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CLOSING THE ITALIAN DIGITAL GAP

THE ROLE OF SKILLS, INTANGIBLES AND POLICIES

OECD SCIENCE, TECHNOLOGY AND INDUSTRY
POLICY PAPERS

March 2022 **No. 126**

OECD
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OECD Science, Technology and Innovation Policy Papers

This paper was approved and declassified by the Committee for Industry, Innovation and Entrepreneurship (CIIE) on 23 November 2021 and prepared for publication by the OECD Secretariat.

Note to Delegations:

This document is also available on O.N.E under the reference code:
DSTI/CIIE(2021)24/FINAL

Closing the Italian digital gap: The role of skills, intangibles and policies

Flavio Calvino†, Stefano DeSantis¥, Isabelle Desnoyers-James†, Sara Formai‡, Ilaria Goretti†, Silvia Lombardi¥, Francesco Manaresi†, Giulio Perani¥

†: OECD – Science, Technology and Innovation Directorate

‡: Bank of Italy – Department of Economics and Statistics

¥: ISTAT, Italian National Statistical Institute

This paper provides an in-depth analysis of the digitalisation of Italian firms. The study identifies the main factors that affect the diffusion of digital technologies and their returns among Italian firms, highlighting the crucial role of public policies. It uses a unique data infrastructure that integrates information on digital technology adoption, firm performance, and workers' and managers' skills. The analysis shows that the low digitalisation of Italian firms, especially of SMEs, can be traced back to the low levels of three factors: i) workers' skills, ii) management capabilities, and iii) accumulation of intangible assets. Indeed, micro and small firms with high-skilled workers experience higher productivity returns from technology adoption; the lack of managerial capability can explain up to one-third of the North-South differential in digital technology adoption; R&D expenditures can boost firms' ability to fully exploit digital technologies. These factors are also crucial to maximise the effectiveness of public policies supporting firm digitalisation and the paper discusses the most relevant policy levers that can help close the Italian digital gap. It shows that the deployment of high-speed broadband infrastructure raises productivity only among more skilled firms; micro and small enterprises that benefitted from the hyper-depreciation subsidy, a recent fiscal incentive, experience higher returns when managers are high-skilled. Finally, the analysis shows that the COVID-19 crisis contributed to further widening the digital gap between Italian firms, favouring ex-ante more digitalised companies, suggesting that public policies play a crucial role for the post-COVID-19 recovery.

JEL codes: D22, D24, O14

Keywords: digitalisation, skills, management, intangibles

Acknowledgements

This report "Closing the Italian Digital Gap: the Role of Skills, Intangibles and Policies" is the result of a collective effort of several economists and statisticians of the OECD, the Bank of Italy and the Italian National Statistical Institute (ISTAT). The analysis was developed within the framework of the Bank of Italy – ISTAT project on the Transformation of the Italian Productive System (TraSPI). The OECD gratefully acknowledges a voluntary contribution of the Italian government. Chiara Criscuolo contributed with several insights and supervised the project. The paper has also benefited from helpful suggestions and valuable comments from Maria Benedetta Francesconi, Marielda Caiazzo, Paolo Carnazza and Marco Calabro' (Italian Ministry of Economic Development – MiSE), Dirk Pilat and Sarah Box (OECD), Federico Cingano and Francesca Lotti (Bank of Italy), Stefano Costa (ISTAT), Gilad Be'ery (Ministry of Economy and Industry of Israel) and from insightful discussions with several WPIA and CIIE Delegates throughout the development of this project. We are indebted to Matteo Bugamelli (World Bank) and Domenico Monducci (Sant'Anna School of Advanced Studies) for their support and vision in creating the TraSPI project, to the Italian Authority for Communications (AGCOM) for providing data on broadband diffusion, to the Italian Union of Chambers of Commerce (Unioncamere) for the data on the localisation of the Digital Innovation Hubs and the PIDs, to Antoine Dechezleprêtre and Milenko Fadic (OECD) for data on localisation of universities and STEM programs, to Alexander Himbert (OECD) for data on intangible assets from the INTAN-Invest database, and to Andrea Linarello (Bank of Italy) for supporting and easing our work on the data.

Executive summary

Digitalisation is a key driver of productivity growth in modern economies. Yet, its uneven diffusion among firms has increased productivity dispersion, raised wage inequality and reduced inclusiveness. During the recent COVID-19 crisis economies have become more digitalised, but increasing evidence shows that digital divergence between technology leaders and the rest of firms has increased.

These trends are particularly worrisome for Italy. Over the last 25 years, the Italian business sector, characterised by a large share of micro and small firms and by leader firms that are both fewer and smaller than their foreign counterparts, displayed an increasing gap in the adoption of digital technologies and in intangible investments relative to other OECD countries. The resulting "digital gap" is one of the key drivers of the sluggish aggregate productivity growth registered in Italy.

This report focuses on how to close the Italian "digital gap". It analyses the roots of this gap and focuses on the most effective policy levers that may help close it. It does so by taking an in-depth analytical perspective that leverages a unique data infrastructure that allows taking into consideration a large set of factors, inside and outside the firm, that affect digital technology adoption and its returns, also over the COVID-19 pandemic.

It shows that adoption rates of digital technologies in Italy are extremely skewed: small and young firms have very low levels of digital technology adoption, also in comparison with their counterparts in other OECD countries. Moreover, they are less likely to adopt bundles of different digital technologies, which are associated with higher productivity gains and are usually key to adopt advanced technologies. Closing the "digital gap" requires to identify which factors are preventing the digital transformation of these smaller firms, and tailor policies to tackle them.

The analysis identifies three key complementary factors to close the Italian "digital gap": workers' skills, management capabilities, and investments in intangibles. Indeed, the lack of skilled workforce, the lack of managerial skills and capabilities, and the low levels of investments in complementary intangible assets are the key within-firm drivers of low digitalisation in Italy, particularly among micro and small firms.

Skilled workers (those with tertiary level of education) play a key role for technology adoption and for increasing firm revenues. High-skilled firms, especially micro and small ones, also realise larger productivity gains from adopting digital technologies.

Skilled executives are better able to manage the increasing complexity of digital technologies and their complementarities with skilled workers. Indeed, managerial skills are significantly related to higher technology adoption and firms with more skilled managers register higher returns to advanced digital technologies.

Among intangible assets, R&D expenditures are key to boost a firm's ability to realise the full potential of digital technology adoption. Digital technologies tend also to increase the likelihood that R&D activities result in a new patent. In this context, the analysis highlights how R&D tax credits in Italy have significantly increased R&D expenditures, supporting in particular innovative firms that were ex-ante less R&D intensive.

These complementary factors are crucial to boost the effectiveness of policies for firm digitalisation. The report focuses on two relevant public policies implemented by the Italian Government to support the digitalisation of the economy: the development of a high-speed broadband infrastructure (so called "Next Generation Access" broadband) and a subsidy to support investments in digital technologies (called "hyper-depreciation for Industry 4.0 technologies").

On average, the development of NGA infrastructure is found to increase the adoption of only some less advanced technology (such as cloud services and management software). However, when broadband infrastructure reaches a firm that has a more skilled workforce, it supports the adoption of more advanced digital technologies, with positive effects on firm's productivity.

The recent introduction of the "hyper-depreciation for Industry 4.0 technologies" has also raised the adoption of digital technologies by Italian firms, with positive effects on output, employment and productivity. Yet, the lack of skilled workers and managers limited the effectiveness of the policy among micro and small firms. Complementing this subsidy with support for skills and capabilities of workers and managers is, thus, key to maximise its effectiveness in reducing the digital gap of these firms.

One key channel to do so is the development of a high-quality education system. The analysis highlights the important role of STEM programs, with tertiary STEM education significantly boosting the supply of skilled workers, which are better complements to digital technology adoption. The report also discusses the importance of strengthening the secondary technical and vocational education, to reduce the mismatch between the competencies provided and those requested by the business sector.

While improvements in the education system may take some time to realise their returns, shorter-term interventions may include support to the upskilling of firms and workers through financial incentives to training programs, which may particularly favour firms that invest in both human capital and digital technologies.

Relatedly, improving managerial skills and capabilities is crucial to support the digital transformation, especially of micro and small firms. Existing evidence shows that financial support to expenditures on consultancy and advisory services – when targeted to high-quality providers – can be effective in boosting managerial capabilities. Consultants, coaches, and advisors can help existing managers develop the soft skills needed to guide the firm in the digital transformation. The transmission of these soft skills and knowledge may also be fostered by local institutions and one-stop shops aimed at supporting firm's digitalisation (such as the Digital Innovation Hubs or the Competence Centres).

During the COVID-19 crisis, the technological divide between less and more digital firms has been widening: ex-ante more digital firms have suffered less from the shock, both in terms of revenues and in terms of the probability to close their activities. A larger part of their workforce has been using teleworking arrangements, and they have invested more in digitalisation and human capital acquisition during the crisis relative to less digital firms.

Closing the digital gap of Italian firms requires a renovated policy effort in the post-pandemic world. The recently approved National Recovery and Resilience Plan allocates substantial resources to digitalisation, innovation and competitiveness of the business sector. The effectiveness of these interventions will crucially rely on the ability to develop a comprehensive policy package that complements financial incentives to technology adoption and infrastructural investments with interventions to improve the digital skills of the workforce and the capabilities of managers.

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1. Introduction

The slowdown of productivity growth that characterised recent decades has sparked a lively debate among academics and policy-makers on its possible causes and on which policies may allow to reverse this long-term trend. For most OECD countries, the slowdown has been particularly evident since the early 2000s, and worsened significantly after the Global Financial Crisis (OECD, 2015[1]; IMF, 2017[2]; Goldin et al., 2021[3]).

Recent OECD work has shown that the slowdown hides substantial heterogeneity within countries and sectors and increasing gaps between best performers and the rest of the economy, also within narrowly-defined industries (Andrews, Criscuolo and Gal, 2016[4]; Berlingieri, Blanchenay and Criscuolo, 2017[5]; Berlingieri et al., 2020[6]). While firms at the global frontier continued to increase their productivity steadily, the rest of the business population did not keep pace. These increasing divergences between leaders and laggards have been fostered by the digital transformation, and the extent to which the potential of digital technologies is exploited effectively only by few firms rather than by most businesses (Berlingieri et al., 2020[6]).

Indeed, at one side, digital technologies have the potential to boost value added creation, reducing costs of search, replication, transportation, tracking, and verification (Goldfarb and Tucker, 2017[7]), and favouring the emergence of new business models throughout the economy. On the other side, though, digital technologies require absorptive capacity and increasingly sophisticated complementary investments in knowledge and intangible assets to be effectively used. These intangibles are scalable at low cost and non-rival. This creates scale economies that, together with the network effects associated with ICTs, may reinforce the position of leaders and possibly unleash winner-takes-most dynamics, increasing the polarisation of economies (OECD, 2021[8]). Moreover, limited possibility to use intangible assets as collateral may prevent small and credit constrained firms to use credit to finance their accumulation.

During the pandemic, digitalisation has played a major role in shaping firms' response to the recent COVID-19 pandemic. The social distancing restrictions forced firms to reorganise their production, to effectively use teleworking and online sales and purchases of goods and services. This has generated a strong acceleration of digital adoption by firms. Yet, existing evidence point to significant heterogeneity in adoption rates, with stronger increases among firms that were already digital (Riom and Valero, 2020[9]; Bloom et al., 2020[10]; EIB, 2021[11]; McKinsey, 2021[12]; World Bank, 2021[13]; DeStefano and Timmis, forthcoming[14]). The positive aggregate effect of increased digitalisation on productivity may, thus, be coupled with a strengthening of pre-existing digital divides, with potential negative effects on long-term growth.

In order to tackle these issues, it is crucial that researchers and policy-makers go beyond aggregate or sectoral data, to study the microeconomic factors that prevent the digital diffusion among smaller and less productive firms, and to design policies to address the most relevant bottlenecks and frictions. This calls for renewed efforts in data collection, firm-level analyses, and in developing a comprehensive and effective policy mix tailored around the country's specificities.

This study focuses on the case of Italy, a country characterised by a generally low adoption of digital technologies and low accumulation of complementary intangible assets. Consistently with such patterns, productivity growth in the country has been particularly subdued over the last 25 years (Bugamelli et al., 2018[15]). Not only the large shares of micro and small firms are less productive than their European counterparts (Berlingieri et al., 2017[16]), but also Italian frontier firms are less productive and smaller than those at the global frontier.

National Accounts data show that the Italian gap in ICT investments vis-à-vis other OECD countries is substantial and has been increasing over time. Data from ICT surveys show that the gap is particularly prominent among e-sales and advanced technologies, and it has been coupled with lower investments in ICT training and skills. Data from the INTAN-Invest database complement these findings by showing that Italian firms tend to invest less in complementary intangible assets, such as organisational capital and R&D activities.

The available aggregate data, however, can only scratch the surface of the Italian digital gap, as they do not allow to study firm-level heterogeneity in adoption rates, provide extremely limited information on different technologies, and do not allow to study whether adopted technologies are used effectively. This significantly limits the policy implications that can be drawn from their analysis.

Microdata are crucial to tackle these questions. They allow comparing different groups of firms to study the heterogeneity in adoption rates of different digital technologies and the complementarities they have with skills and intangibles assets, as well as to evaluate the effects of frictions to adoption and effective use of digital technologies, and that of specific policy interventions.

Exploiting a unique database, this work aims at better understanding how to boost digital technology adoption and returns to adoption in Italy. We focus, in particular, on the process of technology diffusion across firms of different dimension and productivity, on what barriers they might face and how to boost their returns to adoption, with particular attention to the role of public policies.

To guide our analysis, we provide a conceptual framework that highlights the factors that may foster or hinder the digital transformation and returns to adoption for different types of Italian firms. This framework builds upon the most recent academic literature and considers key issues in the policy debate. Each element of the framework is related to the international literature, as well as to the specificities of the Italian case.

At one side, we study the role of factors and characteristics within the firm, such as skills, management and organisational structure. At the other side, we analyse the role of several key external barriers: broadband infrastructure, financial resources, the development of tertiary education (with a focus on STEM courses), the role of knowledge and technological spillovers, and the effect of policies aimed at financially supporting the adoption of advanced digital technologies.

The role of each of these factors is assessed building and exploiting a unique data infrastructure, developed thanks to the collaboration and joint efforts carried out by the OECD, the Italian National Institute of Statistics (ISTAT), the Bank of Italy, and the Italian Ministry of Economic Development. This data infrastructure merges detailed information from firm balance sheets, matched employer-employee data, firm imports and exports records, and surveys on innovation activities and technology adoption, as well as local-level information on credit availability (from matched bank-firm data), tertiary education, broadband infrastructure, and institutions aimed at supporting the innovative ecosystem (e.g., innovation hubs, competence centres, etc.). It allows to analyse at the firm level, with a unique breadth and depth the determinants and the returns of the adoption of several digital technologies, encompassing broadband connectivity, cybersecurity, Industry 4.0 technologies (e.g., Internet-of-things, big data, advanced automation), cloud computing, managerial software, and the use of e-platforms to sell the firm's products and services.

With this database, we first characterise the digital transformation in Italy, with particular attention on i) who adopts different digital technologies – focusing on sectoral, regional, firm size and age differential, as well as on differences between leader and laggard firms; ii) how technologies are adopted, identifying the existence of bundling between different technologies.

Beyond significant differences across sectors, regions (with higher adoption in the North), and technologies, we find that digital technology adoption is more common among larger and older firms. The size differentials are pronounced in the case of enabling technologies, management software, cloud, and advanced digital technologies, while they are less evident for e-sales. Among micro-firms, though, the youngest ones prove to be more likely to adopt the digital technologies considered. Leaders, i.e., firms with highest labour productivity, systematically exhibit higher adoption rates than laggards in most digital technologies (the only exception being sales on e-platforms).

Digital technologies are typically used in bundles. Indeed, almost 60% of digital adopters use a bundle of more than one technology and about 40% of them adopt three or more, with important complementarities among the technologies adopted. Productivity tends to increase in the number of technologies adopted, although with decreasing marginal returns.

We then provide an empirical analysis of the role of factors internal and external to the firm in driving digital technology adoption and its returns. For each of these factors, we study its impact on the probability of adopting digital technologies and its effect on the returns of these technologies (i.e., its degree of complementarity or substitutability).

The analysis of the determinants inside and outside the firm highlights a key role of workers and management skills, R&D and spillovers, broadband infrastructure, STEM education, finance, as well as a crucial role of public policy in affecting digital technology adoption and its returns.

Indeed, firms with a high share of high-skilled workers are typically more likely to adopt digital technologies. Furthermore, technology adoption and skills have positive returns in term of productivity, but there exist significant complementarities between the two. Skills appear particularly relevant to realise more fully the returns from adoption of bundles of digital technologies across smaller firms.

Firms with a higher share of skilled top executives are more likely to adopt digital technologies and exhibit higher returns to adoption. Furthermore, top management skills significantly boost the returns of worker skills, advanced digital technologies, and their complementarity. Beyond top executives, middle managers – and especially high-skilled ones – seem to play an important role to deal with technological complexities in digitally sophisticated firms.

We find evidence of a strong association between R&D activities and technology adoption. The analysis shows that R&D intensive firms are more likely to adopt technologies, and that advanced digital technologies increases the likelihood that R&D activities generate a patent. In this context, we study the role of the R&D tax credit implemented in Italy since 2015 in supporting intra-mural expenditure among ex-ante R&D performers (i.e. *intensive* margin), and we document its distribution across firms. The policy introduced a tax credit on the incremental R&D expenditures (relative to the pre-policy period). We highlight how the policy generated an increase in R&D expenditures that can mostly be traced back to firms that were performing little R&D activities before the policy, consistently with the incremental feature of the incentive. On the other hand, however, changes in the way the data have been collected over the years prevent us from studying the impact of the tax credit on the *extensive* margin (i.e., firms that were not performing R&D or new firms).

We then turn to other policy factors that affect firm digitalisation in Italy. First, we look at the diffusion of ultra-high-speed broadband infrastructure, usually called Next Generation Access (NGA) broadband. We find that the strong increase in NGA infrastructure observed since 2012 had positive effects on the adoption of some digital technologies, such as cloud services and management software. However, on average it has no impact on the adoption of advanced digital technologies and on real outcomes, such as revenues and labour productivity. Positive effects on advanced technologies and productivity are found only among firms with ex-ante more skilled workforce, consistently with the idea that broadband supply represents a supporting factor in the digitalisation of firms, but only for firms who have the necessary skills and capabilities.

Second, we consider the role of tertiary education, with a particular focus on STEM programs. We find that the presence of universities and other tertiary degrees in the area where the firm is located is significantly and robustly correlated with the adoption of advanced digital technologies. The correlation is stronger if the tertiary degree has a STEM program, and is increasing in the quality of the STEM faculty (as measured by scientometric indicators). Importantly, we find that local STEM tertiary education is particularly important for technology adoption by micro and small firms, consistent with the idea that larger firms can access wider labour markets. We also highlight a key channel of the positive effect of STEM education on technology adoption: STEM education increases the complementarity between skilled workers and technology adoption.

Third, we focus on a recent policy intervention aimed at boosting the adoption of digital technologies, called the hyper-depreciation of investments in Industry 4.0 (I4.0) technologies. The policy aims at supporting technology adoption by increasing the amortisation charge up to 150% of the value of an interconnected (I4.0) tangible asset purchased. We provide an evaluation of the effect of this policy on the adoption of digital technology and on firm input accumulation and productivity. We find the policy to positively affect adoption rates of advanced digital technology and to have significant effects on labour productivity. However, most of the impact accrues to larger firms. Yet, we find that if associated with skilled management, the productivity returns of the policy are larger for micro and small firms. This result highlights again the importance of considering the complementarities between skills and technologies to boost the returns of policy interventions.

We also look at other external factors. We provide novel evidence on spillovers in digital technology adoption, particularly among firms belonging to the same sector and among exporters active in the same sector and destination market. Importantly sector-level spillovers are found to be diminishing in the sector concentration of revenues (as measured by the Herfindhal-Hirschmann Index), consistent with the idea that negative spillover effects may kick-in where markets are less contestable.

We also study the role of finance in shaping the digital transformation of Italian firms. First, we provide evidence that digital adopters are less leveraged than other firms. We then show that exogenous drops in local credit supply reduce the likelihood that firms adopt this technology, as an unexpected tightening in financial constraints forces firms to cut investments. We also find that a positive shock to local credit supply has no effect on technology adoption. This asymmetry is consistent with the asymmetric effect of credit supply on productivity, found by previous researches (Manaresi and Pierri, 2019[17]), and can be explained by lower levels of credit constraints among potential adopters in normal times.

We turn to analyse the role of digitalisation during the COVID-19 pandemic. Exploiting a unique survey that interviewed around 40 000 firms in November 2020, we find clear evidence that the impact of the crisis has been uneven between more and less digitalised firms, with the latter less likely to face closures and more likely to increase their revenues during the pandemic, also thanks to a more intense use of teleworking. Moreover, while investments in digital technologies have increased on average, the digital gap between more and less digitalised firms has widened: ex-ante more digital firms invested more in digital technologies, human capital and training, and R&D. Importantly, these results hold within narrowly defined industries and hold constant firm geographic localisation, and its pre-crisis productivity and size.

We conclude by discussing the main policy implications of our findings. Lack of diffusion of digital technologies among smaller and less productive firms is dragging down Italian productivity growth. Our analysis has highlighted three main factors that limit the digital diffusion among micro and small firms: i) lack of complementary skills among workers, ii) low skills and capabilities of executives and middle-managers, and iii) subdued investments rates in R&D and other intangible assets.

To boost technology diffusion, policy-makers need to implement a comprehensive policy mix affecting incentives and capabilities (Berlingieri et al., 2020[6]). In the case of Italy, the financial incentive for the adoption of advanced digital technologies (so-called, hyper-depreciation subsidy, recently reformed into a tax credit) are found to be effective in increasing digital uptake and productivity. Yet, to increase their effect on smaller firms, they need to be properly coordinated with policies for digital skills and managerial capabilities.

Policies aimed at incentivising training in advanced digital technologies (as, for instance, the tax credit "Credito d'Imposta Formazione 4.0") should be strengthened and streamlined, in order to increase their take-up and effectiveness. Moreover, the policy should include methods for assessing (possibly on a randomly selected subsample of beneficiaries) the quality and effects of the subsidised training activities. This would allow to improve the policy or complement it with additional interventions overtime, as this information is collected and analysed. Longer-term improvements in worker skills would need a further development of the Italian tertiary education, particularly for what regards STEM programs. Moreover, strengthening the transmission of digital competencies in secondary vocational and technical schools may also be key to improve complementarities between secondary graduated workers and digital technologies. The recent National Plan of Recovery and Resilience allocates considerable resources on secondary and tertiary education. Policies on this topic should take into consideration its potential spillovers on digital diffusion: the intervention should be coordinated with those directed at boosting digital technology adoption, and potential complementarities should be exploited.

Managerial skills and capabilities are often considered extremely difficult to address by policies. Yet, managerial advisory, coaching, and mentoring have been proven effective in inducing firm reorganisation and raising productivity. Existing policies, such as the voucher for digitalisation, should be properly evaluated and, if effective, strengthened. One key limitation is the general lack of awareness of the existing policy instruments by firms (OECD, 2020[18]): strengthening awareness campaigns also through stronger involvement by relevant stakeholders and local Chamber of Commerce is thus crucial. More generally knowledge transfer could be further supported by strengthening the effectiveness and coordination among the network of Digital Innovation Hubs and Competence Centres (also together with the forthcoming European Digital Innovation Hubs).

The analysis has highlighted also the relevance of R&D in digital technology adoption. It has uncovered how advanced digital technologies are positively associated with the probability that R&D generate patents, hinging on important complementarities between innovative activities and technologies. Yet, cross-country data show that micro and small firms perform comparatively less R&D activities than their OECD counterparts. The R&D

tax credit has been found effective in raising R&D expenditures, particularly of firms that were ex-ante performing little R&D activities. Further analyses are necessary to understand its effect on other firms that are currently out of the scope of analysis and its impact on the *extensive* margin (the probability that firms start doing R&D). Combining the tax credit with policies to support skills, knowledge, and managerial capital may allow the effectiveness of the financial incentive also for ex-ante non-innovative and non-digitalised firms.

Other policy areas have been touched in our analysis. The deployment of NGA broadband infrastructures has been found to increase the adoption of *some* digital technologies (namely, cloud services and management software). NGA infrastructures are also found to strengthen the effect of other incentives, such as the hyper-depreciation subsidy, and are complementary with the presence of more skilled workforce.

Policies supporting investments in digital technologies, such as the hyper-depreciation analysed in this report, are currently implemented by defining the list of assets that are eligible to the financial incentive. Allowing for the periodic update of such list may be important to allow the policy to remain up-to-date with respect to technological progresses. Moreover, these policies may be developed further to target the production process (possibly considered within the value chain), rather than the purchase of a single asset.

We find that the contraction of credit supply has detrimental effects on digital technology adoption. Policy-makers should thus try to prevent negative shocks to the provision of credit, and support investments in digital technologies and intangibles in case of local or aggregate credit crunches (e.g., if a local bank enters in distress). At the same time, *positive* supply shocks do not significantly affect digital adoption. This result is consistent with the finding that digital intensive firms are less dependent on external finance in normal times, and calls for the importance of developing capital markets to support finance for digital adopters, while intervening on credit markets when credit dries up.

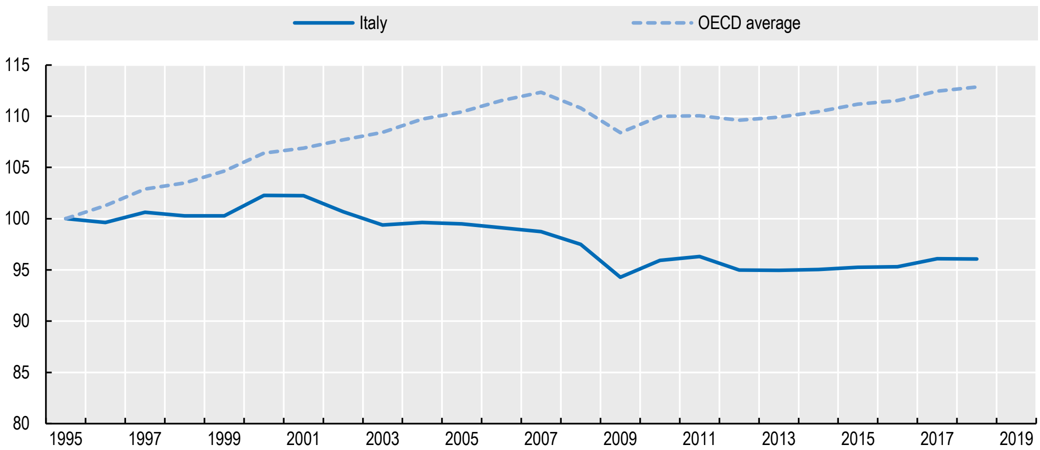
The remainder of the study is structured as follows. Section 2 provides cross-country evidence from National Accounts, sectoral data and ICT surveys that identify the Italian digital gap and characterise it with a cross-country comparison. Section 3 introduces the data used throughout the analysis and provides a first descriptive analysis of the Italian digital gap and highlights the existence of complementarities between digital technologies, which result in technology bundles. Section 4 studies the role of the structural and policy factors in shaping the digitalisation of Italian firms. Section 5 focuses on the relationship between digital technologies and the COVID-19 crisis in Italy. Section 6 concludes providing policy implications for our findings.

2. The digital gap of the Italian economy: key macroeconomic facts

Over the last 25 years, the Italian economy has struggled in keeping pace with other OECD countries. From 1995 to 2018, Italian GDP grew by less 0.6% per year, around 2 percentage points lower than the OECD average. The size of the Italian economy increased less than the OECD average until 2007, it fell more significantly during the Great Recession and the sovereign debt crisis, and it experienced a lower recovery since 2013.

The aggregate performance of the Italian economy appears tightly linked to its productivity dynamics (Bugamelli et al., 2018[15]; Pellegrino and Zingales, 2017[19]; Hassan and Ottaviano, 2013[20]). Indeed, Italy experienced a stronger and longer-lasting productivity growth slowdown than other OECD countries. In particular, since 1995, Italian multifactor productivity (MFP) stopped growing, declining from 2001 to 2009, and stagnating since then, while MFP among other OECD countries increased on average by almost 13% (Figure 2.1).

Figure 2.1. Multifactor productivity – index 1995=100



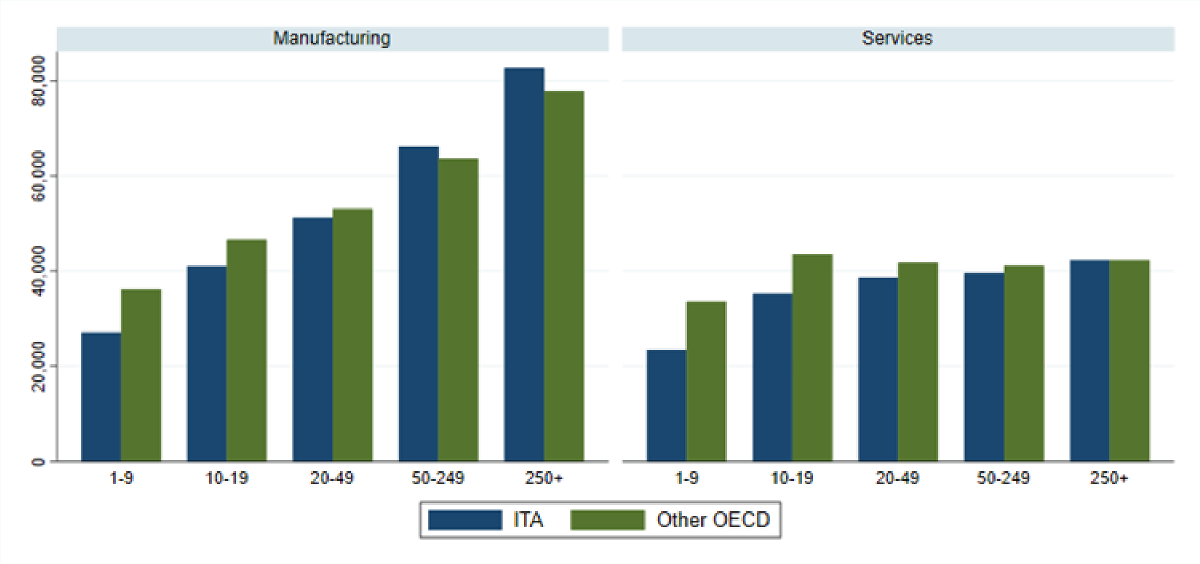
Note: All economy; see (OECD, 2019[21]) for the definition of multifactor productivity and its estimate.
Source: OECD, Productivity Statistics (database), https://doi.org/10.1787/data-00685-en (accessed in October 2020).

These aggregate productivity dynamics hide significant heterogeneity within and across Italian sectors and reflect structural features of the Italian economy.

Indeed, the Italian economy is characterised by significant heterogeneity in productivity performance across firms. A number of studies highlight that Italy has a fragmented productive systems, with few (even fewer than in other countries, mostly medium and large) highly productive firms, which coexist with a large number of (mostly small and old) laggards (Bugamelli et al., 2018[15]; Berlingieri et al., 2017[16]; Dosi et al., 2012[22]).

While micro and small firms are at the centre of the Italian economy, representing more than 95% of the total number of firms, their productivity performance is significantly lower than in other European countries (Berlingieri et al., 2017[16]). This is shown in Figure 2.2, which focuses on multifactor productivity by size class in Italy vis-à-vis other OECD countries, and may point challenges in selection over the firm’s life cycle.

Figure 2.2. Slow productivity growth in Italy is driven mostly by micro and small firms



Note: Multifactor productivity is the Solow-residual from an estimate of a value added production function, following Wooldridge (2009[23]).
Source: OECD, MultiProd database.

