for firms that were more digitalised before the pandemic – as they already had, e.g., the complementary skills and intangible assets necessary for adoption. Empirical evidence on which of these two channels dominate is still limited – especially at the international level. The next subsection is dedicated to exploring empirically these issues.

4.1.1. Going digital during the pandemic: the role of ex-ante firm characteristics

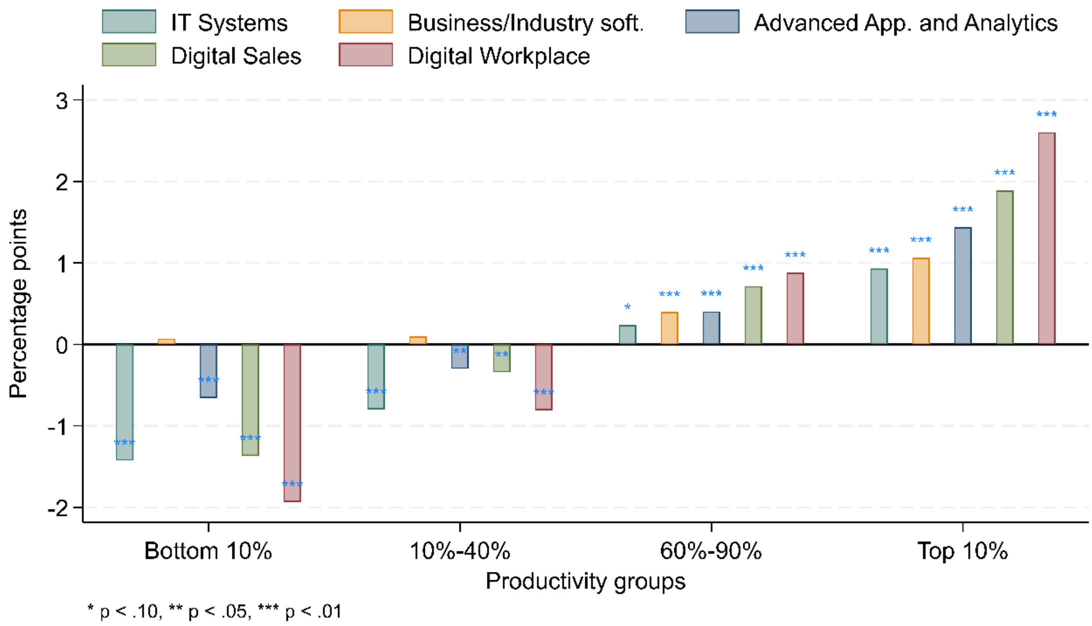
This subsection explores the relationship between the introduction of new digital technologies during the pandemic and pre-existing levels of productivity, size, digitalisation, and other relevant firm and sectoral characteristics. In particular, the analysis focuses on the broad technology classes "IT Systems", "Advanced Applications and Analytics", "Business/Industry software", "Digital Sales" and "Digital Workplace".

> *Firms that were more productive before the pandemic had higher probability of going digital during the crisis*

This subsection focuses on the relation between pre-pandemic firm productivity and likelihood of introducing new digital products over the pandemic. Notably, Figure 3 displays the link between firm productivity groups[24] in 2019 and the extent to which firms have gone digital during the pandemic, across five technology classes. Overall, the figure shows that firms that were less productive before the pandemic exhibit a lower probability of introducing new digital products during the pandemic, for all the technology classes considered. On the contrary, more productive firms – especially those in the top 10% of the productivity distribution before the pandemic – display a higher probability of adopting new digital products during the COVID-19 pandemic.[25] These results account for a range of potential confounding factors internal to the firm (e.g., size, digitalisation, age and firm structure) and external to the firm (country and sector), which may have a role in influencing the adoption of digital technologies at the firm-level (as discussed in the digital technology adoption framework presented in Section 2.1).[26] These findings appear in line with other results from the literature, pointing to a positive role of ex-ante capabilities and productivity on further digital diffusion during the pandemic. For example, Costa et al. (2022[55]) show that, in Italy, low-capabilities firms put in place minimalistic responses, e.g., in terms of re-organisational choices and technological adoption. Conversely, high-capabilities firms exhibited a notable reaction to the crisis, accelerating digitalisation strategies and reorganising the workplace. DeStefano and Timmis (forthcoming[31]) also find that, overall, firms that were ex-ante more productive adopted more advanced digital technologies during the pandemic.

Figure 3. Firm productivity in 2019 and likelihood of introducing new digital products during the pandemic

Regression coefficients for labour productivity groups, by digital technology classes (reference productivity group: 40%-60%)



Note: The figure displays the relationship between firm labour productivity (in 2019) and the probability of introducing new digital products in 2020 and/or 2021, for each digital technology class ("IT Systems", "Digital Sales", "Digital Workplace", "Advanced Applications and Analytics", "Business/Industry software"). For each technology class, the estimated regression model is an LPM that employs a dummy for digital technology class adoption as dependent variable and includes – in addition to the productivity group – size class, age class, and other complementary factors (IT staff, and an ex-ante digitalisation index) as main independent variables (see Table A B.1 in Annex). The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. The labour productivity proxy is computed as (log) turnover over employment in 2019 (see Table A A.2). Productivity groups are computed within country-sector (2-digit NACE sectors). Productivity coefficients are computed w.r.t. the 40%-60% productivity group. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Results for the "missing productivity" group are not reported. The commented results are robust to the log of labour productivity in 2019, excluding plants at the top 1% of the productivity distribution, employing a logit model as the main regression model, and to the use of a different proxy for digitalisation (IT intensity) as control. Results generally hold within classes, i.e., for digital applications within each technology class (cf. Table A B.2 in Annex). In the figure, results are ordered w.r.t. the magnitude of coefficients of digital classes for the productivity group "Top 10%".
Source: authors' elaborations on the Spiceworks database.

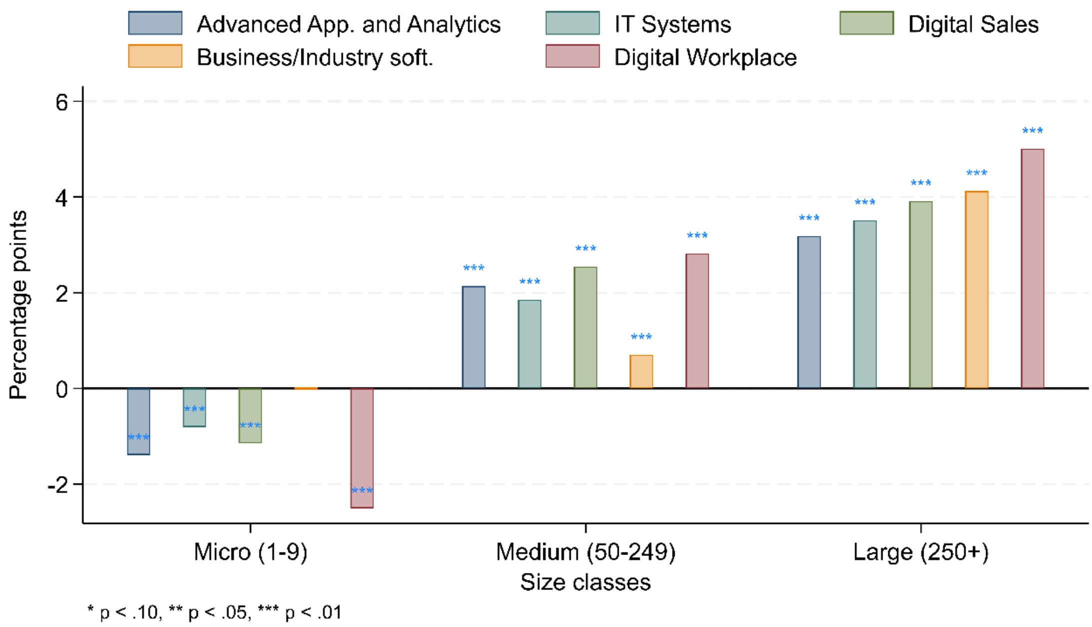
Firms that were larger before the pandemic are associated with higher probability of going digital during the crisis

Figure 4 illustrates the link between firm size prior to the pandemic and the likelihood of introducing new digital products during the crisis – focusing separately on each technology class. As in the previous model, this is done while accounting for various confounding factors such as sectoral and country fixed effects, along with other pre-crisis firm characteristics. The figure suggests that there appears to be a positive association between the size of firms before the pandemic and the likelihood of introducing new digital products during the crisis, across all technology categories considered. Indeed, for every technology class, the estimated coefficients increase along with size, being negative for the class Micro (1-9) and positive (and increasing) for larger firms. Notably, the strongest relationship is observed for "Digital Workplace", which are technologies intrinsically related, e.g., to scale (see Subsection 2.1).

Furthermore, this relation is in line with estimates accounting for firm structure (reported in Table A B.1 in the Annex). Indeed, multi-plant domestic firms and multinational enterprises (MNEs) are significantly associated with higher likelihoods of adopting new digital products across technology classes. This suggests that firms operating at larger scales before the pandemic may have been better positioned or more inclined to leverage and integrate digital technologies in their operations (see Subsection 2.1), a finding in line with the analysis by DeStefano and Timmis (forthcoming[31]).

Figure 4. Firm size in 2019 and likelihood of introducing new digital products during the pandemic

Regression coefficients for size classes, by digital technology classes (reference size class: 10-49)



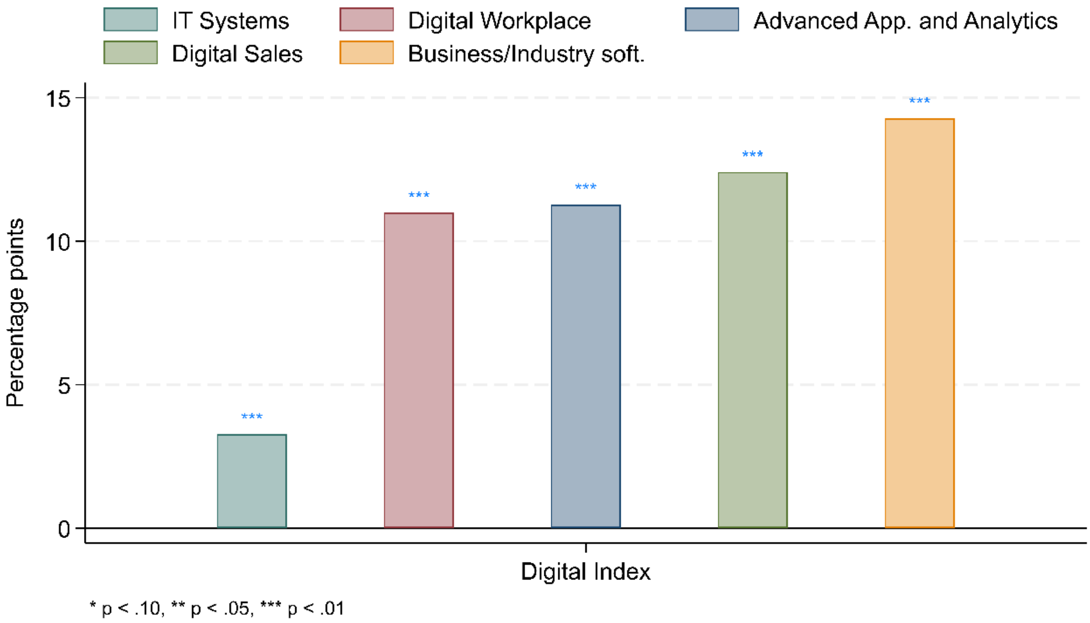
Note: The figure displays the estimated link between firm size (in 2019) and the probability of introducing new digital products in 2020 and/or 2021, for each digital class ("IT Systems", "Digital Sales", "Digital Workplace", "Advanced Applications and Analytics", "Business/Industry software"). For each technology class, the estimated regression model is an LPM with a digital technology class adoption dummy as dependent variable and includes productivity group, age class, and other complementary factors (IT staff, and an ex-ante digitalisation index) as main explanatory variables (the figure displays estimated size coefficients, see also Table A B.1 in Annex). The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. Size class coefficients are estimated w.r.t. the 10-49 size class. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Included macro-sectors are NACE sectors C, D, E, F, G, H, I, J, K, L, M. Results for size class "missing" are not reported. The results reported in the figure are robust to using employment in 2019 as a continuous variable in logs, employing a logit model as regression model, and to using different proxies for digitalisation (IT intensity, see Table A B.3). Results generally hold within classes, i.e., for digital applications within each class. Digital applications for which there is a negative association between size and introduction of new digital products are reported in Table A B.2 in the Annex. In the figure, results are ordered w.r.t. the magnitude of coefficients of digital classes for size class "250+".
Source: authors' elaborations on the Spiceworks database.

Firms that were more digital before the pandemic had higher probability of going digital during the crisis

Figure 5 shows the association between firm digitalisation before the pandemic and the probability of introducing new digital products during the crisis, for each technology class.[27] The ex-ante level of firm digitalisation is computed as an index that accounts for the overall number of digital functionalities (across digital classes) w.r.t. the maximum number of digital functionalities (across digital classes) for each country-sector. In this sense, the index aims at capturing the overall digitalisation level/complexity of firms.[28]

Figure 5. Firm digitalisation in 2019 and likelihood of introducing new digital products during the pandemic

Regression coefficients for digitalisation index, by digital technology classes



Note: The figure displays the relation between firm digitalisation (in 2019) and probability of introducing new digital products during the pandemic, for each digital technology class ("IT Systems", "Digital Sales", "Digital Workplace", "Advanced Applications and Analytics", "Business/Industry software"). The ex-ante level of digitalisation is computed as an index [0,1] which accounts for the overall number of digital functionalities (across classes) at the plant level w.r.t. the maximum number of digital functionalities (across classes) available for each country-sector (2-digit) (see Table A A.1. for details about digital functionalities). The digitalisation index is then standardised to have mean 0 and s.d. 1 (z-score).
The estimated regression model is an LPM with, as dependent variable, a digital class adoption dummy and includes the digitalisation index, productivity performance group, size and age classes, firm structure, and presence of IT staff as main independent variables (the figure displays digitalisation coefficients for the complete model, see Table A B.1 in the Annex). The digital class dummy is equal to 1 if the firm has introduced a new digital product during the pandemic crisis. If the coefficient of the digitalisation index is, for example, 0.1 for a given technology class, it means that a one standard deviation increase in the digitalisation index (i.e., being more digitally advanced than the average by one standard deviation) is associated with a 10-percentage point increase in the probability of the firm introducing a new digital product during the pandemic in the given class, *ceteris paribus*. Results are robust to using the log of employment in 2019 as independent variable and to employing a logit regression model. Results generally hold within classes, i.e., for digital applications within each class (see Table A B.2 in the Annex). Each regression includes 2-digit sector-country fixed effects and employs robust standard errors.
Source: authors' elaborations on Spiceworks data.