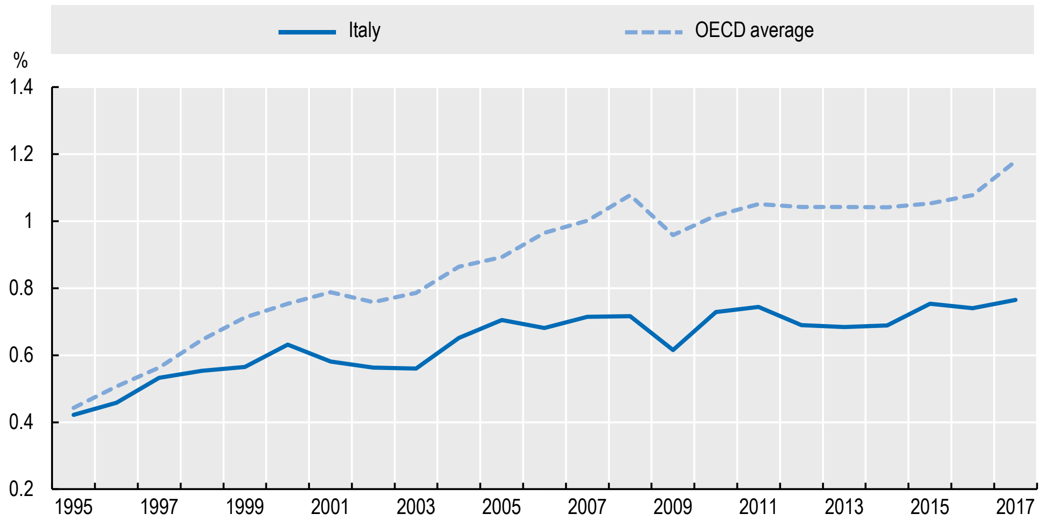
At the same time, frontier firms are characterised by lower size with respect to other countries (OECD, 2015[1]; Bugamelli et al., 2018[15]), again suggesting potential improvements in resource allocation. Evidence from cross-country firm balance sheets shows that the distance from Italian frontier firms and their global counterparts has been increasing over the last two decades, particularly in the service sector (Lotti and Sette, 2019[24]).

2.1. The Italian digital gap in the National Accounts

In this context, the adoption and effective use of digital technologies can significantly improve the competitiveness of both the large number of micro and small firms lagging behind, as well as the one of leading firms at the national frontier. Indeed, on the one hand the digital transformation can allow leaders to innovate and thrive, ultimately keeping up with the global frontier. On the other hand, by embracing the digital transformation laggards become more productive and can exert competitive pressures on the national frontier itself. However, the Italian productive system displays a significant gap relative to other OECD countries in the extent to which firms are embracing the digital transformation.

Several macroeconomic indicators provide evidence of this digital gap. In terms of tangible investments, National Accounts show that the accumulation of ICT assets has lost momentum relative to the OECD average at least since 1997 (Figure 2.3), going from being in line with OECD average during the mid-1990s (around 0.4-0.5% of aggregate GDP) to be lower than one third in 2017 (0.8% of GDP, compared to 1.2% for the OECD average).

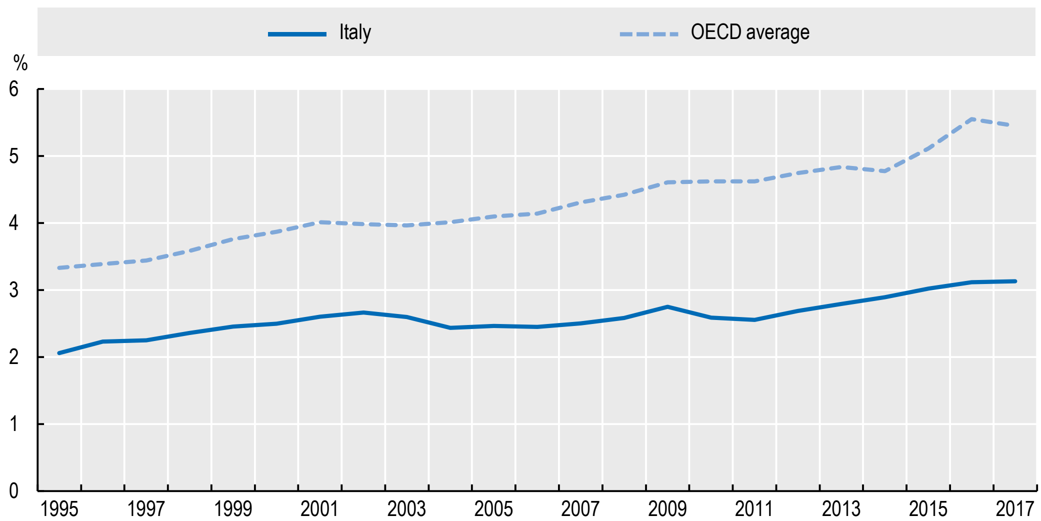
Figure 2.3. Investments in ICT capital – percentage of GDP



Source: OECD, National Accounts Statistics Database (accessed in October 2020).

Besides tangible assets, the digital transformation relies on several intangible assets. Some of them, such as software and databases, are complementary to tangible digital capital. Others, like R&D, are crucial to increase the absorptive capacity of firms. According to official National Accounts, Italy had historically lower accumulation rates of intangible investments (equal 2% of GDP in 1995, against an OECD average of 3.4%; Figure 2.4). This gap started widening in the early 2000s and continued afterwards. As of 2017, Italian intangible investments were slightly above 3% of GDP, while for the OECD average they topped 5.5%.

Figure 2.4. Investments in intangible capital – percentage of GDP



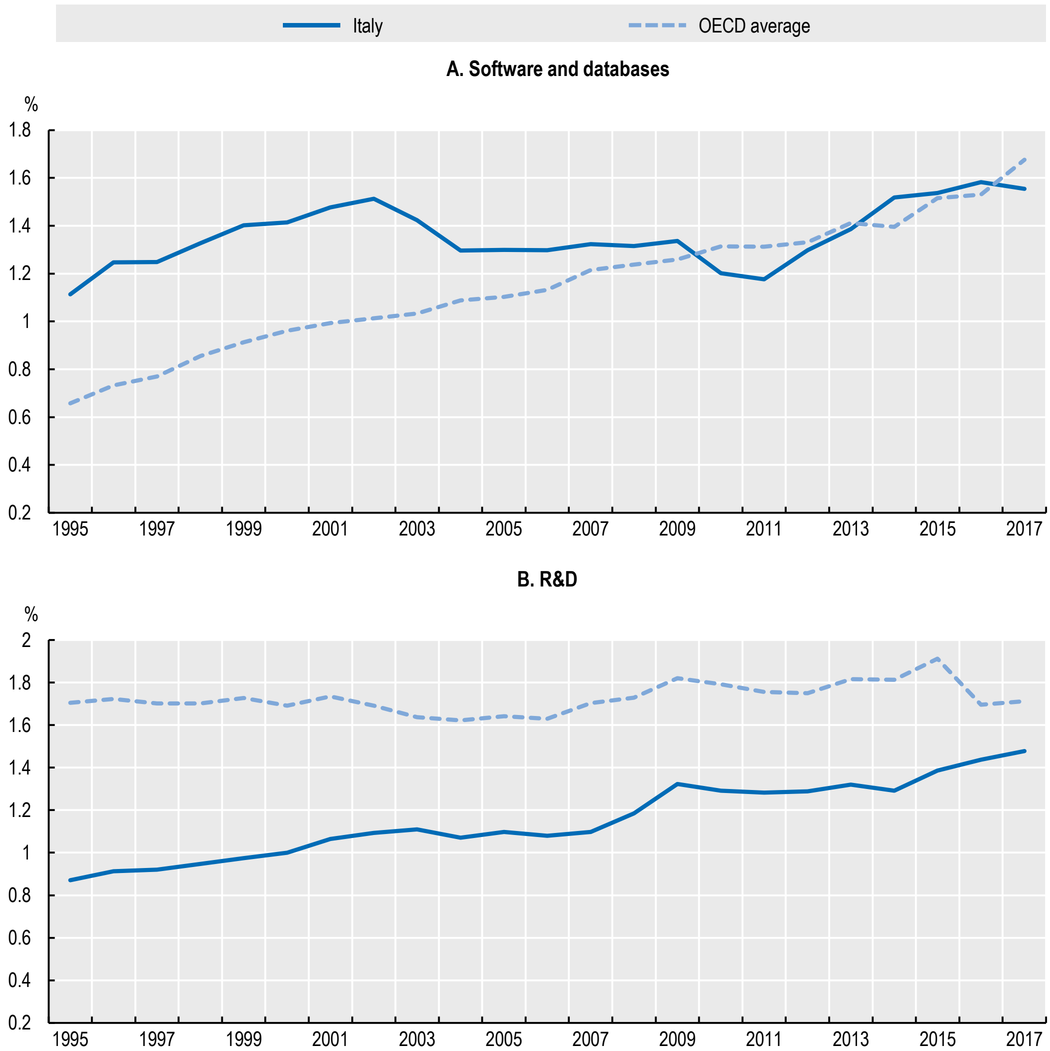
Source: OECD, National Accounts Statistics Database (accessed in October 2020).

Before the Great Recession, Italian investments in software and databases as a share of GDP were higher than the OECD average (Panel A of Figure 2.5). During the 2000s, however, this advantage shrank and, by 2009, Italy was positioned in the ballpark of the

OECD average of 1.3% of GDP. After the financial crisis, investments in software and databases increased at the same pace of the one experienced by other OECD countries.

National Accounts data on R&D investments as a share of GDP show a significant gap relative to the OECD average (Panel B of Figure 2.5). The gap has narrowed overtime: a first increase in Italian R&D investments can be appreciated during the Great Financial Crisis (GFC, henceforth), and a second boost was registered since 2015. Gonzalez-Torres, Manaresi and Scoccianti (2020[25]) show that the increase during the GFC can be explained by positive selection of intangible intensive start-ups as a result of the credit crunch: intangible-intensive start-ups were able to overcome the increase in the cost of external finance by leveraging their higher profitability. The increase in R&D investments experienced since 2015, instead, is associated with the tax credit introduced by the Italian government for this type of expenditures (see Section 4.5 and Bank of Italy (2018[26]), chapter 6 "Firms").

Figure 2.5. Investments in different types of intangibles as a percentage of GDP



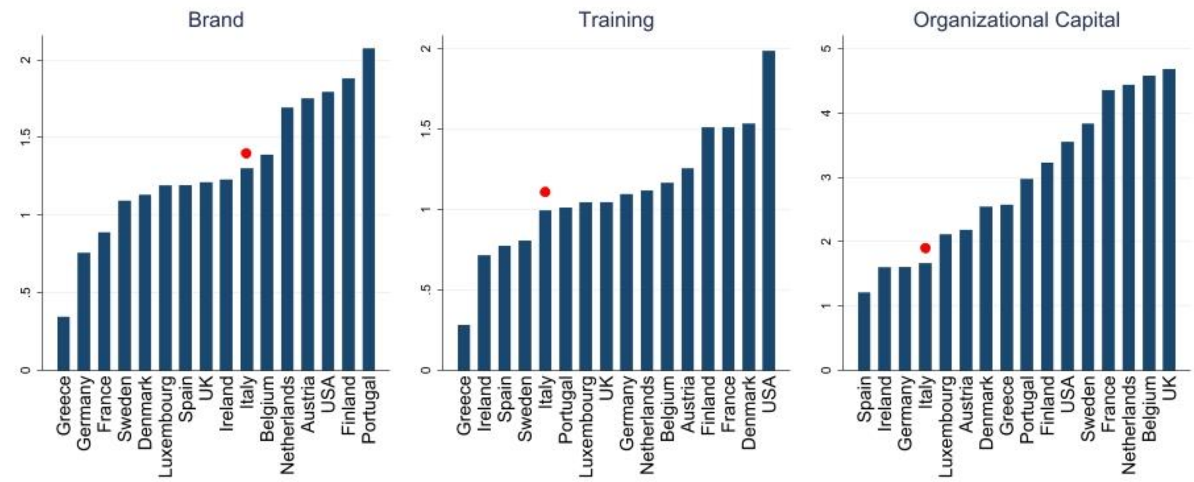
Source: OECD, National Accounts Statistics Database (accessed in October 2020).

2.2. The Italian gap in investments in intangible capital

Many relevant intangible investments, which are key for the digital transformation of firms, are not accounted for in National Accounts. Skills and competencies of workers and managers, in particular, are key complements of digital technologies (see Section 4.2). Investments in these types of intangibles by the business sector have been measured by the INTAN-Invest project (Corrado, Hulten and Sichel, 2009[27]). They are collected under the broad category of "Economic competencies", knowledge assets in which the firm invests, but that might not have intellectual property. These include investments to boost the brand of the firm (which encompasses marketing expenditures), investments in workers' human capital through on-the-job training, and investments in organisational capital. The latter is defined as the "cumulated knowledge that is built up in firms through investment in organising and changing the production process", and encompasses both knowledge and organisational improvements by internal managers and expenditures on management consultancies.

Figure 2.6 shows the distribution of investments in these three types of intangibles across countries, as a share of the business sector adjusted aggregate value added,[1] in 2015 (the latest year for which complete information on intangibles is available). Italy has comparatively high investments in brands, topping around 1.2% of the aggregate value added in the business sector. Conversely, Italian investments in training of workers and in organisational capital remain in the lower end of the distribution. Yet, the amount of resources needed to fill the gap between Italy and the median country is far smaller in the case of training (less than 0.1 percentage points) than in the case of organisational capital (for which more than 1% of aggregate value added would be needed).

Figure 2.6. Investments in economic competencies as a percentage of gross value added in the business sector – 2015



Note: Value added is adjusted to take into consideration the capitalisation of intangibles not accounted for by the National Accounts. The red dot identifies Italy.
Source: Authors' elaborations on INTAN-Invest database.

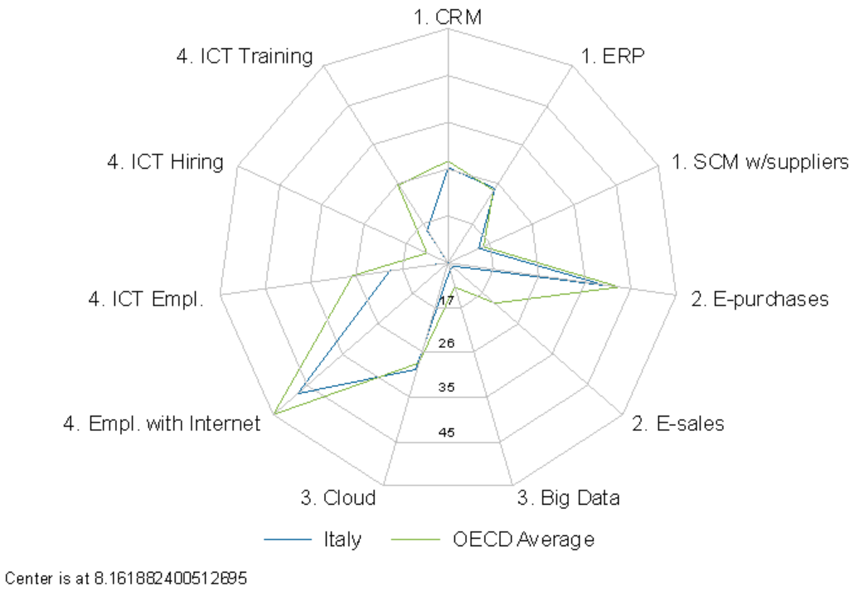
2.3. Cross-country comparison in digital technology adoption

The following figures exploit data collected by OECD, by identifying a set of questions that are comparable across ICT surveys conducted in different OECD countries over the period 2015-18. This allows to further depict the digital gap in technology adoption by Italian firms, in a cross-country perspective. The information is collected for different types of technologies that can be broadly classified into four groups: management technologies (CRM, ERP, SCM), use of online transactions (e-sales and e-purchases), adoption of advanced digital technologies (big data and cloud computing) and human capital and capabilities (share of employees connected to the Internet, share of firms with ICT employees, share of firms performing ICT training, share of firms hiring ICT personnel). Figure 2.7, which focuses on adoption rates holding sectoral heterogeneity fixed and comparing Italy with other OECD countries, shows that the gap in digital technology adoption is not homogeneous across technologies. In particular, there is no gap in management technologies (CRP, ERP, SCM) or in cloud computing, but there are significant gaps in e-sales and in big-data, the only advanced digital technology for which there is comparable information across countries. Finally, there is a significant gap between Italy and the OECD average also in the availability of ICT skills in the workforce, consistently with findings from the INTAN-Invest database.

Figure A A.2 in Annex A further explores these dynamics focusing on firms in different size classes. The gaps in the use of e-sales and ICT training is present in all size categories, while those in ICT personnel and big data analytics is more relevant for smaller firms.

The evidence so far points to the existence of a digital gap between Italian firms and their counterparts in other OECD countries. Yet, these aggregate data do not allow to analyse with sufficient depth the heterogeneity of this gap in the economy, nor to identify the factors that may explain it or to assess existing policies aimed at reduce it. For this purpose, we develop a rich data infrastructure that is described in the next Section.

Figure 2.7. Results of the ICT surveys, holding fixed sectoral distribution – 2015-18



Source: OECD, "ICT Access and Usage by Households and Individuals", *OECD Telecommunications and Internet Statistics* (database), https://doi.org/10.1787/b9823565-en.

3. Data and descriptive analysis

The analysis is based on a uniquely rich data infrastructure, developed thanks to the collaboration and joint efforts carried out by the OECD, the Italian National Institute of Statistics (ISTAT), the Bank of Italy, and the Italian Ministry of Economic Development. It combines detailed information from firm balance sheets, matched employer-employee data, firm imports and exports records, and surveys on innovation activities and technology adoption, as well as local-level information on credit availability (from matched bank-firm data), tertiary education, broadband infrastructure, and institutions aimed at supporting the innovative ecosystem (e.g., innovation hubs, competence centres, etc.). A more detailed description of each data sources at the firm, individual and sectoral level is available in Annex B.

This data infrastructure allows to analyse at the firm-level, with a unique breadth and depth, the determinants and the returns of the adoption of several digital technologies, including broadband, cybersecurity, Industry 4.0 technologies (e.g., Internet-of-things, big data, advanced automation), cloud computing, managerial software, and the use of e-platforms.

In this context, the next paragraphs provide a descriptive characterisation of the digital transformation in Italy, with particular attention on i) who adopts different digital technologies – focusing on sectoral, regional, firm size and age differential, as well as on differences between leader and laggard firms; ii) how technologies are adopted, identifying the existence of bundling between different technologies (see Annex B for additional discussions).[2]

A first stylised fact uncovered is the existence of significant differences across technologies, sectors and regions in digital technology adoption. In particular, as shown in Figure A B.1 in Annex B, in 2018 over 52% of firms were using management software, and adoption of enabling technologies ranged from 27% for cybersecurity to 43% for broadband. These adoption rates are significantly higher with respect to those of the various advanced digital technologies, which do not exceed 7%. Adopters represent a disproportionate share of employment, and even a higher share in terms of value added. This may be a first indication that adopters tend to be larger and more productive than non-adopters, with a relevant exception represented by adopters of e-sales, which are concentrated in the trade sector (as discussed below), usually characterised by low value added per worker.

Focusing on the sectoral distribution of technologies adopted, presented in Figure A B.2 in Annex B, highlights limited evidence of sectoral specialisation in the adoption of enabling technologies, such as broadband and fast mobile connection, or management software. Cybersecurity, instead, is slightly more diffused in manufacturing, largely reflecting the larger size of its firms. Other technologies are more concentrated in some sectors of economic activity: e-sales is more widely diffused in the Trade, restaurants and transportation sector, and simulations of interconnected machines, advanced automation or 3D printing, are more concentrated in manufacturing. Big data and augmented/virtual reality exhibit instead higher shares of adoption in the information sector.

Focusing on the geographical distribution of adoption rates, Figure A B.3 in Annex B highlights that adoption rates are typically higher in the North, with gaps with the rest of Italy that are evident for most groups of technologies. A relevant exception is e-sales, which exhibits a more homogeneous geographical distribution across the four macro-regions considered. Geographical differentials in adoption rates are broadly consistent with differences in productivity and growth between the North and the South of Italy (Ciani, Locatelli and Pagnini, 2018[28]), and are not driven by differences in sectoral composition across macro-regions.[3]

A second stylised fact is that digital technology adoption mostly occurs in larger and older firms (Table A B.1 in Annex B). Size differentials are pronounced in the case of enabling technologies, management software, cloud, and advanced digital technologies, while they are less evident for e-sales. Among micro-firms, though, the *youngest* ones prove to be more likely to adopt the digital technologies considered. Comparing adoption rates in Italy with those in the United States (as reported by Zolas et al. (2020[29])) suggests that Italian firms (with the sole exception of large very old ones) have lower adoption rates, and that differences are more prominent for young and small firms (Table A B.2 in Annex B). This is consistent with the Italian digital gap being particularly relevant for these types of firms.

A third stylised fact is that leaders, i.e., firms with highest labour productivity, systematically exhibit higher adoption rates than laggards, except when focusing on e-sales. This is shown in Table 3.1 below, which suggests that adoption rates tend to be increasing in labour productivity, with leaders typically exhibiting higher adoption of digital technologies than middle-productivity and laggard firms. This result is consistent with digital technology adoption being one important determinant of productivity divergence. Differences in adoption rates are particularly strong for enabling technologies, cloud, and advanced digital technologies, while a notable exception to this pattern is, once again, represented by e-sales.[4]

Table 3.1. Adoption rates by labour productivity deciles

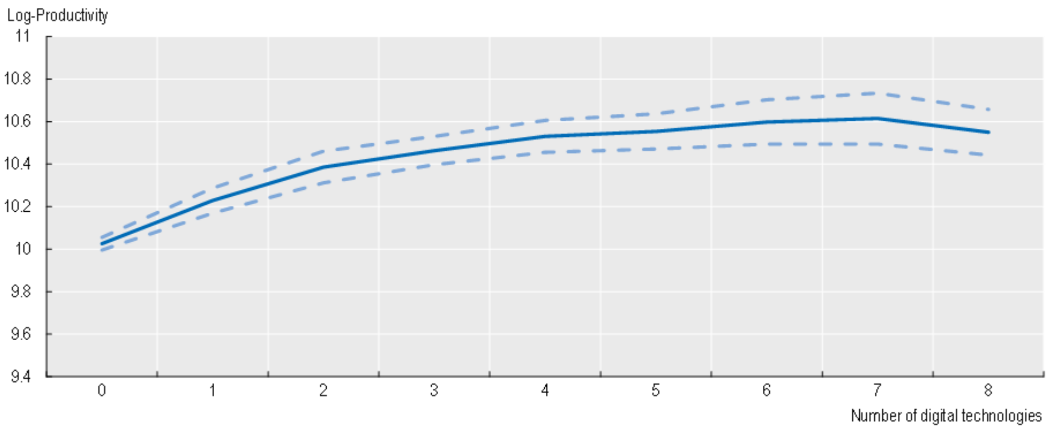
	Laggards (decile 1)	Middle (deciles 2-9)	Leaders (decile 10)
Enabling	24.1%	31.0%	39.8%
Management	38.8%	37.3%	48.2%
Cloud	13.2%	16.7%	23.0%
E-sales	15.6%	13.0%	14.8%
Advanced	5.7%	5.8%	9.1%

Note The table reports differences in adoption rates focusing on firms with different labour productivity performance in 2018, distinguishing between leaders (firms in the top 10% of the labour productivity distribution within each sector), laggards (firms in the bottom 10% of the same distribution), and middle firms (firms belonging to the 2nd-9th deciles of the same distribution). Deciles are computed within three-digit NACE Rev.2.2 sectors. The model controls for size-age and sector-region unobserved heterogeneity.
Source: Authors' elaboration on ISTAT data.

Finally, the unique data infrastructure assembled allows to provide first evidence on the complementarities existing among different digital technologies. This evidence shows that digital technologies are typically used in bundles. Indeed, almost 60% of digital adopters use a bundle of more than one technology and about 40% adopt three or more, with important complementarities among technologies adopted (Figure A B.4 in Annex B). Among adopters of advanced technologies, almost 90% of firms also adopts some enabling technology, 72% also adopt management technologies, and less than 40% also use cloud computing (Figure A B.5 in Annex B). Comparing bundling for advanced technologies with e-sales on platforms further suggests that these technologies exhibit different sets of complementarities with other digital technologies. Although enabling technologies play an important role in both cases, but to a larger extent for advanced technologies, the balance between management and cloud is different.

Complementarity does not only means that technologies are used together, but also that their combined use increases firm output. Figure 3.1 focuses on labour productivity dynamics for firms adopting a different number of digital technologies. It shows that – at least up to seven technologies – productivity tends to be increasing in the number of technologies adopted, but the marginal returns are decreasing. The decrease appears even stronger when using more than nine digital technologies. Despite widening error bars, these patterns may be related to the increases in complexity brought by the use of a large number of technologies, which usually include the most advanced ones.

Figure 3.1. Labour productivity by number of technologies adopted



Note: Results of a regression that controls for region-sector and size-age fixed effects. The 95% confidence intervals are estimated from standard errors that allow for serial correlation at the region and sector level.
Source: Authors' elaboration on ISTAT data.

4. Explaining the Italian digital gap: microeconomic evidence

4.1. Conceptual framework

This section outlines a conceptual framework aimed at guiding the analysis of the factors that may foster or hinder the digital transformation of firms, and the extent to which digital technologies are effectively used. The framework is presented schematically in Figure 4.1 and briefly described below. A more extensive review of the literature and the empirical evidence upon which this framework builds is instead available in Annex C.

As shown in Figure 4.1, the conceptual framework puts digital technology adoption centre stage. A set of developments or disruptions brought by technological change, competitive pressures or changes in demand may induce firms to adopt new digital technologies. Digital technology adoption is then supposed to affect firm productivity, key outcome of interest for policy makers. Yet, both the decision to adopt and ex-post returns to adoption may be influenced by several factors.

These factors are grouped distinguishing the ones *internal* from the ones *external* to the firm. The first group includes firm characteristics – such as sector of activity, firm size and age – and firm capabilities, including those related to human capital – such as the quality of its workforce and management – and those related to technology – including whether the firm has adopted other (complementary or substitute) technologies, or whether complementary intangible assets (like R&D expenditures or intellectual property) are present. The second group focuses on the availability of broadband infrastructure, easiness to access external finance, technology spillovers arising at the sectoral or geographical level, the quality of the education system and its ability to supply digital skills, and public policies aimed at fostering firm digitalisation.

While this list of drivers is broad, it is by no means complete. Several factors both internal to the firm, such as firm ownership and control, and external to it, such as labour market frictions or the role of training, have been omitted. This is not because of their lack of relevance, but rather because available data (although extremely comprehensive) do not cover these topics with sufficient information.

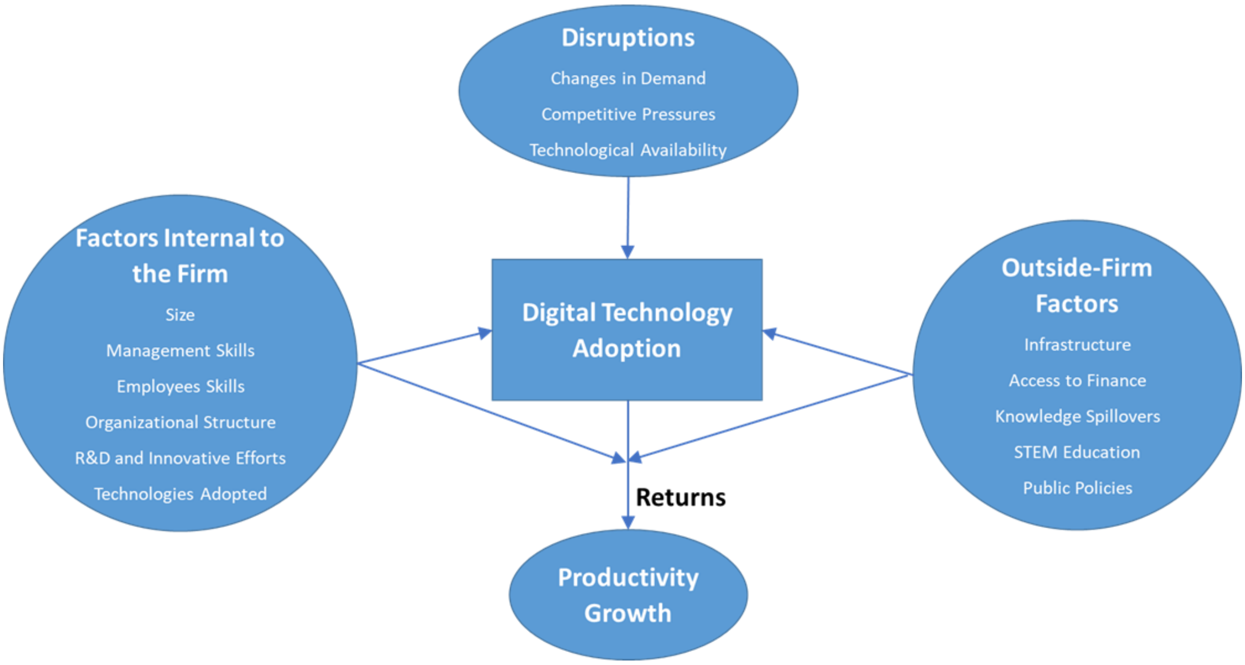
Importantly, links among some of the internal factors considered and technology adoption are not unidirectional. Indeed, the adoption and use of new digital technologies may have feedback effects as it may bring substantial changes in organisational structure, firm size, the input and skills mix, and induce complementary innovation. These changes are not instantaneous and may be costly to implement, but may be crucial to fully realise returns from technology adoption and boost productivity.

A successful combination of firm characteristics and capabilities enabling digital technology adoption, low external barriers, together with the adjustments required to enhance firm ability to effectively use new techniques increasingly ICT-based, would positively affect returns to adoption and firm efficiency.

We exploit the data infrastructure described in Section 3 to study the factors inside and outside the firm that support technology adoption and its returns.

Section 4.2 summarises the analysis of within-firm factors, which is described in more detail in Annex C. The results point to the relevance of workforce skills, of skills and capabilities of managers, and of other intangible assets (notably, R&D activities), the analysis of these within-firm factors is instrumental for the analysis of various policies that affect the digital transformation of Italian firms. The analysis then focuses on the role of NGA broadband diffusion (Section 4.3), the development of tertiary education (Section 4.4), and on policies that provide financial support to R&D activities and digital technology adoption (Sections 4.5 and 4.6). We then conclude summarising additional results on the presence of spillover effects in digital technology adoption and on the role of finance in explaining adoption (Section 4.7), which are detailed in Annex C.

Figure 4.1. Drivers of digital technology adoption and of its returns



Source: Authors' conceptualisation based on available data sources and literature review.

4.2. Within-firm determinants of technology adoption and its returns

We first focus on the role of the skills of the workforce, proxied by their level of education. The analysis highlights how having a larger than median share of high-skilled (tertiary educated) workers is positively associated with the adoption of all digital technologies (with the exception of enabling technologies), and that for most digital technologies the combined presence of high-skilled workforce is associated with larger productivity returns from the adoption of digital technologies, showing evidence of complementarities between skills and technologies (panels A and B of Figure A C.4 in Annex C).[5]

Besides the evidence for single digital technologies, the analysis also shows that firms with more skilled workforce display higher returns from larger bundles of technologies (panel C of Figure A C.4 in Annex C). These productivity gains are particularly large for micro and small firms. For a firm with less than 20 employees adopting one single digital technology, having a high-skilled workforce is associated with a productivity gain of around 30% relative to firms that do not adopt any technology. For micro and small firms adopting seven technologies or more, this productivity gain is over 70% (Figure A C.5 in Annex C).

A structural econometric analysis based on the estimation of a production function allows to better identify and quantify the complementarities between workforce skills and digital technology adoption. The analysis focuses in particular on advanced digital technologies, given their larger productivity gains, while controlling for the adoption of other digital technologies. According to our estimate, in almost all sectors of the private economy tertiary educated workers are complements to advanced digital technology adoption, especially in the Information sector and in Professional and business services (Figure A C.6 in Annex C). Most sectors also display evidence of substitutability between advanced digital technologies and primary educated workers. The degree of complementarity/substitutability with secondary educated workers varies by sectors (being positive in Manufacturing and Accommodation and Tourism, not statistically different from zero in Trade and Transportation, negative in Other private services and Construction).

Interestingly, the analysis highlights important regional differentials in the complementarity between high skilled workforce and advanced digital technologies, even controlling for regional differences in sectoral composition (Figure A C.7 in Annex C). In particular, positive complementarities are only present among firms located in North-Centre Italy, while firms located in Southern Italy show complementarity between advanced technologies and *secondary* educated workers (all firms in Italy display negative complementarity between technologies and primary educated workers). We discuss the various factors that may explain these regional differences, including the different skills of secondary and tertiary educated workers across Italy, as well as the existence of contextual factors that may dampen skill returns in Southern Italy.

Among them, we focus on the role of managerial skills. A growing literature shows that managerial quality is key to support firm-level productivity growth. Theory considers managers as booster of technology adoption among firms, as it is argued they may increase their returns and their complementarities with other firm inputs. We bring this hypothesis to the data by estimating the impact of managerial skills, as proxied by the education of the top executive on the returns of digital technologies, high-skilled workers, and their complementarity. The analysis shows that firms managed by a high-skilled top executive display larger returns of both inputs and larger complementarity among them (Figure A C.16 in Annex C). Importantly, managerial skills are unevenly distributed geographically in Italy (Figure A C.17 in Annex C): the lack of managerial skills in firms located in Southern Italy may explain up to one-third of the North-South differential in the complementarity between advanced digital technologies and high-skilled workers.

Besides the skills of the top-executives, our detailed information on administrative and managerial positions of each Italian firms allows to analyse the much less studied role of middle managers (i.e., individuals that have managerial roles in the firm but are not members of its administrative board). The presence of a layer of middle managers in the firm, between top executives and workers, may indicate a more complex organisational structure and a more horizontal decision-making process, factors that may be associated with significant productivity gains (Bloom, Sadun and Van Reenen, 2008[30]). Our analysis shows that firms with middle managers are more likely to adopt richer bundles of digital technologies. We also study the role of skills among middle managers. We find that the skills of the top-executive are positively associated with the presence and skills of middle managers (Figure A C.18 in Annex C), consistent with more skilled top-executive being able to implement more complex organisational structures and with assortative matching by skill levels among managers. Even holding fixed the skill of the top-executive, education of the middle manager is positively associated with firm's technology adoption (Figure A C.20 in Annex C).

The analysis then focuses on other intangible assets, besides managerial and organisational capital, that can be measured with the data in our hands. We focus in particular on R&D activities and the presence of intellectual property products (patents, trademarks, and designs). We find that R&D is strongly associated with higher adoption of digital technologies (though particularly among larger firms – Figure A C.22 in Annex C), while a differential role of other intellectual property products is both statistically and economically small.

4.3. The diffusion of ultra-speed broadband infrastructure

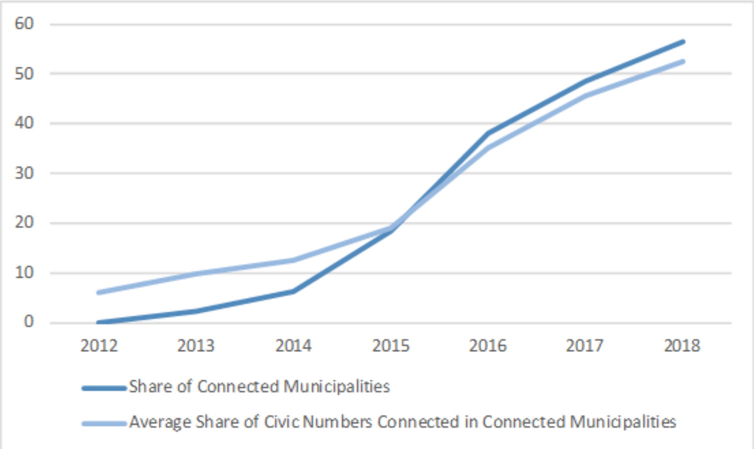
To study the role of broadband infrastructure on the adoption of digital technologies and their effective use, we exploit detailed municipal data on the supply of Next Generation Access (NGA) connection over the period 2012-18, together with data on the demand for fast-speed Internet connection by firms and households (for which information is available from 2014).

In particular, for each year, we observe the share of house numbers that were physically connected to the Internet via NGA (our measure of supply), and the share of fast-speed Internet contracts out of all telephone/Internet contracts (our measure of demand).

Back in 2012, NGA technologies was covering less than 20 Italian municipalities, and the average share of house numbers connected via NGA among those municipalities was just 6%. Over the period 2012-18, though, NGA broadband supply increased markedly (also thanks to the policies implemented to support its deployment). By 2018, over 56% of municipalities were connected, and the average share of house numbers connected among those municipalities was over 52% (Figure 4.2).

While the supply of NGA broadband infrastructure widened, also the demand for fast-speed Internet connection increased: according to our data, the share of fast-speed Internet contracts out of total telephone and/or Internet contracts increased from 3.8% in 2014 to over 20% in 2018.

Figure 4.2. Diffusion of NGA broadband connection across Italian municipalities, 2012-18



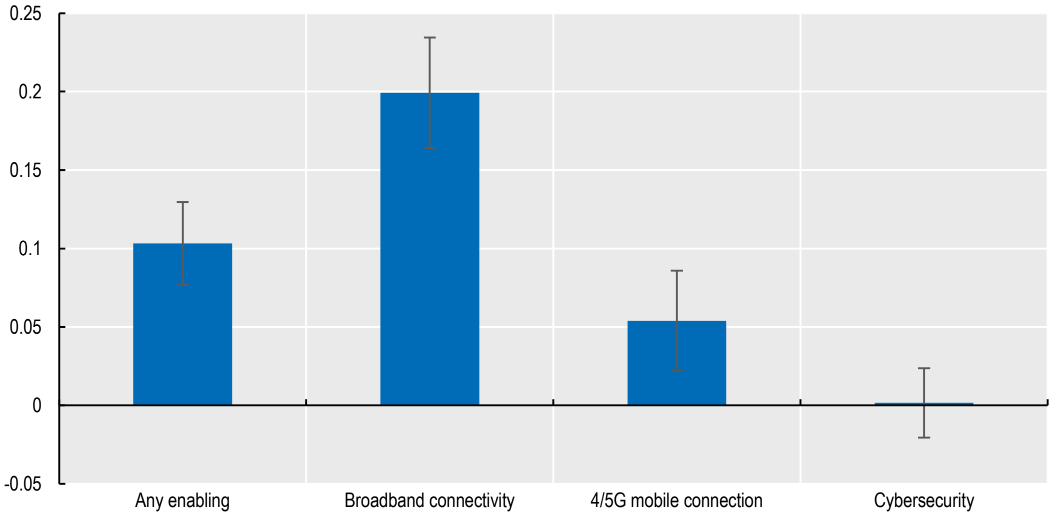
Note: The figure reports the share of municipalities in which at least one house number is connected to NGA broadband network ("connected municipalities") and the average share of house numbers that are connected to NGA broadband network out among connected municipalities.
Source: Authors' elaboration on AGCOM data.

Our aim is to estimate the impact of the increase in NGA broadband supply on firm digitalisation. For this purpose, we exploit within sector-region-year variability in the diffusion of NGA broadband infrastructure between 2012 and 2018 and we relate it with the adoption rates of Italian firms from the 2018 Italian Census of firms. Crucially, we control for changes in demand for fast-speed Internet connection, as measured by the change in the share of fast-speed Internet contracts.[6]

Our identification strategy relies on the assumption that the increase in the NGA broadband supply is uncorrelated with firm-level factors that may affect digitalisation, input accumulation, or productivity, after conditioning on sector-region fixed effects and changes in broadband demand. One critical confounding factor is the size of the municipality, as the most important and large Italian cities were connected to NGA broadband services since 2012 and their firms have larger adoption rates for several, unrelated, reasons (such as sectoral specialisation and agglomeration economies). To deal with this issue, we exclude the 20 capitals of regions, to obtain a more homogeneous sample, and we include proxies of municipal size as controls (either measured with the number of house numbers, or with the population and its density). We find reassuring evidence in favour of our identification assumption. Focusing on smaller cities, we find that the diffusion of broadband infrastructure is not correlated with ex-ante firm characteristics.[7]

Figure 4.3 shows that NGA broadband diffusion positively affects the adoption of enabling technologies. According to our estimate, a 100% increase in NGA broadband coverage over the period would induce a 12% rise in adoption rates, roughly half of the increase observed over the period.

Figure 4.3. The effect of NGA broadband supply on the adoption of enabling technologies



Note: The figure reports the coefficients β obtained by estimating the following linear probability model for each technology *k*:

$$\Pr(adoption^k)_i = \beta \frac{\Delta NGA}{Tot.Civic_m} + X_m + \gamma_{sr} + Size_i \times Age_i + \varepsilon_i$$

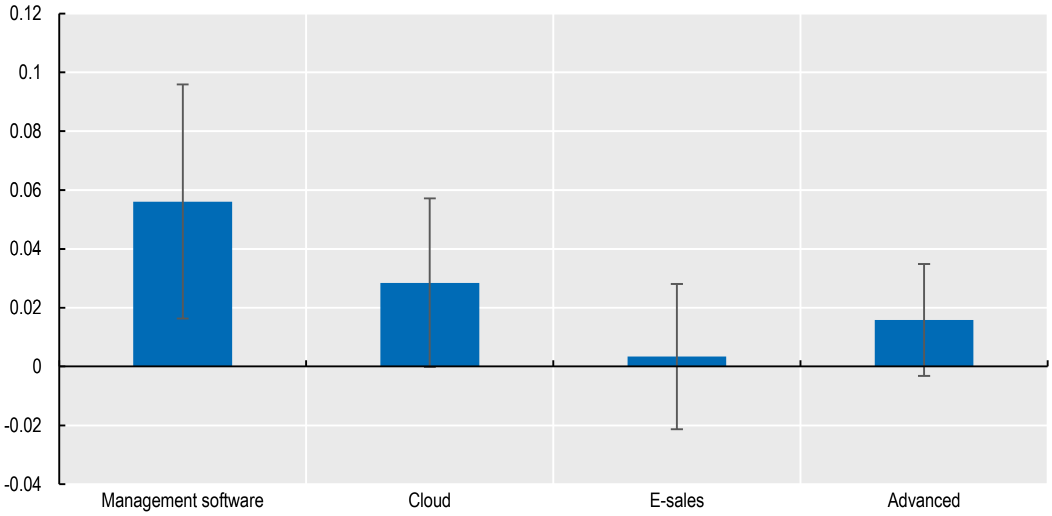
where *i* is a firm, *m* the municipality where it is located, *s* is its two-digit sector and *r* its region. $\frac{\Delta NGA}{Tot.Civic_m}$ is the 2012-18 increase in the number of house numbers connected to NGA broadband over total house numbers, X_m is a vector of controls that includes change in broadband Internet contracts over total contracts, and the log of total house numbers in the municipality. γ_{sr} is a vector of sector-region fixed effects, and $Size_i \times Age_i$ is a vector of size-age dummies. The error term ε_i is allowed to display serial correlation at the sector and region level.

Source: Authors' elaboration on AGCOM and ISTAT data.

Among enabling technologies, most of the effect is driven the adoption of fast broadband Internet connection. This result provides evidence of the effective "strength" of our identification strategy, and shows that the increase in the supply of NGA broadband infrastructure has a positive and significant effect on broadband adoption.[8] Interestingly, we also find a positive effect on the use of fast mobile connection, pointing to possible complementarities between the speed of Internet connection in the office and the one used for mobile services. Finally, we find no effect on the adoption of cybersecurity technologies. This result is worrisome: as the quantity and quality of information flows increase thanks to broadband infrastructure, so is the threat of cyber-attacks. This points to the importance of fostering cyber-security investments among firms, and in particular among micro and small firms, a goal which is increasingly recognised by the policy community (G20, 2021[31]).

We then turn to the impact of NGA broadband on the adoption of other digital technologies (Figure 4.4). We identify a positive effect on the adoption of management software, a result that can be related to the crucial role of connectivity in today's ERP and CRS software (Forbes, 2020[32]).

Figure 4.4. The effect of NGA broadband supply on the adoption of digital technologies



Note: The figure reports the coefficients β obtained by estimating the following linear probability model for each technology k:

$$\Pr(adoption^k)_i = \beta \frac{\Delta NGA}{Tot.Civic_m} + X_m + \gamma_{sr} + Size_i \times Age_i + \varepsilon_i$$

where i is a firm, m the municipality where it is located, s is its two-digit sector and r its region. $\frac{\Delta NGA}{Tot.Civic_m}$ is the 2012-18 increase in the number of house numbers connected to NGA broadband over total house numbers, X_m is a vector of controls that include change in broadband Internet contracts over total contracts, and the log of total house numbers in the municipality. γ_{sr} is a vector of sector-region fixed effects, and $Size_i \times Age_i$ is a vector of size-age dummies. The error term ε_i is allowed to display serial correlation at the sector and region level.

Source: Authors' elaboration on AGCOM and ISTAT data.

We also find a smaller but significant effect on the adoption of cloud technologies, which is consistent with the evidence from the United Kingdom (DeStefano, Kneller and Timmis, 2020[33]).

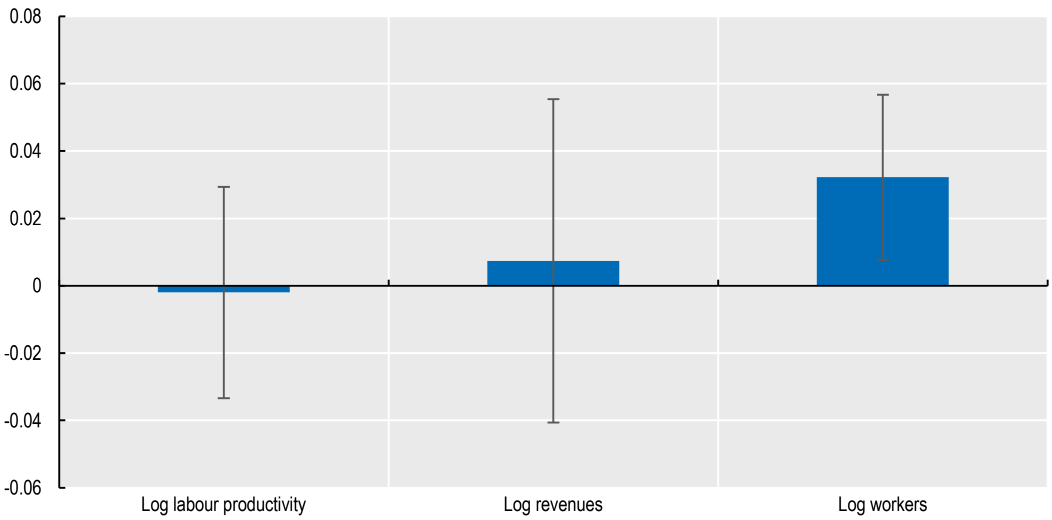
On average, we do not find any significant effect on the adoption of advanced technologies. Interestingly however, if we split firms by the ex-ante skill intensity of the workforce (measured in 2012 among incumbent firms), we find that NGA broadband raised advanced technology adoption among more skilled firms (see Figure A A.4 in Annex A). This is consistent with the idea that the availability of NGA broadband infrastructure may favour the adoption of more advanced digital technologies, but is not substitute to necessary pre-conditions such as the availability of adequate skills and intangible assets.

Our data allows us to assess whether the availability of NGA broadband infrastructure significantly affects firm productivity. On average, we do not find any significant effect. Figure 4.5 shows that on average NGA broadband supply does not significantly affect neither labour productivity nor its components.

However, we do find positive effects of broadband supply when we restrict to firms that were ex-ante more skilled (see Figure A A.5 in Annex A). This result is consistent with what obtained for advanced technologies, and show that the benefits of the broadband infrastructure can be particularly captured by firms that are endowed with skilled workforce.

Moreover, as more skilled firms are usually more productive, this result also points to an unequal allocation of the benefits of the infrastructure, which may have fostered productivity divergence.[9]

Figure 4.5. The effect of NGA broadband supply on labour productivity, revenues, and employment



Note: The figure reports the coefficients β obtained by estimating the following regression model for each dependent variable y (labour productivity, revenues, and workers):

$$\log y_i = \beta \frac{\Delta NGA}{Tot.Civic_m} + X_m + \gamma_{sr} + Size_i \times Age_i + \varepsilon_i$$

where i is a firm, m the municipality where it is located, s is its two-digit sector and r its region. $\frac{\Delta NGA}{Tot.Civic_m}$ is the 2012-18 increase in the number of house numbers connected to NGA broadband over total house numbers, X_m is a vector of controls that includes change in broadband Internet contracts over total contracts, and the log of total house numbers in the municipality. γ_{sr} is a vector of sector-region fixed effects, and $Size_i \times Age_i$ is a vector of size-age dummies. The error term ε_i is allowed to display serial correlation at the sector and region level.
Source: Authors' elaboration on AGCOM and ISTAT data.

All in all, results point to a significant effect of NGA broadband infrastructure on digital technology adoption. To boost its impact on more advanced technology, as well as its returns in terms of labour productivity, NGA broadband supply should be accompanied by significant investments in workforce skills. This calls for the need for a comprehensive digitalisation policy that combines investments in physical capital with those in knowledge and intangible assets.

4.4. STEM education

As already clear from the analysis above, education plays a key role to fully take advantage of advanced digital technologies and to allow workers to develop the skills required to cope with technological change. This section zooms in on the role of STEM programs, and their quality, to close the digital gap and boost digital technology adoption and its returns in Italy.

This is based on information on the location and quality of institutions offering STEM education programs in Italy (see Annex B for further details on this data source). As a measure of quality of education the focus is on the mean normalised citation score (MNCS), a widely used field-normalised scientometric indicator.[10] The information on location and quality of universities offering STEM programs is combined with the available information on firm-location. This allows to explore the extent to which being in the same municipality of a STEM university may affect firm-level digital technology adoption and its returns. Figure 4.6 reports the geographical distribution of universities with STEM programs, together with their relative MNCS.

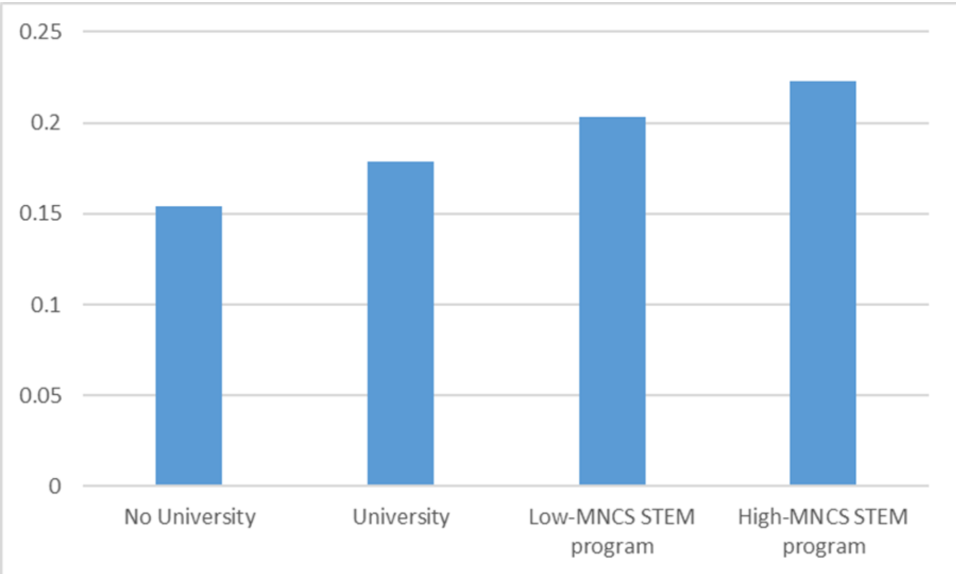
Figure 4.6. Universities with STEM program and their MNCS score

Note: Localisation of universities with STEM programs. The size of the dot signals their MNCS score.
Source: Authors' elaboration on OECD and CWTS data.

There are relevant challenges that need to be mentioned when carrying out this exercise. These include the role of possible omitted confounding factors and issues related to reverse causality. Omitted variable bias is addressed in the following by including a comprehensive set of fixed effects in the regressions estimated (region-industry and size-age-industry fixed effects), that allow to control for a significant number of potential confounding factors at very detailed level. Results are remarkably robust to changes in these fixed effects structure, which shows *a fortiori* that the presence of omitted variables is unlikely to drive our results.[11] Reverse causality may however remain an issue which calls for caution in interpreting causally the findings presented: Universities may locate where the demand for skilled workers by firms is *ex ante* higher, or STEM programs may be developed where firm digitalisation is higher. Unfortunately, the cross-sectional nature of the information on both university localisation and digital technology adoption prevents us to address this challenge.

Keeping this caveat in mind, Figure 4.7 starts by presenting the relation between the share of tertiary-educated workers within firms and the presence of universities in the same municipality in which the firm is located, separately focusing on institutions offering STEM programs of high or low (above or below average MNCS) quality.[12] Figure 4.7 highlights that there is a higher share of tertiary-educated workers in firms that are located in a municipality in which also a university is present. This share increases when the university also offers STEM programs and is highest when STEM program are of high quality.

Figure 4.7. Share of highly educated workers and education



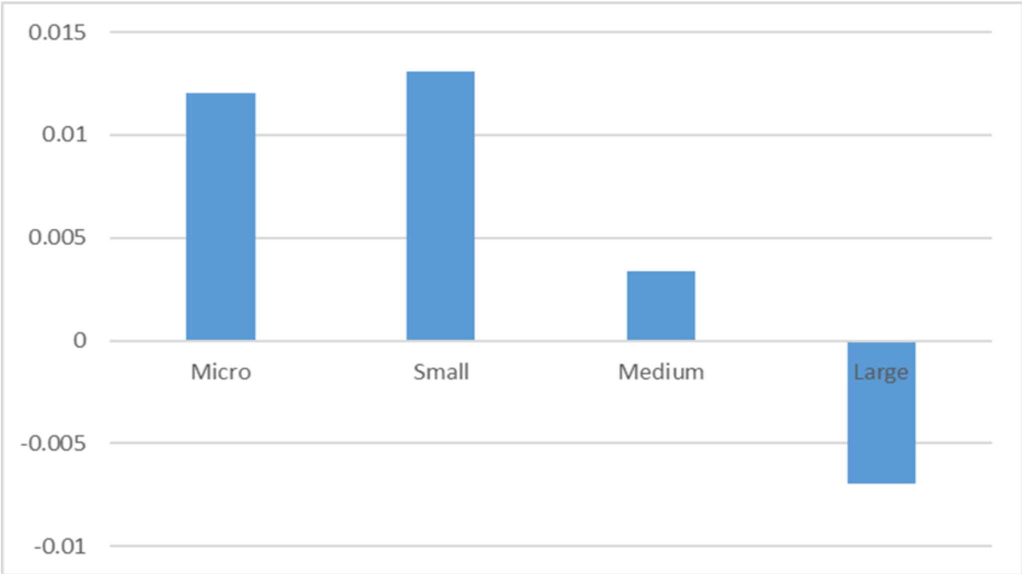
Note: Results of a regression of the share of highly educated workers in the firm on dummies signalling whether, in the municipality where the firm is located, there is a university, that university has a STEM program, and that STEM program has above-median MNCS. The regression includes region-industry and size-age-industry fixed effects. Standard errors are allowed to display serial correlation at the region-industry level.
Source: Authors' elaboration on ISTAT and OECD data.

STEM programs are also positively correlated with adoption rates of advanced digital technologies. This is shown in Figure 4.8, which focuses on the differentials in the share of firms adopting advanced digital technologies, comparing firms located in a municipality where STEM programs are offered with those located elsewhere.

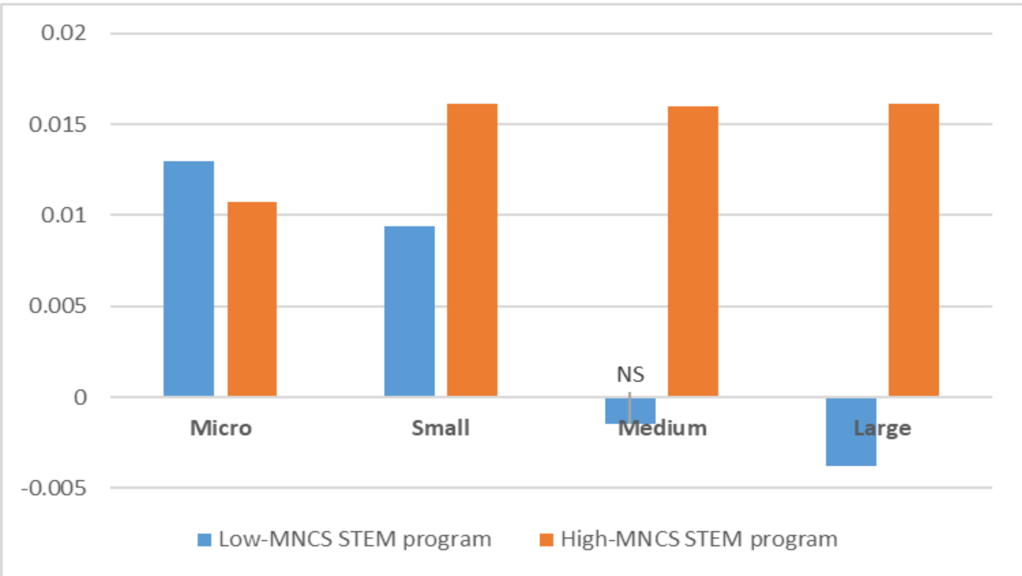
The figure shows that co-location with an institution offering STEM programs corresponds to higher shares of adoption particularly in micro and small firms (Panel A). When distinguishing STEM programs by their quality (Panel B), though, it is evident that low quality programs (blue bars) seem to be associated with higher shares of adoption in micro and small firms only, while high-quality programs (orange bars) are associated with higher adoption across the board.

Figure 4.8. STEM programs and advanced technology adoption by firm size class

Panel A. All STEM programs



Panel B. High- vs. low-quality STEM programs



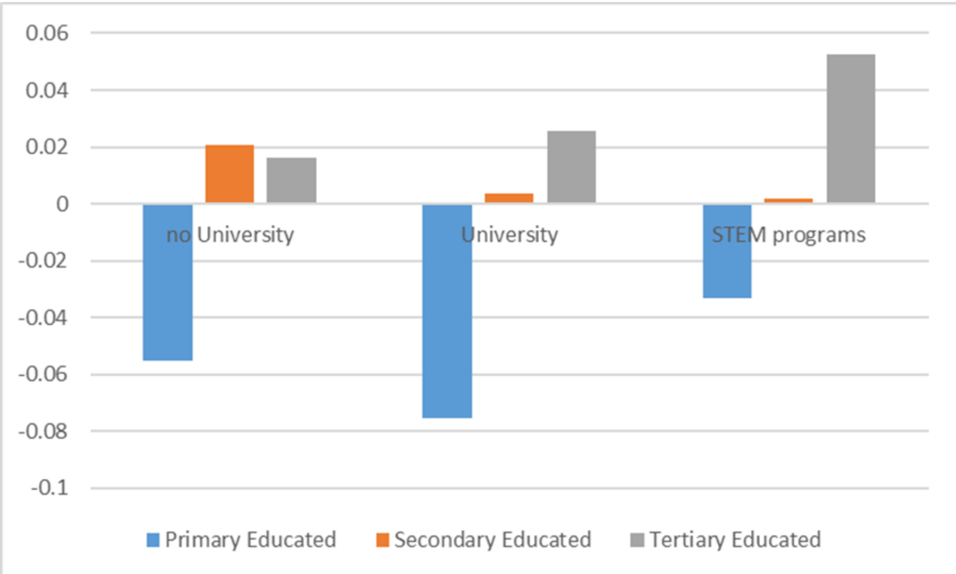
Note: Results of a regression of a dummy equal to 1 if the firm has adopted any advanced digital technology on a set of dummies signalling whether, in the municipality where the firm is located, there is a university, that university has a STEM program, and that STEM program has above-median MNCS (only in panel B). To focus on the result of interest, the figure reports only the coefficient of the STEM dummy and the STEM with above-median MNCS dummy. The regression includes region-industry and size-age-industry fixed effects. Standard errors are allowed to display serial correlation at the region-industry level, NS = not statistically different from zero with $p<0.05$.
Source: Authors' elaboration on ISTAT and OECD data.

The within-firm analysis summarised in Section 4.2 and detailed in Annex C has highlighted the relevance of the quantity and quality of tertiary educated workers in explaining adoption and returns of advanced digital technologies. The supply of tertiary workers is directly affected by the availability of universities: we can, thus, study whether the presence of universities, particularly of STEM programs, can boost the complementarity between tertiary-educated workers and digital technologies. For this purpose, we exploit the structural econometric framework detailed in Box A C.1 in Annex C. In particular, for the year 2018 we estimate a production function differently when there is no university, when there is a university without a STEM program, and when there is a STEM program. We estimate production functions specific to each two-digit sector, and then average results using sector-level revenue shares.

The results, presented in Figure 4.9 show that STEM programs seem to be key in boosting complementarities between high education and digital technologies. Indeed, complementarities are significantly higher in the case of STEM programs when focusing on tertiary-educated workers.

Overall, the analysis presented above suggests that improving the quality and quantity of STEM education may contribute to reduce the digital gap by increasing adoption of advanced digital technologies and their returns among both SMEs and larger firms.

Figure 4.9. STEM programs and complementarity between skills and advanced technology adoption



Note: The figure plots the estimated cross-elasticity of digital technologies and log-employment, distinguishing between primary, secondary and tertiary educated. The cross-elasticity is obtained from a production function estimate which follows the methodology outlined in Box A C.1 in Annex C.
Source: Authors' elaboration on ISTAT and OECD data.

4.5. The R&D tax credit

Evidence discussed above (and presented in Annex C) has shown that R&D activity is strongly associated with higher adoption of digital technologies. Policies aimed at incentivising R&D investments might, thus, ultimately boost the digital transformation. Since 2015, Italy has introduced an R&D tax credit, subsequently strengthened in 2017 and 2018. The tax credit applies to incremental investments in R&D, relative to the expenditures incurred in the pre-policy period. In 2015, two different deduction rates were introduced depending on the type of expenditure: a higher tax credit for extra-mural expenditures and highly qualified personnel (50%), while a lower, but still substantial, deduction for the other types of intra-mural investments (25%). From 2017, until 2018, the allowance was raised, and the tax credit was levelled at 50% for all types of R&D expenses.

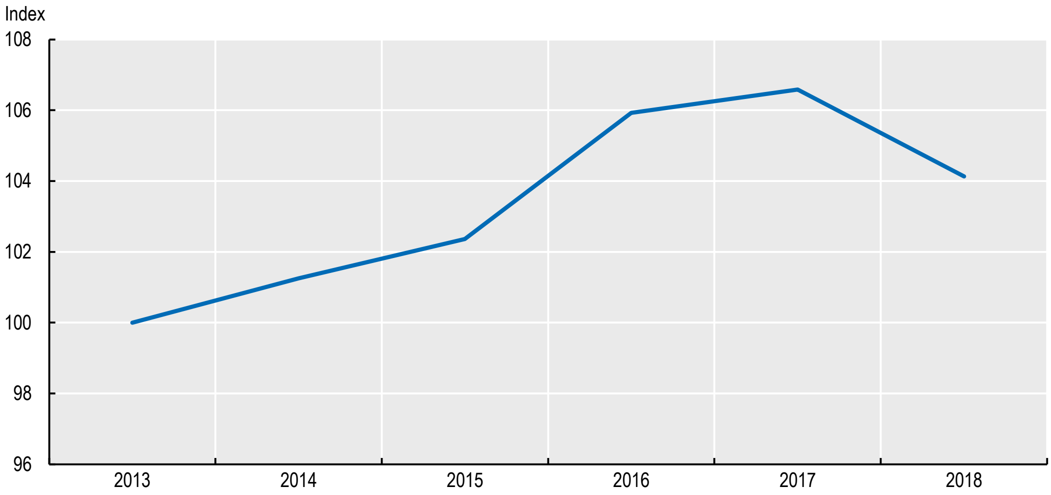
We exploit information from the R&D surveys for the years 2013-18 to study the impact of the policy. The survey covers around 18 000 firms per year, but its size has been increasing over time. The changes in the sample design do not allow to compare how the number of firms doing R&D has changed after the introduction of the incentive (i.e., the "*extensive margin*"), but solely the evolution of R&D expenditures among firms performing such activity before the incentive was implemented (i.e., the "*intensive margin*"). Moreover only information on intramural R&D is consistently available over the period (from 2015 onwards extramural expenditures have not been recorded). For this reason, in the analysis we focus solely on intramural R&D.

Lack of information on the actual take-up of the policy, and the lack of an exogenous instrument, also limits our ability to assess its effects causally.[13] We therefore focus on documenting the trends in R&D expenditures during the policy period and the evolution of its distribution.