Notably, the more firms are ex-ante digitalised, the higher is the associated probability of introducing new digital products during the pandemic (across the board). Indeed, for all technology classes ("IT Systems", "Digital Sales", "Digital Workplace", "Advanced Applications and Analytics", "Business/Industry software"), the correlation is positive and significant. Interestingly, the class "IT Systems" – related overall to less advanced digital applications such as "IT Architecture", "IT Development" or "Web Architecture" –, while positively associated to ex-ante firm digitalisation, displays the coefficient with the lowest magnitude. Conversely, other digital classes – generally more advanced – show higher coefficients for the digitalisation index. As discussed by Zolas et al. (2020[13]) and in Subsection 2.1, this may be related to the fact that more sophisticated technologies generally require higher levels of complementary technologies and capabilities (see also Subsection 4.2.1), as well as specific diffusion patterns within the considered sample.

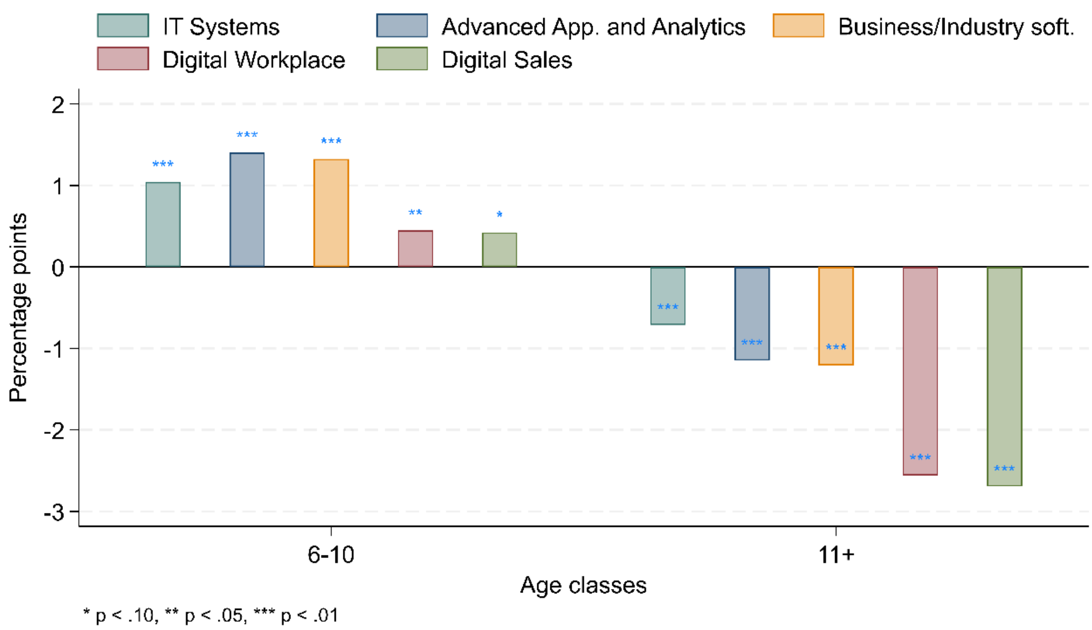
Overall, these findings align with other results from the literature, pointing to a positive role of ex-ante digitalisation on further digital diffusion during the pandemic. For example, evidence from the United Kingdom shows that previous (ex-ante) adopters were more likely to adopt further digital technologies and strengthen their digital capabilities during the COVID-19 crisis (Riom and Valero, 2020[33]; Oliveira-Cunha, Riom and Valero, 2021[34]). Similarly, EIB (2022[37]) and EIB (2023[38]) find that ex-ante more digital firms invested more during the pandemic compared to less digitalised firms. Taking into account the role of ex-ante digital complexity is important also to better characterise the role of other firm characteristics. Indeed, as displayed in the complete regression reported in Table A B.1 in the Annex, one can notice a decrease in the magnitude of the size and productivity coefficients when introducing the digitalisation index (while those remain positive and significant). This may suggest that firms' pre-existing level of digital capabilities were indeed key for the introduction of new digital tools during the crisis and explain some of the positive relationship between size and ex-ante productivity performance with digital adoption.

Firms that were younger, active in more advanced sectors, and, to some extent, equipped with higher levels of human capital had higher probability of going digital during the crisis

Figure 6 shows the link between firm age and the extent to which firms have gone digital during the pandemic period. The figure suggests that firms that were older before the pandemic are associated with lower probability of introducing new digital products during the pandemic, for all the considered technology classes. On the contrary, younger firms – especially those in the 6-10 age class – displayed a higher probability of adopting new digital products during the COVID-19 pandemic. This could be attributed to several factors. On the one hand, older firms may have had legacy systems that were not easily integrated with new digital solutions (Cao and Iansiti, 2022[71]). Conversely, firms in the 6-10 age class might have demonstrated greater adaptability in embracing digital solutions during the pandemic as – given their relative youth – they likely benefited from existing modern digital capabilities, facilitating a smoother integration of new digital products. Additionally, being in the 6-10 age may have implied a higher level of stability, for example vis-à-vis start-ups (in the 0-5 age class).

Figure 6. Firm age in 2019 and likelihood of introducing new digital products during the pandemic

Regression coefficients for age classes, by digital technology classes (reference age class: 0-5)



Note: The figure displays the relation between firm age (in 2019) and the probability of introducing new digital products in 2020 and/or 2021, for each digital class ("IT Systems", "Digital Sales", "Digital Workplace", "Advanced Applications and Analytics", "Business/Industry software"). For each technology class, the estimated regression model is an LPM that employs the digital technology class adoption dummy as dependent variable and includes productivity class, size class, firm structure, and other complementary factors (IT staff and an overall digitalisation index) as main independent variables (see Table A B.1 in Annex). The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. Age class coefficients are computed w.r.t. the 0-5 age class. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Results for "missing age" class are not reported. Results are overall robust to employing a logit regression model and using a different proxy for digitalisation (IT intensity, see Table A B.3). In the figure, results are ordered w.r.t. the magnitude (absolute value) of the estimated coefficients for age class "11+".
Source: authors' elaborations on Spiceworks data.

Additional analyses (presented in the Annex) show that firms active in more advanced sectors[29] and equipped with higher levels of human capital were those displaying a higher likelihood of going digital during the pandemic. In particular, firms active in "High-tech" and "Medium-high-tech" manufacturing sectors were associated with higher likelihoods of introducing new digital products across digital classes, as compared to those active in low-tech and medium-low-tech manufacturing sectors (see Table A B.4 in Annex). Similarly, focusing on Services, firms active in "Knowledge-intensive services" were associated to higher likelihoods of introducing new digital products (see Table A B.4 in Annex). Regarding human capital, regression results show that firms having IT staff (see Subsection 3.1) were, to some extent, associated with higher likelihood of going digital (in particular, the human capital dummy coefficient appears positive and significant – though with low magnitude. See Table A B.1).[30]

Digital adoption vis-à-vis upgrading over the pandemic

In this subsection, the analysis further disentangles the extent to which firms have gone digital over the pandemic, distinguishing among the extensive and intensive margins of digitalisation: digital "adoption" (first adoption of a technology class) and digital "upgrading" (introduction of a new digital product in a pre-existing digital class). Indeed, over the crisis, some firms may have adopted completely new technologies while other may have strengthened their technological base installing complementary tools and applications.

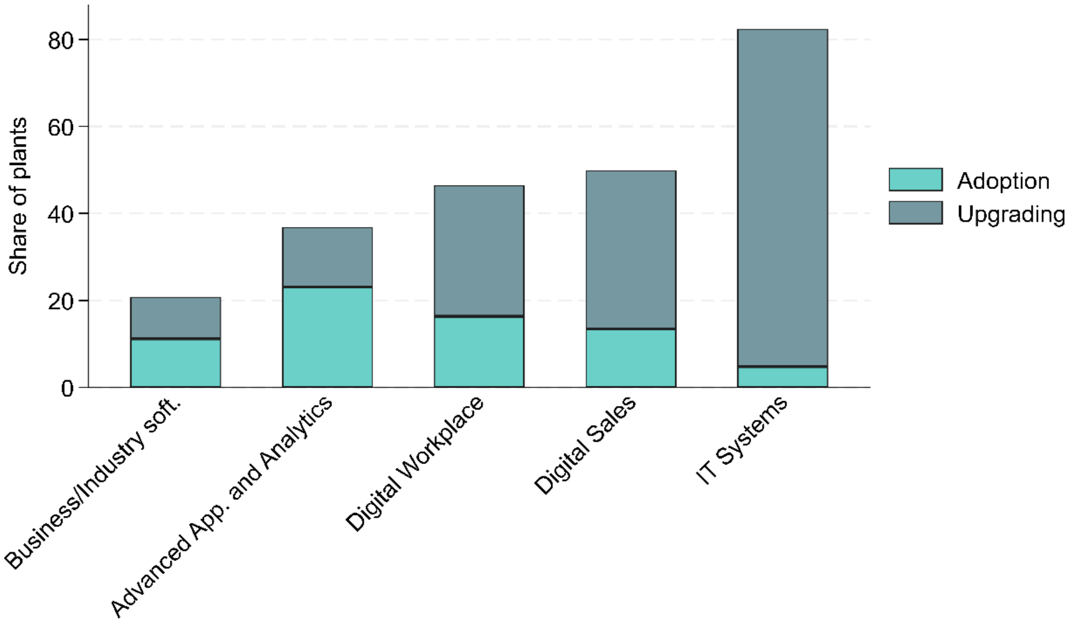
Figure 7 shows the shares of firms introducing new digital technologies during the pandemic according to the intensive and extensive margins of digitalisation and to the five technology classes analysed above: "IT Systems", "Advanced Applications and Analytics", "Business/Industry software", "Digital Sales" and "Digital Workplace". The figure shows that almost all firms installing products related to "IT Systems" de facto upgraded their technological base, i.e., strengthened their "IT Systems" with new complementary products or applications. At the same time, "Advanced Applications and Analytics" was the technology class with the highest number of new adopters, i.e., with the majority of firms introducing those technologies for the first time during COVID-19. This evidence may be consistent with the concept of hierarchies in technology adoption discussed above, i.e., more advanced technologies are adopted at later stages (see also next subsection) vis-à-vis more basic enabling applications – generally more widespread across the business population. Also, the evidence seems consistent with the need of firms to move online during the pandemic – and the related need of having a more solid IT architecture as well as having new (more advanced) tools to re-orient business operations in the digital sphere.

Table A B.4 in the Annex provides additional evidence on how firm ex-ante characteristics have shaped both the intensive and the extensive margins of digitalisation. In particular, adopters are compared to non-adopters, while upgraders are compared to non-upgraders.[31] Overall, the results commented in the previous subsections for the whole sample of firms hold, both at the intensive and extensive margins of digitalisation.[32] In other words, firms that adopted a given technology class during the pandemic tended to be more digital, larger, and more productive vis-à-vis non-adopting counterparts. Similarly, for firms that were already active in a digital class, those more productive, digital, and larger had higher probability of upgrading their technological base. Again, this appears consistent with a notion of sequentiality in digital technology diffusion (Zolas et al., 2020[13]), especially if technologies introduced at later stages are more complex or advanced.[33]

To further extend this last point, Subsection 4.2 takes a novel perspective to specifically focus on the role of supporting technologies for adoption, as well as the role of digital bundles.

Figure 7. Share of firms introducing new digital products during the pandemic (technology class adoption vis-à-vis upgrading)

Share of establishments by technology class and type (adoption or upgrading of a digital class)



Note: The figure reports the share of plants introducing new digital products by technology classes (see also Figure 7) and digitalisation type (adoption or upgrading). "Adoption" refers to the introduction – for the first time – of a given digital technology class (i.e., the adoption of a new digital product in a given digital technology class – see Table 1). "Upgrading" refers to plants that were already active in a given digital technology class before the pandemic and that introduced a new digital product.
Source: authors' elaborations on Spiceworks data.

Wrapping up: firms with higher capabilities – including digital ones – before the pandemic were better able to digitalise over the crisis

In light of the presented evidence, the digital evolution of firms during the pandemic appears influenced by several ex-ante characteristics, including size, productivity, and pre-existing levels of digitalisation. Firms that were in higher quantiles of the productivity distribution in 2019 were more likely to implement digital improvements during the pandemic. Notably, top-performing firms were more likely to integrate new digital products across all technology classes — namely, "IT Systems", "Digital Sales", "Digital Workplace", "Advanced Applications and Analytics", and "Business/Industry software". In a similar vein, the evidence suggests that larger firms had a higher likelihood of introducing new digital products during the pandemic.

During the pandemic, firms either expanded their existing endowment of digital technologies or adopted new ones. Largely, firms bolstered their foundational "IT Systems", while many adopted technologies like "Advanced Applications and Analytics" for the first time. Pre-crisis digitalisation emerges as a relevant determinant for subsequent digital advancements. The analysis indicates a coherent relation across all technology classes: firms that were more digitally advanced pre-pandemic exhibited a higher propensity to integrate new digital products. Firm age also appeared to play a significant role in digital diffusion. Specifically, older firms were less likely to integrate new digital tools, whereas younger firms, especially those aged between 6 and 10 years, exhibited a higher probability of adopting new digital products. Furthermore, sector-specific analyses show that firms in high-tech manufacturing and knowledge-intensive services were more prone to further digitalise.

Overall, while aspects like size, productivity, and sectoral characteristics significantly influenced firms' digitalisation during the pandemic, pre-existing firms' digital capabilities appear to have been pivotal. The following subsection will delve deeper into this aspect, focusing on specific digital applications, to better understand the role of prior digitalisation in shaping firm responses.

Taken together, the evidence presented above points to an acceleration in the diffusion of digital technologies, linked to the specificities of the COVID-19 crisis.[34] Nonetheless, it also confirms that pre-existing digital and productivity gaps may have played a role in the extent to which firms went digital during the pandemic, with potentially relevant implications for social and economic outcomes.