As discussed, we examine how the policy has incentivised expenditures among firms that already performed R&D before the implementation of the tax credit (i.e., the *intensive* margin). To obtain a balanced panel, we restrict the analysis to R&D performers (with positive average intramural expenditure in 2013-14) that are observed over the entire period considered.[14] These firms were ex-ante major players in R&D activities (their average R&D expenditure in 2014 were twice as high as R&D performers who then exited the sample during the period), were larger, more productive and had higher revenues than the rest of the firms - while having mostly the same macro-sectoral distribution (Table A A.1 in Annex A).

For these firms, we record an acceleration in intramural R&D spending since 2016. By 2017, average R&D expenditure topped at almost 106% of its 2013 levels, slightly declining by 2% year-on-year in 2018 (Figure 4.10).

Figure 4.10. Average expenditure on intramural R&D – 2013=100

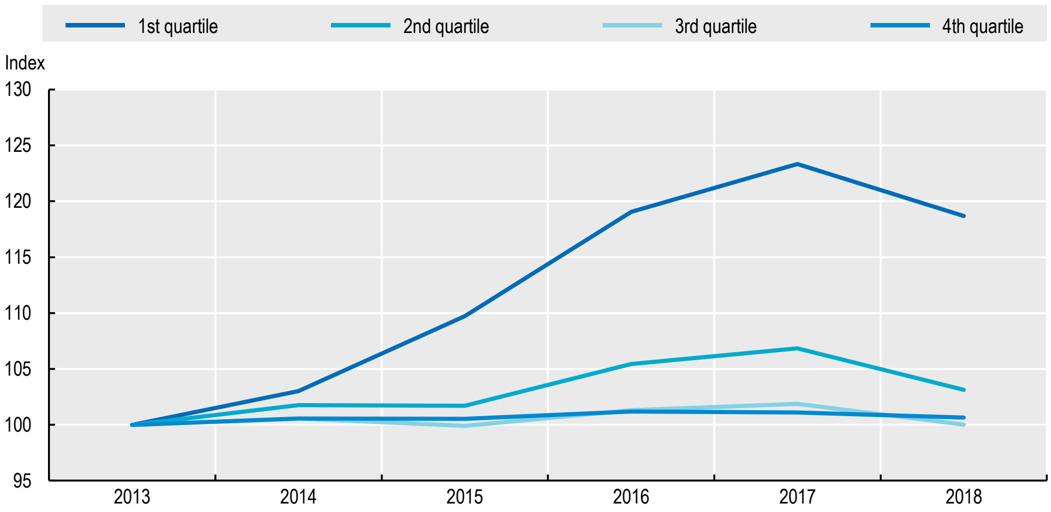


Note: The figure is based on a sample of firms that have positive average intramural R&D expenditure in 2013-14 and were surveyed every year over the period 2013-18, excluding observations that were attributed based on expectation of previous responses.
Source: Authors' elaboration on ISTAT, R&D survey.

Likely because of the incremental feature of the benefit, the aggregate increase has been entirely driven by firms that ex-ante were performing less R&D (Figure 4.11). Indeed, R&D investments of firms belonging to the first quartile of R&D expenditure in the pre-policy period (2013-14) rose by around 20%, firms belonging to the second quartile rose by around 5%, while firms belonging to the upper half of the distribution did not increased their average expenditure. Thus, on the *intensive* margin (firms that were already performing R&D), the policy seems to have effectively contributed to the diffusion of R&D activities among firms that were previously less R&D intensive.

On the other side, though, future research is needed to determine whether the R&D tax credit has incentivised expenditures among other types of firms that are currently out of the analysis, as well as has induced new firms to start doing R&D (i.e., the *extensive* margin). To this purpose, other sources of information (e.g. Tax Agency data) should be exploited to properly identify the characteristics of the R&D tax credit and its changes over time and to assess the causal impact of the policy on firms' innovative activity and digital technology evolution.

Figure 4.11. Average expenditure on intramural R&D by quartiles of the 2013-14 distribution of R&D expenditures – 2013=100



Note: The figure is based on a sample of firms that have positive average intramural R&D expenditure in 2013-14 and were surveyed every year over the period 2013-18, excluding observations that were attributed based on expectation of previous responses. Quartiles are defined on the basis of the distribution of average expenditure on intramural R&D in 2013-14.
Source: Authors' elaboration on ISTAT, R&D survey.

4.6. Supporting digital adoption: an evaluation of the hyper-depreciation subsidy

A key component of the Italian national plan for the digitalisation of the business sector was the introduction, since the end of 2016, of a fiscal incentive on investment on Industry 4.0 tangible assets, called "hyper-depreciation". This measure introduced a total tax depreciation of up to 250% of the cost of new "smart" and interconnected equipment. This policy has been deemed strategic by all successive governments and has been confirmed over the period 2016-19, and further reformed in 2020.

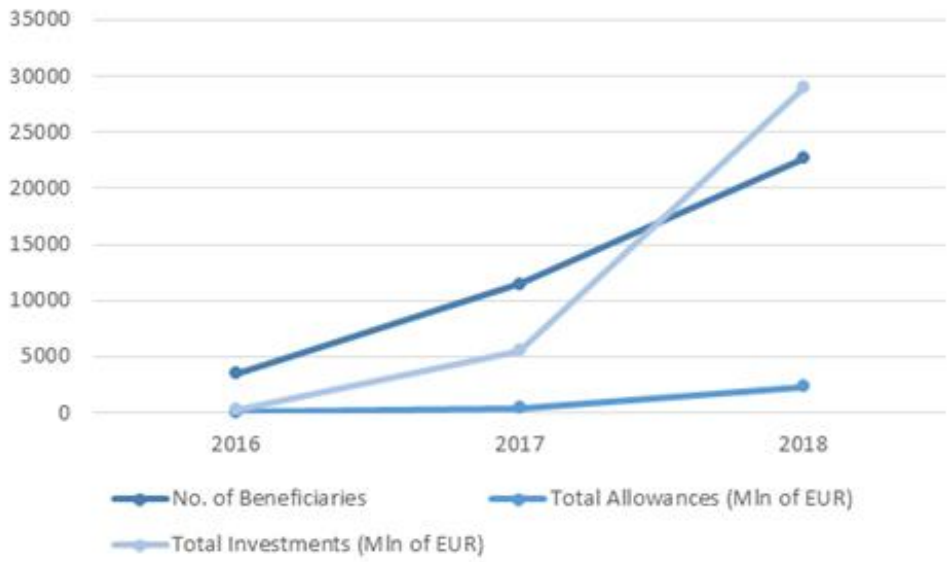
In this section, we provide an empirical analysis of its effects. Our analysis builds on a recent policy evaluation performed by researchers of the Italian Industrial Federation and of the Ministry of Economy and Finance (Bratta et al., 2020[34]) – BRAM, henceforth. Their work analyses extensively the characteristics of the beneficiaries, showing that medium-sized and large firms are overrepresented among them, and that manufacturing firms are both the majority of beneficiaries and have made more than 80% of total investments subsidised. BRAM also shows that beneficiaries were ex-ante more productive, more profitable, less leveraged, and more digitalised. Finally, using a propensity-score matching technique, it finds that the policy generated positive impacts on employment, by increasing hirings while not affecting job separations. The effect is found to be stronger for larger firms.

Our work extends their analysis in four dimensions. First, we provide a more complete assessment of the take-up of the policy: the Tax Agency data that we exploit include all Italian firms (while BRAM focused on incorporated firms only) and is more updated than the one used by BRAM. Second, we use information on digital technology adoption from the 2018 Census of Italian firms to estimate the impact of the policy on firm digitalisation (the main objective of the policy). Third, we extend their evaluation to a broader set of outcome variables (which includes revenues and labour productivity). Finally, we highlight relevant treatment heterogeneity, with better managed firms being able to obtain larger productivity gains, and the diffusion of NGA broadband being complementary to the financial incentive introduced by the policy.

4.6.1. Take-up of the policy and characteristics of the beneficiaries

Over the period 2016-18, over 30 000 firms benefitted from the hyper-depreciation, with a significant increase over time (Figure 4.12).[15] Almost EUR 2.8 billion of tax allowances have been provided over the period. We exploit the methodology of BRAM (see Box 4.1) to estimate the corresponding amount of investments subsidised: our estimate indicate roughly EUR 5 billion in 2017 and almost EUR 30 billion in 2018.[16]

Figure 4.12. The hyper-depreciation policy: number of beneficiaries, total allowance and total investments subsidised – 2016-18



Source: Authors' elaboration on ISTAT and Italian Tax Agency.

Box 4.1. Estimating the amount of subsidised investments by the hyper-depreciation

Tax Agency data do not provide the value of the investments for which the firm asks the tax depreciation. It only provides the amount of the tax allowance. To obtain an estimate of the corresponding investments subsidised, we follow Bratta et al. (2020[34]) and exploit information on law-mandated amortisation rates.

The starting point is the consideration that the observed allowance E of firm i investing an amount I_{ik} in asset k is equal to:

$$E_{ik} = \frac{I_{ik} * (1 + 150\%) * \varphi_k}{2} - \frac{I_{ik} * \varphi_k}{2}$$

where φ_k is the tax depreciation rate for an asset of type k, and the ratios are divided by two because the value of the investment is halved in the first year. In Italy, amortisation rates of tangible fixed investments have been set by a Ministerial Decree of 1988 and have not been changed so far. They vary by sector and type of asset purchased (although the information from firm balance sheets does not allow to distinguish different types of assets among tangibles).

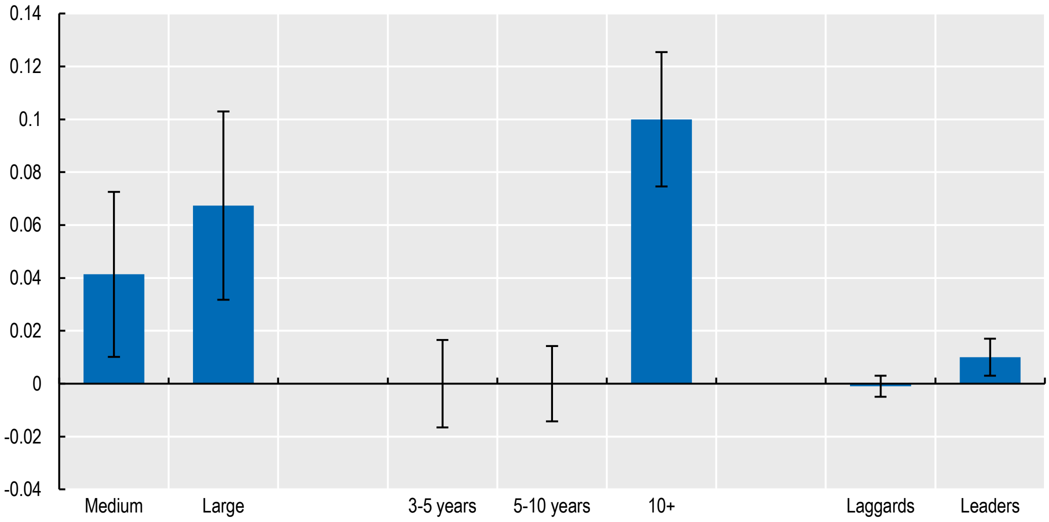
To move from single asset to firm-level total investments, we use the estimate of average sector-level depreciation rates from BRAM.

It is thus possible to retrieve an estimate of the subsidised investment using:

$$I_i = \frac{2E_i}{1.5 * \bar{\varphi}_i}$$

We studied the characteristics of the beneficiaries. In terms of sectoral composition, we confirm the results of BRAM: over 80% of total investments subsidised were made in the manufacturing sector, with trade ranking second with around 5% of total investments. In addition, we look at the heterogeneity of beneficiaries by regressing a dummy equal to 1 if the firm has benefited from the hyper-depreciation on controls for size, age, and productivity. We confirm that firms that benefited from the policy are more likely to be larger and more productive than non-beneficiaries (Figure 4.13). In addition, we also find that older firms are particularly overrepresented in the policies.

Figure 4.13. Ex-ante firm characteristics and use of the hyper-depreciation



Note: The figure plots the coefficients estimated from a regression of a dummy equal to 1 if the firm used the hyper-depreciation over the period 2017-18 on a set of size, age, and productivity decile dummies. The baseline category is composed of micro and small firms with less than three years of age and belonging to the middle part (deciles 2-9) of the productivity distribution. The model also controls for sector-region unobserved heterogeneity. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT and Tax Agency data.

4.6.2. Effects of the policy and their heterogeneity

To estimate the effects of the policy, we have to identify an adequate control group against which to measure the performance of treated firms. Absent any viable instrumental variable application (the policy is horizontal over the entire business sector, and the Law-mandated depreciation rates are found to be significantly correlated with firm characteristics), we resort to a propensity score matching technique to identify the control group (see Box 4.2).

Box 4.2. Propensity score matching to assess the impact of the hyper-depreciation strategy

To define the vector of controls that contribute to generate the propensity score, we consider several firm characteristics observed in year 2013. They include, firm size, age, sector dummies, productivity, and skill of the workforce (the share of high skilled workers), as well as the growth rate of employment and productivity between 2012 and 2013. The key identification assumption is that, conditional on the propensity score, being a beneficiary is as-good-as-randomly allocated. We indirectly test this assumption by analysing whether various variables (crucially, also some *not* included in the propensity score matching algorithm) are uncorrelated with treatment status, within each quartile of the propensity score distribution. Moreover, we test for similar pre-policy trends in revenues, employment and productivity, within each quartile of the propensity score distribution, over the period 2011-13 period. Results reassuringly show no evidence of confoundedness or different pre-trends (Table A A.2 in Appendix A).

We then move to estimate the effect of the hyper-depreciation on the adoption of various digital technologies. In particular, we perform a WLS estimate (with weights equal to the propensity score) of the following linear probability model:

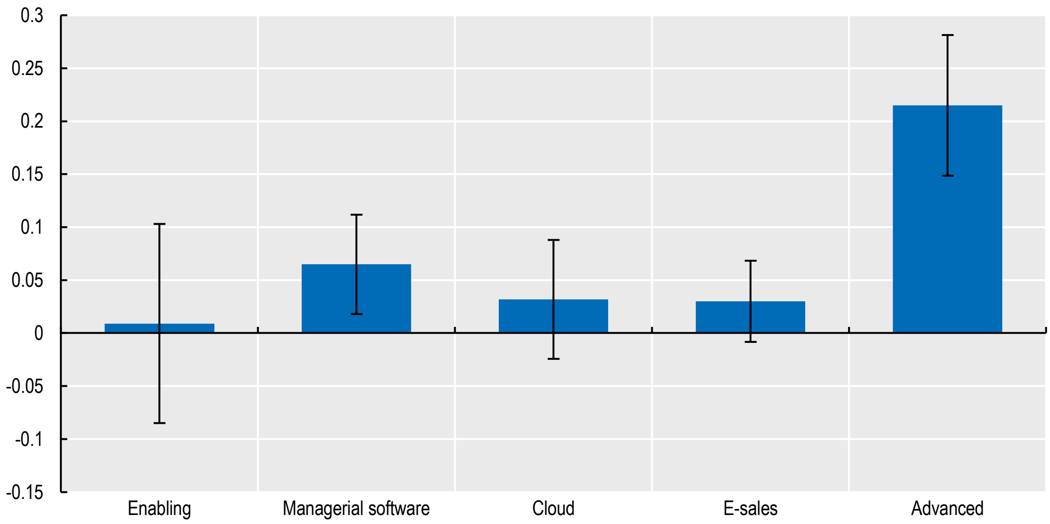
$$1(Tech_{ik} = 1) = \beta\, 1(Hyper_i = 1) + \gamma_{swar} + \varepsilon_i$$

Equation 1

where γ_{swar} is a vector of fixed effects defined for each sector s, size w, age a, and region r. The error term ε_i is allowed to display serial correlation at the sector and size-region levels.

Results are reported in Figure 4.14. The policy is found to boost significantly the adoption of advanced digital technologies, its main objective. In addition, a positive though small effect is also found on the adoption of managerial software. In an unreported regression, we also find a positive effect though less precisely estimated effect on the adoption of cybersecurity technologies: the policy would have increased the likelihood of having performed investments in cybersecurity by 6.5 percentage points (around one-fourth of the average adoption rate among all Italian firms, $p<0.1$). This result is important: as the introduction of advanced digital technologies boosts the flow of sensitive information over the Internet and Intranet networks, firms need to strengthen their resilience to cyberattacks, which become potentially more harmful. We find also that the policy fostered investments in other complementary enabling technologies, such as fast mobile (4G/5G) Internet connections.

Figure 4.14. Effect of the hyper-depreciation on technology adoption - 2018



Note: The figure plots the results of estimating the following model:

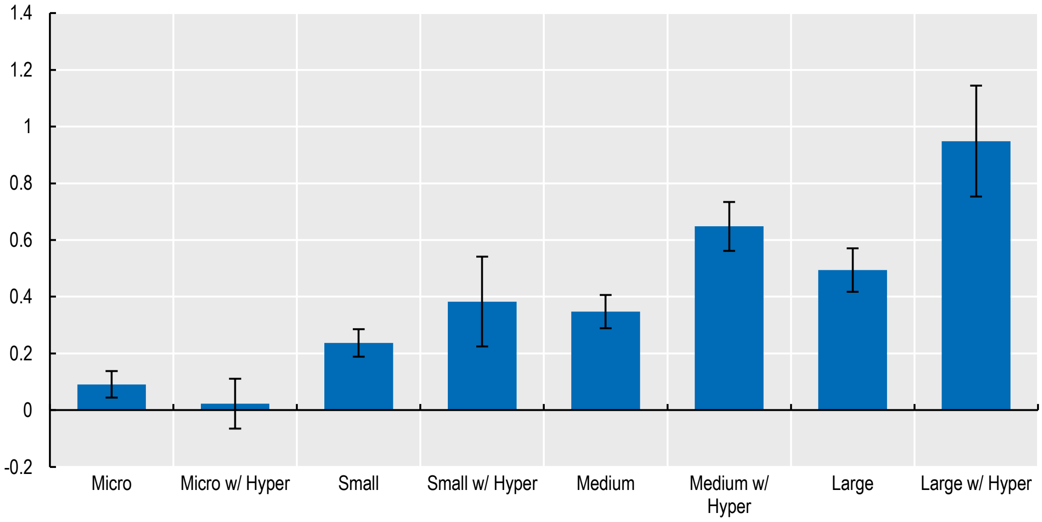
$$1(Tech_{ik} = 1) = \beta\, 1(Hyper_i = 1) + \gamma_{swar} + \varepsilon_i$$

for each technology k, where $1(Hyper_i = 1)$ is a dummy equal to 1 if the firm i has used the hyper-depreciation benefit and γ_{swar} is a sector-size-age-region fixed effects. Observations are weighted by their propensity score. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT and Tax Agency data.

Among advanced technologies, we identify positive effects for those that are directly targeted by the subsidy. In particular, we estimate a positive increase in the probability of adopting Internet-of-Things, advanced automation, 3D printing, and simulation of interconnected machines. We find a very small positive effect for AR/VR technologies, while big data analytics do not appear to benefit from the incentive.

The positive effect on the adoption of advanced digital technologies stems largely from medium-sized and large firms, while the impact among micro and small beneficiaries has been more limited (Figure 4.15). We then dig deeper in the zero effect reported for micro and small firms. We find that the net zero is mostly the result of a positive effect of the policy in micro and small firms that had ex-ante more skilled manager and workforce.[17] Conversely, for micro and small with low skill workers, the effect is generally negative but far from statistical significance.

Figure 4.15. Adoption rates of advanced technologies among beneficiaries of the hyper-depreciation and their counterfactual control group



Note: The figure plots the results of estimating the following model:

$$1(Tech_{ik} = 1) = \beta\ 1(Hyper_i = 1) \times Size_i + \gamma_{swar} + \varepsilon_i$$

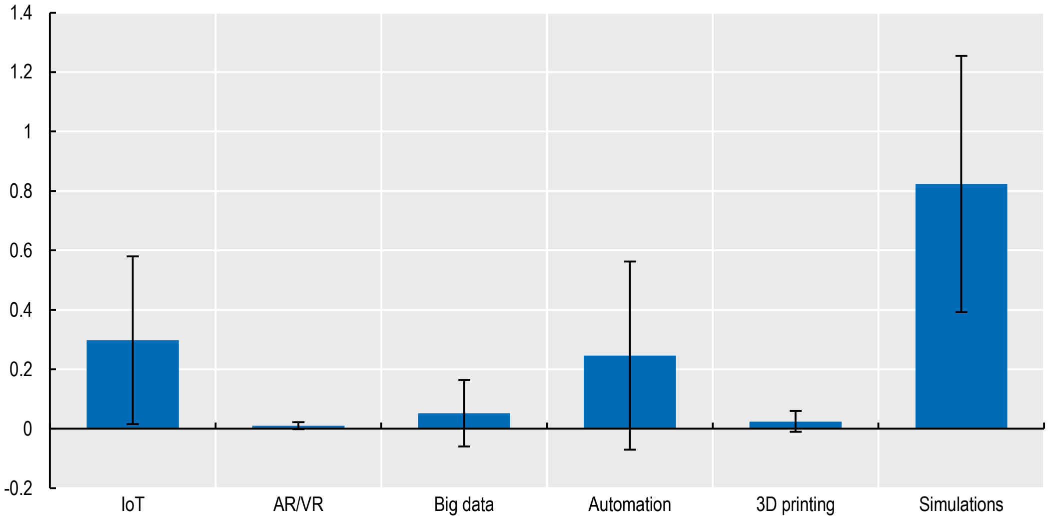
for each technology *k*, where $1(Hyper_i = 1)$ is a dummy equal to 1 if the firm *i* has used the hyper-depreciation benefit, $Size_i$ is a set of size dummies, and γ_{swar} is a sector-size-age-region fixed effects. Observations are weighted by their propensity score. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT and Tax Agency data.

We also study whether the hyper-depreciation interacts with the availability of NGA infrastructure, to highlight potential complementarities between policies. As the adoption of I4.0 technologies usually entails a significant increase in the amount of information exchanged, ultra-fast Internet connection can raise the capabilities of adopters. To test this hypothesis, we ran the model:

$$\begin{aligned}1(Tech_{ik} = 1) = \beta\ 1(Hyper_i = 1) + \delta\ 1(Hyper_i = 1)\\ * NGA\ growth_m + \theta NGA\ growth_m + X\sigma\\ + \gamma_{swar} + \varepsilon_i\end{aligned}$$ **Equation 2**

where $NGA\ growth_m$ is the growth in NGA coverage between 2012 and 2018 (measured as a ratio of total house numbers) and X is a vector of controls that include the increase in the demand for fast broadband connection and the size of the municipality. We find that broadband boosted the effect of the policy on IoT and simulations of interconnected machines, with positive effects also on advanced automation (though barely not statistically significant at $p<0.05$). These results point to important complementarities between infrastructure investments and policies aimed at increasing firm-level technology adoption.

Figure 4.16. Complementarity between hyper-depreciation and NGA supply for advanced digital technologies



Note: The figure plots the results of estimating the following model:

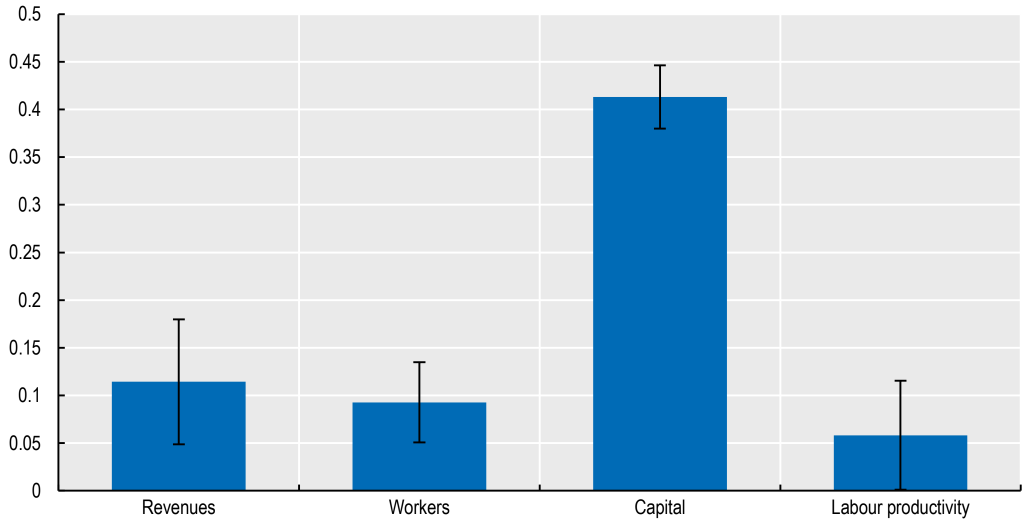
$$1(Tech_{ik} = 1) = \beta\ 1(Hyper_i = 1) \times \frac{\Delta NGA}{Tot.Civ_i} + \gamma_{swar} + \varepsilon_i$$

for each technology k, where $1(Hyper_i = 1)$ is a dummy equal to 1 if the firm i has used the hyper-depreciation benefit, $\frac{\Delta NGA}{Tot.Civ_i}$ is the growth of house numbers covered by NGA in the municipality where the firm is located, and γ_{swar} is a sector-size-age-region fixed effects. Observations are weighted by their propensity score. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT, AGCOM and Tax Agency data.

We then move to study the effect of the policy on revenues, employment (its size and quality) and labour productivity. In this case, we exploit the availability of firm information back in 2015 and we use the 2015-18 growth rate of revenues, workers, and labour productivity, as well as three-year changes in the share of high and medium skilled workers, as dependent variables.

Results reported in Figure 4.17 show that the policy induces positive effects on firm performance. In particular, it is associated with an increase in revenues of around 11%, in labour input by 9% and in capital by around 40% over the three years window. Labour productivity increased by slightly more than 5.5%. The increase in employment is particularly driven by tertiary educated workers, which increase by 12%, relative to an increase of around 7% in secondary and primary educated workers (Figure 4.18). As a result there is a small but significant increase in the share of tertiary educated workers (of around half of a percentage point). Interestingly, additional heterogeneity results show that the positive real effects are found to be stronger among micro and small firms with more skilled top-executives (Figure 4.19).

Figure 4.17. Effect of the hyper-depreciation on firm outcomes – growth rate between 2015 and 2018

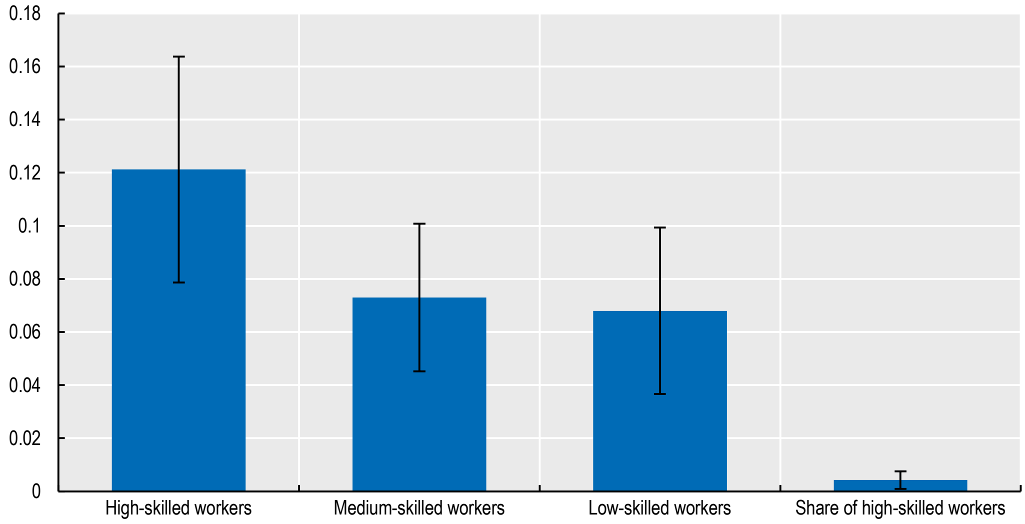


Note: The figure plots the results of estimating the following model:

$$y_i = \beta\, 1(Hyper_i = 1) + \gamma_{swar} + \varepsilon_i$$

where $1(Hyper_i = 1)$ is a dummy equal to 1 if the firm *i* has used the hyper-depreciation benefit and γ_{swar} is a sector-size-age-region fixed effects. The dependent variables *y* are (log) revenues, (log) number of workers, log (capital), and (log) labour productivity. Observations are weighted by their propensity score. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT and Tax Agency data.

Figure 4.18. Effect of the hyper-depreciation on skill education

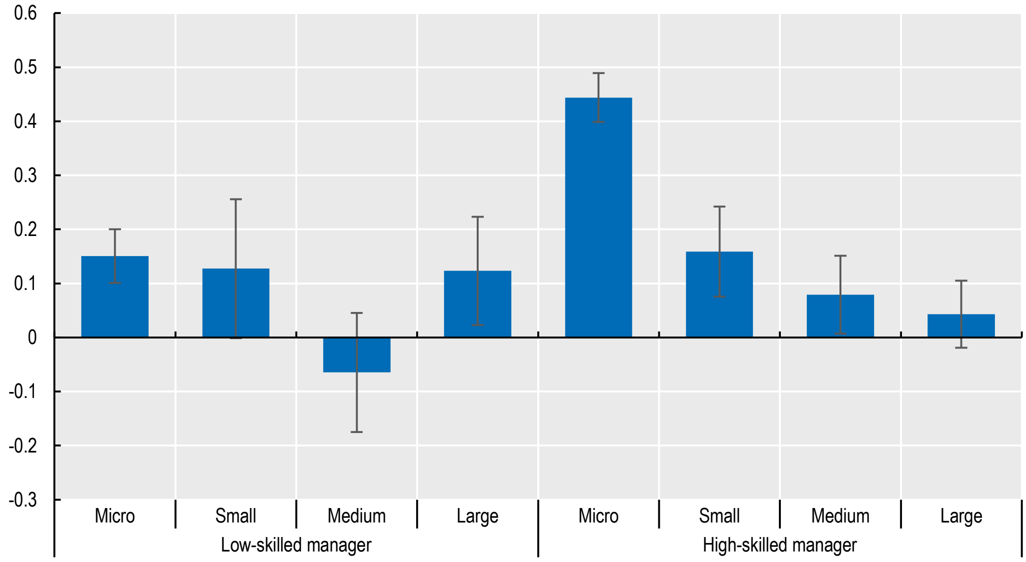


Note: The figure plots the results of estimating the following model:

$$y_i = \beta\, 1(Hyper_i = 1) + \gamma_{swar} + \varepsilon_i$$

where $1(Hyper_i = 1)$ is a dummy equal to 1 if the firm *i* has used the hyper-depreciation benefit and γ_{swar} is a sector-size-age-region fixed effects. The dependent variables *y* are inverse-hyperbolic sine of the number of high-, medium- and low-skilled workers and the share of high-skilled workers on total workforce. Observations are weighted by their propensity score. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT and Tax Agency data.

Figure 4.19. Effect of the hyper-depreciation on labour productivity by skill of the top-executive



Note: The figure plots the results of estimating the following model:

$$y_i = \beta\, 1(Hyper_i = 1) * Size_i * HSManager_i + \gamma_{swar} + \varepsilon_i$$

where $1(Hyper_i = 1)$ is a dummy equal to 1 if the firm *i* has used the hyper-depreciation benefit, $Size_i$ is a set of size-dummies, $HSManager_i$ is a dummy equal to 1 if the firm *i* had a tertiary educated top-executives in 2015, and γ_{swar} is a sector-size-age-region fixed effects. The dependent variables *y* is the firm's (log) labour productivity. Observations are weighted by their propensity score. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT and Tax Agency data.

Summing up, the analysis has uncovered important real effects on revenues, capital and productivity. The increase in employment was stronger for high-skilled workers, who are found to be crucial to the effective use of advanced technology adoption.

The analysis also shows that, on average, the policy has mostly benefited medium to large firms, who represent the larger share of beneficiaries, yet micro and small firms who displayed more skilled managers were more likely to use this policy and displayed higher returns in terms of revenues, employment and productivity than larger firms. Finally, the analysis has shown how the positive effects of the hyper-depreciation policy have been particularly relevant in municipalities were the diffusion of broadband infrastructure increased the most.

Overall, the results of these analyses point to the effectiveness of financial incentives in boosting innovative activities and the adoption of advanced digital technologies. They may tend to benefit mostly medium to large firms, who may have not be those in most need of the support, as ex ante less constrained in the accumulation of new capital. However, results also show that micro and small firms with high-skilled managers, which may be an indicator of high potential, can disproportionally benefit from these policies. This further suggest key policy actions that foster the reduction of the technological gap between small and large firms, it is thus crucial to complement financial incentives with policies aimed at boosting specific intangible assets, such as the skills and competencies of the management. These may take various forms, from boosting the awareness on the importance of managerial and organisational capital among micro and small firms, to support the use of consulting services, coaching and mentoring for managers.

4.7. Additional factors outside the firm: spillovers and finance

The data infrastructure allows to study the role of additional determinants of the digital transformation. In Annex C, in particular, we study the relevance of spillover effects and of the availability of external finance.

For spillovers, we exploit standard methodologies developed to assess their existence in the case of R&D and patenting to the case of digital technologies. In particular, we estimate how much a firm's probability of adoption is affected by the (revenue-weighted) share of adopters in the same market. We consider four different types of markets: the firm two-digit sector, its province, the export destination market and the import origin country. We find spillovers to be positive and particularly relevant at the sector and export destination market level, while spillovers at the level of import origin country matter only for management software (which include also software to manage firm's participation in GVCs) and province-level spillovers matter for enabling technologies (likely because of the local-level availability of broadband infrastructure). We also provide evidence that the positive spillover effects are dampened by product market concentration, consistent with the existence of a winner-takes-most effect that lowers the positive diffusion channel of technology adoption.

The analysis of the role of external finance starts from the descriptive assessment of the financing strategies of adopters and non-adopters. The analysis shows that adopting firms are generally less leveraged throughout their life cycle, particularly when technology adoption is coupled with complementary intangible assets. This result, consistent with recent evidence from Italy (Gonzalez-Torres, Manaresi and Scoccianti, 2020[25]), shows that internal capital is a more important source of finance for digital firms than for non-digital ones. We then exploit credit supply shocks, estimated at the sector-province level from matched bank-firm data, to assess whether credit supply affects technology adoption. Consistent with the descriptive assessment, we find that a positive credit supply shock does not boost technology adoption. Conversely, an unexpected negative shock significantly reduces the probability that the firm adopts digital technologies, particularly those (such as automation or Internet-of-Things) that require higher initial fixed costs. Thus, while on average adopters are not found to be credit constrained (so that positive shocks to credit supply are ineffective in increasing adoption), a negative shock tightens the constraint forcing firms to cut on investments, including those in digital technologies. The results point to the relevance of supporting a stable flow of credit to firms, to avoid sudden credit shortages, while developing Italian capital markets to allow broader access to non-credit finance by micro and small firms.

5. The impact of COVID-19 on the digital gap of Italian firms

The pandemic has disrupted the life of all individuals around the world, changing the way we consume, work and produce. The business sector has been severely hit: industrial production in Italy fell by 11.4% in 2020, GDP contracted by 8.9% (ISTAT, 2021[35]). The drop has been heterogeneous across sectors: Trade, transportation and hospitality and Arts and entertainment experienced the greatest contraction in value added (around 15% year-on-year), while the impact on Financial and Real estate services was much more limited (a drop of less than 3%), and Information and communication registered an increase in aggregate value added of 1.8%.

The positive performance of IT services is not surprising: digital technologies have been crucial in allowing companies to continue producing and selling, and people to continue working, during the lockdowns and afterwards. For this reason, firms have significantly accelerated their pace of digitalisation, and broadened their use of digital technologies (Criscuolo, 2021[36]; OECD, 2021[8]) Digital technologies adoption among Italian firms has significantly increased: cloud adopters rose from 23% in 2018 to 59% in 2020, while e-commerce adopters increased by 43% (ISTAT, 2021[37]).

At the onset of the pandemic Italy was among the European countries with the lowest adoption of teleworking. The COVID-19 crisis triggered a rapid acceleration of this practice: the share of employees teleworking[18] rose from less than 5% in January to 20% in March 2020, and it levelled-off at 15% until December (ISTAT, 2021[37]).

While there is evidence of an overall strengthening of the digital transformation in Italy, little is known about how the gap between more and less digital firms has been affected by the pandemic. A priori, the effect is ambiguous. At one side, the incentive to invest in digital technologies may have been stronger for firms that were ex-ante less digital, as their poor use of digital technologies represented an existential threat during the pandemic. At the other side, however, investing in digital technologies and introducing teleworking has been less costly for firms that were ex-ante more digitalised, as they already had the complementary knowledge, skills and intangible assets necessary for an effective digital transformation.

International empirical evidence on which of these two channels dominate is still limited, but generally points to a widening of the digital gap. According to a recent survey administered by the European Investment Bank, digital firms in the United States and the European Union are more likely to expect that COVID-19 will lead to an increase in the use of digital technologies (EIB, 2021[11]). Data from the United Kingdom show that previous adopters were 30% more likely to adopt further digital technologies and strengthen their digital capabilities during the crisis.

In this section, we provide novel evidence of the relationship between firm digitalisation and the COVID-19 crisis. In particular, we aim at answering two questions:

a) Were ex-ante more digitalised firms better able to cope with the COVID-19 shock?

b) Has the COVID-19 shock widened the digital gap among firms?

To answer these questions, we exploit a survey administered by ISTAT in November 2020 to assess the impact of COVID-19 on Italian firms (henceforth, “COVID-19 survey”). The COVID-19 survey collected information on revenues, investments, digitalisation, and teleworking over the period June-November 2020 for over 40 000 firms. Crucially for our analysis, the sampling procedure was specifically designed so that the survey was administered among a subset of firms that participated to the 2018 Census, while maintaining national representativeness[19]. We, thus, merged the COVID-19 survey with information on labour productivity and adoption of digital technologies from 2018.

These data are used to assess whether ex-ante digital intensive firms have been hit differently by the COVID-19 crisis and whether these firms have differently invested in digital assets (see Box 5.1 for details of the empirical strategy).

Box 5.1. Digitalisation and the COVID-19 crisis: empirical strategy

We consider two simple econometric models for our analysis. In the first one, we relate our dependent variable of interest with a dummy equal to 1 if the firm has adopted a specific digital technology.

$$DV_i = \beta Tech_{ih} + X\delta + \lambda_s + \vartheta_r + \varepsilon_i \qquad \text{Equation 3}$$

where DV_i is a dependent variable corresponding to several outcomes which assess the impact of COVID-19 on firms. $Tech_{ih}$ is equal to one whether, in 2018, the firm adopted a technology $h \in [enabling, management\ softw., cloud, advanced]$. We estimate Equation (3) on each technology separately. Controls X include labour productivity and firm size measured in 2018. λ_s, ϑ_r are fixed effects capturing unobserved heterogeneity at sector and geographic area levels, respectively. We allow the error term ε_i to display serial correlation at two-digit sector level.[1] In the second empirical model, we study the role of technology bundles. We thus estimate the following:

$$DV_i = \sum_{k=1}^{11} \beta_k NoTech_{it}^k + X\delta + \lambda_s + \vartheta_r + \varepsilon_i \qquad \text{Equation 4}$$

where $NoTech_{it}^k$ reflects the number of technologies adopted by firm in 2018. We use the same set of controls and fixed effects, as well as the same assumption on ε_i, as in Equation (3).[2]

Heterogeneity of the effect of ex-ante digitalisation by productivity

To assess whether the effect of ex-ante digitalisation on the COVID-19 shock has been heterogeneous over the productivity distribution, we divide firms into three productivity groups on the basis of the within-sector labour productivity distribution in 2018[3] and we estimate the following model:

$$\begin{aligned} Pr(Closure)_i = {} & \beta_1 Tech_{ih} + \beta_2 D_2 * Tech_{ih} + \beta_3 D_3 * Tech_{ih} \\ & + \gamma_2 D_2 + \gamma_3 D_3 + X\delta + \lambda_s + \vartheta_r + \varepsilon_i \end{aligned} \qquad \text{Equation 5}$$

Notes:

1. Observations are weighted using sampling weights provided by ISTAT.

2. We test the robustness of our results, assessing whether they are sensitive to two different model specifications: we re-run models (1) and (2) using a four-digit sector classification, and we include narrowly defined size-sector-geographic area fixed effects. All results discussed below are robust to these tests.

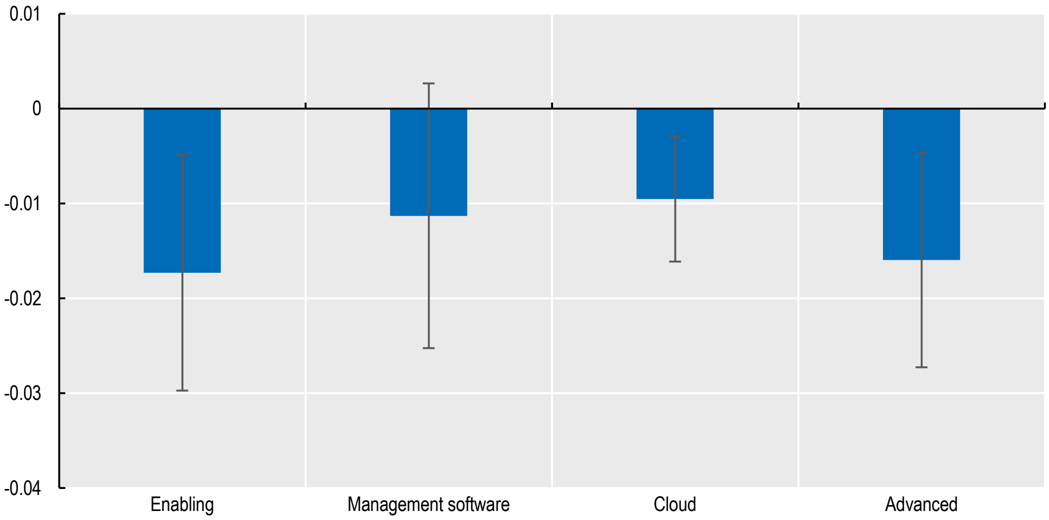
3. The three groups correspond respectively to firms belonging to the 1st quartile, the 2nd and the 3rd, and the 4th quartile of the within-sector labour productivity distribution in 2018.

5.1. The impact of the COVID-19 on the performance of Italian firms, by initial level of digitalisation

The COVID-19 survey provides two indicators of the impact of the crisis on firm performance. It assesses whether, at the time of the interview, the firm was temporarily or permanently closed; and whether revenues dropped, remain unchanged or increased over the period June-October 2020, relative to the corresponding months of 2019.

Ex-ante digital firms have been more likely to remain open during the pandemic. Figure 5.1 shows results of estimating Equation (3) on a dummy =1 if the firm did not close (either temporarily or permanently). Having adopted an enabling technology or an advanced technology before the crisis reduced the probability of closing by around 1.5 percentage points (against an average probability of closure of around 6%). The association for other digital technologies is slightly smaller and, in the case of management software, not precisely estimated.

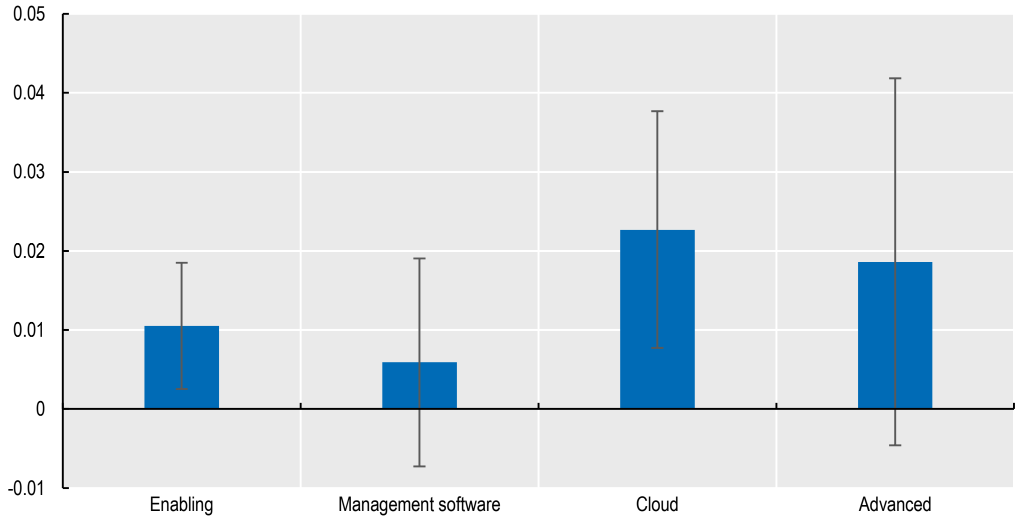
Figure 5.1. Probability that the firm is temporarily or permanently closed in November 2020 and digital technology adoption – different technologies



Note: The figure reports the coefficients of estimated Equation (3) for each technology separately, where the dependent variable is a dummy =1 if the firm did not close (either temporarily or permanently) in November 2020. The bars represent differences in probability of closure compared to the base category of firms without that specific technology.
Source: Authors' elaboration on ISTAT, COVID-19 survey, November 2020.

Ex-ante digital firms have been more likely to register an increase in revenues in 2020, relative to 2019. Figure 5.2 shows the results of estimating Equation (3)) on a dummy equal to 1 if the firm reported an increase in revenues between June and October 2020, compared to the same period of 2019. Companies that adopted enabling technologies and used cloud services before the emergency were more likely to report an increase in revenues. A sizeable but not precisely estimated association has also been found for firms that invested in advanced digital technologies. Additional results show that the probability of registering a very large drop in revenues (i.e., larger than 10%) is negatively associated with firm ex-ante digitalisation.[20]

Figure 5.2. Probability that revenues increased y-o-y over June-October 2020 and digital technology adoption – different technologies

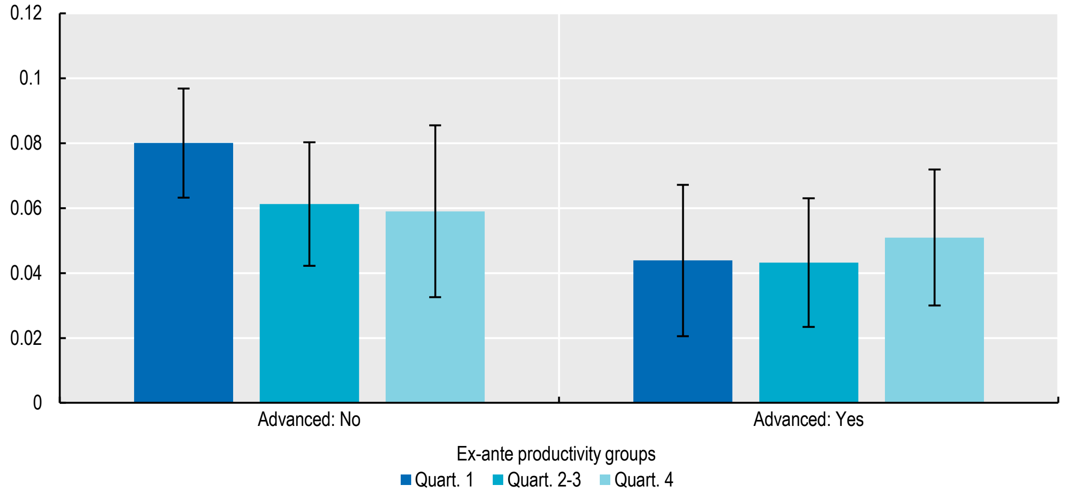


Note: The figure reports the coefficients of estimated Equation (3) for each technology separately, where the dependent variable is a dummy =1 if the firm reported an increase in revenues between June and October 2020, compared to the same period of 2019. The bars represent differences in probability compared to the base category of firms without that specific technology.
Source: Authors' elaboration on ISTAT, COVID-19 survey, November 2020.

We then study whether the impact of digitalisation on the effects of the crisis has been heterogeneous across the productivity distribution (see Box 5.1 for details of the empirical strategy). Figure 5.3 plots the probabilities of closure by November 2020 estimated from Equation (5) for each productivity group, and distinguishing adopters and non-adopters of advanced technologies[21]. Digital adoption plays a key role in reducing the probability of closure among less productive firms. Among non-adopters, the probability of closure is declining in firm ex-ante productivity. Technology adoption lowers the likelihood of closure particularly in firms belonging to the lower quartile of the productivity distribution.

Conversely, in an unreported estimate, we find no heterogeneity by productivity in the impact of ex-ante digitalisation on firm's revenues during 2020.[22] Thus, digital technologies have generally improved revenues and reduced the probability of closure for all firms during the pandemic, but have been particularly relevant for the resilience of less productive firms.

Figure 5.3. Probability of closure by firm productivity and adoption of advanced digital technologies



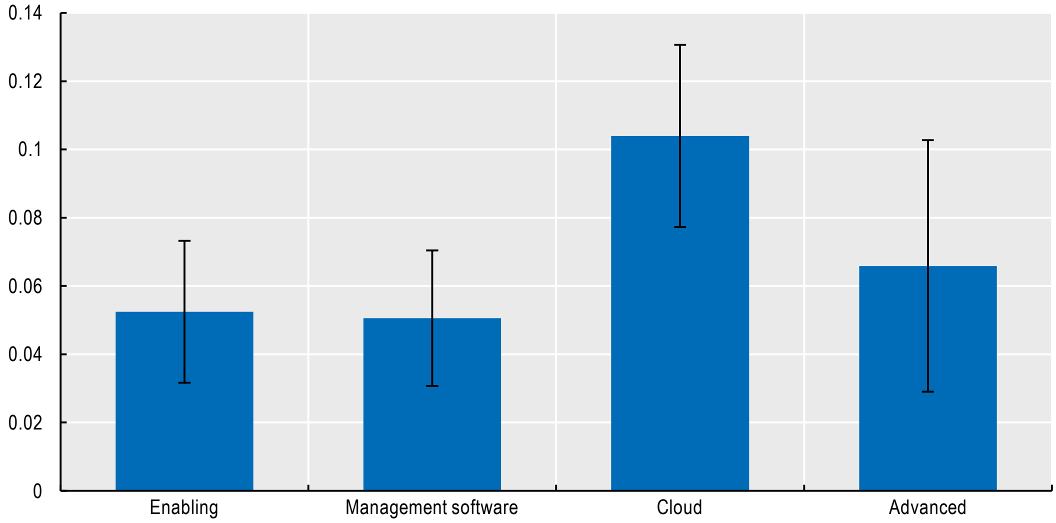
Note: The figure reports the probability of closure by November 2020 estimated from Equation (5), distinguishing between productivity groups and adopters and non-adopters of advanced technologies. The three productivity groups correspond respectively to firms belonging to the 1st quartile, the 2nd and the 3rd, and the 4th quartile of the within-sector labour productivity distribution in 2018.
Source: Authors' elaboration on ISTAT, COVID-19 survey, November 2020.

One of the key channels through which ex-ante more digitalised firms have been able to better cope with the COVID-19 crisis has been their ability to implement teleworking during the pandemic.

Figure 5.4 reports results of estimating Equation (3)) with the probability of adopting teleworking between June and November 2020 as a dependent variable. Teleworking has been more likely among firms which were already digitalised before the pandemic. The use of cloud services, in particular, is associated with a 10% increase in the probability of having introduced teleworking. This effect is large, corresponding to around half of the average probability of introducing teleworking, and is consistent with the idea that cloud applications are "the backbone of remote work" (Forbes, 2020[38]), as they allow organisations to support remote employees, regardless of their geographical location.

Besides the role of specific digital technologies, the overall degree of digitalisation of the firm may play a key role in explaining the likelihood that it exploited teleworking during the COVID-19 crisis. Figure A A.8 in Annex A plots results from Equation (4) and it shows that the probability of teleworking is increasing in the number of technologies previously adopted. The correlation is sizeable: moving from one to five technologies increases by ten times the likelihood of adopting teleworking.

Figure 5.4. Probability of having adopted teleworking over June-November 2020 and digital technology adoption – different technologies



Note: The figure reports the coefficients of estimated Equation (3) for each technology separately, where the dependent variable is a dummy =1 if the firm has implemented teleworking between June and November 2020, compared to the same period of 2019. The bars represent differences in probability compared to the base category of firms without that specific technology.
Source: Authors' elaboration on ISTAT, COVID-19 survey, November 2020.

5.2. The impact of the COVID-19 crisis on the digital divide between Italian firms

To assess whether the digital divide has increased during the COVID-19 crisis, we exploit two sets of information elicited by the COVID-19 survey.

First, the questionnaire asked firms how they had changed their communication and collaboration activities. We classify possible answers into four groups:

a. improving the speed of Internet connection (via broadband and mobile connection),

b. improving digital communication within the firm (e.g., with video-conferences, instant messaging, etc.),

c. introducing digital applications for management and monitoring of projects,

d. improving infrastructures for remote working (for instance, by providing laptops or using cloud services).

Second, the survey collected information on the change in total investments in 2020 relative to the previous year, distinguishing also by type of investment performed. We focus, in particular, on expenditures in R&D, Digital technologies, Human capital, and Internationalisation.

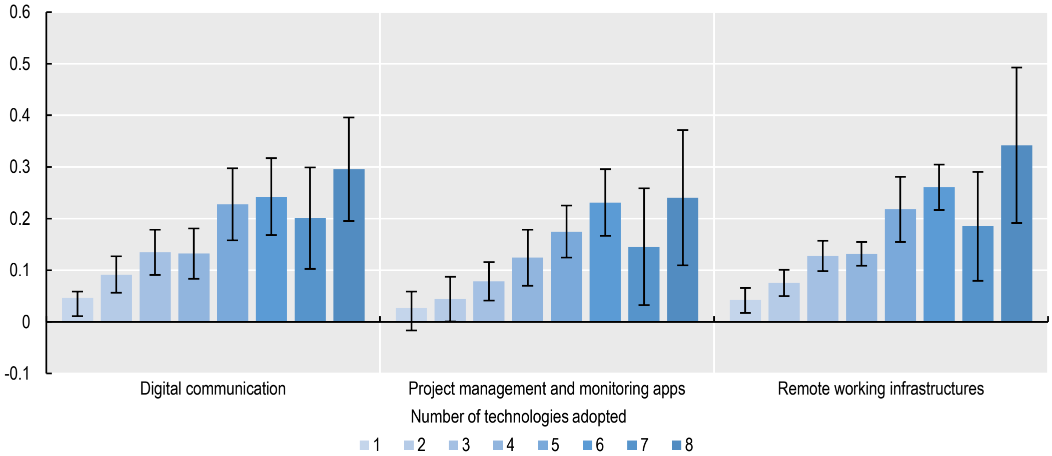
5.2.1. Digital communication and collaboration activities

The likelihood that a company improved its digital communication and collaboration activities as a consequence of COVID-19 is higher for firms which had already adopted enabling, management, cloud or advanced technologies in 2018 (see Figure A A.9 in Annex A).

Figure 5.5 shows that this probability is increasing in the number of technologies adopted before the crisis. This is especially true for improvements in internal digital communication, in the use of project management and monitoring apps, as well as for remote working infrastructures; while unreported results indicate that for improvements in broadband or mobile connection the link with ex-ante digital adoption is generally less strong and much less statistically significant.

Overall, the findings suggest that the digital gap may have increased during the pandemic, with pre-COVID adopters investing more than the other firms.

Figure 5.5. Probability of improving digital communication and collaboration by digital technology adopted – bundles of technologies



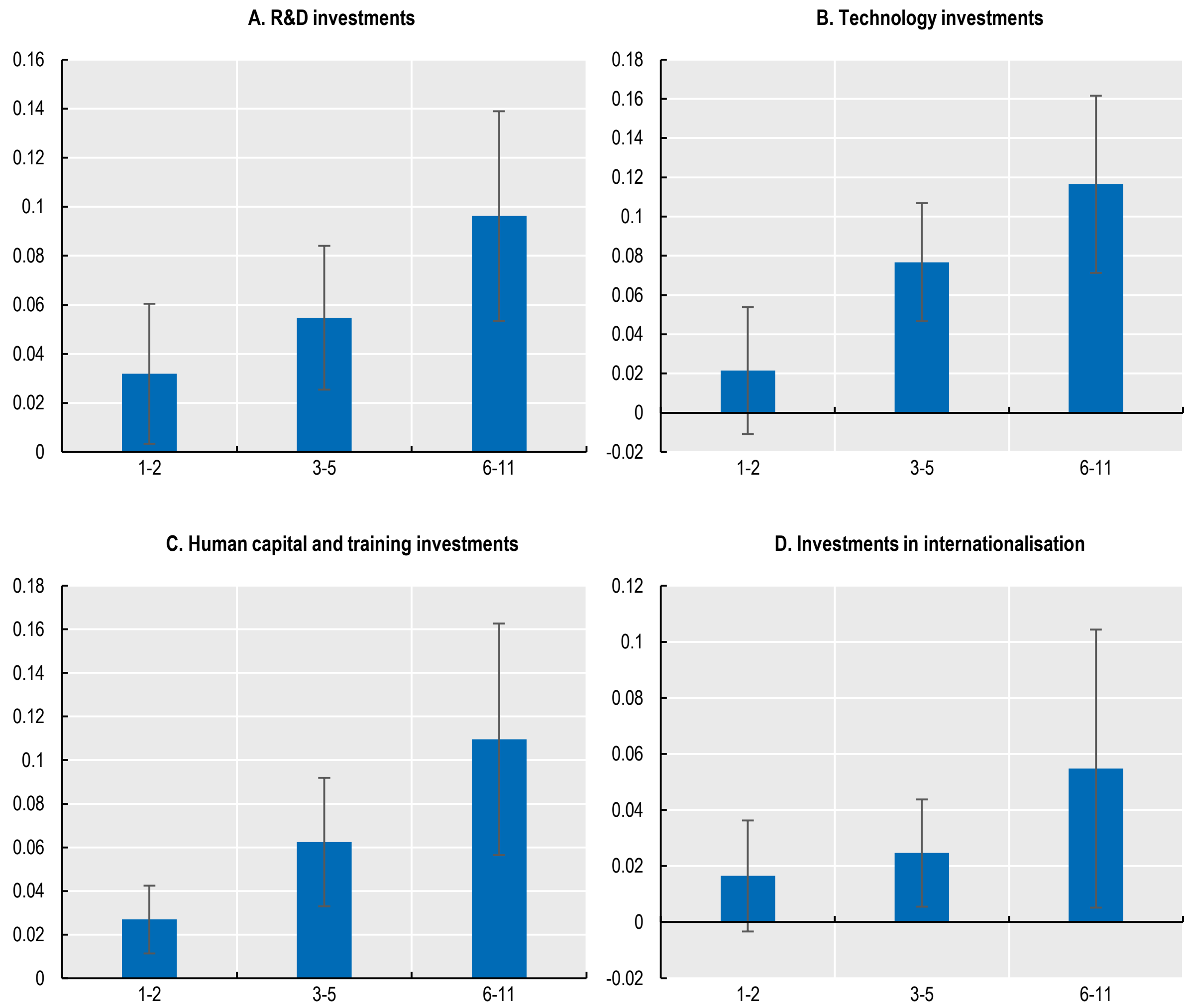
Note: The figure combines the coefficients of Equation (4) estimated separately for each dependent variable that captures the firm's digital communication and collaboration: internal digital communication, project management and monitoring apps, and remote working infrastructures. Unreported results for broadband/ mobile connection are available upon request. The dependent variable is coded 1 whether digital communication was introduced, improved, or foreseen as a consequence of COVID. The bars indicate differences in the probability of improving firm's digital communication and collaboration compared to the base category of zero technologies. Results are reported up to eight technologies, as firms with more technologies are too few to correctly identify the corresponding parameters.
Source: Authors' elaboration on ISTAT, COVID-19 survey, November 2020.

5.2.2. Investments

The drop in total investments registered during the COVID-19 crisis appears broadly similar in size between digital and non-digital firms. Evidence of this is shown in Annex A, where Figure A A.10 plots the results of estimating Equation (4) on a dummy equal to 1 if the firm reports to have reduced its investments between June and December 2020, relative to the same period of 2019. Coefficients, which represent difference in probability compared to the base category of firms without any technology in 2018, are generally very small in size and never statistically different from zero. The general drop in investments is likely related to the overall drop in demand and, particularly, on the rise in uncertainty which has been broad throughout the economy during 2020.

While total investments dropped similarly, the type of investments made during the COVID-19 crisis differed markedly between digital and non-digital firms. In particular, more digitalised firms have invested more resources in R&D, digital technologies, human capital and training, and firm internationalisation. These results are shown in Figure 5.6 that reports, for each type of investments, the coefficients obtained from estimating Equation (4) on a dummy equal to 1 if the firm has increased accumulation. To ease the graphical analysis, we group the number of technologies adopted in 2018 in four categories (0, 1-2, 3-5, and 6-11 technologies).

Figure 5.6. Probability that the firm increased its investments by type of expenditure and number of technologies adopted in 2018



Note: The figure combines coefficients of estimated Equation (4) for each type of investments considered: R&D, Digital technology, Human capital and training, Internationalisation of investments. Dependent variable equal to one if investments in 2020 increased relative to 2019. The number of technologies adopted in 2018 are grouped in four categories (0, 1-2, 3-5, and 6-11 technologies) and the bars indicate differences in probability compared to the base category of zero technologies.
Source: Authors' elaboration on ISTAT, COVID-19 survey, November 2020.

The results of the analysis of the COVID-19 survey have provided evidence on how digitalisation has been related to the COVID-19 crisis.

At one side, digitalisation has increased firm resilience and reduced the negative effect of the pandemic on revenues.

On the other side, our evidence shows that the pandemic has been accompanied by an increase in the gap between more and less digitalised firms. Indeed, while overall investments have been generally depressed by low demand and high uncertainty, the composition of investment expenditure has differed markedly by the ex-ante degree of digitalisation of the firms. More digitalised firms have invested more significantly in productivity-enhancing expenditures on digital technologies, R&D, human capital, and internationalisation. We may thus expect both the digital gap and the productivity divergence to be strengthened by the current crisis.

This result calls for a strong and comprehensive policy package aimed at supporting digital diffusion among less productive and less digital-savvy firms.

6. Conclusions and policy implications

Digitalisation is a crucial driver of productivity growth and structural change in modern economies. Yet, its uneven diffusion among firms has increased productivity dispersion, raised wage inequality and reduced inclusiveness. The COVID-19 crisis has overall boosted digitalisation in the economy, but it may have also reinforced trends in digital divergence between technology leaders and the rest of firms, which may hinder growth and prosperity in the long run.

These trends are particularly worrisome for Italy: the lack of dynamism of its economy, characterised by a large share of micro and small firms and by leader firms that are both fewer and smaller than their foreign counterparts, is accompanied by low and disperse adoption rates of digital technologies and lower investments in intangibles. The resulting digital gap between Italy and other OECD countries is a key driver of the sluggish growth that has plagued Italian productivity over the last 25 years.

During the COVID-19 crisis, low levels of digitalisation have represented a key element of fragility for Italian firms. Our analysis shows that less digitalised firms have been hit harder by the shock, suffering from a larger drop in revenues and an increased risk of temporary or permanent closure. The pandemic has indeed widened the digital gap, as firms that were ex-ante more digitalised invested more resources on digital technologies and complementary intangible assets during the crisis.

These trends can be reverted. The Italian government has already allocated substantial resources to policies aimed at supporting digital technology diffusion and the digital transformation among firms, within the framework of the various Industry, Firm, and Transition 4.0 Plans that have been implemented from 2015 to nowadays. These policies have encompassed a large set of financial subsidies to investments in digital assets (such as the hyper-depreciation subsidy) and to innovation activities (such as the R&D tax credit), as well as the implementation of a network of local institutions aimed at raising digital awareness and capabilities among firms. The recent National Recovery and Resilience Plan (*Piano Nazionale di Ripresa e Resilienza* – PNRR, henceforth) allocates additional resources (30.6 billion EUR) to digitalisation, innovation and competitiveness of the business sector. Most of these resources are planned to support the digital transition of Italian firms, through public investments in infrastructures and a broadening and a strengthening of some of the fiscal incentives to private investment already in place.

In this context, we have analysed two policies implemented by the 4.0 Plans between 2015 and 2018, the R&D tax credit and the hyper-depreciation subsidy. The R&D tax credit has significantly increased R&D expenditures, and its specific design (targeting firm's incremental expenditures relative to its pre-policy levels) has supported in particular innovative firms that were ex-ante less R&D intensive. Given the evidence on the important role of R&D in increasing the absorptive capacity of digital technologies among firms, these subsidies may also contribute to the digital transformation of the economy.