4.2. The diffusion of key applications over the COVID-19 pandemic: digital commerce, cloud, collaborative software, and analytics

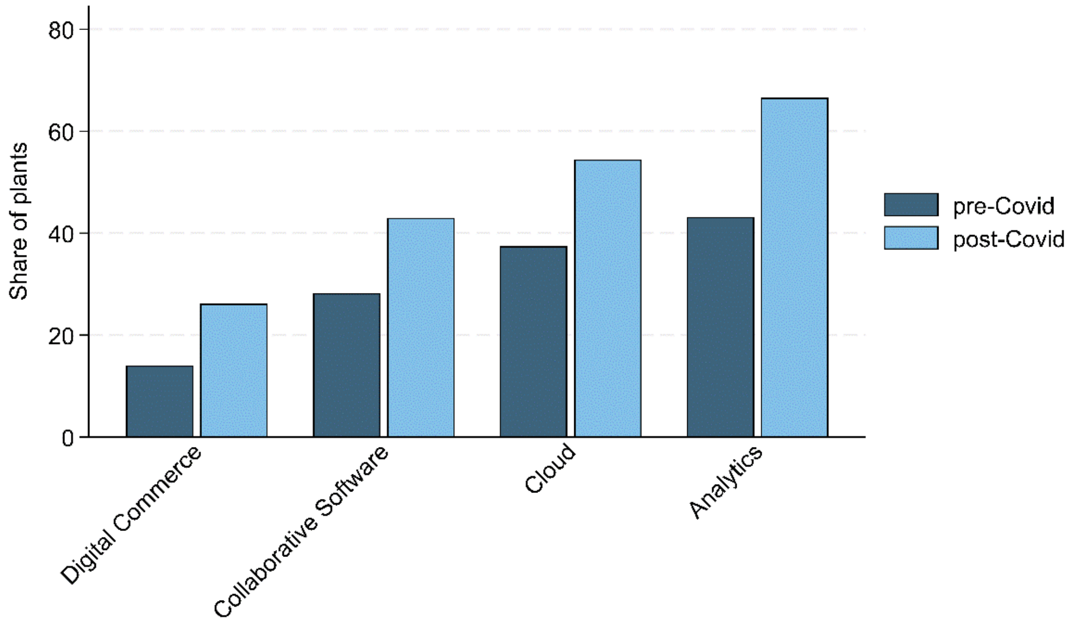
The previous subsection discussed a series of results about digitalisation during the pandemic, focusing on broad groups of technologies ("IT Systems", "Advanced Applications and Analytics", "Business/Industry software", "Digital Sales" and "Digital Workplace").[35] In particular, the analysis showed that a considerable share of firms went digital over the pandemic. "IT Systems" was the class with the highest share of firms introducing new tools, followed by "Digital Sales" and "Digital Workplace" technologies. In addition, results showed that further digitalisation was more likely for firms that were more productive, larger, and more digitalised before the pandemic.[36] Indeed, those firms likely had complementary capabilities and skills to further advance in their digitalisation process and react to the new challenges imposed by the pandemic. Furthermore, the analysis disentangled the extensive and intensive margins of digitalisation, showing that the vast majority of firms introducing new digital tools de facto upgraded pre-existing digital capabilities rather than adopting completely new technologies. This was particularly the case for "IT Systems", comprising more foundational digital applications. Digital (first) adoption was relatively higher for "Advanced Applications and Analytics", and also noteworthy for "Digital Sales" and "Digital Workplace" technologies.

This subsection extends previous analyses and gives particular emphasis to the *first adoption* of "Digital Commerce", "Analytics", "Collaborative Software" and "Cloud", some of the digital applications that diffused the most during COVID-19 (as showed in Figure 8).[37]

For example, "Analytics" reached almost 70% of firms in the overall sample after the pandemic vis-à-vis about 40% before the pandemic. Similarly, the share of firms equipped with "Collaborative Software" and "Cloud" grew significantly during the pandemic – moving from about 30% and 40% to about 40% and 55%, respectively.[38] The number of firms having "Digital Commerce" almost doubled in the overall sample (even if the absolute overall diffusion remained relatively low).[39] These dynamics are confirmed by a number of other studies, such as DeStefano and Timmis (forthcoming[31]), Ragoussis and Timmis (2023[32]), Riom and Valero (2020[33]), and Riom, Valero and Oliveira-Cunha (2021[34]) (see also Subsection 2.2). Indeed, "Cloud" and "Collaborative Software" were likely essential for remote work setups and team coordination, ensuring smooth communication and data access remotely. Similarly, "Analytics" (including Marketing Analytics and Web Analytics) were likely key to monitor sales and customers online and better re-orient sales through online channels. "Digital Commerce" (e.g., e-commerce platforms and payment processing) was likely pivotal during the pandemic to facilitate online purchases, adapting to the changing consumer behaviour and ensuring sales online.

Figure 8. Digital applications that were adopted the most during the pandemic

Share of plants by top four digital applications, pre- and post-COVID



Note: The figure displays the four digital applications that were adopted the most during the pandemic, as given by the cumulative share of plants having the given application before (2019) and after (2021) COVID-19. Applications that diffused the most are defined as those with (i) the highest growth in the cumulative number of plants having adopted for the first time the given digital application (end of 2021 vs end of 2019) and (ii) a share of diffusion of at least 10% during the pandemic years. The bars (pre- and post-COVID) are ordered w.r.t. the share of adoption. In the figure, "Digital Commerce" is the digital application with the highest growth in diffusion (+87%), followed by "Analytics" (+54%), "Collaborative Software" (+52%), and "Cloud" (+46%). Results refer to the overall sample of firms, i.e., are computed across sectors and countries. The results do not consider the role of digital upgrading.
Source: authors' elaborations on Spiceworks data.

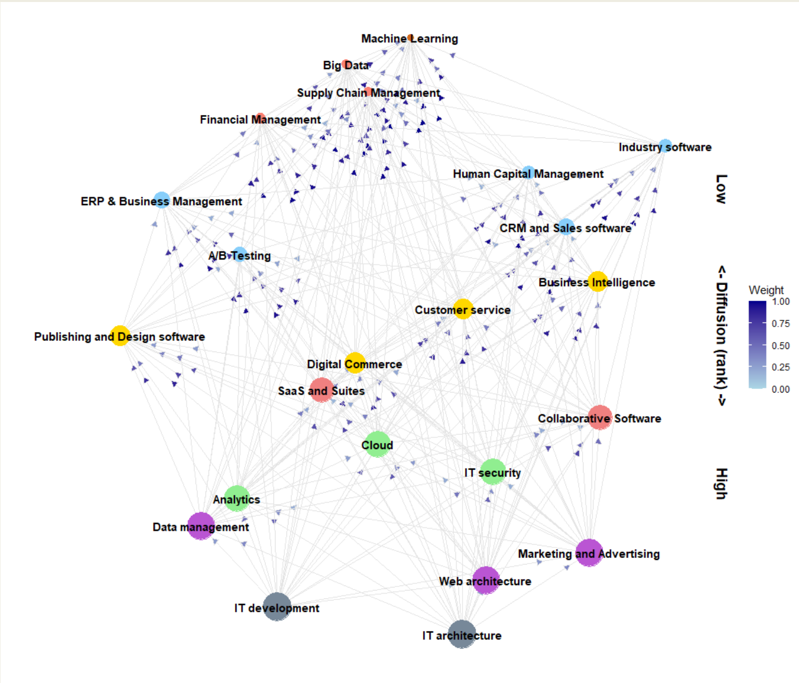
In the following subsections, further emphasis is given to the drivers and patterns of "Cloud", "Digital Commerce", "Analytics", and "Collaborative Software" adoption over the pandemic. Subsection 4.2.1 focuses on how the pre-existing level of digitalisation – in particular the role of complementary supporting technologies – influenced adoption. On the other, Subsection 4.2.2 focuses on the patterns of adoption of these applications, exploring the role of digital bundles. Both subsections rely on a co-occurrence network analysis, described in Box 4.1, which proposes a novel methodology to disentangle technological relations among digital applications.[40]

Box 4.1. Complementarities in the use of digital technologies: zooming in on the co-occurrences of digital applications

The adoption of digital technologies by firms typically builds on the presence of intangible and complementary assets and technologies. Indeed, the adoption of digital tools may often require, leverage, or build upon a set of pre-existing ICT technologies, skills, and capabilities (Zolas et al., 2020[13]). For example, before firms can effectively leverage the potential of Cloud services, they may first need to establish robust data management systems to collect, store, and process data. Similarly, the adoption of Machine Learning and AI may require the presence of complementary Cloud and Big Data technologies (Cho et al., 2023[73]). Additional examples are discussed in the main text, below.

To visually display and assess the co-occurrences among digital technologies mapped in the Spiceworks database, Figure 9 displays a network analysis performed on digital technology applications present across firms in 2019.

Figure 9. Digital applications co-occurrences: network analysis

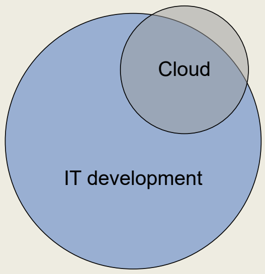


Note: The figure displays a network analysis performed on digital technology applications in 2019. Each node corresponds to a given technology application (see Table 1 for the list of applications). Nodes are ordered on the vertical axis (from the bottom to the top) according to their (decreasing) absolute level of diffusion in the sample (i.e., less diffused applications are displayed at the top of the graph). An edge between any two nodes is drawn if digital applications co-occur in the sample, i.e., if there are firms that have both digital applications. Edges are directed and weighted based on conditional probabilities of occurrence of each pair of applications (see further details in the Box Note below). For each given application, inward connected applications are defined as complementary supporting applications. Horizontally complementary applications are defined as applications having similar levels of diffusion across the sample of firms and connected by almost undirected edges (see also Note below). Different groups of horizontal applications are displayed with different node colours. Edges connecting horizontal applications are removed to avoid redundancy.
Source: authors' elaborations on Spiceworks data

In the network, each node corresponds to a given technology application (see Table 1 for the list of applications). Nodes are ordered on the vertical axis (from the bottom to the top) according to their (decreasing) level of diffusion in the sample (i.e., less diffused / central applications are displayed at the top of the graph). An edge between any two nodes/applications is drawn if the digital applications co-occur in the sample, i.e., if there are firms that have both digital applications. For example, there is an edge between "IT Development" and "Cloud" when there are firms having both applications. Each edge is later directed and weighted, based on conditional probabilities of occurrence of each pair of applications (see also the Note below, at the end of the box).

In particular, a direction from node (application) A to node (application) B is drawn if it is more likely that technology A is present when B is also present rather than vice versa (i.e., $P(A|B) > P(B|A)$). For example, an edge directed from "IT Development" to "Cloud" is drawn as most firms using "Cloud" are also using "IT Development", while not all firms using "IT Development" necessarily use "Cloud" (see Figure 10, which illustrates the relation among "IT Development" and "Cloud").

Figure 10. Co-occurrence of IT Development and Cloud



Note: The figure illustrates the occurrences of "IT Development" (blue circle), "Cloud" (grey circle), and related co-occurrences (intersection). The size of circles and intersection reflect the relative diffusion and co-occurrence of the two digital applications in the sample in 2019. In descriptive terms, for firms having "Cloud" it is more likely to have also "IT Development" rather than for firms having "IT Development" to also have "Cloud", i.e. $P(IT\ Dev.|\ Cloud) > P(Cloud|\ IT\ Dev.)$. In Figure 9, this corresponds to a directed edge from "IT Development" to "Cloud".
Source: authors' elaborations on Spiceworks data.

Each edge has then an assigned weight which is proportional to the strength of the directed relation, i.e., to the difference in conditional probabilities. For example, for the directed edge "IT Development" → "Cloud", as $P(IT\ Dev.|\ Cloud) > P(Cloud|\ IT\ Dev.)$, the weight W will be equal to $W = P(IT\ Dev.|\ Cloud) - P(Cloud|\ IT\ Dev.)$. It follows that the highest possible weight tends to 1 (e.g., for applications A and B with A → B, B always co-occurs with A and A is significantly more diffused than B). For instance, in Figure 9, the relation "IT Development" → "Machine Learning" has a weight close to 1, as "Machine Learning" almost always co-occurs with "IT Development". and the latter is substantially more diffused across firms.

Given the ensemble of directed relations, the size of each node is defined as proportional to the number of outward arrows. In other words, the more outward edges originate from a given node (application), the larger the size of the node. Conversely, the smaller the size of the node, the higher the number of inward arrows (see also the Note below, at the end of the box).

For each given application, *inward* connected applications are defined as complementary *supporting* applications. According to this definition, in the example above, "IT Development" is defined as a supporting technology for "Cloud". Similarly, "Digital Commerce" has ten supporting technologies, i.e. "IT Architecture", "IT Development", "Web Architecture", "Marketing and Advertising", "Data Management", "IT Security", "Cloud", "Analytics", "Collaborative Software", "Suites and SaaS" (see also the analysis in Subsection 4.2.1 and 4.2.2). The application with the highest number of supporting technologies is "Machine Learning", displayed at the top of the network.

Horizontally complementary applications are defined as applications having similar levels of diffusion and conditional probabilities, i.e., connected by almost undirected edges (weight close to zero). Horizontal applications are reported in Figure 9 with the same colour (see the Note below for further details). For example, "Analytics", "IT Security" and "Cloud" are defined, in this case, as horizontal applications. Similarly, other sets of horizontal applications emerging from the analysis are, e.g.: "Digital Commerce", "Customer Service", "Publishing and Design software", and "Business Intelligence"; "Collaborative Software" and "Suites and SaaS" (see also the analysis in 4.2.2).

Note: The conditional probability of A given B is defined as the probability of both A and B occurring over the probability of B occurring ($P(A|B) = P(A \cap B)/P(B)$); conversely, the probability of B given A is defined as the probability of both A and B occurring over the probability of B occurring ($P(B|A) = P(A \cap B)/P(A)$). Nodes displayed with the same colour have similar levels of diffusion and a weight lower than 0.15. The displayed relations overall hold also removing pairs of applications with maximum conditional probability lower than 0.6.

4.2.1. Firm-level drivers of adoption: the role of complementary supporting technologies

The adoption of digital technologies often requires the presence of complementary assets and skills. Indeed, as outlined in section 2.1 ("digital adoption framework"), digital tools – especially more advanced ones – often build on a set of pre-existing ICT technologies and capabilities. This is in line with the idea that technological change is a cumulative process [see e.g., Dosi and Nelson (2010[74])], particularly the case when it comes to the digital transformation.

For example, before firms can effectively leverage the potential of cloud services, they may first need to establish robust data management systems to collect, store, and process data (Cho et al., 2023[73]). Similarly, the adoption of analytics may presuppose a basic use of data-driven decision making and might also demand foundational tools that gather relevant data points, ensuring that firms can then analyse these datasets to extract business insights. The use of e-commerce may first require an online presence and the ability to target customers with relevant marketing and advertising tools. When considering the adoption of collaboration software, the presence of a strong cloud and foundational ICT architecture may be pivotal, as collaboration software usually operates within a cloud-based environment, allowing for seamless synchronisation, real-time updates, and access from multiple locations. The same argument applies, more generally, to advanced digital technologies such as AI and ML, increasingly reliant on intangible complementary assets and vast amount of data to train algorithms (Haskel and Westlake, 2017[19]; Calvino and Fontanelli, 2023[12]; DeStefano, De Backer and Moussiegt, 2017[5]).

Overall, the adoption of some digital technologies may have a hierarchical and sequential pattern, with more sophisticated technologies possibly implemented only after more basic applications (Zolas et al., 2020[13]). The next subsection further explores this empirically – based on the detailed data at hand and the methodology described in Box 4.1 – translating the discussion onto the digital applications that diffused the most over COVID-19. Notably, the following analysis focuses more closely on the adoption of "Cloud", "Analytics", "Collaborative Software" and "Digital Commerce", and how the presence of complementary supporting technologies influenced patterns of adoption.