Our evaluation of the hyper-depreciation subsidy shows that it has raised the adoption of digital technologies by Italian firms, with positive effects on output, employment and productivity. Yet, the analysis also highlights how the lack of skills among workers and managers of micro and small firms is limiting the effectiveness of this policy. Furthermore, the policy is currently based on a list of eligible assets that has been defined in 2017: this list should be updated periodically, in order to keep it up-to-date with respect to the fast-expanding technological frontier. Moreover, our analysis has identified how digitalisation is a complex and comprehensive process that entails various complementary technologies and other inputs: the incentive may, thus, be reformed to support the overall digitalisation of the production process (also in relationship with the value chains), rather than to target the acquisition of a single asset. The recent transformation of the depreciation into a tax credit has likely improved the possibility for smaller and fast growing firms to benefit from the policy, as these firms are more likely to incur temporary losses which would prevent them from exploiting the hyper-depreciation.

The PNRR allocates over EUR 30 billion to support education and research, and around one third of this amount is expected to be devoted to support the link between research and firms and technological transfer. Indeed, from the detailed analysis conducted in this report of the factors, both internal and external to firms, that may boost technology adoption and its returns, the quality of human capital has emerged as crucial along several dimensions. In order to increase the skills of the workforce the analysis has furthermore highlighted the key role of high-quality tertiary education, particularly in STEM fields. Indeed, tertiary education in STEM programs is key to boost the complementarities between of labour and advanced digital technologies. The analysis also identified low or negative complementarities between secondary educated workers and digital technologies. This may reflect –besides the low number of tertiary educated workers– a mismatch between the competencies provided by secondary education and the firm's production technology. Secondary vocational education may need, thus, to be supported to keep up with the pace of increasing technological improvements and fast-changing needs in the business sector.

It is important that these policy interventions are coordinated with those aimed at supporting the digital transition of firms, acknowledging their complementarity. In the short term, policy interventions may further support the upskilling of firms and workers through financial incentives to training programs. For this purpose, a streamlining of the Tax Credit for I4.0 Training, aimed at identifying and removing the bottlenecks that lower its take-up, seems particularly necessary. At the same time, a proper evaluation of this policy should be programmed.

Besides workers' education and competencies, the analysis highlighted the crucial importance of managerial skills and capabilities to close the Italian digital gap. A skilled manager raises the returns of digital inputs, and increases their complementarity with skilled workers. The research has found that complementarities between digital technologies and skilled workers are significantly lower for firms located in Southern Italy than for those in the North-Centre. Back-of-the-envelope calculations show that around 1/3 of this difference may be explained by the lower managerial skills of Southern firms.

The goal of improving managerial skills and capabilities is not new to policy-makers. During the Marshall Plan, the United States organised management training trips for Italian manager to US firms. Evidence shows that this policy had substantial long-term positive effects on firm performance (Giorcelli, 2019[39]). Recent evidence from a subsidy program implemented by the Italian government to hire a managerial consultant to boost the export capabilities of SMEs (so-called "Temporary Export Manager") shows that consultancy and advisory can be an effective tool to boost managerial capabilities (Manaresi et al., 2021[40]). More recently, the Ministry of Economic Development has implemented a subsidy program to hire a managerial consultant to support firm digitalisation and innovation. The subsidised consultancies started in 2020 and their effects have yet to be estimated.

Technology adoption can be supported by policies aimed at improving the transfer of knowledge and the acquisition of "soft skills" by firms, The Government has implemented a network of Digital Innovation Hubs and Competence Centres, which is now active over the territory: given its potential key role in transferring knowledge and competencies to firms and workers, further research should be devoted to its evaluation, and further efforts may be put by the Government in strengthening its effectiveness and fostering its integration with the forthcoming European Digital Innovation Hubs that are going to be opened throughout the EU over the next few years.

Another important area of policy intervention, also according to the PNRR, is the development of ultra-fast broadband infrastructure. Our data shows that the Italian Strategy for the Ultra-Broadband has generated a significant boost in NGA coverage over the years 2012 to 2018. Yet, Italian coverage remains below the EU median, with FTTH fibre reaching just less than 34% of households (MITD, 2021[41]). The empirical analysis shows that the supply of NGA infrastructure *per se* raises the adoption of fast Internet connection by firms, and improves the adoption of management software and cloud services. The impact of NGA services on more advanced digital technologies and on firm performance is, however, on average more limited, but it is significantly positive for firms with more skilled workforce, suggesting that high-speed broadband infrastructure is an important enabler of returns to adoption, although not the only one. Yet, we also find that the provision of NGA infrastructure has been instrumental in increasing the effectiveness of other digitalisation policies. Our analysis shows, in particular, that it has increased the returns of the hyper-depreciation subsidy, by raising its effects on revenues and productivity.

The availability of external finance is generally considered an important factor in supporting the digitalisation process. Our analysis has explored the role of bank credit supply. We find that an *increase* in credit supply is not associated with increased digital technology adoption. However, we also find that a *drop* in credit supply lowers adoption, particularly of more advanced digital technologies such as Internet-of-Things technologies, advanced automation, computational simulations, and big data analytics. Thus, while digital investments are generally not financed through credit (as confirmed empirically by the lower leverage of digital adopters), a tightening in credit constraints forces firms to reduce longer-term investments to favour short-term working capital. Maintaining a stable provision of credit to the business sector, while supporting the development of the Italian capital markets (OECD, 2020[42]), may thus favour the digitalisation process.

Beside the policy implications tailored to the Italian case, the analysis brings several implications to the attention of policy-makers outside Italy that are interested in supporting the digital transformation. The study has highlighted the complexity of the digital transformation, which entails a rich pattern of complementarities across technologies, inputs, skills, and firm organisation, as well as spillovers. These complementarities call for broad, comprehensive and coherent policy packages.

These packages must be designed in each country on the basis of a clear knowledge of which specific frictions are of first-order importance *in that specific economic and institutional context*. On this respect, this analysis represents a first attempt to exploit the massive availability of firm-level information to inform policy-makers about the state of the digital transformation and the policy levers that need to be pulled. Once a comprehensive data infrastructure is created and kept up to date, it can be used to implement further analyses and policy evaluations importantly contributing to evidence-based policy making within the country.

Some relevant future lines of research can be highlighted here. First, the current research does not cover thoroughly the relationship between digitalisation and competition. While we provide evidence that lack of competition may hinder positive spillovers in technology adoption, we argue that more research on the existence and characteristics of business-stealing effects in product and service markets is necessary. This is particularly relevant in the aftermath of the pandemic, given the evidence that the crisis has further increased the digital divide among firms. Second, future research may focus on the impact of digital technologies on inclusive employment, possibly leveraging detailed information on skills and labour outcomes of young workers. Third, the data infrastructure may allow to study in-depth the relationship between digital technologies and firm internationalisation, leveraging detailed product-level data on imports and exports. Finally, the digital transition may play a key role in supporting the green transition: future analyses may focus on whether and how digitalisation policies allow Italian firms to reduce their emissions and help to reach environmental goals.

Endnotes

[1] Value added is adjusted to take into account the capitalisation of non-National Accounts intangibles (Corrado et al., 2012[148]).

[2] The core dataset used for this analysis is the 2018 Census of Italian firms, which includes a comprehensive module on digital technologies that is used in combination with other firm and worker level information (see Annex A for additional details). For the remainder of the paper, the word "adoption" refers to both investments in enabling and advanced technologies and usage of management software, cloud and e-sales on platforms (henceforth e-sales).

[3] Interestingly, adoption rates of advanced technologies are significantly lower in the Centre than in the North and the South. Further analyses show that this lower adoption of advanced technologies is driven by advanced automation.

[4] At one side, this finding is consistent with low costs of adoption, which boosts the use of this technology also by less productive firms: as a result, there is adopters are less selected. On the other side, though, this result may signal that this technology does not significantly affect productivity. This may happen, for instance, if the fees that platforms apply to e-sales are able to reap most of the extra-profits generated from their use.

[5] All these results are obtained holding fixed sectoral-regional unobserved heterogeneity and the firm size and age. Details of the estimation strategy are available in Annex C.

[6] In a robustness test, we also distinguish between household and business contracts to allow for differentiated demands. All results are confirmed.

[7] Results available upon request.

[8] Crucially, this result (as well as the followings) is robust to controlling for changes in demand for broadband connectivity, as proxied by the 2012-18 increase in broadband Internet contracts over total Internet contracts.

[9] Consistently, in additional results – available upon request – we find that ex-ante more productive firms benefited the most in terms of both advanced technology adoption and of labour productivity gains.

[10] MNCS compares the citation impact of a paper with the mean impact of similar papers published in the same economic subfield and publication year.

[11] More formally, we have tested for the role of omitted variable bias by following the methodology of Altonji, Elder and Taber (2005[147]). The correlation between the unobservable determinant of university location and the share of highly educated workers (result in Figure 4.7) should be higher than 58% to explain the estimated effect, under the null of no "true" effect of university. Similarly, the correlation between the unobservable determinant of university location and the adoption of advanced digital technology (result in STEM programs are also positively correlated with adoption rates of advanced digital technologies. This is shown in Figure 4.8, which focuses on the differentials in the share of firms adopting advanced digital technologies, comparing firms located in a municipality where STEM programs are offered with those located elsewhere.

The figure shows that co-location with an institution offering STEM programs corresponds to higher shares of adoption particularly in micro and small firms (Panel A). When distinguishing STEM programs by their quality (Panel B), though, it is evident that low quality programs (blue bars) seem to be associated with higher shares of adoption in micro and small firms only, while high-quality programs (orange bars) are associated with higher adoption across the board.

Figure 4.8) should be higher than 72% to explain the estimated effect.

[12] The figure is based on a regression that controls for firm's size-age-sector-region unobserved heterogeneity.

[13] Because of the incremental feature of the policy, and inasmuch R&D costs are convex, firms that were ex-ante more intensive in R&D had lower net marginal gains from the tax credit. In principle, one could use the implied B-index, based on ex-ante R&D expenditures, as an instrument for R&D increase. Yet empirically, we found firms that had different R&D intensity and different shares of expenditures subject to the 50% and 25% tax credit to differ substantially in observable pre-policy characteristics. This casts doubt on the exclusion restriction that would need to be assumed to perform an instrumental variable estimate.

In addition, the lack of information on the take-up prevents us /to estimate the causal effect of the policy via propensity score matching and difference-in-differences techniques.

[14] Observations for which the R&D expenditures were attributed based on expectation of previous responses were excluded.

[15] While the hyper-amortisation was introduced in 2017, it also encompassed purchases made during the last months of 2016 for assets installed in the following year.

[16] Estimate of the total amount of investments subsidised are based on sector-level amortisation rates, which in Italy are defined by law.

[17] Results available upon request.

[18] Considering firms with three employees at least.

[19] The sample was representative of the population of Italian firms with three employees or more (https://www.istat.it/it/files//2020/12/REPORT-COVID-IMPRESE-DICEMBRE.pdf).

[20] Results available upon request.

[21] To simplify, we focus on advanced digital technologies, but results are qualitatively similar also in the case of other digital technologies.

[22] Results available upon request.

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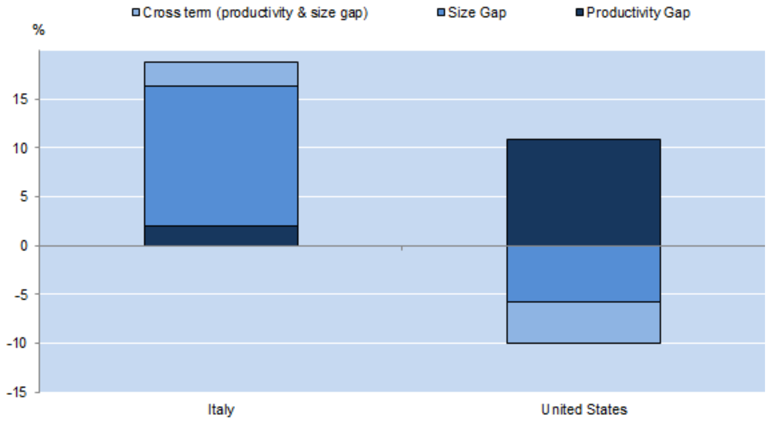
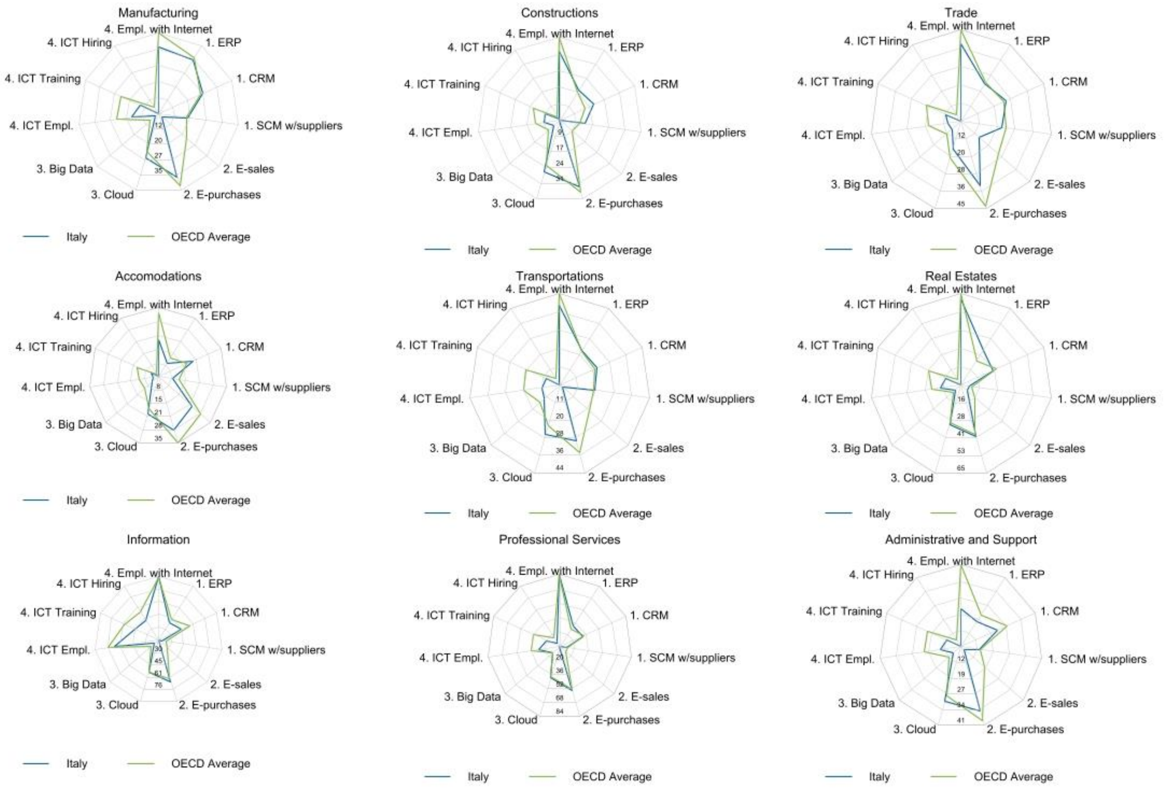
Annex A. Additional tables and figures

Figure A A.1. Labour productivity gap between national and global frontier – Italy and the United States



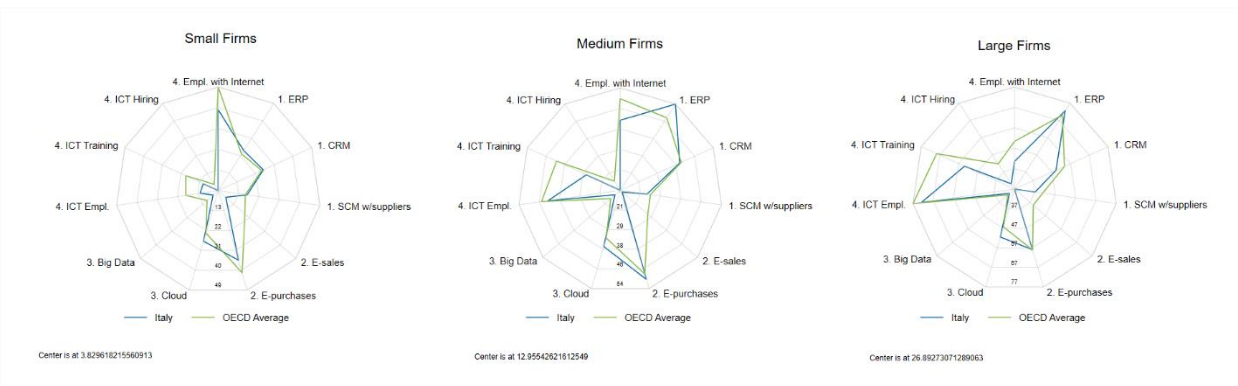
Source: Andrews, Criscuolo and Gal (2015[43]), "Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries", https://doi.org/10.1787/5jrql2q2jj7b-en.

Figure A A.2. Results of the ICT surveys, by sector – 2015-18



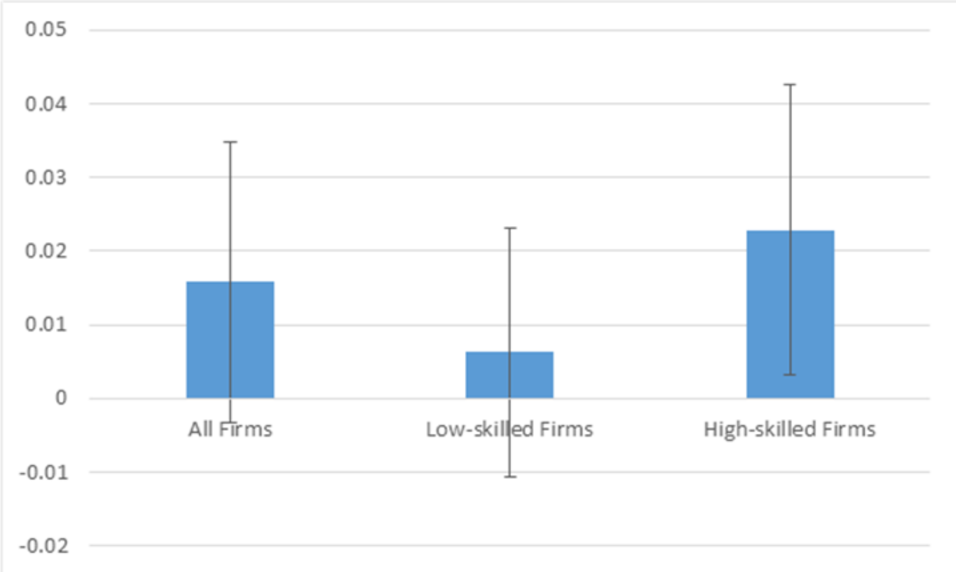
Source: OECD, "ICT Access and Usage by Households and Individuals", *OECD Telecommunications and Internet Statistics* (database), https://doi.org/10.1787/b9823565-en.

Figure A A.3. Results of the ICT surveys by size class, holding sectoral distribution fixed – 2015-18



Source: OECD, "ICT Access and Usage by Households and Individuals", *OECD Telecommunications and Internet Statistics* (database), https://doi.org/10.1787/b9823565-en.

Figure A A.4. The effect of NGA broadband supply on the adoption of advanced digital technologies – by skill intensity in 2012



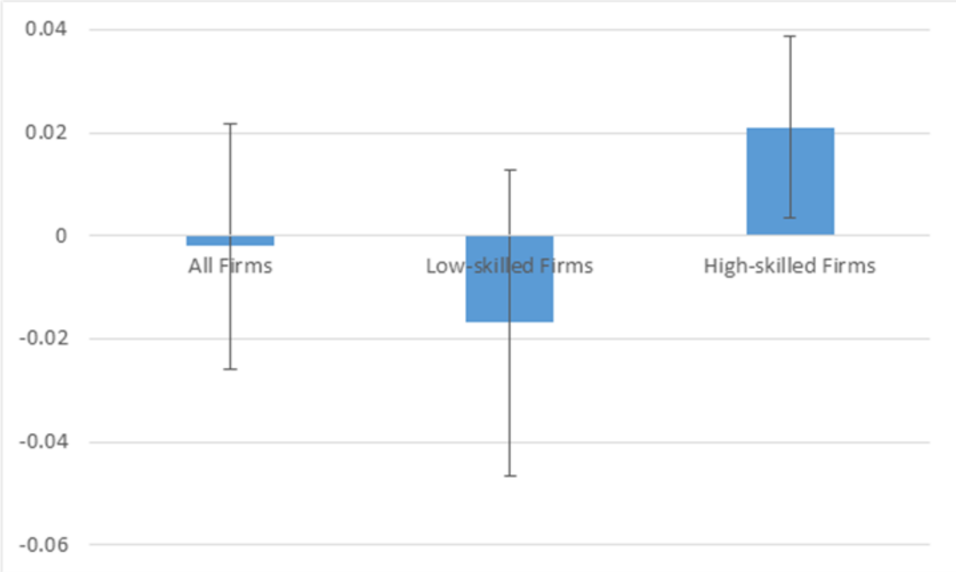
Note: The figure reports the coefficients β obtained by estimating the following linear probability model, separately for low-skilled and high-skilled firms (with workforce skill measured in 2012):

$$\Pr(adoption^k)_i = \beta \frac{\Delta NGA}{Tot.Civic_m} + X_m + \gamma_{sr} + Size_i \times Age_i + \varepsilon_i$$

where *i* is a firm, *m* the municipality where it is located, *s* is its two-digit sector and *r* its region. $\frac{\Delta NGA}{Tot.Civic_m}$ is the 2012-18 increase in the number of house numbers connected to NGA broadband over total house numbers, X_m is a vector of controls that include change in broadband internet contracts over total contracts, and the log of total house numbers in the municipality. γ_{sr} is a vector of sector-region fixed effects, and $Size_i \times Age_i$ is a vector of size-age dummies. The error term ε_i is allowed to display serial correlation at the sector and region level.

Source: Authors' elaboration on AGCOM and ISTAT data.

Figure A A.5. The effect of NGA broadband supply on labour productivity – by skill intensity in 2012



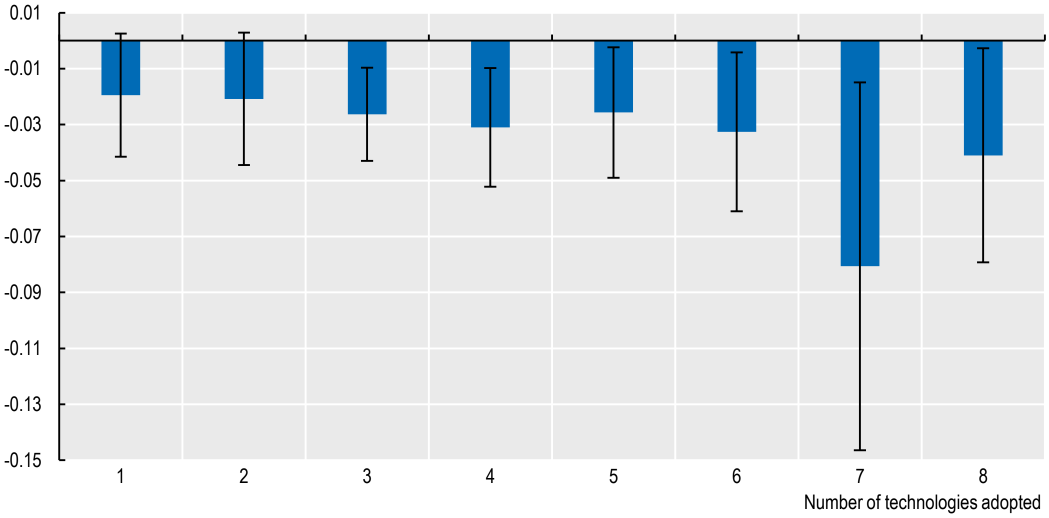
Note: The figure reports the coefficients β obtained by estimating the following regression model, separately for low- and high-skilled firms (with workforce skill measured in 2012):

$$\log y_i = \beta \frac{\Delta NGA}{Tot.Civic_m} + X_m + \gamma_{sr} + Size_i \times Age_i + \varepsilon_i$$

where *i* is a firm, *m* the municipality where it is located, *s* is its two-digit sector and *r* its region. The dependent variable *y* is labour productivity, $\frac{\Delta NGA}{Tot.Civic_m}$ is the 2012-18 increase in the number of house numbers connected to NGA broadband over total house numbers, X_m is a vector of controls that include change in broadband internet contracts over total contracts, and the log of total house numbers in the municipality. γ_{sr} is a vector of sector-region fixed effects, and $Size_i \times Age_i$ is a vector of size-age dummies. The error term ε_i is allowed to display serial correlation at the sector and region level.

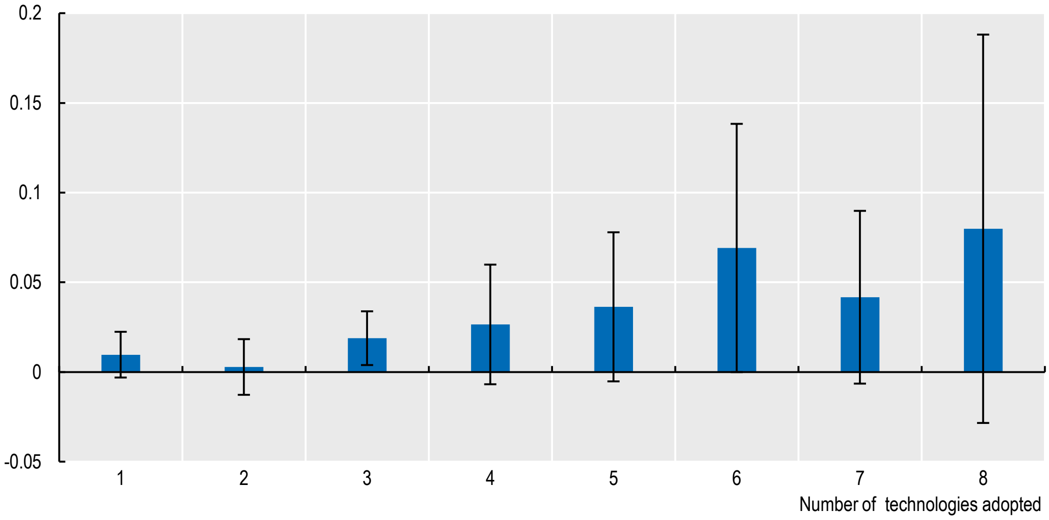
Source: Authors' elaboration on AGCOM and ISTAT data.

Figure A A.6. Probability that the firm is temporarily or permanently closed in November 2020 and digital technology adoption – bundles of technologies



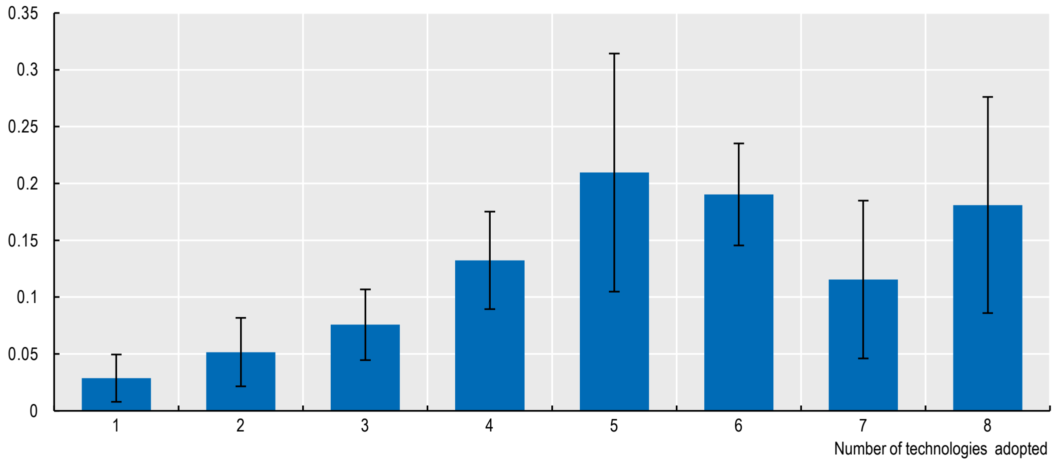
Note: The figure reports the probability of closure, either temporary or permanent, in November 2020 by number of technologies adopted in 2018. The bars represent the coefficients of estimated Equation (4), and they indicate differences in the probability of closure compared to the base category of zero technologies. Results are reported up to eight technologies, as firms with more technologies are too few to correctly identify the corresponding parameters.
Source: ISTAT, COVID-19 survey, November 2020.

Figure A A.7. Probability that revenues increased y-o-y over June-October 2020 and digital technology adoption – bundles of technologies



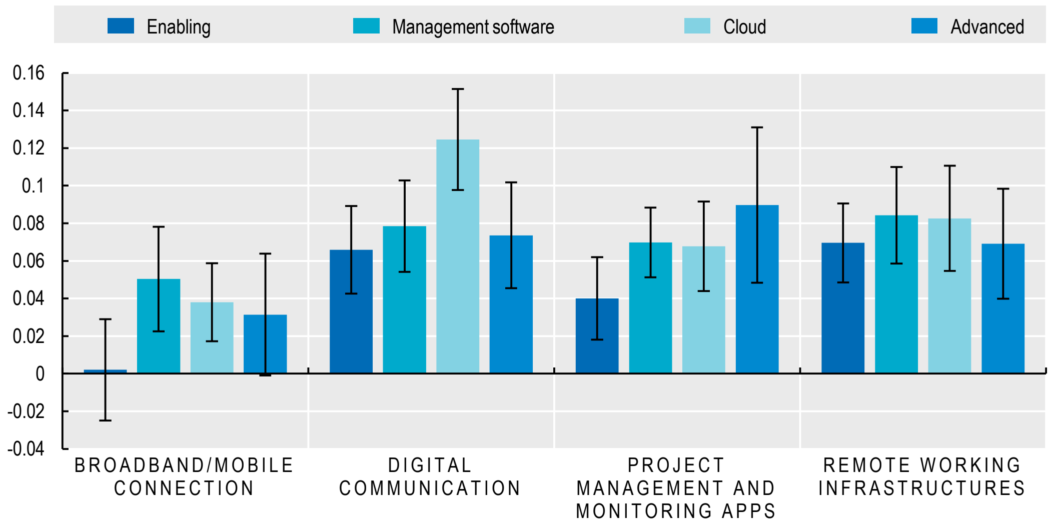
Note: The figure reports the probability of experienced an increase in revenues over June-October 2020, relative to the same period of 2019, by number of technologies adopted in 2018. The bars represent the coefficients of estimated Equation (4), and they indicate differences in probability compared to the base category of zero technologies. Results are reported up to eight technologies, as firms with more technologies are too few to correctly identify the corresponding parameters.
Source: ISTAT, COVID-19 survey, November 2020.

Figure A A.8. Probability of having adopted teleworking over June-November 2020 and digital technology adoption – bundles of technologies



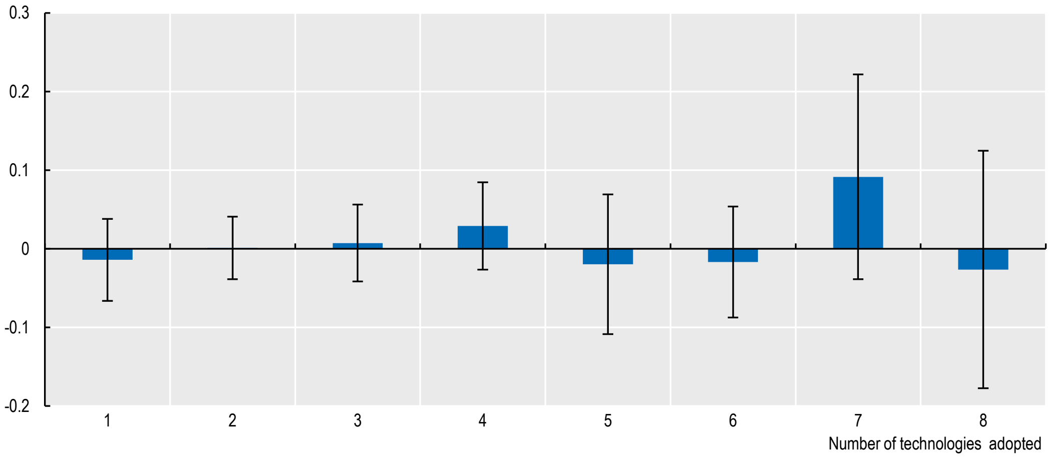
Note: The figure shows the probability of implementing teleworking over June-November 2020 by number of technologies adopted in 2018. The bars represent the coefficients of estimated Equation (4), and they indicate differences in probability compared to the base category of zero technologies. Results are reported up to eight technologies, as firms with more technologies are too few to correctly identify the corresponding parameters.
Source: ISTAT, COVID-19 survey, November 2020.

Figure A A.9. Probability of improving digital communication and collaboration by digital technology adopted – different technologies



Note: The graph combines the coefficients of Equation (3) estimated for each technology separately and for each dependent variable that captures the firm's digital communication and collaboration: broadband/mobile connection, internal digital communication, project management and monitoring apps, and remote working infrastructures. The dependent variable is coded 1 whether digital communication was introduced, improved, or foreseen as a consequence of COVID.
Source: ISTAT, COVID-19 survey, November 2020.

Figure A A.10. Probability that the firm reduced its investments by number of technologies adopted in 2018



Note: The figure shows the probability of reducing investments between June and December 2020, relative to the same period of 2019, by number of technologies adopted in 2018. The bars represent the coefficients of estimated Equation (4), and they indicate differences in probability compared to the base category of zero technologies. Results are reported up to eight technologies, as firms with more technologies are too few to correctly identify the corresponding parameters.
Source: ISTAT, COVID-19 survey, November 2020.

Table A A.1. Descriptive statistics of the R&D survey sample analysed in Section 4.5

	Group A	Group B	Group C
Year 2014			
R&D expenditure	2139.51	976.68	1356.12
Revenues	94370946	36623046	61208982
Labour productivity	77007.54	67558.36	724994.52
Firm size		Percentage	
Micro	13.98	17.99	17.15
Small	35.2	45.33	41.62
Medium	32.74	29.84	29.46
Large	19.18	6.84	11.76
Firm age		Percentage	
< 7 years	7.39	11.66	9.71
7-15 years	19.21	21.04	20.69
15+	73.4	67.3	69.59
Sector		Percentage	
Manufacturing	73.21	70.28	70.49
Construction	1.21	1.47	1.52
G-I	4.63	5.61	5.81
Information	11.68	12.23	11.94
L-N	9.27	10.4	10.24
Observations	3598	4330	8781

Note: Group A: firms whose average R&D expenditure in period 2013-14 was positive and are observed every year over the 2013-18 period; group B: firms whose average R&D expenditure in period 2013-14 was positive and are not observed every year over the 2013-18 period; group C: all firms whose R&D expenditures was non-missing over the period 2013-14.
Source: ISTAT, R&D survey.

Table A A.2. Balancing of 2013 firm-level characteristics and 2011-2013 trends between firm using and not using the hyper-depreciation – by quartile of the propensity score

Variables	Propensity score					No. of observations
	Q1	Q2	Q3	Q4		
Log-Revenues (2013)	-0.092	-0.012	0.094	0.121		25 271
Log-Employment (2013)	0.014	0.094	-0.047	-0.030		25 271
Log-Capital (2013)	-0.121	-0.081	0.09	0.247		25 271
Log-Productivity (2013)	-0.112	-0.033	0.043	0.099		25 271
Share of tertiary educated workers (2013)	-0.065	-0.032	0.01	0.027		25 271
Share of intangible capital (2013)	-0.01	-0.005	0.025	0.046		25 271
Revenue growth (2011-13)	-0.124	-0.063	0.081	0.188		23 406
Employment growth (2011-13)	0.08	0.065	-0.023	-0.077		23 406
Productivity growth (2011-13)	-0.052	-0.046	0.035	0.054		23 406

Note: The table reports the standardised difference of the average of each variable between firms using the hyper-depreciation and firms not using the hyper-depreciation within each quartile of the propensity score distribution. For each variable, industry-sector-size-age partial effects are initially partialled out.
Source: Authors' elaborations on ISTAT and Tax Agency data.

Annex B. Data and descriptive analysis

Data

Firm-level data

The backbone of the database is the registry of Italian firms (ASIA) that collects information on industry and location of around four millions of active firms over the period 2012-18.[1] Several firm-level datasets are linked to ASIA. The FRAME-SBS data provides yearly information on firm income statement: revenues, wage bill, intermediate goods and services, value added, profits and losses, and EBITDA. For incorporated firms (around 700 thousands per year, representing over 70% of total value added), also detailed balance sheet information on assets and fixed capital stock is available.

Information on innovative activities and technology adoption is obtained through three surveys administered by ISTAT: the ICT survey, the Community Innovation Survey (CIS), and the R&D survey. The ICT survey is administered each year to a representative sample above ten employees. The sample size has been slightly increasing overtime, moving from around 18 000 firms in 2012 to over 22 000 in 2018. It collects information on digital technology adoption, ICT skills and training of the workforce, and firm's subjective assessments of which factors may hinder/foster technology adoption. The survey has two main limitations: (i) both the content and the framing of several questions change overtime, and (ii) the sampling strategy has a cross-sectional design, so that it is not possible to follow how technology adoption changes overtime for the same firm. The first limitation implies that, when studying diffusion of digital technologies overtime, the focus needs to be on a specific set of questions (and technologies) which are present in several years. The second limitation prevents from performing a panel analysis to identify the effect of the adoption of a technology. Then, as discussed in the next sections, a structural analysis of firm behaviour and arguably exogenous cross-sectional changes in the costs/returns of technology adoption are needed to identify such an effect. Also the CIS has a cross-sectional sampling design and covers, every two years, firms above ten employees. In contrast with the ICT survey, though, the information gathered is remarkably consistent overtime: firms are asked about the type of innovative activities performed, distinguishing between process and product innovation, about their financing, and the partnerships with public and private organisations. The R&D survey is instead administered to a representative sample of all active firms with at least one employee and collects detailed information on R&D activities, identified according to the Frascati Manual (OECD, 2015[44]).

The Census of Italian firms represents an additional precious source of information on technology adoption, firm restructuring, and workforce management. It was administered in 2018 and collected data from a representative sample of almost 300 000 firms. Its large sample size and the extensive details on the questions on its digital technology module make it an ideal starting point for the main parts of the descriptive analysis.

Among the relevant information for the purpose of the current analysis, the Census of Italian firms includes questions on investments carried out by firms over the period 2016-18 on several groups of advanced and less advanced digital technologies, including broadband, 4G/5G, cybersecurity, big data, internet of things, advanced automation, 3D printing or virtual reality. It also includes questions on the use of management software, cloud computing or on the use of online platforms for selling product or services.

Another relevant source of firm-level data comes from the Italian Tax Authority, which provided to ISTAT detailed information on an incentive granted to firms to foster their innovative activities and technology adoption. The so-called “hyper-amortisation” scheme subsidised firm’s investments in Industry 4.0 technologies. This information is crucial to perform the policy evaluation exercise detailed in Section 5.

Finally, data sourced from Unioncamere provide information on all applications for intellectual property products filed at the European Patent Office over the period 2011-18. Both patents, trademarks, and industrial designs are included. This information can be matched to firm-level data using the firm’s fiscal code.

Individual-level data

While firm-level data is the backbone of the comprehensive data infrastructure, additional individual-level information on workers and skills can be linked to firm-level data to further explore other relevant element, especially related to workers, management and skills.

In particular, linked employer-employee data prepared by ISTAT cover the census of all Italian workers over the period 2012-18. Information include gender, age of the worker, as well as her/his contracts with any firm observed in ASIA. Working positions are divided into part-time and full-time, and between directors, white collars, blue collars, and apprentices.

Since 2014, information on worker’s education is also available: the highest educational qualification of each individual is collected, with detail between first, second, and tertiary levels (bachelor, master, or PhD), and between vocational and non-vocational curricula. This information is matched with two additional databases containing information on firm managers and owners.

Sectoral- and local-level data

Furthermore, additional sources allow to obtain sector-local level information on factors that may hinder or foster firms’ digital transformation of Italian firms. Information is then matched to the firm-level database by exploiting firm localisation.

One of these sources is provided by the Italian Authority for Communications (AGCOM), and includes municipal-level data on broadband speed at yearly frequency. We obtained information on the share of addresses that are connected to the broadband infrastructure (distinguishing three broadband speeds: under 30 Mbps, between 30 and 100 Mbps, and above 100 Mbps). We also obtained the number of broadband contracts as a share of all internet contracts (distinguishing between family and business contracts).

We exploited firm-bank matched data on total credit granted in each year, from the Italian Credit Registry administered by the Bank of Italy, to estimate credit supply shifters that vary at the sector-municipality level. For this purpose, following the methodology of Amiti and Weinstein (2018[45]), it is possible to divide the growth rate of credit from each bank to each firm in Italy into firm-year and bank-year components. The former can be considered a proxy of firm-level demand shifters, while the latter are bank-level supply shifters. Supply shifters can then aggregated across banks for each two-digit sector and each municipality using lagged share of credit granted by each bank in each sector-municipality as weights. For confidentiality reasons, all municipalities where there are less than three banks active will be excluded from analysis based on these data.

Finally, the OECD collected information on the localisation of each university and faculty in Italy. Notably, we identify whether in each campus there a Science, Technology, Engineering, or Maths (STEM) program is administered. This information is then matched with CWTS Leiden Ranking on the scientific performance of each field of research in the universities.

Descriptive analysis: characterising the digital transformation in Italy

Building on the unique data infrastructure described above, this Section presents a descriptive analysis of the digital transformation in Italy. It particularly focuses on analysing heterogeneity of the digital transformation across different types of firms and across technologies, and on uncovering the relevance of complementarities across digital technologies.

The core dataset used for this analysis is the 2018 Census of Italian firms. The data includes a comprehensive module on digital technologies that will be used, in combination with other firm and worker level information in the following.

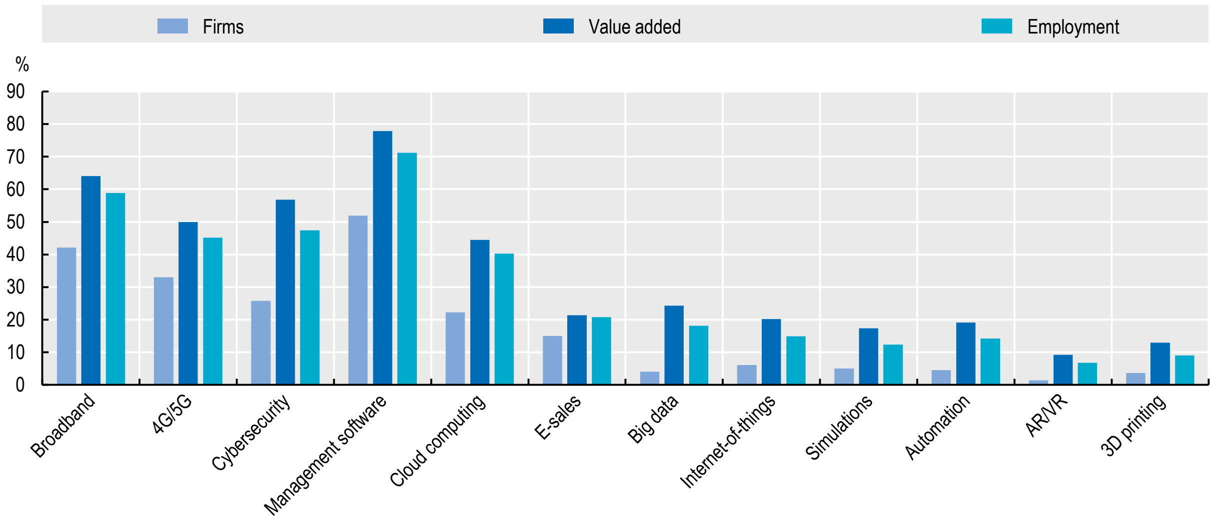
The digital technology module provides detailed information on firm digital adoption. For three types of technologies (management software - such as CRM or ERP -, cloud services, and the use of online platforms for e-sales) the questionnaire collects information on its usage by the firm in 2018. For other technologies, the questionnaire asks whether the firm has invested in them over the period 2016-18. These technologies include broadband, 4G/5G, cybersecurity, big data, Internet-of-things, simulations of interconnected machines, advanced automation (robots, intelligent systems), 3D printing, augmented reality or virtual reality. Among the latter group of technologies, we distinguish between "enabling technologies" (broadband, 4G/5G, and cybersecurity) that allow an effective use of production technologies, and "advanced technologies" (big data, IoT, simulations, advanced automation, 3D printing, and AR/VR). As discussed in Section 2.3, cross-country comparisons of ICT surveys show that the Italian gap in technology adoption is particularly relevant for advanced technologies and e-sales, while Italian firms display adoption rates of management software and cloud computing that are on the ballpark of the OECD average.

For the remainder of the paper, we use the word "adoption" to refer to both investments in enabling and advanced technologies and usage of management software, cloud and e-sales on platforms (e-sales, henceforth). In principle, because technologies may be adopted prior to the 2016-18 period, adoption rates computed using information on investments over this period should be considered as lower bounds of actual adoption rates. However, given the fast depreciation rates of these investments (particularly in the case of advanced technologies) it is unlikely that a firm was using them in 2018 without having actively invested in these technologies over the period 2016-18.

Sectoral and regional differentials in digital technology adoption

Using the 2018 Census of Italian firms, we start by exploring adoption rates of each digital technology by Italian businesses.[2] This is presented in Figure A B.1 which shows that there is considerable variation in the extent to which firms invest on or use different digital technologies.

Figure A B.1. Adoption rates, aggregate value added and aggregate employment of adopting firms by digital technologies, year 2018



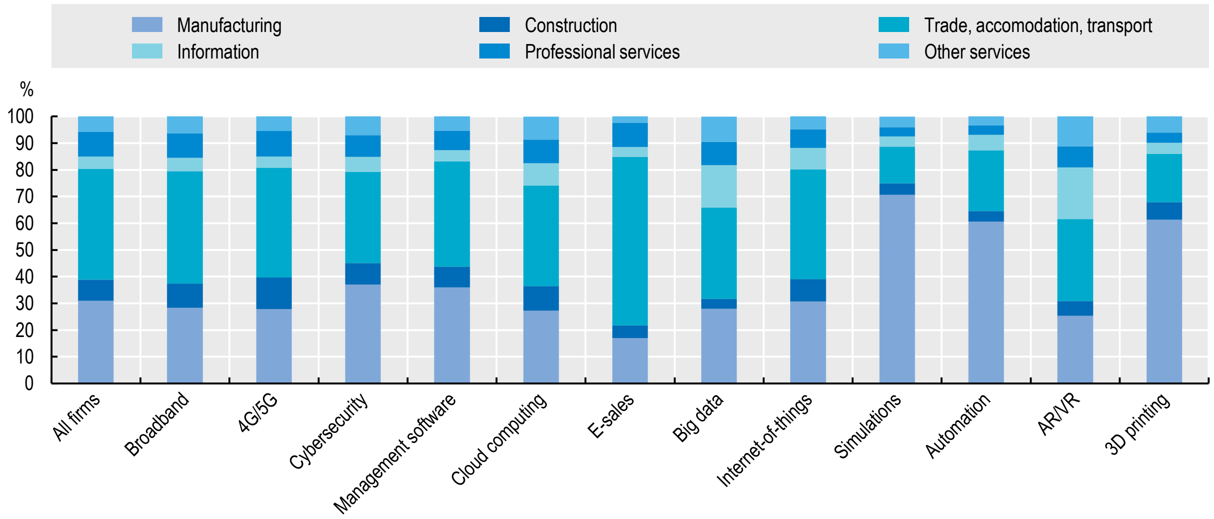
Source: Authors' elaboration on ISTAT data.

In particular, in 2018 over 52% of firms was using management software. Adoption of enabling technologies ranged from 27% for cybersecurity to 43% for broadband. These adoption rates are significantly higher with respect to those of the various advanced digital technologies, which do not exceed 7%.

The figure also shows that adopters represent a disproportionate share of employment, and even a higher share in terms of value added. This may be a first indication that adopters tend to be larger and more productive than non-adopters. The relevant exception is represented by adopters of e-sales, for which the share of value added is broadly similar to the one of employment: this is not surprising as these firms are most likely concentrated in the trade sector, usually characterised by a low value added per worker.

Figure A B.2 shows the sectoral distribution of adopters. The first bar represents the sectoral distribution of Italian firms, distinguishing Manufacturing; Construction; Trade, restaurants and transportation services; Information services; Professional services; and Other services. Other bars represent the sectoral distribution of firms adopting the different technologies analysed.

Figure A B.2. Sectoral distribution of adopters of digital technologies

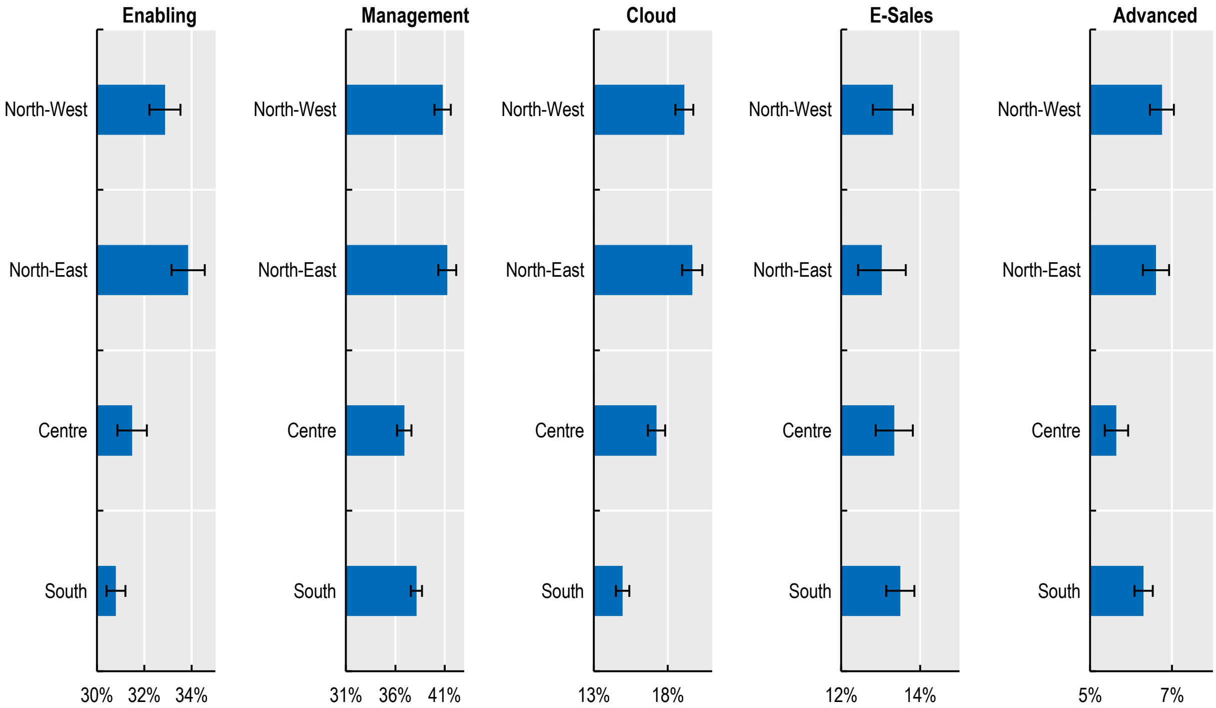


Source: Authors' elaboration on ISTAT data.

The sectoral distribution of adopters of enabling technologies such as broadband and fast mobile connection, as well as of management software, resembles the one of all Italian firms, with no evidence of a specific sectoral specialisation. Cybersecurity, instead, is slightly more diffused in the manufacturing sector (which collects 38% of adopters, against 30% of all firms), largely reflecting the larger size of firms in this sector.[3] Other technologies are more concentrated in some sectors of economic activity. This is the case for e-sales, which is more widely diffused in the Trade, restaurants and transportation sector, or of simulations of interconnected machines, advanced automation or 3D printing, which are more concentrated in manufacturing. Big data and augmented/virtual reality exhibit instead higher shares of adoption in the information sector.

Another relevant source of variation in technology adoption is related to the geographical distribution of adoption rates. In particular, Figure A B.3 shows adoption rates in four different macro-regions in Italy: North-West, North-East, Centre, and South and Islands, after partialling-out sectoral heterogeneity. The figure highlights that adoption rates are typically higher in the North, with gaps with the rest of Italy that are evident for most groups of technologies. A relevant exception is e-sales, which exhibits a more homogeneous geographical distribution across the four macro-regions. The geographical differentials in adoption rates are broadly consistent with the differences in productivity and growth between the North and the South of Italy (Ciani, Locatelli and Pagnini, 2018[28]), and are not driven by differences in sectoral composition across macro-regions.[4]

Figure A B.3. Adoption rates across Italian geographic areas



Note: Results of regressions of a dummy equal to 1 if the firm adopts the technology on dummies for macro-areas, controlling for two-digit sector fixed effects. The baseline group is North-West, for which the value reports the average adoption rate across sectors. Bars report the 95% confidence interval, robust to serial correlation at the sector level.
Source: Authors' elaboration on ISTAT data.

Size, age, and productivity differentials in technology adoption

Several firm characteristics may be related to adoption decisions. In particular, several factors (e.g., scalability of technologies and complementary intangibles, or financial frictions), we may expect adoption rates to increase in firm size. Moreover, in an economy where innovation and technology diffusion is driven by vibrant start-ups, we may expect higher adoption rates among younger firms. Table A B.1 shows how adoption rates change by size and age, controlling for sectoral and regional heterogeneity. It shows that the distribution of adoption rates is significantly skewed, with older and larger firms that generally exhibit higher rates of adoption than their smaller counterparts. Age is negatively correlated with technology adoption among micro-firms (where young business are more likely to correspond to truly *de novo* start-ups).

Adoption rates of e-sales on platforms are instead more evenly distributed across size classes. This is consistent with platforms representing an opportunity for firms to cut the fixed costs related to establishing a private infrastructure for online sales, which allows also smaller firms to starts selling through the Internet.

Table A B.1. Adoption rates of digital technologies by size and age

Enabling

	Micro	Small	Medium	Large
<=5 years old	25.9%	56.7%	64.1%	76.8%
6-10 years old	25.3%	59.1%	69.8%	77.4%
10+	24.8%	62.2%	78.1%	89.1%

Management software

	Micro	Small	Medium	Large
<=5 years old	34.5%	44.1%	54.4%	73.3%
6-10 years old	34.3%	46.0%	63.5%	75.7%
10+	33.9%	50.0%	69.8%	81.5%

E-sales

	Micro	Small	Medium	Large
<=5 years old	15.2%	15.7%	14.9%	20.8%
6-10 years old	14.4%	15.8%	16.3%	23.2%
10+	11.8%	14.6%	16.9%	24.2%

Cloud

	Micro	Small	Medium	Large
<=5 years old	18.8%	20.9%	27.3%	48.4%
6-10 years old	16.1%	21.0%	32.2%	46.6%
10+	14.2%	22.3%	32.8%	51.5%

Advanced

	Micro	Small	Medium	Large
<=5 years old	4.6%	12.9%	18.0%	30.3%
6-10 years old	4.3%	13.9%	23.9%	29.8%
10+	3.7%	15.0%	32.1%	47.1%

Note: Results report the adoption rates by size and age obtained by estimating the following linear probability model:

$$Tech_{isr} = Size_i \times Age_i\beta + \gamma_{sr} + \varepsilon_{isr}$$

where $Tech_{isr}$ is a dummy equal to 1 if the firm i active in NACE rev.2.2 two-digit sector s and region r adopts the technology listed in the title of each panel, and γ_{sr} is sector-region unobserved heterogeneity.
Source: Authors' estimate on ISTAT data.

Skewed adoption rates by age and size have also been recently found in the United States, exploiting the 2018 Annual Business Survey. In a recent paper, Zolas et al. (2020[29]) provide the results of a similar linear probability model for a dummy equal to 1 if the firm adopts any "business technology", a category which, in their study, broadly corresponds to the "advanced digital technology" used in this work. Differently from our model, they do not control for sectoral and geographic unobserved heterogeneity. Table A B.2 reports Table 17 from Zolas et al. (2020[29]) and replicates the econometric model of Zolas et al. for Italy. Even if the average comparison may be affected by some differences in the definition of the dependent variable, it is still interesting to see how the difference in adoption rates between young-small firms and the rest is much stronger in Italy than in the

United States.[5] This is consistent with the evidence reported in Chapter 2 that shows that the digital gap is particularly relevant for micro and small Italian firms.

Table A B.2. Size-age coefficients for business technologies/advanced digital technologies – United States and Italy

United States

	Firm size			
Firm age	1 to 9	10 to 49	50 to 249	250+
0 to 5	0.1	0.19	0.25	0.31
6 to 10	0.09	0.17	0.24	0.3
11 to 20	0.08	0.16	0.23	0.31
21+	0.07	0.14	0.26	0.37

Italy

	Firm size			
Firm age	1 to 9	10 to 49	50 to 249	250+
0 to 5	0.04	0.13	0.18	0.31
6 to 10	0.04	0.14	0.25	0.3
11 to 20	0.04	0.16	0.31	0.45
21+	0.04	0.16	0.35	0.5

Source: The first panel reports the results of Zolas et al. (2020[29]) – Table 17), the second reports authors' elaboration on ISTAT data.

The data allows us to study how adoption rates are correlated with firm productivity, measured as value added per worker, holding fixed size, age, sectoral and geographic differentials. Table A B.3 reports differences in adoption rates focusing on firms with different labour productivity performance in 2018, distinguishing between leaders (firms in the top 10% of the labour productivity distribution within each sector), laggards (firms in the bottom 10% of the same distribution), and middle firms (firms belonging to the 2nd-9th deciles of the same distribution).[6]

Table A B.3. Adoption rates by labour productivity deciles

	Laggards (decile 1)	Middle (deciles 2-9)	Leaders (decile 10)
Enabling	24.1%	31.0%	39.8%
Management	38.8%	37.3%	48.2%
Cloud	13.2%	16.7%	23.0%
E-sales	15.6%	13.0%	14.8%
Advanced	5.7%	5.8%	9.1%

Note: Results of a linear probability model that controls for sector-region and size-age fixed effects.
Source: Authors' elaborations on ISTAT data.

Table A B.3 suggests that adoption rates tend to be increasing in labour productivity, with leaders typically exhibiting higher adoption of digital technologies than middle-productivity and laggard firms. This result is consistent with digital technology adoption being one important determinant of productivity divergence. The differences in adoption rates are particularly strong for enabling technologies, cloud, and advanced digital technologies. In these cases, adoption rates among leaders are 1.6-1.7 times higher than among laggards. For advanced technologies in particular, the main divide seems to be between the best firms and the rest, while for the others adoption rates increase throughout the productivity distribution.

A notable exception to this pattern is, once again, the use of platforms for e-sales. In this case, adoption rates are very similar among firms with different productivity. At one side, this finding is consistent with low costs of adoption, which boosts the use of this technology also by less productive firms: as a result, there is adopters are less *selected*. On the other side, though, this result may signal that this technology does not significantly *affect* productivity. This may happen, for instance, if the fees that platforms apply to e-sales are able to reap most of the extra-profits generated from their use.

With this analysis, it is not possible to disentangle selection from effect, neither for e-sales nor for any other type of digital technology. In Box A C.1, we devise a structural econometric model of firm optimisation (and the related production function) to identify how digital technologies affect firm performance, and how they are complementary to other inputs used by the firm.

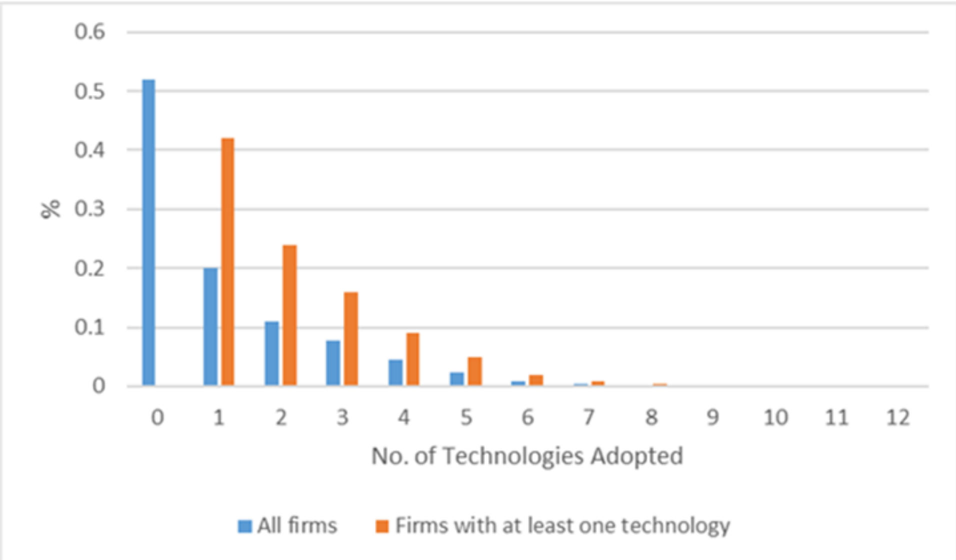
Evidence on bundling of digital technologies

The unique data infrastructure assembled allows to provide first evidence on the complementarities among digital technologies, an issue discussed in the conceptual framework.

In particular, adopting a cluster of technologies may be subject to relevant complementarities and allow leverage the gap a firm has with respect to its competitors (Milgrom and Roberts, 1990[46]; Castellacci, 2002[47]; Gomez and Vargas, 2012[48]).

In this context, Figure A B.4 uncovers the extent to which Italian firms use different digital technologies together. This phenomenon is referred to as bundling. In particular, Figure A B.4 shows that among adopters almost 60% of firms use a bundle of more than one technology, and about 40% of them adopt three or more technologies.

Figure A B.4. Distribution of firms by number of technologies adopted

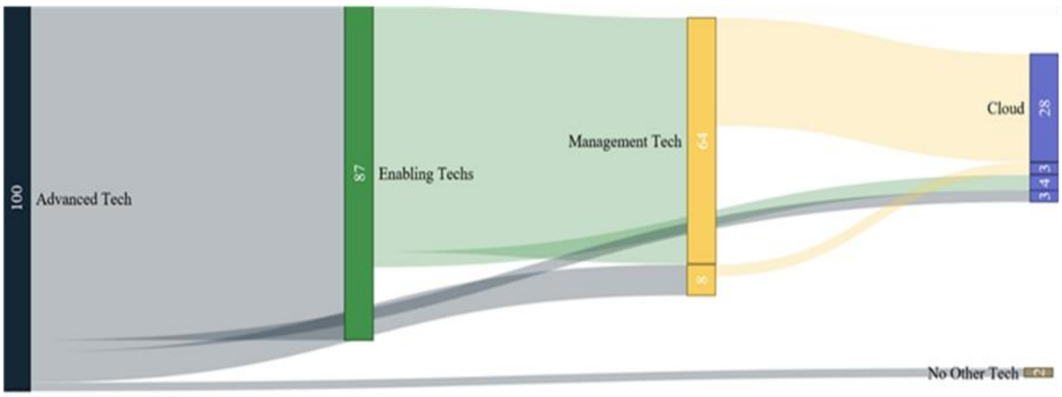


Source: Authors' elaboration on ISTAT data.

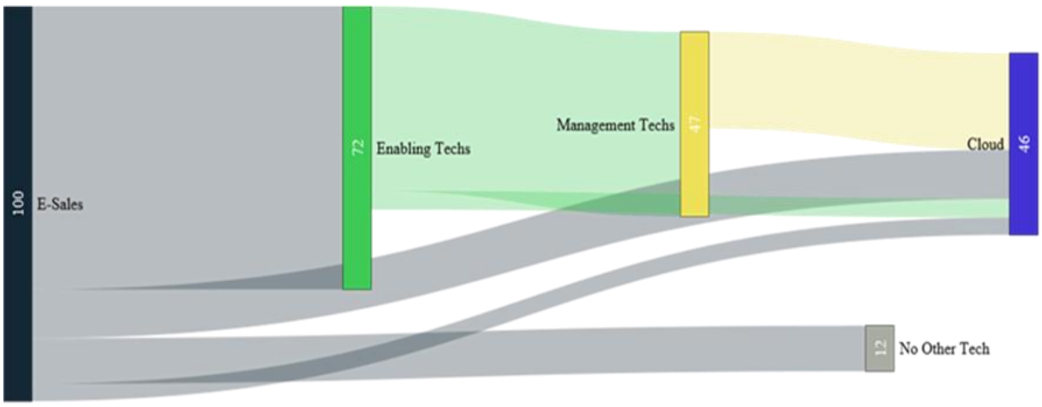
Further focusing on complementarities across technologies and bundling, Figure A B.5 – panel A restricts the attention to adopters of advanced digital technologies (6.5% of all Italian firms) and analyses how this group of firms uses simultaneously different types of technologies. Among adopters of advanced technologies, almost 90% of firms also adopts some enabling technology, 72% also adopt management technologies, and less than 40% also use cloud computing. In total, over 98% of advanced technology adopters have at least one of these three additional sets of technologies.