The presence of complementary supporting technologies installed before the pandemic favoured the adoption of key digital applications over the pandemic

This subsection analyses the role of complementary supporting technologies in shaping the adoption of key digital applications ("Cloud", "Analytics", "Collaborative Software" and "Digital Commerce"). The exploration includes supporting technologies derived from the network in Box 4.1, which provides an analysis of relations among digital applications and their co-occurrences.

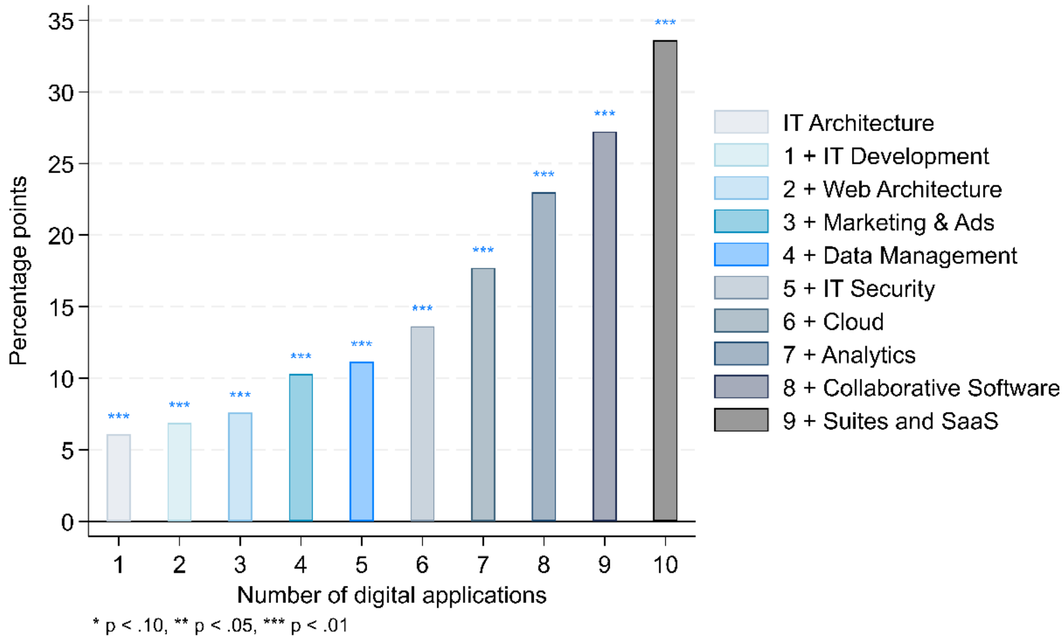
Figure 11 illustrates the relationship between the number of digital applications a firm had in 2019 and its likelihood to adopt “Digital Commerce” for the first time during the pandemic. Specifically, it reports the probability of “Digital Commerce” adoption during COVID-19 in relation to the cumulative number of pre-existing supporting applications (see Box 4.1 for the definition), also controlling for other firm characteristics (size, productivity, age, human capital, firm structure, country and sector fixed effects).[41] The displayed association indicates that the probability of adoption significantly increases with the number of technologies a firm had in place before the pandemic.[42]

For instance, focusing on the “IT Architecture” application, the regression analysis suggests a higher likelihood of “Digital Commerce” adoption for firms that had this application before the pandemic – as compared to those that did not. This result appears intuitive, as a firm equipped with foundational IT devices was likely better able to integrate and leverage new digital tools during the pandemic. Moreover, the likelihood of “Digital Commerce” adoption increases as the count of pre-pandemic technologies rises. For example, firms equipped with both “IT Architecture” and “IT Development” applications had a higher likelihood to adopt “Digital Commerce” compared to firms that only had “IT Architecture” in place. One can also notice an increase in the estimated coefficient across the two specifications, which raises further as additional technologies are taken into account. Indeed, considering, e.g., the last column (to the right), corresponding to the presence of ten digital applications,[43] one can notice that the cumulative probability is substantially higher than the case with fewer applications included. This likely indicates a compounded effect, where the presence of multiple pre-existing supporting technologies increases the probability of new technology adoption (in this case, “Digital Commerce”) – in line with the presence of technological complementarities in digital adoption.

There are many potential reasons explaining why these technologies may have supported the adoption of e-commerce solutions. The “IT Architecture” application (e.g., hardware) essentially forms a stable ICT foundation for digitalisation (DeStefano, De Backer and Moussiegt, 2017[5]). “IT Development” capabilities offer a medium for further IT customisation and strength useful to integrate basic IT functions. A “Web architecture” likely enables online presence, relevant for e-commerce operations. When “Marketing and Advertising” tools are already embedded in operations, firms may strategically reach customers, better channelling them towards digital platforms. “Data Management” systems may ensure storage and retrieval of data, e.g., concerning customers, transactions, and products. To ensure the integrity of digital commerce platforms, “IT Security” is paramount, e.g., to secure transactions and customers’ information. With “Cloud” solutions, digital commerce platforms may gain an additional layer of scalability and accessibility, enabling firms to manage user activity spikes. “Analytics” offers firms a lens into customer behaviours, purchasing patterns, and engagement, shaping business decisions. “Collaborative Software” generally enables streamlined internal communication, allowing strategic, marketing, sales, and supports alignment. Finally, having “Suites and SaaS” solutions may further help firms scale their operations. Overall, it is likely that firms equipped with this ensemble of digital applications would have been better positioned during the rapid shift towards digital commerce caused by lockdowns and social distancing measure. Such technological foundations have likely streamlined their transition and increased overall digital resilience.

Figure 11. Supporting technologies and the adoption of Digital Commerce over the pandemic

Cumulative likelihood of Digital Commerce first adoption by number of supporting technologies



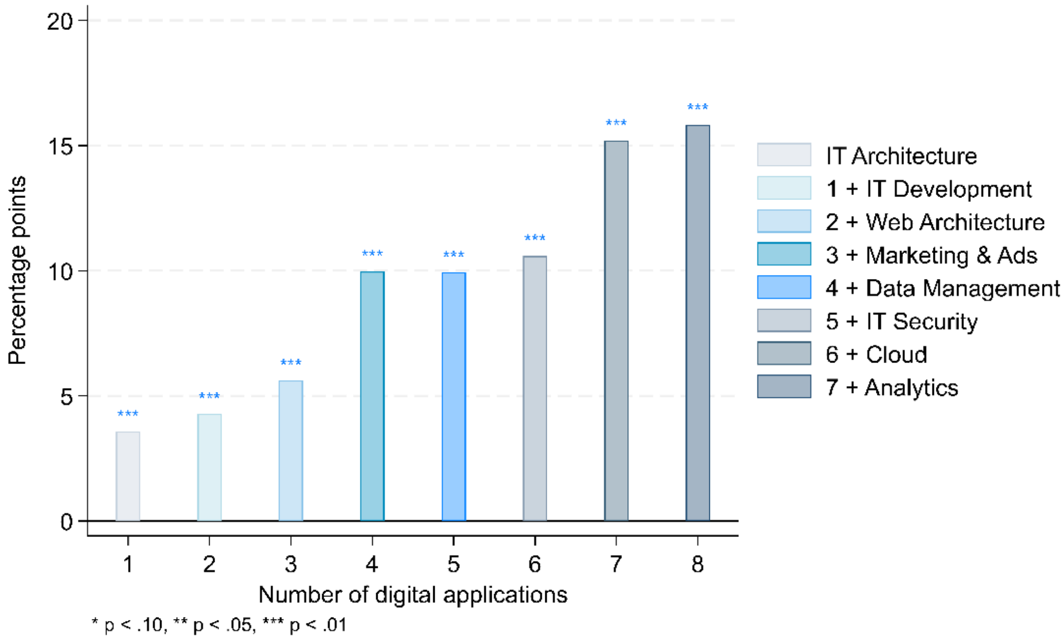
Note: The figure displays the relation between a firm's number of complementary supporting technologies (in 2019) and the probability of adoption of "Digital Commerce" during the pandemic. Each bar reports the estimated coefficient of an LPM that employs the "Digital Commerce" adoption dummy as dependent variable and includes the digital dummy for supporting technologies, productivity, size and age classes, firm structure, and presence of IT staff as main independent variables (see Table A B.6 in the Annex for the complete regression results). The digital dummy for supporting technologies is defined as 1 if the firm had the given set of technologies in 2019, 0 otherwise (Model 1: "IT Architecture"; Model 2: "IT Architecture" and "IT Development"; Model 3: "IT Architecture" and "IT Development" and "Web Architecture", etc.). Details about supporting technologies are given in Box 4.1. Each regression includes 2-digit sector-country fixed effects and robust standard errors. Results are robust to the use of alternative supporting technology ordering.
Source: authors' elaborations on Spiceworks data.

Similar results hold when focusing on "Collaborative Software", another application that was key during the COVID-19 pandemic, as shown in Figure 12 (also in this case, the probability of adoption during COVID-19 is displayed in relation to the cumulative number of pre-existing applications in 2019).[44] In particular, results show that firms that had supporting technologies in place before the pandemic had higher likelihood of adopting "Collaborative Software" during the pandemic.

Indeed, as for "Digital Commerce", an "IT Architecture" may have provided the backbone for integrating collaborative tools, while "Cloud" services ensured easy access and scalability. Online presence, "Advertising and Marketing" software, as well as "Analytics" already in place may have eased the implementation of collaborative tools, e.g., because a workforce which, was already familiar with a digital environment and probably also equipped with complementary skills, was likely more adaptable and receptive to new collaborative tools. Similarly, "Data Management" capabilities already in place may have eased the adoption of collaborative software, as this usually relies upon effective data sharing solutions.[45] Moreover, "IT Security" may have facilitated the adoption of collaboration software as it could guarantee that data and communications remain secure, also reducing potential privacy vulnerabilities (DeStefano, De Backer and Moussiegt, 2017[5]).

Figure 12. Supporting technologies and the adoption of Collaborative Software over the pandemic

Cumulative likelihood of Collaborative Software first adoption by number of supporting technologies



Note: The figure displays the relation between a firm's number of complementary supporting technologies (in 2019) and the probability of adoption of "Collaborative Software" during the pandemic. Each bar reports the estimated coefficient of an LPM that employs the "Collaborative Software" adoption dummy as dependent variable and includes the digital dummy for supporting technologies, productivity, size and age classes, firm structure, and presence of IT staff as main independent variables (see Table A B.7 in the Annex for the complete regression results). The digital dummy for supporting technologies is defined as 1 if the firm in 2019 had the given set of technologies, 0 otherwise (Model 1: "IT Architecture"; Model 2: "IT Architecture" and "IT Development"; Model 3: "IT Architecture" and "IT Development" and "Web Architecture"; etc.). Details about supporting technologies are given in Box 4.1. Each regression includes 2-digit sector-country fixed effects and robust standard errors. Results are robust to the use of alternative supporting technology ordering.
Source: authors' elaborations on Spiceworks data.

Finally, the presence of complementary supporting technologies also appears to have facilitated the adoption of "Analytics" and "Cloud" during the pandemic – as illustrated in Table A B.8 and Table A B.9 in the Annex.[46] Also in this case, IT tools likely served as foundational support for this digital transition. Since "Analytics" often delves into marketing and web metrics, pre-existing marketing and advertising software could have favoured its integration.[47] Furthermore, considering that effective data management is crucial for both "Analytics" and "Cloud" – demanding systematic organisation, storage, and access to data – pre-existing capabilities in this domain might have facilitated the adoption of these digital solutions.

Overall, the presence of complementary supporting technologies appears key for the adoption of new digital technologies over the pandemic.[48] The adoption of further digital applications (such as "Cloud" and "Analytics") was facilitated by the ex-ante presence of IT capabilities (such as IT architecture, development, and web tools), data management and security tools, as well as pre-existing digital communication and engagement software (e.g., Marketing and Adverting software). Furthermore, additional digital capabilities played a significant role in the adoption of "Digital Commerce" and "Collaborative Software" applications, which usually benefit from enhanced data accessibility, real-time insights, scalability, and cost efficiencies (as potentially provided, e.g., by cloud and analytics).

All in all, while the COVID-19 crisis undoubtedly acted as a catalyst, accelerating the adoption of digital technologies, it appears that the base for this swift transition was largely dependent on firms' pre-pandemic digital capabilities, especially the presence of supporting technologies.[49]

The next subsection further develops the analysis of the role of digital complementarities over the COVID-19 pandemic, investigating the role of digital bundles.

4.2.2. Did firms adopt key digital applications in bundles during the pandemic?

As the adoption of digital technologies by firms typically builds on the presence of intangible and complementary assets and technologies, possibly with a hierarchical pattern, Subsection 4.1.1 focused on the adoption of key applications during the pandemic, showing that "Cloud", "Digital Commerce", "Analytics" and "Collaborative Software" were more likely adopted if firms already had supporting technologies in place before the pandemic.

Empirical studies often focus on determinants of adoption for single technologies (Cho et al., 2023[73]). An emerging strand of literature is instead focusing on the joint use of digital technologies. This is the case, for example, of the above-mentioned study by Zolas et al. (2020[13]), which finds that firms tend to use technologies in bundles, with more advanced technologies adopted after more basic, enabling ones. Similarly, a recent work by Cho et al. (2023[73]) focuses on new generation digital technologies (NGDTs, such as AI, Big data, augmented reality, Robotics, IoT) and studies the simultaneous use of those technologies for a sample of Korean firms. The authors find that, after controlling for various firm characteristics, NGDTs are generally used in bundles rather than in isolation – with the use of technologies that require data (such as AI) accompanied by technologies that generate large amounts of information (such as IoT and Big Data) and facilitate its storage and processing (Cloud).

This subsection builds on and significantly contributes to this strand of literature, focusing on the role of digital technology bundles over the COVID-19 pandemic.[50] In particular, while the previous subsection disentangled the role of pre-existing technological base in shaping adoption patterns of each key application, this subsection more closely focuses on joint adoption patterns of digital applications over the pandemic.

Over the pandemic, the adoption of key digital applications was more likely to happen in bundles rather than in isolation

The following exploratory analysis focuses on the adoption of *horizontally*-related digital applications over the pandemic. Horizontally, related applications are defined as applications with comparable levels of diffusion[51] across firms and with a common set of supporting technologies (see Box 4.1 for further details). For example, horizontal applications related to "Digital Commerce" are: "Customer Service", "Publishing and Design software", and "Business Intelligence" applications.[52] "Collaborative Software" results related to "Suites and SaaS", while "Cloud" and "Analytics" result also related to "IT Security".

Table 2 shows estimated probabilities of joint adoption for "Cloud", "Analytics" and "IT Security" applications, Table A B.11 (in Annex) shows results across "Digital Commerce", "Customer Service", "Publishing and Design software", and "Business Intelligence", while Table A B.12 focuses on "Suites and SaaS" and "Collaborative Software". These capture the likelihood of adopting the focus application (in column) in 2020/2021 given the adoption of a horizontally-related application (in row) over the pandemic.[53]

The correlation analysis highlights the existence of complementarities in the adoption of digital applications over COVID-19. Indeed, for all the three tables, relevant estimated coefficients are positive and significant. For example, one can notice an increase in the likelihood of adopting "Cloud" in 2020/2021 if a firm also adopted "Analytics" in 2020/2021, and vice versa.[54] Similarly, Table A B.11 shows that, e.g., adoption of "Digital Commerce" was likely accompanied by the adoption of "Customer Service", "Publishing and Design software", and "Business Intelligence" applications during the pandemic, and vice versa.[55] Finally,

Table A B.12 in the Annex reports that the adoption of “Collaborative Software” (“Suites and SaaS”) was also more likely to happen given the adoption of “Suites and SaaS” (“Collaborative Software”).

The observed complementarities in the adoption of digital applications can be attributed to several underlying factors. First, some digital applications may be designed to complement each other. For instance, “Cloud” often lays the ground for “Analytics” tools, enabling firms to efficiently manage vast amount of data. This approach may better ensure that data storage, retrieval, and processing occur in tandem (Cho et al., 2023[73]). Similarly, the concurrent adoption of “Digital Commerce” and “Customer Service” applications may have occurred because firms selling products online may benefit from efficiently addressing customer concerns. In this respect, using dedicated customer management software may have allowed firms to enhance the overall online experience. Moreover, there may also be economic incentives tied to combined adoption, i.e., adopting certain digital applications collectively might result in cost savings. For example, some software providers might propose combinations of “Collaborative Software” with “Suites and SaaS” at lower overall prices. Furthermore, the simultaneous integration of complementary technologies may result easier to manage vis-à-vis staggered implementation (Cao and Iansiti, 2022[71]).

Table 2. Adoption in bundles over the pandemic: Cloud, Analytics, and IT Security

Regression results coefficients for the adoption of each pair of digital applications over the COVID-19 pandemic

Dependent variable → Independent variable ↓	Cloud	IT Security	Analytics
Cloud	.	0.21***	0.14***
IT Security	0.22***	.	0.16***
Analytics	0.11***	0.13***	.
Supporting tech. (2019)	Yes	Yes	Yes
Firm characteristics (2019)	Yes	Yes	Yes
Country-sector FE	Yes	Yes	Yes

Note: The Table displays the relation between the first adoption of given digital applications (in row) and the probability of simultaneously adopting the corresponding horizontally-related digital application (in column). The estimated regression model is an LPM that employs the digital application dummy as dependent variable and includes the digital “bundle” dummy (focusing on the relevant related application), supporting technologies, size and age classes, firm structure, and presence of human capital as main independent variables (see Table A B.11 for the complete list of results). The digital application and bundle dummies are equal to 1 if firms have adopted (for the first time) the corresponding digital applications during the pandemic crisis. Results are robust excluding the “supporting technologies” dummy. Also, results are robust to the inclusion of the productivity variable as an alternative regressor. Each regression includes 2-digit sector-country fixed effects and robust standard errors.
Source: authors’ elaborations on Spiceworks data.

Overall, this analysis suggests that, over the pandemic, key applications (such as “Cloud”, “Digital Commerce”, “Analytics” and “Collaborative Software”) were likely adopted in bundles with related complementary digital applications. This dynamic points again at how the digital transformation of firms relies on the successful implementation and use of complementary capabilities, technologies, and skills.

Wrapping up: firms already equipped with complementary supporting technologies were better able to adopt key applications – Analytics, Cloud, Collaborative Software, Digital Commerce – over the COVID-19 crisis

In light of the presented analysis, the digital evolution of firms during the pandemic appears significantly influenced by pre-existing levels of digitalisation. In particular, firms that were equipped with higher levels of digital capabilities (supporting technologies) were better able to adopt key applications – such as “Cloud”, “Digital Commerce”, “Analytics”, and “Collaborative Software” – over the COVID-19 crisis.

Overall, the integration of digital applications like “Cloud” and “Analytics” was streamlined by the ex-ante presence of IT capabilities, such as IT architecture, development, and web tools. Data management, security tools, and pre-established digital communication and engagement platforms, like marketing and advertising software, seem to have further eased this process. Moreover, additional capabilities played a role in the adoption of “Digital Commerce” and “Collaborative Software” applications, which usually benefit from enhanced data accessibility, real-time insights, scalability, and cost efficiencies – as potentially provided, e.g., by cloud and analytics.

In addition, “Cloud”, “Digital Commerce”, “Analytics”, and “Collaborative Software” applications were often more likely integrated in conjunction with other horizontally-related digital applications, with a similar level of overall diffusion, rather than in isolation. For example, the analysis suggests that “Cloud”, “Analytics” and “IT Security” were more likely to be adopted in bundles. Similarly, “Digital Commerce” was further complemented by digital applications such as “Customer Service”, “Business Intelligence”, and “Publishing and Design software”. Such bundled adoption further highlights the notion that successful digital transformation hinges on a suite of interrelated capabilities and skills.

5 Conclusions, policy discussion, and next steps

This work has discussed the most recent evidence about patterns of digital technology diffusion in the aftermath of the COVID-19 pandemic, especially focusing on the firm-level determinants of digital technology diffusion.

Relative to previous crises, the social distancing restrictions specific to the COVID-19 pandemic have forced many firms to reorganise quickly and heavily their activities.

The sudden changes brought by the COVID-19 outbreak induced not only a rapid adjustment to remote working and online delivery of goods and services but also more broadly affected the patterns of adoption of digital technologies and their returns, possibly widening pre-existing divergences between different groups of firms.

The analysis presented in this work and the most recent international evidence available to date suggest indeed that the pandemic has accelerated the introduction of digital technologies by firms, both in novel technology classes as well as in terms of upgrading existing ones. The analysis also highlights some degree of heterogeneity across technology classes in the extent to which firms have gone digital during the pandemic, with higher shares of firms introducing new tools related to “IT Systems”, “Digital Sales”, and “Digital Workplace” technologies.

Pre-existing digital and productivity gaps among firms, as well as their pre-pandemic characteristics, have played an important role in shaping firms’ ability to react to the crisis and, relatedly, in introducing new technologies. Indeed, firms that were more digital, more productive, and larger before COVID-19 were those increasing more significantly their digital technology installs during the pandemic. In particular, pre-existing digital capabilities appear to have been pivotal. Indeed, the ex-ante presence of supporting technologies – identified using a novel methodology based on network analysis – favoured the adoption of key applications during the pandemic, such as “Analytics”, “Cloud”, “Digital Commerce”, and “Collaborative Software”.

Different likelihoods of digital adoption across different groups of firms, coupled with heterogeneous returns to digital technology adoption, might result in increasing divergences among the best-performing, highly digital savvy, firms and the rest of the business population after the COVID-19 pandemic – increasing the polarisation of economies already observed before the crisis. In this context, policy makers can play a role more crucial than ever for fostering an inclusive digital transformation in the post-pandemic era.

Governments can promote technology diffusion through a mix of policies affecting firms’ incentives and capabilities and capturing synergies across different policy areas. Such mix 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.

Critical areas for policy attention include: (i) human capital, including focusing on upskilling and reskilling workers and boosting ICT skills and high-quality STEM education – as digital transformation shifts the demand for skills but also fostering communication and organisational skills [see Borgonovi et al.

(2023[75])]; (ii) digital capabilities, including incentivising the digital transformation, improving knowledge production and sharing (also through sensible patent policies) as well as supporting R&D, and easing the financing of intangibles; (iii) digital infrastructure, reducing digital and connectivity gaps; and (iv) business-friendly framework conditions, focusing on fostering competition, ensuring a level-playing field, and reducing barriers to entry and growth, as well as addressing the new regulatory issues of the digital economy (importantly those related to data and AI).

These complementary policies may allow digital technology diffusion and its returns to be more widespread across firms and sectors, ensuring an inclusive digital transformation in the aftermath of COVID-19, likely bringing double dividends for several economic and social outcomes.

This analysis is complementary to other recent OECD works focusing on the economic implications of COVID-19 [e.g. Schwellnus, Haramboure and Samek (2023[1]); Criscuolo et al. (2021[2]); OECD (2021[3])] and converges in findings with e.g. Calvino and Fontanelli (2023[12]) and Calvino et al. (2022[7]), highlighting the importance of complementary assets for the digital transformation and the role of policy.

Although comprehensive in several respects, the current analysis could be extended in different directions. For instance, the analysis of the complementarities among different digital technologies could be further extended beyond applications that were key during the COVID-19 pandemic. Also, country, time, and sectoral specificities in the patterns of technological complementarities could be explored further, conditional on data availability. Furthermore, additional analysis could be carried out focusing on digital technology diffusion within firms, e.g., focusing on MNEs that operate across different countries, and possibly on the role of COVID-19 affecting intra-firm technology diffusion.

Endnotes

[1] Other internal (such as firm ownership and control) and external (labour market frictions or the role of training) factors have been omitted. Also, Figure 1 does not display the links and feedback effects among some of the internal factors considered, technology adoption, and firm performance.

[2] The authors explore the patterns of AI use in firms across 11 countries using a distributed microdata approach based on a harmonised statistical code executed in a decentralised manner on official firm-level surveys.

[3] The authors find also that shares of AI users also appear to some extent higher across younger firms. This is consistent with the idea that start-ups often bring to the market more radical innovations and are more able to be disruptive in their processes and business models.

[4] In general, technological change, competitive pressures or changes in demand may induce firms to adopt new digital technologies [see Calvino et al. (2022[7]) for more details]. Figure 1, presented above, focuses on changes implied by the COVID-19 shock.

[5] The authors also released a website with real-time information and updates, available at the following link: https://wfhmap.com/.

[6] Other studies include, e.g., Morikawa (2021[48]) and Bloom, Mizen and Shivani (2021[45]). Several recent papers also find similar results using job postings data [see Bloom et al. (2023[39]) for a list of references].

[7] As baseline measure of digitalisation, the authors use the industry-wise measure of Calvino et al. (2018[78]) and highlight that results are robust across a wide range of digitalisation measures (ICT input and employment shares, robot usage, online sales, intangible assets, and digital skills listed on online profiles).

[8] With a different but related perspective, Doerr et al. (2021[77]) find that firms headquartered in jurisdictions with better digital infrastructure generated relatively higher revenue during the shock period.

[9] Similarly, Raj, Arun and Calum (2023[76]) document the positive effects of digital platform usage on resilience across small business restaurants during the pandemic.

[10] The authors suggest that the cost of the social distancing is lower in places where firms adopt IT more heavily, even if also in high-IT areas not everyone is shielded from the economic consequences of lockdowns. For example, the authors find that IT does not shield low-skilled workers from the economic consequences of the COVID-19 shock.

[11] In particular, the authors argue that short-time work schemes have been successful in reducing the potential negative employment effects of the crisis – larger in regions with low digital capital endowments.

[12] At the sectoral and country level, Jaumotte et al. (2023[58]) stress that greater digitalisation translated into smaller losses in hours worked, especially in non-contact-intensive sectors. Similarly, the authors show that higher digitalisation in a sector reduced labour productivity losses.

[13] The Aberdeen Spiceworks database experienced a redesign between 2019 and 2020 (introduction of a new vintage with changes in the structure of data and some variables, as well as availability of new information on digital presence). For the year 2020 both vintages are available allowing a comprehensive mapping and integration of information across years.

[14] This includes NACE sectors C, D, E, F, G, H, I, J, K, L, M. Plants classified as “Government Body”, “Local Government Body”, “Non-profit Organization”, and “Cooperative” are not included in the analysis.

[15] In the following, the terms “establishment”, “plant” and “firm” are used interchangeably. The analyses also take into account the role of enterprise structure: single-plant firms (standalone), multi-plant domestic firms (branch), multination enterprises (multi-plant firms having plants in more than one country).

[16] The main establishment characteristics include employment, turnover, and labour productivity (computed as turnover over employment for plants with non-missing information). Values for turnover and labour productivity are only used for the year 2019 and therefore not deflated. Productivity groups used for the analysis in Subsection 4.1.1 are computed within 2-digit sectors for each country. As explained in subsection 3.2, the analysis further employs country-sector (2-digit) fixed effects to account for unobserved sectoral and country heterogeneity. Establishments with information on digital products are lower in number and larger with respect to the average firm in the overall sample (see Table A A.2 in Annex for further details).

[17] Information about digital products used in the analysis refers to the newer vintage, which includes information on the timing of adoption of digital products as well as “confidence rankings” information about specific digital products. In the analysis that follows, information about digital products is retained if the confidence ranking is >=90%. The results are overall robust to the inclusion of products with confidence rankings lower than 90% (i.e., with confidence rankings between 60-74% and 75-89%). See also footnote 18. The analysis does not directly include the role of potential product drops across years, which appear to be limited [see also similar analyses using the Spiceworks data, e.g., Cao and Iansiti (2022[71])].

[18] In the database (newer vintage), functionalities are named “product categories”. The database further groups “product categories” in more aggregate “product series”. To better disentangle relations among digital technologies, and building on the related literature about new digital technologies (see also Section 2), the analysis relies on a related classification of “digital applications” (see Table A A.1 and Table A A.2 for information on digital applications in Annex for further details). Findings are overall robust to the use of “product series” as main technological classification.

[19] Notably, the index is computed as the number of digital functionalities over the maximum number of digital functionalities available at the country-sector (2-digit) level (see Table A A.2).

[20] The analysis is overall robust to the use of a logit model as an alternative specification.

[21] In particular, in addition to the log of labour productivity, the analysis in Section 4.1.1 also considers (log) labour productivity groups (Bottom 10%, 10%-40%, 40%-60%, 60%-90%, Top 10%) computed at the country-sector (2-digit) level. See also Subsection 3.1.

[22] The digitalisation index has been defined in footnote 19. The number of complementary technologies will be discussed in Section 4.2. As additional proxy of digitalisation, the analysis also considers the intensity of IT budget spending (in log) [see also, e.g., De Stefano, Kneller, and Timmis (2018[68])]. The variable IT budget is the sum of IT budget for computers, servers, storage, hardware, communication, software, and services (in thousand dollars); the intensity variable is computed as IT budget over employment (see also Subsection 3.1 and Table A A.2).

[23] Information on human capital refers to the presence of "IT staff" and/or "IT staff that are IT developers" in 2019. The variable for 2019 is defined as 1 if a plant has non-missing employment and reports the presence of "IT staff" and/or "IT staff that are IT developers". Similar results are obtained employing other specifications of the human capital dummy (e.g., employing the human capital from the new Spiceworks vintage for 2020).

[24] In particular, the analysis displays labour productivity groups, capturing the relative position of firms in the sectoral labour productivity distribution within each country (see also Section 3). Results are robust to the use of log labour productivity, as a continuous variable.

[25] For example, the probability of introducing new "Digital Workplace" products is about 3 percentage points higher for firms in the top 10% productivity group compared to firms in the reference productivity group, holding all else constant. Similarly, the probability (for "Digital Workplace") is about 2 percentage points lower for firms in the bottom 10% productivity group compared to firms in the reference productivity group, *ceteris paribus*.

[26] One could further disentangle the productivity relationships within each technology class. In particular, it is worth mentioning that the positive relationships with productivity hold for most "digital applications" (cf. also Subsection 4.2). See Table A B.4 in Annex for further details.

[27] Also in this case, the regression controls for sectoral and country characteristics, as well as other firm characteristics – including ex-ante productivity; see Table A B.1 in the Annex.

[28] More details about digital functionalities are available in Section 3.1, Table 1, Table A A.1, and Table A A.2. The digitalisation index is standardised to have mean 0 and standard deviation 1. Results are robust to the computation of the digitalisation index using applications, i.e., deriving the index as the overall number of digital applications available pre-pandemic at the firm level w.r.t. the maximum number of digital applications for each country-sector.

[29] The analysis refers to the Eurostat classification based on NACE Rev. 2 codes at the 2-digit level. High-technology sectors include codes 21 and 26. Medium-high technology includes codes 20, and 27 to 30. Medium-low technology is covered by codes 19, 22 to 25, and 33. Low technology encompasses codes 10 to 18, and 31 to 32. Knowledge-intensive services (KIS) are classified by NACE Rev. 2 codes at the 2-digit level as follows: 50-51, 58-63, 64-66, 69-75, 78, 80, and 84-93. Less knowledge-intensive services (LKIS) encompass codes 45 to 47, 49, 52 to 53, 55 to 56, 68, 77, 79, 81, 82, and 94 to 99. The analysis compares – for manufacturing – High-technology and Medium-high technology sectors with Low and Medium-Low sectors. For services, it compares Knowledge-intensive services and Less knowledge-intensive services with other services.

[30] For "Digital Sales" the human capital coefficient is not significant but positive. See Table A B.1 in Annex for further details. See Subsection 3.1 and footnote 23 for information about the human capital dummy. Similar results are obtained employing the human capital dummy for 2020.

[31] This approach translates in a split-sample regression, which considers, on the one hand, firms that were not active in a given digital class in 2019 and that might have eventually adopted during the crisis (adopters vs non-adopters); on the other hand, the approach considers firms that were active in a given digital class, and that might eventually have upgraded during the crisis (upgrader vs non-upgraders). The split sample is performed at the level of digital class.

[32] For the class "IT Systems", results for adopters vs. non-adopters are not computed, as almost all firms were already active in "IT Systems" in 2019.

[33] In the above presented evidence, there is no distinction among applications and products in terms of complexity.

[34] While a longer time-series would have facilitated the investigation of differential pre- and post- pandemic trends, these findings seem also consistent with the descriptive dynamics of first adoption for digital applications (see Subsection 4.2).

[35] See subsection 3.1 (Table 1) for additional details on the digital technology classes, as well as in Table A A.1 in the Annex.

[36] These results hold for broad classes (see Table A B.1) and, overall, for digital technology applications (see Table A B.2).

[37] Adoption is intended as first adoption of a new digital application, in contrast to digital upgrading, as previously defined. Applications that diffused the most are defined as those with (i) the highest growth in the cumulative number of plants having (adopted) the given digital application (end of 2021 vs end of 2019) and (ii) a share of diffusion of at least 10% during the pandemic years. Other applications with high growth in diffusion were, in order, e.g., "Publishing and Design software", "CRM & Sales software", "ERP and Business Management", "Human Capital Management" and "Customer Service".

[38] These figures do not include information on subsequent acquisition of digital tools.

[39] These dynamics hold at the aggregate level, i.e., across sectors and countries.

[40] The analysis builds upon and extends the work of Hosseinioun et al (2023[79]) that uses a similar network analysis to disentangle relations between different sets of skills.

[41] The analysis is based on the empirical approach presented in Subsection 3.2. In particular, the analysis employs a linear probability model which accounts for a set of firm characteristics (as for the analysis performed in subsection 4.1.1). The analysis focuses on digital *adoption*, i.e., it analyses firms that did not have "Digital Commerce" in place before the pandemic.

[42] See Table A B.12 in the Annex for complete regression results.

[43] These applications include: "IT Architecture", "IT Development", "Web Architecture", "Marketing and Advertising", "Data Management", "IT Security", "Cloud", "Analytics", "Collaborative Software", "Suites and SaaS".

[44] In this case, included applications are “IT Architecture”, “IT Development", “Marketing and Advertising software”, “Data Management”, “IT Security”, “Cloud”, and “Analytics”. Included supporting applications are those derived in Box 4.1. Also for this part, the analysis is based on the empirical approach presented in Subsection 3.2. The analysis controls for a set of firm characteristics (size, productivity, age, human capital, firm structure, country and sector fixed effects). The analysis focuses on firms that did not have “Collaborative Software” in place before the pandemic.

[45] Nonetheless, there is no noticeable change in the cumulative probability of adoption of “Collaborative Software” when accounting also for the presence of Data Management (in Figure 12, class 5 vs. class 4).

[46] Specifically, firms equipped with “IT Architecture”, “IT Development”, "Marketing and Advertising software", "Data Management" prior to the pandemic were more likely to adopt “Analytics” and “Cloud” services during the crisis.

[47] Similarly, “Cloud” services, often used to scale up operations, may have aligned well with firms already equipped with marketing and advertising tools.

[48] The above commented analysis focus on specific supporting technologies, as identified through the descriptive analysis in Box 4.1. As a robustness, additional model specifications for the adoption of “Cloud”, “Digital Commerce”, “Analytics” and “Collaborative Software” are tested using the aggregate digital index as well as the IT intensity indicator used in Subsection 4.1.1. These results confirm the positive role of ex-ante digitalisation.

[49] The analysis also in this case highlights the importance of ex-ante productivity levels. Indeed, the estimated relation with productivity is in line with the discussion in Subsection 4.1.1, i.e., more productive firms were overall more likely to adopt new digital applications over the pandemic (cf. also Table A B.1).

[50] In other words, the analysis focuses on the joint adoption of digital applications for the first time during COVID-19.

[51] The analysis presented in Box 4.1 refers to the year 2019.

[52] These applications have similar level of diffusion (see Box 4.1 for further details) and have as supporting applications “IT Architecture”, “IT Development”, “Web Architecture”, “Marketing and Advertising”, “Data Management”, “IT Security”, “Cloud”, “Analytics”, “Collaborative Software”, “Suites and SaaS”. See also the analysis in Subsection 4.2.1.

[53] This analysis is exploratory and, also considering the simultaneous setting, is just a first step into exploring the joint adoption of horizontally-related digital applications. The analysis is based on the empirical approach presented in Subsection 3.2. In particular, the analysis employs a linear probability model which accounts for a set of firm characteristics (as for the analysis performed in Subsection 4.1.1). The analysis focuses on first digital adoption, i.e., for each dyad, it analyses firms that did not have the applications in place before the pandemic. As the analysis focuses on adoption, each regression considers firms that were not active in the given applications before COVID-19. Similar results are confirmed focusing on firms that acquired new digital tools for pre-existing applications.

[54] The same applies for the “IT Security” application.

[55] Similarly, adoption complementarities (with positive and significant coefficients) are present among the other digital applications (not reported).

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Annex A. Additional information about technologies and sample

Table A A.1. Complete technology classification

Digital class	Digital application	Digital functionality
Advanced Applications and Analytics	Analytics	Web Analytics
		Marketing Analytics
	A/B Testing	A/B Testing
	Machine Learning	Machine Learning
	Big Data	Big Data
	Production printer	Production printer
Digital Sales	Digital Commerce	Payment Processing, E-commerce platform, Retail software, E-Commerce Platform/Software, Site & Cart Abandonment
	CRM & Sales software	Appointment Scheduling, Configure/Price/Quote, Customer Relationship Management, Lead Generation, Other Sales Software, Sales Enablement, Sales Performance Management
	Customer Service	Contact Centre Management, Customer Feedback Management, Help Desk Management, IT Service Management, Live Chats, Other Customer Service Software, Partner Management
	Marketing and Advertising	Ad Exchanges, Ad Serving, Ad Verification & Optimization, Advertising Networks, Advocacy Marketing, Affiliate Networks, Call Tracking, Content Marketing, Customer Experience Management, Data Management Platforms, Demand-Side Platforms, Digital Advertising, Email Marketing, Email Software, Event Management, Loyalty & Gamification, Marketing Automation, Marketing Performance Management, Media, Native Advertising, Other Advertising Software, Other Marketing Software, Personalized Marketing, Product Information Management, Retargeting, Search Marketing, Social Media Systems, Supply Side Platforms, Video Advertising Networks
Digital Workplace	Cloud	Infrastructure as a Service (IaaS), Platform as a Service (PaaS)
	Collaborative Software	Collaborative/Integrated Software, Project Management Software, Document management, Groupware Software, Other Collaboration Software
	Publishing and Design software	Graphic Design, CAD/CAM, Design & Publishing Software
	Suites and SaaS	Software as a Service (SaaS), Office Suites
Industry/Business software	Industry software	Academic & Education Management, Automotive Marketing, Construction, Fundraising & Donation Management, Healthcare Marketing, Hotel Management, Hotel Reservations, Legal & Professional Service, Manufacturing, Medical, Other Vertical Industries Software, Philanthropic, Public Sector, Real Estate Marketing, Real Estate Property Management, Sustainability, Ticketing Systems
	Business Intelligence	Business Intelligence
	Human Capital Management	Human Resources Management, Applicant Tracking Systems, Recruitment Marketing
	ERP & Business Management	Enterprise Resource Planning, Business Process Management, Enterprise Application Integration, Enterprise Management, Governance Risk & Compliance, Other Operations Software, Procurement, Service & Field Support Management, Software Configuration Management
	Financial Management	Enterprise Asset Management, Accounting, Accounting/Finance/Treasury, Blockchain, Enterprise Asset Management
	Supply Chain Management	Supply Chain Management, Inventory Management
IT Systems	IT Architecture	Backup & Recovery, Click-to-Call, Desktop Management Tools, Desktop Virtualization, Disk Drive, Handset Operating System, High Performance Workstation, IBM/PCM Mainframe, LAN

		Operating System, Multimedia, Network Attached Storage, Office Copier, Operating System, Personal Computing Peripheral, Personal Desktop Computer, Personal Portable Computer, Phone System, Power System, Printer, Server, Server Management Tools, Server Virtualization, Smartphone, Storage Area Network, Storage as a Service, Storage Management, Tablet Computer, Tape Library, Video Conferencing, Voice over IP
	IT Development	Frameworks & Libraries, Programming Languages, Application Development Tools, Application Server Software, Containerization, Content Delivery Networks, Domain Name Services, Enterprise Mobility Management, IT Infrastructure & Ops Management, Other IT Development/Infrastructure, Portal Management, Program Testing/Debugging, Testing & QA
	Web Architecture	CAPTCHA, Charting, Geographic Info Systems, Other Web Tools & Plugins, Push Notifications, Site Search, Social Media Platform, Translation, Unified Communications Services, Visitor Counters, Web Content Management Systems, Web Design & Development Services, Web Hosting, Web Services, Website Builders, Widgets
	Data Management	Data Integration, Data Management, Database Management
	IT Security	Advanced Threat Protection, Anti-Virus, Data Loss Prevention Software, Disaster Recovery, Email Security, Endpoint Detection & Response, Endpoint Security, Firewall Software, Identity & Access Management, IT Asset Management, LAN Switch, Network Management Software, Other Security Software, Router, Security Information & Event Management, Security Information & Event Management (SIEM), Surveillance Equipment, Virtual Private Network

Note: "Cloud" is measured by the presence of IaaS or PaaS functionalities (Cao and Iansiti, 2022[71]). Non-classified products are not included.
Source: authors' elaborations on Spiceworks data.

Table A A.2. Descriptive statistics – plants with information about digital products vis-à-vis plants in the overall sample

Variable (2019)		Plants with information on products		Full sample	
	Class	Share	Observations	Share	Observations
Productivity	Bottom 10%	6.3	59 114	6.04	94 676
	10%-40%	20.1	188 504	18.7	292 957
	40%-60%	14.41	135 169	13.57	212 631
	60%-90%	22.18	208 041	21.34	334 379
	Top 10%	7.44	69 783	7.42	116 315
Size	1-9	16.82	157 757	36.83	344 145
	10-49	41.83	392 243	21.96	576 990
	50-249	14.11	132 283	10.66	167 013
	250+	3.07	28 796	2.15	33 725
Age	0-5	7.82	73 295	11.09	173 827
	6-10	13.34	125 094	15.17	237 638
	11+	76.54	717 807	72.1	1 129 656
Human capital	0	96.74	907 187	97.49	1 527 436
	1	3.26	30 585	2.51	39 403
Firm structure	Single-plant	40.47	379 489	43.36	679 377
	Multi-plant	39.05	366 170	40.91	640 927
	MNEs	20.49	192 113	15.73	246 535
		Plants with information on products		Full sample	
		Mean (s.d.)	Observations	Mean (s.d.)	Observations
IT intensity (log)		7.88 (1.29)	703 549	7.82 (1.25)	1 108 459
Product functionalities		10.34 (9.75)	937 771	-	-
Digital index		0.14 (0,13)	937 771	-	-

Note: The Table reports descriptive statistics for the key variables used for the analyses. The IT spending variable accounts for the sum of IT budget for computers, servers, storage, hardware, communication, software, and services (in thousand dollars 2019). The IT intensity variable is computed as IT budget over employment in 2019. The human capital variable accounts for the presence of IT staff/developers at the plant level. The digital index is computed as the number of digital functionalities at the firm-level over the maximum number of functionalities available at the country-sector (2-dig) level. The index is reported before the (z-score) standardisation. Productivity groups are computed within sample and within each country-sector (2-dig). Missing shares are not reported.
Source: authors' elaborations on Spiceworks data.

Annex B. Additional regression analysis

Table A B.1. Regression results for technology classes

	Advanced Applications and Analytics			Business/Industry software			Digital Sales			Digital Workplace			IT Systems		
Micro (1-9)	-0.014***	-0.022***	-0.014***	-0.002*	-0.010***	-0.000	-0.010***	-0.020***	-0.011***	-0.020***	-0.033***	-0.025***	-0.005***	-0.010***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Medium (50-249)	0.036***	0.034***	0.021***	0.026***	0.023***	0.007***	0.040***	0.040***	0.026***	0.042***	0.041***	0.028***	0.022***	0.022***	0.019***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Large (250+)	0.081***	0.078***	0.031***	0.102***	0.099***	0.041***	0.093***	0.090***	0.039***	0.098***	0.094***	0.049***	0.050***	0.048***	0.035***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Age 6-10	0.009***	0.009***	0.014***	0.007***	0.007***	0.013***	-0.001	-0.002	0.004*	-0.000	-0.001	0.004**	0.009***	0.009***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 11+	-0.022***	-0.022***	-0.011***	-0.026***	-0.025***	-0.012***	-0.039***	-0.039***	-0.027***	-0.036***	-0.036***	-0.026***	-0.010***	-0.010***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Human Capital	0.042***	0.022***	0.007**	0.065***	0.029***	0.010***	0.025***	0.017***	0.001	0.041***	0.023***	0.009***	0.021***	0.016***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Multi	0.039***	0.034***	0.030***	0.007***	0.001	-0.004***	0.040***	0.035***	0.030***	0.049***	0.042***	0.038***	0.024***	0.022***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MNE	0.155***	0.146***	0.076***	0.150***	0.138***	0.050***	0.166***	0.157***	0.080***	0.209***	0.197***	0.128***	0.067***	0.062***	0.042***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Bottom 10%		-0.011***	-0.007***		-0.004**	0.001		-0.018***	-0.014***		-0.023***	-0.019***		-0.015***	-0.014***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
10%-40%		-0.006***	-0.003**		-0.002*	0.001		-0.007***	-0.004**		-0.010***	-0.008***		-0.008***	-0.008***
		(0.002)	(0.002)		(0.001)	(0.001)		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.001)
60%-90%		0.008***	0.004***		0.008***	0.004***		0.011***	0.007***		0.012***	0.009***		0.004***	0.003*
		(0.002)	(0.002)		(0.001)	(0.001)		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.001)
Top 10%		0.030***	0.014***		0.031***	0.011***		0.035***	0.018***		0.041***	0.026***		0.014***	0.009***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
Digital Index			0.113***			0.143***			0.124***			0.110***			0.033***
			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)
Obs.	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757	937 757
R-sq.	0.104	0.105	0.142	0.112	0.114	0.199	0.103	0.103	0.145	0.110	0.111	0.144	0.041	0.041	0.046
Country-Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the digital technology class dummy as dependent variable and include size class, age class, firm structure, and other complementary factors (human capital, digitalisation) as main independent variables. The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). The ex-ante level of digitalisation is computed as an index [0,1] which accounts for the overall number of digital functionalities (across classes) at the plant level w.r.t. the number of digital functionalities (across classes) for each country-sector (see Table A A.1). The digitalisation index is standardised to have mean 0 and s.d. 1. "Multi" identifies plants belonging to domestic firms. "MNE" identifies plants belonging to MNEs. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported.

Results are robust using the log of labour productivity and employment in 2019, excluding plants at the top 1% of the productivity distribution, employing a logit model as the main regression model, and using a different proxy for digitalisation as control (see Table A B.3). Results generally hold within classes, i.e., for digital applications within each class (cf. Table A B.2).
Source: authors' elaborations on Spiceworks data.

Table A B.2. Digital applications regression coefficients

Digital class	Digital application	Size	Productivity	Digitalisation
Advanced Applications and Analytics	Analytics	✓	✓	×
	A/B Testing	×	✓	✓
	Machine Learning	×	✓	✓
	Big Data	✓	✓	✓
	Production printer	✓	×	✓
Digital Sales	Digital Commerce	×	×	✓
	CRM & Sales software	✓	✓	✓
	Customer Service	✓	✓	✓
	Marketing and Advertising	✓	✓	✓
Digital Workplace	Cloud	✓	✓	✓
	Collaborative Software	✓	✓	✓
	Publishing and Design soft.	✓	✓	✓
	Suites and SaaS	✓	✓	✓
Industry/Business software	Industry software	✓	✓	✓
	Business Intelligence	✓	✓	✓
	Human Capital Management	✓	✓	✓
	ERP & Business Management	✓	✓	✓
	Financial Management	✓	✓	✓
	Supply Chain Management	×	×	✓
IT Systems	IT Architecture	✓	✓	✓
	IT Development	✓	✓	×
	Web Architecture	✓	✓	✓
	Data Management	✓	✓	×
	IT Security	✓	✓	✓

Note: The Table reports main robustness results for digital applications regressions. In particular, the Table displays the relations between size, productivity, and digital index coefficients and the likelihood of introduction of new digital tools related to each digital application. For each digital application, a linear probability regression is run, following the empirical approach presented in Section 3.2 and the analysis commented in Section 4.1.1. A tick mark (✓) means that, for the given digital application and variable (size, productivity, digitalisation), the relation is positive and significant. In most cases, if a relation does not hold it is because the given coefficient appears not significant.
Source: authors' elaborations on Spiceworks data.

Table A B.3. Regression results for technology classes: alternative specification for digitalisation

Dependent variable	Advanced Applications and Analytics	Business/Industry software	Digital Sales	Digital Workplace	IT Systems
Bottom 10%	-0.012***	-0.004**	-0.020***	-0.024***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
10%-40%	-0.006***	-0.002*	-0.007***	-0.011***	-0.009***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
60%-90%	0.008***	0.008***	0.010***	0.013***	0.004***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Top 10%	0.033***	0.032***	0.037***	0.043***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Micro (1-9)	-0.024***	-0.012***	-0.023***	-0.034***	-0.012***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Medium (50-249)	0.037***	0.022***	0.041***	0.043***	0.024***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Large (250+)	0.084***	0.097***	0.094***	0.099***	0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Age 6-10	0.012***	0.006***	0.001	0.003	0.013***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Age 11+	-0.020***	-0.026***	-0.036***	-0.032***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Human capital	0.021***	0.032***	0.015***	0.024***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Multi	0.040***	-0.002	0.038***	0.049***	0.023***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
MNE	0.134***	0.139***	0.150***	0.187***	0.057***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
IT intensity	0.000	0.000	0.002***	0.003***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	703 533	703 533	703 533	703 533	703 533
R-sq	0.117	0.129	0.114	0.120	0.045
Country-Sector FE	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the digital technology class dummy as dependent variable and include size class, age class, firm structure, and other complementary factors (human capital, IT intensity) as main independent variables. The variable IT budget is the sum of IT budget for computers, servers, storage, hardware, communication, software, and services (in 1 000 dollars); the IT intensity variable is computed as IT budget over employment (see also Subsection 3.1 and Table A A.2).The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. “Multi” identifies plants belonging to domestic firms. “MNE” identifies plants belonging to MNEs. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported. Results are robust using the log computer intensity (number of PCs over employment) as an alternative proxy of technology intensity (see also Section 3).
Source: authors’ elaborations on Spiceworks data.

Table A B.4. Regression results for technology classes – Manufacturing and Services

	Advanced Applications and Analytics		Business/Industry software		Digital Sales		Digital Workplace		IT Systems	
	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.
Bottom 10%	-0.015***	0.000	0.003	0.003	-0.019***	-0.007***	-0.029***	-0.011***	-0.023***	-0.010***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.002)
10%-40%	-0.007**	-0.001	0.004	0.000	-0.001	-0.003*	-0.013***	-0.005***	-0.009***	-0.007***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
60%-90%	0.006*	0.005***	0.004	0.005***	0.011***	0.006***	0.012***	0.008***	0.007***	0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Top 10%	0.020***	0.012***	0.021***	0.008***	0.027***	0.013***	0.036***	0.021***	0.015***	0.006***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.002)
Age 6-10	0.015***	0.011***	0.018***	0.010***	0.006	0.000	0.007	0.002	0.013***	0.009***
	(0.005)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)
Age 11+	-0.008**	-0.018***	-0.005	-0.020***	-0.021***	-0.034***	-0.024***	-0.031***	-0.007**	-0.010***
	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
Human capital	-0.002	-0.003	-0.006	0.018***	0.004	-0.019***	0.010*	-0.002	0.012***	0.006***
	(0.006)	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.002)
Micro (1-9)	-0.001	-0.008***	0.011***	0.004***	0.004	-0.003*	-0.018***	-0.019***	0.002	-0.006***
	(0.003)	(0.002)	(0.003)	(0.001)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)	(0.001)
Medium (50-249)	0.022***	0.017***	-0.000	0.007***	0.024***	0.023***	0.035***	0.022***	0.028***	0.014***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Large (250+)	0.043***	0.027***	0.054***	0.038***	0.065***	0.026***	0.087***	0.029***	0.053***	0.028***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.002)
Multi	0.024***	0.032***	-0.006***	-0.003**	0.021***	0.038***	0.034***	0.043***	0.016***	0.025***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
MNE	0.091***	0.079***	0.055***	0.064***	0.098***	0.090***	0.141***	0.143***	0.044***	0.046***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
Digital Index	0.072***	0.119***	0.106***	0.142***	0.093***	0.120***	0.077***	0.109***	0.019***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Medium-high tech	0.009***		0.027***		0.014***		0.025***		0.006***	
	(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
High-tech	0.052***		0.067***		0.058***		0.058***		0.035***	
	(0.004)		(0.003)		(0.004)		(0.004)		(0.003)	
KIS		0.125***		0.115***		0.138***		0.126***		0.075***
		(0.002)		(0.001)		(0.002)		(0.002)		(0.001)
LKIS		0.129***		0.073***		0.112***		0.059***		0.061***
		(0.001)		(0.001)		(0.002)		(0.002)		(0.001)
Obs.	217 248	720 523	217 248	720 523	217 248	720 523	217 248	720 523	217 248	720 523
R sq.	0.076	0.139	0.133	0.191	0.099	0.137	0.103	0.140	0.025	0.043
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs focusing separately on Manufacturing and Services sectors. The models employ the digital technology class dummy as dependent variable and include size class, age class, firm structure, and other complementary factors for 2019 as main independent variables. The regressions for manufacturing include dummies "medium-high-tech" and "high-tech", that refer to the Eurostat classification based on NACE Rev. 2 codes at the 2-digit level. High-technology sectors include codes 21 and 26. Medium-high technology includes codes 20, and 27 to 30. Medium-low technology is covered by codes 19, 22 to 25, and 33.

Low technology encompasses codes 10 to 18, and 31 to 32. The analysis compares – for manufacturing – High-technology and Medium-high technology sectors with Low and Medium-low sectors (base category). The regressions for services include dummies "LKIS" and "KIS", that refer to the Eurostat classification based on NACE Rev. 2 codes at the 2-digit level. Knowledge-intensive services (KIS) are identified by the following NACE Rev. 2 codes at the 2-digit level: 50-51, 58-63, 64-66, 69-75, 78, 80, and 84-93. Less knowledge-intensive services (LKIS) encompass codes 45 to 47, 49, 52 to 53, 55 to 56, 68, 77, 79, 81, 82, and 94 to 99. The analysis compares KIS and LKIS with other services. The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). "Multi" identifies plants belonging to domestic firms. "MNE" identifies plants belonging to MNEs. Each regression includes country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients not reported. Results are robust to the use of log labour and employment variables. Missing class coefficients are not reported. Constant not reported.
Source: authors' elaborations on Spiceworks data.

Table A B.5. Regression results for first adoption and upgrading

Dependent variable	Advanced Applications and Analytics		Business/Industry software		Digital Sales		Digital Workplace		IT Systems
	Adoption	Upgrading	Adoption	Upgrading	Adoption	Upgrading	Adoption	Upgrading	Upgrading
Bottom 10%	-0.014***	0.004	-0.001	0.006	-0.021***	-0.009***	-0.029***	-0.010***	-0.015***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
10%-40%	-0.006***	0.001	0.000	0.001	-0.010***	0.001	-0.011***	-0.006**	-0.008***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
60%-90%	0.001	0.009***	0.002	0.012***	0.005*	0.009***	0.006**	0.013***	0.003**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Top 10%	0.012***	0.020***	0.008***	0.022***	0.010***	0.023***	0.019***	0.033***	0.009***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Micro (1-9)	-0.018***	-0.013***	-0.003**	0.004	-0.016***	-0.006***	-0.031***	-0.020***	-0.010***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Medium (50-249)	0.032***	0.017***	0.007***	0.012***	0.018***	0.031***	0.031***	0.030***	0.021***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Large (250+)	0.040***	0.022***	0.028***	0.039***	0.033***	0.041***	0.038***	0.052***	0.035***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.006)	(0.003)	(0.002)
Age 6-10	-0.008**	0.018***	0.016***	0.003	-0.002	0.008***	0.002	0.006**	0.009***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)
Age 11+	-0.035***	-0.008***	-0.010***	-0.029***	-0.026***	-0.025***	-0.028***	-0.022***	-0.010***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Human capital	0.006	0.007*	-0.000	0.011**	-0.018***	0.011***	0.000	0.012***	0.011***
	(0.005)	(0.004)	(0.003)	(0.005)	(0.007)	(0.003)	(0.006)	(0.003)	(0.002)
Digital Index	0.153***	0.189***	0.074***	0.161***	0.038***	0.124***	0.099***	0.118***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)
Multi	0.042***	0.018***	0.004***	-0.008***	0.029***	0.030***	0.051***	0.030***	0.025***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
MNE	0.078***	0.074***	0.023***	0.094***	0.042***	0.087***	0.096***	0.136***	0.044***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Obs.	528 694	409 041	705 158	232 556	344 390	59 333	408 493	529 241	889 805
R-sq.	0.119	0.362	0.075	0.315	0.066	0.147	0.091	0.163	0.056
Country-Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the digital technology class dummy as dependent variable and include size class, age class, firm structure, and other complementary factors (human capital, digitalisation) as main independent variables. The technology class dummy is equal to 1 if the firm has introduced a new digital product for the given technology class in 2020 and/or 2021. The Table includes, on the one hand, results for firms that were not active in a given digital class in 2019 and that might have eventually adopted (or not) during the crisis (adopters vs non-adopters; Table label "Adoption"); on the other hand, the approach considers firms that were active in a given digital class before the crisis, and that might eventually have upgraded (or not) during the crisis (upgrader vs non-upgraders; Table label "Upgrading"). For the class "IT Systems", results for adopters vs. non-adopters are not computed, as almost all firms were already active in "IT Systems" in 2019. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). The ex-ante level of digitalisation is computed as an index [0,1] which accounts for the overall number of digital functionalities (across classes) at the plant level w.r.t. the number of digital functionalities (across classes) for each country-sector (see Table A A.1.). The digitalisation index is standardised to have mean 0 and s.d. 1. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported.
Source: authors' elaborations on Spiceworks data.

Table A B.6. Regression results for the first adoption of Digital Commerce

	1	2	3	4	5	6	7	8	9	10
n. supporting tech	0.061***	0.069***	0.076***	0.103***	0.111***	0.136***	0.177***	0.230***	0.272***	0.336***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Micro (1-9)	0.011***	0.011***	0.012***	0.013***	0.013***	0.012***	0.012***	0.011***	0.011***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medium (50-249)	0.002*	0.001	0.001	0.000	0.001	0.001	0.001	0.002	0.002*	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Large (250+)	0.040***	0.039***	0.038***	0.036***	0.036***	0.035***	0.035***	0.035***	0.035***	0.034***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bottom 10%	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.003	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
10%-40%	0.004***	0.004***	0.004***	0.005***	0.005***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
60%-90%	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Top 10%	0.004**	0.003**	0.003*	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 6-10	0.000	0.001	0.001	0.002	0.002	0.002	0.002	0.003*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 11+	-0.009***	-0.008***	-0.007***	-0.006***	-0.006***	-0.007***	-0.007***	-0.006***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Human capital	0.020***	0.020***	0.020***	0.019***	0.020***	0.019***	0.020***	0.021***	0.019***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Multi	-0.007***	-0.008***	-0.007***	-0.008***	-0.008***	-0.007***	-0.007***	-0.006***	-0.004***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MNE	0.034***	0.032***	0.031***	0.024***	0.024***	0.024***	0.024***	0.024***	0.025***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	806 183	806 183	806 183	806 183	806 183	806 183	806 183	806 183	806 183	806 183
R-sq.	0.069	0.071	0.072	0.077	0.077	0.080	0.082	0.087	0.086	0.086
Country-Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the dummy "adoption of Digital Commerce" as dependent variable and include size class, productivity class, age class, firm structure, and other complementary factors (human capital, number of supporting technologies) as main independent variables. The dummy "supporting technologies" accounts for the number of supporting technologies; each column reports results for the corresponding number of supporting technologies. In particular, column 1 reports regression results when the number of supporting technologies is equal to 1 (presence of "IT Architecture"). Column 2 reports regression results when the number of supporting technologies is equal to 2 (presence of "IT Architecture" and "IT Development"), etc. See also Subsection 4.2.1 for the specification of supporting technologies. The adoption dummy is equal to 1 if the firm has introduced "Digital Commerce" for the first time in 2020 and/or 2021. The regression models refer to firms that were not active in "Digital Commerce" in 2019. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported. Results are robust using the variable "number of supporting technologies" (ranging from 0 to 10) as an alternative specification.
Source: authors' elaborations on Spiceworks data.

Table A B.7. Regression results for the first adoption of Collaborative Software

	1	2	3	4	5	6	7	8
n. supporting tech	0.036***	0.043***	0.056***	0.100***	0.099***	0.106***	0.152***	0.158***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Micro (1-9)	-0.037***	-0.036***	-0.036***	-0.034***	-0.035***	-0.035***	-0.036***	-0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medium (50-249)	0.018***	0.017***	0.017***	0.015***	0.016***	0.016***	0.016***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Large (250+)	0.023***	0.022***	0.022***	0.018***	0.020***	0.020***	0.020***	0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bottom 10%	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
10%-40%	-0.010***	-0.010***	-0.010***	-0.009***	-0.009***	-0.009***	-0.009***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
60%-90%	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Top 10%	0.022***	0.021***	0.021***	0.020***	0.020***	0.021***	0.021***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 6-10	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 11+	-0.015***	-0.014***	-0.014***	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Human capital	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Multi	0.043***	0.043***	0.042***	0.041***	0.041***	0.042***	0.042***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MNE	0.120***	0.119***	0.117***	0.110***	0.112***	0.114***	0.114***	0.116***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	673 249	673 249	673 249	673 249	673 249	673 249	673 249	673 249
R-sq.	0.105	0.106	0.108	0.113	0.111	0.110	0.111	0.109
Country-Sector FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the dummy "adoption of Collaborative Software" as dependent variable and include size class, productivity class, age class, firm structure, and other complementary factors (human capital, number of supporting technologies) as main independent variables. The dummy "supporting technologies" accounts for the number of supporting technologies; each column reports results for the corresponding number of supporting technologies. In particular, column 1 reports regression results when the number of supporting technologies is equal to 1 (presence of "IT Architecture"). Column 2 reports regression results when the number of supporting technologies is equal to 2 (presence of "IT Architecture" and "IT Development"), etc. See also Subsection 4.2.1 for the specification of supporting technologies. The adoption dummy is equal to 1 if the firm has introduced "Collaborative Software" for the first time in 2020 and/or 2021. The regression models refer to firms that were not active in "Collaborative Software" in 2019. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported. Results are robust using the variable "number of supporting technologies" (ranging from 0 to 8) as an alternative specification.
Source: authors' elaborations on Spiceworks data.

Table A B.8. Regression results for the first adoption of Analytics

	1	2	3	4	5
n. supporting tech	0.048***	0.061***	0.077***	0.150***	0.157***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Micro (1-9)	-0.024***	-0.023***	-0.023***	-0.021***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Medium (50-249)	0.042***	0.041***	0.041***	0.038***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Large (250+)	0.061***	0.059***	0.059***	0.053***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Bottom 10%	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
10%-40%	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
60%-90%	0.003	0.003	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Top 10%	0.019***	0.018***	0.018***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age 6-10	-0.013***	-0.012***	-0.012***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age 11+	-0.044***	-0.043***	-0.042***	-0.040***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Human capital	0.014***	0.014***	0.013***	0.011**	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Multi	0.049***	0.048***	0.048***	0.046***	0.047***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MNE	0.114***	0.112***	0.110***	0.099***	0.101***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	532 866	532 866	532 866	532 866	532 866
R-sq.	0.098	0.099	0.100	0.109	0.107
Country-Sector FE	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the dummy "adoption of Analytics" as dependent variable and include size class, productivity class, age class, firm structure, and other complementary factors (human capital, number of supporting technologies) as main independent variables. The dummy "supporting technologies" accounts for the number of supporting technologies; each column reports results for the corresponding number of supporting technologies. In particular, column 1 reports regression results when the number of supporting technologies is equal to 1 (presence of "IT Architecture"). Column 2 reports regression results when the number of supporting technologies is equal to 2 (presence of "IT Architecture" and "IT Development"), etc. See also Subsection 4.2.1 for the specification of supporting technologies. The adoption dummy is equal to 1 if the firm has introduced "Collaborative software" for the first time in 2020 and/or 2021. The regression models refer to firms that were not active in "Collaborative software" in 2019. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). The digitalisation index is standardised to have mean 0 and s.d. 1. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported. Results are robust using the variable "number of supporting technologies" (ranging from 0 to 5) as an alternative specification.
Source: authors' elaborations on Spiceworks data.

Table A B.9. Regression results for the first adoption of Cloud

	1	2	3	4	5
n. supporting tech	0.086***	0.086***	0.090***	0.135***	0.135***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Micro (1-9)	-0.031***	-0.031***	-0.031***	-0.030***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Medium (50-249)	0.031***	0.031***	0.031***	0.030***	0.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Large (250+)	0.052***	0.051***	0.053***	0.049***	0.051***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bottom 10%	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
10%-40%	-0.010***	-0.010***	-0.010***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
60%-90%	0.006***	0.006***	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Top 10%	0.026***	0.026***	0.026***	0.025***	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age 6-10	-0.005**	-0.005*	-0.005*	-0.004	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age 11+	-0.018***	-0.017***	-0.017***	-0.015***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Human capital	0.009**	0.009**	0.008*	0.008*	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Multi	0.037***	0.037***	0.038***	0.037***	0.037***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MNE	0.144***	0.143***	0.144***	0.137***	0.139***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	586 393	586 393	586 393	586 393	586 393
R-sq.	0.094	0.094	0.093	0.098	0.096
Country-Sector FE	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the dummy “adoption of Cloud” as dependent variable and include size class, productivity class, age class, firm structure, and other complementary factors (human capital, number of supporting technologies) as main independent variables. The dummy “supporting technologies” accounts for the number of supporting technologies; each column reports results for the corresponding number of supporting technologies. In particular, column 1 reports regression results when the number of supporting technologies is equal to 1 (presence of “IT Architecture”). Column 2 reports regression results when the number of supporting technologies is equal to 2 (presence of “IT Architecture” and “IT Development”), etc. See also Subsection 4.2.1 for the specification of supporting technologies. The adoption dummy is equal to 1 if the firm has introduced “Cloud” for the first time in 2020 and/or 2021. The regression models refer to firms that were not active in “Cloud” in 2019. The labour productivity proxy is computed as (log) turnover over employment in 2019. Productivity groups are computed within country-sector (2-digit sectors). Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Productivity coefficients are computed w.r.t. the 40%-60% class; size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Constant not reported. Results are robust using the variable “number of supporting technologies” (ranging from 0 to 5) as an alternative specification.
Source: authors’ elaborations on Spiceworks data.

Table A B.10. Complete regression results for adoption in bundles: Cloud, Analytics

	Cloud and IT Security		Cloud and Analytics		Analytics and IT Security	
	IT Security	Cloud	Cloud	Analytics	IT Security	Analytics
Bundle	0.212***	0.216***	0.118***	0.143***	0.127***	0.159***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Micro (1-9)	0.004**	-0.024***	-0.020***	-0.014***	0.001	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Medium (50-249)	0.012***	0.023***	0.027***	0.030***	0.017***	0.031***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Large (250+)	0.033***	0.031***	0.049***	0.039***	0.034***	0.040***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Age 6-10	0.008***	-0.004	-0.012***	-0.011***	0.004	-0.009**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Age 11+	-0.000	-0.013***	-0.018***	-0.038***	-0.006**	-0.037***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Human capital	0.008	-0.004	0.017***	0.020***	0.007	-0.002
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Multi	0.002	0.044***	0.042***	0.038***	0.007***	0.043***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MNE	0.022***	0.113***	0.121***	0.062***	0.043***	0.067***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Supp. tech.	0.003	0.076***	0.104***	0.130***	0.028***	0.120***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Obs.	392 495	392 495	374 181	374 181	349 791	349 791
R-sq.	0.078	0.117	0.103	0.115	0.055	0.114
Country-Sector FE	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the digital application adoption dummy as dependent variable and include size class, age class, firm structure, human capital, supporting technologies, and the adoption of a related application as main independent variables. In particular, for each dyad of digital applications A and B (e.g., "Cloud" and "IT Security"), two models are estimated. In the first model, application A is the dependent variable while the other B is the independent variable (bundle dummy). In the second model, application B is treated as the dependent variable while the other A is the independent variable (bundle dummy). The "supporting technologies" dummy accounts for the presence of the five supporting digital applications related to "Cloud", "IT Security", and "Analytics": see also Box 4.1. and Subsection 4.2.1 for the specification of supporting technologies. Each regression model (for a given dyad) refers to firms that did not have both applications in 2019. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Results are robust excluding the "supporting technologies" dummy. Also, results are robust to the inclusion of the productivity variable as an alternative regressor. Constant not reported.
Source: authors' elaborations on Spiceworks data.

Table A B.11. Regression results for adoption in bundles: Digital Commerce

	Digital Commerce and Customer Service		Digital Commerce and Pub. Des. Software		Digital Commerce and Business Intelligence	
	Digital Commerce	Customer Service	Digital Commerce	Pub. Des. Software	Digital Commerce	Business Intelligence
Bundle	0.265***	0.075***	0.096***	0.072***	0.162***	0.049***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Micro (1-9)	0.010***	-0.002***	0.011***	0.001	0.008***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medium (50-249)	0.000	0.004***	0.000	0.010***	-0.001	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Large (250+)	0.019***	0.013***	0.018***	0.030***	0.012***	0.026***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Age 6-10	0.002	-0.001	0.006***	0.004**	0.000	0.003***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Age 11+	-0.005***	-0.006***	-0.002	-0.018***	-0.010***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Human capital	0.022***	-0.009***	0.010***	0.008***	0.010***	0.021***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Multi	-0.005***	0.002***	-0.004***	0.004***	-0.002**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MNE	0.002	0.029***	0.012***	0.035***	0.008***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Supp. tech.	0.206***	0.217***	0.202***	0.167***	0.240***	0.156***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Obs.	758 695	758 695	758 695	758 695	758 695	758 695
R-sq.	0.079	0.094	0.065	0.048	0.075	0.086
Country-Sector FE	YES	YES	YES	YES	YES	YES

Note: The Table displays estimated LPMs that employ the digital application adoption dummy as dependent variable and include size class, age class, firm structure, human capital, supporting technologies, and the adoption of a related application as main independent variables. In particular, for each dyad of digital applications A and B (e.g., “Digital Commerce” and “Customer Service”), two models are estimated. In the first model, application A is the dependent variable while the other B is the independent variable (bundle dummy). In the second model, application B is treated as the dependent variable while the other A is the independent variable (bundle dummy). The “supporting technologies” dummy accounts for the presence of the ten supporting digital applications related to “Digital Commerce”, “Customer Service”, “Business Intelligence”, and “Publishing and Design Software”: see also Box 4.1. and Subsection 4.2.1 for the specification of supporting technologies. Each regression model (for a given dyad) refers to firms that did not have both applications in 2019. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Results are robust excluding the “supporting technologies” dummy. Also, results are robust to the inclusion of the productivity variable as an alternative regressor. Constant not reported.
Source: authors’ elaborations on Spiceworks data.

Table A B.12. Regression results for adoption in bundles: Collaborative software

	Collaborative Software and Suites and SaaS	
	Collaborative Software	Suites and SaaS
Bundle	0.071***	0.062***
	(0.002)	(0.001)
Micro (1-9)	-0.005***	-0.026***
	(0.001)	(0.001)
Medium (50-249)	0.013***	0.014***
	(0.002)	(0.002)
Large (250+)	0.035***	0.012***
	(0.004)	(0.004)
Age 6-10	0.006***	-0.003
	(0.002)	(0.003)
Age 11+	-0.005**	-0.013***
	(0.002)	(0.002)
Human capital	-0.001	0.000
	(0.004)	(0.004)
Multi	0.016***	0.044***
	(0.001)	(0.002)
MNE	0.033***	0.096***
	(0.002)	(0.002)
Supp. Tech.	0.090***	0.130***
	(0.004)	(0.005)
Obs.	523 065	523 065
R-sq.	0.034	0.101
Country-Sector FE	YES	YES

Note: The Table displays estimated LPMs that employ the digital application adoption dummy as dependent variable and include size class, age class, firm structure, human capital, supporting technologies, and the adoption of a related application as main independent variables. In particular, for the dyad "Collaborative Software" and "Suites and SaaS", two models are estimated. In the first model, application A is the dependent variable while the other B is the independent variable (bundle dummy). In the second model, application B is treated as the dependent variable while the other A is the independent variable (bundle dummy). The "supporting technologies" dummy accounts for the presence of the eight supporting digital applications related to "Collaborative Software" and "Suites and SaaS": see also Box 4.1 and Subsection 4.2.1 for the specification of supporting technologies. Each regression model refers to firms that did not have both applications in 2019. Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Size class coefficients w.r.t. the 10-49 class; age class coefficients w.r.t. the 0-5 class. Missing class coefficients are not reported. Results are robust excluding the "supporting technologies" dummy. Also, results are robust to the inclusion of the productivity variable as an alternative regressor. Constant not reported.
Source: authors' elaborations on Spiceworks data.