Figure A B.5. Bundling of digital technologies among adopters of advanced digital technologies and users of online platforms for e-sales

Panel A. Advanced digital technologies



Panel B. E-sales

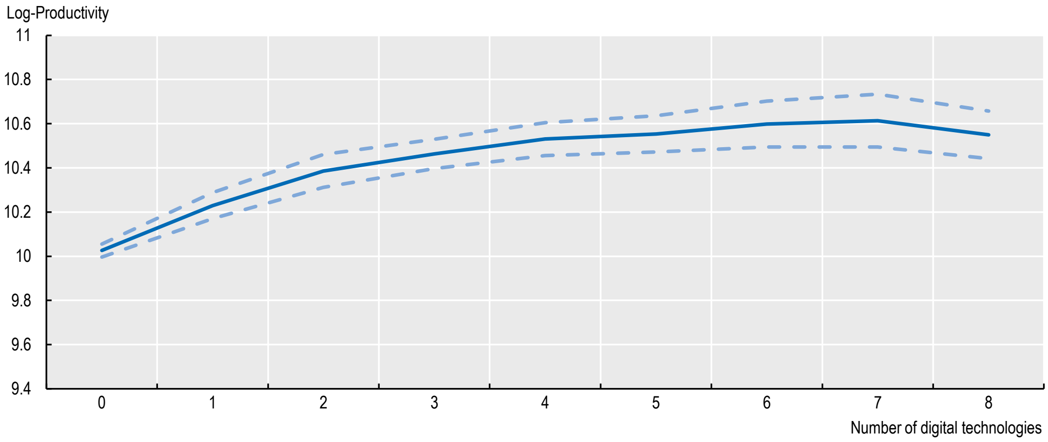


Note: Sankey diagrams of adoption of digital technologies. In panel A, the reference sample is composed of firms that adopted any advanced digital technology. In panel B, the reference sample is composed of firms that use online platforms to perform e-sales.
Source: Authors' elaboration on ISTAT data.

The picture changes in panel B, which restrict the attention to firms that perform e-sales on digital platforms (about 18% of all Italian firms). A higher share (12%) of this group of firms does not adopt other technologies, the share of cloud users is significantly higher, while the share of users of management technologies is significantly lower.

Comparing bundling for advanced technologies with e-sales suggest that these technologies exhibit different sets of complementarities with other digital technologies. Almost no firm uses advanced technologies alone. Furthermore, although enabling technologies play an important role in both cases – but to a larger extent for advanced technologies, the balance between management and cloud is different.

Figure A B.6. Labour productivity by number of technologies adopted



Note: Results of a regression that controls for region-sector and size-age fixed effects. The 95% confidence intervals are estimated from standard errors that allow for serial correlation at the region and sector level.
Source: Authors' elaboration on ISTAT data.

Complementarity does not only means that technologies are used together, but also that their combined use increases firm's output. Figure A B.6 focuses on labour productivity dynamics for firms adopting a different number of digital technologies.[7] It shows that – at least up to seven technologies – productivity tends to be increasing in the number of technologies adopted, but the marginal returns are decreasing.[8] The decrease appears even stronger when using more than nine digital technologies. Despite widening error bars, these patterns may be related to the increases in complexity brought by the use of a large number of technologies, which may include the most advanced ones.

Endnotes to Annex B

[1] The first two-digits (NACE Rev.2.2) are considered, as selected by the firm during its lifetime. The sectoral classification is imposed fixed over time. Firm location is defined as the municipality where the firm has its headquarters (legal head office). This is also fixed over time.

[2] The set of questions assessing *investment* in digital technologies provides related but different information from the one on *use* of technologies. Indeed, technologies may be adopted prior to the 2016-18 period. In this sense, adoption rates of technologies for which information is available on investments are to be considered lower bounds.

[3] Once the different size distribution is taken into account, the higher prevalence of cybersecurity adopters among manufacturing firms drops by ¾, although it remains statistically significant. Results available upon request.

[4] Interestingly, we find adoption rates of advanced technologies to be significantly lower in the Centre relative to both the North and the South of Italy. This is somehow in contrast with the productivity differentials, which generally display a lower performance of Southern regions vis-à-vis the Centre. Further analyses show that lower adoption of advanced technologies in the Centre is driven by advanced automation. This difference cannot be explained by firm size and age differentials, or other firm characteristics such as being part of a group or export orientation.

[5] Medium and large older firms display possibly higher adoption rates in Italy than in the United States. Yet, this direct comparison of specific figures across the two countries may be affected by differences in the technologies included in the bundle and in the definition of adoption. In the United States, "business technologies" include touchscreens, which may be more widely used. Moreover, the US survey asks whether the firm is *using* the technology, while the Italian questionnaire asks if they *invested resources* in the technology over the last three years.

[6] Results presented in Table A B.3 are based on the estimation of the following model:

$$Tech_{isr} = \beta_1 Laggard_i + \beta_2 Middle_i + \beta_3 Leader_i + Size_i \times Age_i \delta + \gamma_{sr} + \varepsilon_{isr}$$

where *Laggard*, *Middle*, and *Leader* are three dummies equal to 1 if the firm belongs, respectively, to decile 1, 2-9, and 10 of the productivity distribution. Deciles are computed within three-digit NACE rev.2.2 sectors. The model controls for size-age and sector-region unobserved heterogeneity.

[7] The figure plots the coefficients β's of the following regression:

$$y_i = \sum_{k=1}^{12} \beta_k NoTech_i^k + \lambda_{rs} + Size_i \times Age_i \theta + \varepsilon_i$$

which controls for sectoral and regional unobserved heterogeneity, as well as for age and size of the firm.

[8] Referring to marginal returns in this context does not imply causal links that cannot be claimed in this simple setting.

Annex C. Explaining the Italian digital gap

A Framework to Understand Digital Transformation in Firms

This section outlines a conceptual framework aimed at guiding the analysis of the factors that may foster or hinder the digital transformation of firms, and the extent to which digital technologies are effectively used. The framework is presented schematically in Figure C.1 and the main elements will be further described and discussed below.

As shown in Figure A C.1, the conceptual framework puts digital technology adoption centre stage. A set of developments or disruptions brought by technological change, competitive pressures or changes in demand may induce firms to adopt the new digital technologies. Digital technology adoption is then supposed to affect firm productivity, key outcome of interest for policy makers. Yet, both the decision to adopt and ex-post returns to adoption may be influenced by several factors.

These factors are grouped distinguishing the ones *internal* from the ones *external* to the firm. The first group includes firm characteristics – such as sector of activity, firm size and age – and firm capabilities, including those related to human capital – such as the quality of its workforce and management – and those related to technology – including whether the firm has adopted other (complementary or substitute) technologies, or whether complementary intangible assets (like R&D expenditures or intellectual property) are present. The second group focuses on the availability of broadband infrastructure, easiness to access external finance, technology spillovers arising at the sectoral or geographical level, the quality of the education system and its ability to supply digital skills, and public policies aimed at fostering firm digitalisation.

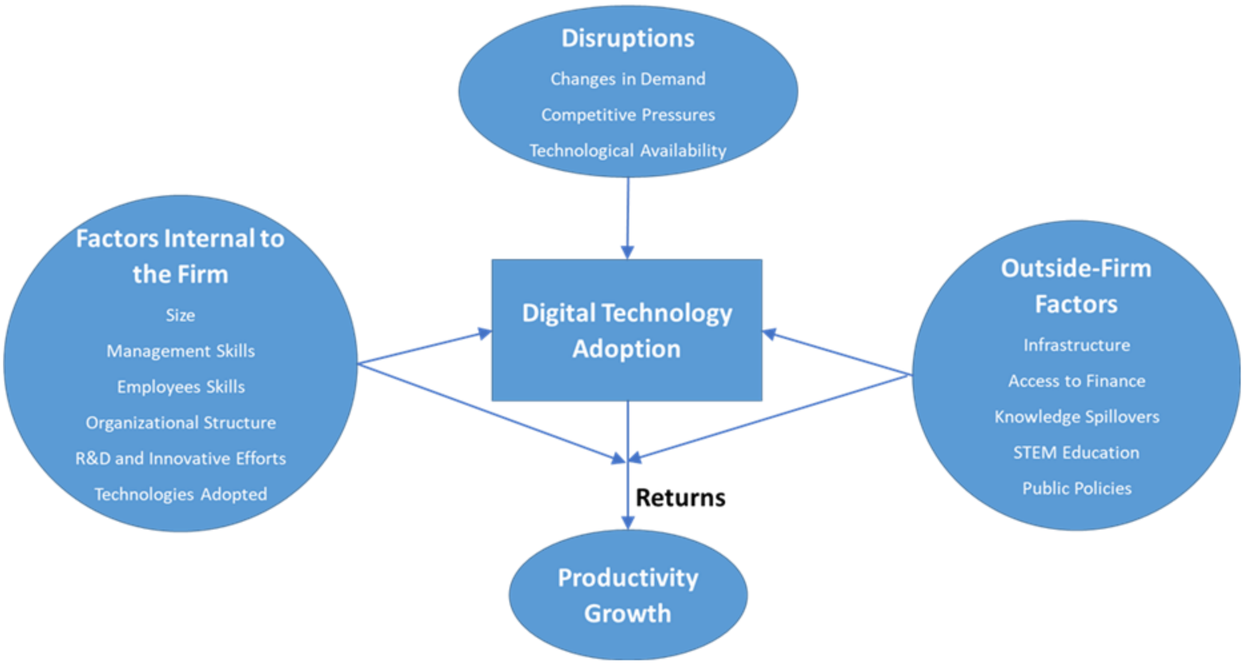
While this list of drivers is broad, it is by no means complete. Several factors both internal to the firm, such as firm ownership and control, and external to it, such as labour market frictions or the role of training, have been omitted. This is not because of their lack of relevance, but rather because available data (although extremely comprehensive) do not cover these topics with sufficient information.

Importantly, links among some of the internal factors considered and technology adoption are not unidirectional. Indeed, the adoption and use of new digital technologies may have feedback effects as it may bring substantial changes in organisational structure, firm size, the input and skills mix, and induce complementary innovation. These changes are not instantaneous and may be costly to implement, but may be crucial to fully realise returns from technology adoption and boost productivity.

A successful combination of firm characteristics and capabilities enabling digital technology adoption, low external barriers, together with the adjustments required to enhance firm ability to effectively use new techniques increasingly ICT-based, would positively affect returns to adoption and firm efficiency.

The rest of the section discusses more in detail the key factors outlined in the conceptual framework also referring to the Italian case, building upon the existing academic and policy literature, with particular emphasis on the specificities of the Italian case.

Figure A C.1. Drivers of digital technology adoption and of its returns



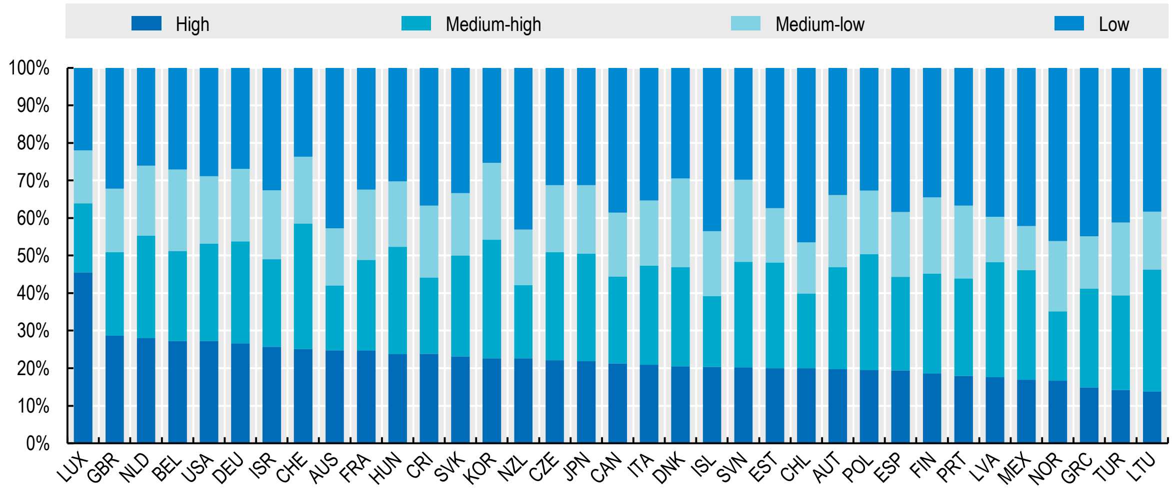
Internal factors

Sectoral specialisation

Among factors internal to the firm, a relevant role is played by firm characteristics, including sector of activity, firm size and age. Digital transformation pervades the economy, but not homogeneously: the extent to which the productive sectors have gone digital varies markedly. To study this heterogeneity, Calvino et al. (2018[49]) have combined several indicators regarding ICT investments and expenditures, human capital, and online sales to produce a taxonomy of digital intensive sectors, highlighting that sectors like computer and electronic manufacturing, telecommunications and IT services belong to the most digital intensive group, while agriculture, mining and construction are among the least ones. For other sectors, the results are less obvious: for instance, pharmaceuticals are medium-low digitalised, while wood and paper products are medium-high. There is also some limited mobility over the period of analysis: R&D and arts and entertainment have become relatively more digital intensive, while computer and electronics and health have been surpassed by other sectors.

Some scholars have argued that sectoral specialisation has played a role in explaining the slow growth of the Italian economy (Sapir and Faini, 2005[50]; De Nardis, 1997[51]), as value added and exports have remained concentrated in more “traditional” sectors characterised by low innovation and low human capital (e.g., textile, clothing, wooden products). In the context of the present analysis, sectoral specialisation does not seem to be at the root of the subdued digital transformation of Italian firms. Figure A C.2 reports the distribution of value added of OECD countries in 2018, by quartiles of the summary indicator of Calvino et al. (2018[49]): Italy is positioned in the middle just after Canada, the modal country in terms of the share of value added generated in highly digitalised sectors.

Figure A C.2. Distribution of value added by sectoral digital intensity – 2018 or latest available year



Note: 2017 for Australia, Canada, Chile, Germany, Japan, Latvia, Lithuania, Portugal, Switzerland; 2016 for Costa Rica and Israel.
Source: OECD, Structural Analysis (STAN) Database, http://oe.cd/stan (accessed in May 2021).

The analysis of National Accounts presented in Section 2 highlights a growing gap in Italian investments in ICT and software, as a share of GDP, relative to the OECD average. Conversely, the gap in R&D expenditures narrowed overtime. By exploiting sectoral accounts, we can further study to what extent these trends can be explained by the Italian sectoral specialisation. For each OECD country for which sectoral accounts data on ICT, software, and R&D accumulation are available for the period 2000-17, we aggregate sector-level growth in investments over value added using Italian sectoral shares in the year 2000. As a result, we obtain the "counterfactual" growth in asset accumulation that would have been obtained by each country if their sectoral specialisation had been the same as Italy, effectively netting-out sectoral differences.[1] Formally, for each country *c*, we aggregate each sector *s* growth in investment over value added as:

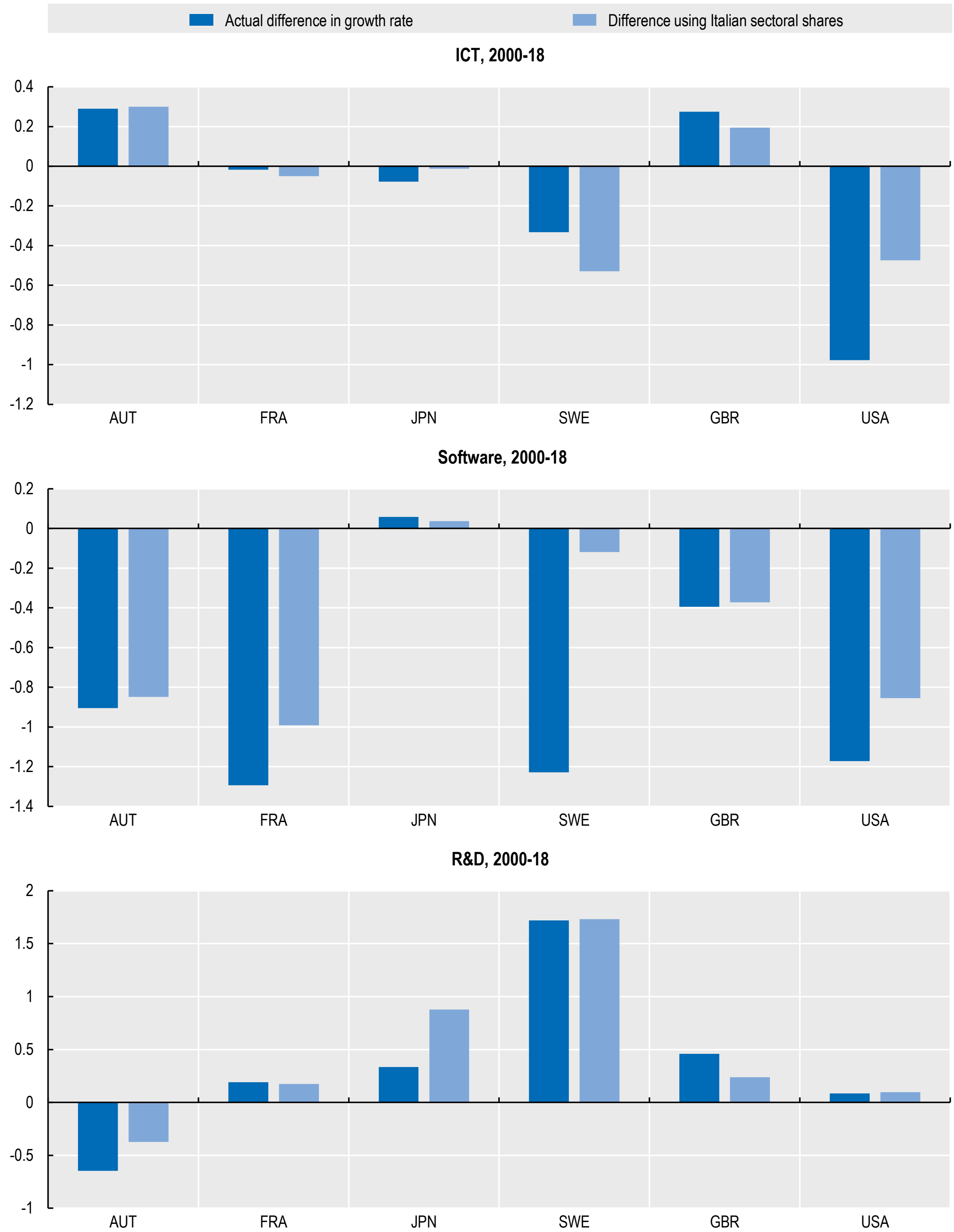
$$CF_c \coloneqq \Delta_{00-17}\frac{I_c}{VA_c} = \sum_s \frac{VA_{IT,s,2000}}{VA_{IT,2000}} * \Delta_{00-17}\frac{I_{cs}}{VA_{cs}}$$

Figure A C.3 shows the difference between Italian accumulation and the counterfactual for each country, and compares it with the difference measured using actual growth in each country. In the case of ICT, the gap in Italian investments relative to France or Sweden would be larger if we kept sectoral distribution fixed and equal to the Italian one at the beginning of the time series. Conversely, the gap relative to Japan or the United States would have more than halved. The second panel shows that sectoral differences are generally unable to explain the gap in investments in software and databases between Italy and most OECD countries. Finally, for R&D, the stronger increase experienced by Italy is generally either unaltered or slightly lessened if we control for sectoral specialisation (with the exception of the comparison with Japan).

All in all, these results show that sectoral specialisation is unlikely to explain the Italian digital gap. We, thus, need firm-level data to explain within-sector adoption rates.

Figure A C.3. ICT investments, software investments, and R&D expenditures as a share of GDP – difference in growth rates between Italy and selected OECD countries, 2000-18

Actual difference and counterfactual difference keeping sectoral change fixed



Note: Sections E, N and S of ISIC Rev.4 are not available for Japan. For R&D, section A is not available for the United States.
Source: OECD, Detailed National Accounts, SNA 2008: Capital formation by activity - ISIC Rev. 4, OECD National Accounts Statistics Database.

Firm size, age and firm dynamics

The size of a firm tends to be significantly related to the extent to which it goes digital. Results from ICT surveys indeed show that a wide range of indicators of digital transformation, encompassing technological adoption, human capital specialisation, as well as the use of digital tools with suppliers and customers, are positively correlated with firm size.

While statistically robust, this stylised fact may be explained by several non-competing causes, including many of the determinants discussed in the next paragraphs (e.g., lack of skills or absorptive capacity, financing constraints, etc.; see also Åstebro (2002[52]). Relevantly, smaller firms may indeed find it more difficult to access external finance (e.g., because they lack collateral), preventing them to invest in new technologies (Canepa and Stoneman, 2005[53]; Gomez and Vargas, 2009[54]; Hottenrott and Peters, 2009[55]). Policy can play a key role to address these challenges, as will be discussed in the following

While smaller firms may benefit significantly from digital technologies, adoption and effective use increasingly rely on complementary assets. Indeed, at one side, many new technologies, such as cloud storages, and cloud-based data analytics, are particularly suitable for smaller firms. Their financial costs are mostly variable in nature, while fixed upfront costs are usually less relevant than in the past. Moreover, some new digital technologies allow in principle significant productivity gains also at lower scales of production. Using 3D printing, for instance, the gains from producing tools at larger scale drop dramatically (The Economist, 2017[56]). On the other side, though, the effective use of digital technologies increasingly relies on intangible assets that display significant economies of scale (Haskel and Westlake, 2018[57]), as they are characterised by high fixed and low variable costs (De Ridder, 2020[58]).

Italy is well-known to have a very fragmented productive sector, with Italian firms with less than ten persons employed representing more than 70% of firms and more than 20% of employment in manufacturing, and nearly 90% of firms and over 40% of employment in private services, ten percentage points more than other OECD countries (OECD, 2020[59]). The share of small firms (with 10 to 49 employees) is broadly similar between Italy and other OECD countries, but in Italy, they represent a significantly larger share of employment, particularly in manufacturing. The small size of Italian firms has been identified as one of the relevant factors behind the dismal performance of the Italian economy in terms of productivity (Berlingieri et al., 2017[16]).

Recent contributions have shown that the size distribution is importantly the result of an underlying process of firm dynamics (Hsieh and Klenow, 2009[60]; Aghion, Akcigit and Howitt, 2014[61]; Criscuolo, Gal and Menon, 2014[62]) where entry of innovative firms and exit of less productive ones can play an important role for relevant economic outcomes. In this regard, the Italian economy is characterised by subdued firm dynamics and limited selection: Italian firms enter the market with smaller size, grow less and for a smaller number of years than other OECD countries (Manaresi, 2015[63]; Calvino, Criscuolo and Menon, 2015[64]). As a result, Italian firms are not only smaller, but also older than the OECD average. Low dynamism and lack of selection may hamper firms' incentive to invest in growth-enhancing technologies.

These considerations allow us to advance some hypotheses on the relationship between size, age and technology adoption in Italy.

a. We may expect technology adoption to be positively correlated with size, though this correlation may be weaker for technologies characterised by lower fixed costs and economies of scale;

b. Given the low dynamism that characterise Italian young firms, we may expect adoption rates to be only mildly correlated with firm age.

Skills and digital technologies

Beyond firm characteristics, human capital available within the firm plays a key role for the uptake and effective use of digital technologies. Scholars have recognised the existence of a tight link between digital technology adoption and worker skills at least since the 1980s. Seminal works by Mark (1987[65]) and Katz and Murphy (1992[66]) found that the diffusion of computers in the workplace affected the structure of occupations and increased skill-premia and wage inequality. These facts led economists to develop the "skill-biased technological change" hypothesis, which posits that digital technologies are complementary to highly skilled workers, thus increasing their demand.

While the skill-biased technological change hypothesis was able to explain the rising wage inequality of the 1980s and the early 1990s, it fell short in explaining the process of job polarisation experienced since the mid-1990s. Indeed, both high wage and low wage occupations experienced an increase in their employment share, at the expenses of middle wage workers. The theory of routine-biased technological change then emerged. This theory argues that digital technologies are increasingly able to substitute workers in carrying out routine tasks (both cognitive and manual), while non-routine cognitive tasks are complemented by the use of digital capital. Non-routine manual tasks, finally, would be largely unaffected by the digital revolution (Autor, Levy and Murnane, 2003[67]). Acemoglu and Restrepo (2021[68]) generalise this conceptual framework, explaining the role of task displacement induced by automation and quantifying its effects on changes in US inequality.

The general theories of skill-biased and routine-biased technological change paved the way to more in-depth analyses of the relationship between digital transformation and skills which take into consideration (i) richer definitions of skills, (ii) a more granular definition of tasks and (iii) the changing characteristics of digital innovations. In this context, Grundke et al. (2018[69]) consider a wide set of cognitive and non-cognitive skills and exploit the PIAAC survey, covering 31 countries, to study how returns to each skills (and their bundles) vary according to the digital intensity of industries (as defined by the taxonomy of Calvino et al. (2018[49])). They find that digital intensive industries particularly reward self-organisation and advanced numeracy skills, and that returns to them and to communication skills are particularly high when bundled together.

As the technology frontier changes, so do skill capabilities needed to embrace it and the complementarities between skills and technology. The increasing connectivity of all phases of production, for instance, pushes the need of cybersecurity skills to avoid thefts of relevant business information and frauds (Hoberg, Krcmar and Welz, 2017[70]). Cloud computing is significantly affecting the IT tasks that need to be performed within the firm boundaries, while big data investments have proven to be particularly productive in labour markets where there are a sufficient concentration of workers trained into new and complementary programming languages (Tambe, 2014[71]).

Finally, the rapid advancements in the use of Artificial Intelligence as a productive technology may significantly affect the skills needed by firms. Indeed, AI seems able to increase the productivity of several types of workers (such as software programmers, Bessen (2016[72])), while renewing existing sectors with new investment opportunities (such as self-driving vehicles, industrial and home robots, chatbots, etc.). At the same time, it may substitute existing labour in non-routine manual tasks not previously affected by digitalisation, such as drivers or call centre operators, as well as in more cognitive tasks, such as those related to predicting prognosis or detecting insurance frauds (Webb, 2020[73]).

Italy fares generally below the OECD average and of its main European counterparts in terms of skill supply. According to data published in the OECD report *Education at a Glance* (OECD, 2021[74]), in 2020 only 20% of Italians aged 25-64 had a tertiary education degree, against 38.6% of the OECD average, 39.7% of Germany and 31.3% of France. Importantly, this gap does not simply reflect the older composition of the Italian population, as it is significant also among individuals under 35 and between 35 and 45 years of age.[2] Significant differentials can be identified also in terms of cognitive skills of adult population, as measured by the PIAAC survey: the Italian average mean score was significantly lower than the OECD average both in literacy and numeracy skills (OECD, 2019[75]).

Lack of adequate education and skills in the workforce have been identified as important limitations preventing digital technology adoption by Italian firms (Bugamelli and Pagano, 2004[76]; Fabiani, Schivardi and Trento, 2005[77]). Low-skilled workforce are found to be unable to adapt to the organisational changes fostered by the digital transformation (Biagi and Parisi, 2012[78]). Moreover, the lower skill-intensity of Italian firms is also found to negatively affect R&D investments (Hall, Lotti and Mairesse, 2012[79]), lowering the absorptive capacity of new technologies. The above discussion, thus, points to the potential relevance of skills in explaining the Italian digital gap. As recently pointed out by Frank et al. (2019[80]), two main limitations hamper the study of skill complementarities for frontier digital technologies: the lack of high-quality data about the nature of work that can keep the pace of technological developments, and the lack of a coherent, empirically informed model of the micro-level process that links human and machine inputs.

In our empirical analysis, we will exploit firm-level information on skills of the workforce and detailed local-level data on the availability of tertiary education (with a specific focus on STEM programs, one of the external factors crucially affecting digital skills availability) to overcome the first limitation, while we will estimate complementarities within the framework of partial-equilibrium firm optimisation to overcome the second one.

Firm management and organisation

Workers' skills are not the only crucial complementary input for technology adoption. To reap the benefits of digital technologies and to exploit the acquired digital skills, firms may need to go through a process of organisational change and redesign. New technologies affect the quantity and the structure of the information available within the firm: as a result, the optimal structure of the organisation changes (Bresnahan, Brynjolfsson and Hitt, 2002[81]). The literature has highlighted a variety of such impacts, encompassing changes in authority relationships, decentralisation of decision authority, changes in the task structure of each workers, and changes in reward schemes.

Different digital technologies may be more effective than others, depending on the firm's organisational structure. Bloom et al. (2014[82]) argue that information technologies, such as ERP or CAM, allow information to become cheaper to access, while communication technologies, such as emails or mobile messages, lower the cost of communicating. The former may foster decentralisation of decision making, while the latter may allow the central decision maker to have better control in production and nonproduction decisions.

Identifying which technology to adopt and which complementary organisational change to implement is typically a difficult, costly, and uncertain task for firms. The monetary and non-monetary costs of these are found to be larger than the cost of the investment in digital technologies *per se* (Hitt and Brynjolfsson, 1996[83]). This helps explain the high variability in the adoption of new technologies by otherwise similar firms, as well as the variability in the outcomes of such adoption.

Organisational changes are the result of a set of strategic choices made by the firm management. High quality managers are thus crucial to allow the digital transformation to fully and effectively unfold. Bloom, Sadun and Van Reenen (2012[84]) found that subsidiaries of US multinationals in the United Kingdom used IT capital more efficiently than domestic firms, and traced this back to better management practices. Queiro (2015[85]) found that manager education positively affects firm productivity, and this effect is channelled by improved use of new technologies.

While better managers would benefit firm's productivity, several frictions may limit their employment: frictions in contractual enforcement (Caselli and Gennaioli, 2013[86]), familism and cronyism (Pellegrino and Zingales, 2017[19]), and more generally owners whose goal is simply to produce subsistence income, rather than grow and thrive (Schoar, 2010[87]). As a result, several firms are poorly managed, often by the owner or by his/her relatives, rather than by professional managers, and this generates significant productivity losses (Bloom and Van Reenen, 2007[88]).

According to the World Management Survey, Italian firms display a significant managerial gap vis-à-vis most OECD countries, and this holds also conditioning on firm size and sectoral specialisation. Around 60% of the gap between Italy and the US seems to be explained by lower product market competition and a higher share of family managed firms (Bloom, Sadun and Van Reenen, 2008[30]). Lower managerial quality is also found to explain the IT gap between Southern and Northern Europe, accounting for more than 30% of the distance between the Italian aggregate productivity and the German one (Schivardi and Schmitz, 2018[89]).

Our empirical analysis aims at identifying the role of management skills in shaping digital technology adoption and its returns. We will follow closely the theoretical framework of Schivardi and Schmitz (2018[35]) and estimate whether complementarities between digital technologies and other firm inputs (notably skilled and unskilled workers) are affected by managerial skills. Our hypothesis is that heterogeneity in managerial skills may play a significant role in explaining the Italian digital gap.

Absorptive capacity, knowledge spillovers and R&D

Absorptive capacity, i.e. the ability of firms to recognise the value of new information, assimilate it, and exploit it commercially. Cohen and Levinthal (1990[90]) are critical for technology adoption in the digital era and for translating adoption into efficiency gains. In the context of the global slowdown in productivity growth, accompanied by increasing divergences between the most productive firms and the rest (Andrews, Criscuolo and Gal, 2016[4]; Berlingieri, Blanchenay and Criscuolo, 2017[5]) absorptive capacity plays a key role to enable laggards firm to catch up (Berlingieri et al., 2020[6]; Andrews, Nicoletti and Timiliotis, 2018[91]). This role is particularly strong in digital intensive sectors, given the increasing technological complexity and more important role of tacit knowledge that characterise the digital transformation.

Absorptive capacity is importantly related to some of the dimensions already discussed, notably human capital, skills, and management. However, it is not simply the sum of individual abilities to assimilate information, but is also determined by organisational structure, communication within the organisation, and internal distribution of knowledge (Cohen and Levinthal, 1990[90]).

Some characteristics of the technology to adopt, and of its underlying knowledge base, may affect the extent to which firms can assimilate information on how to use and profit from it. These include the degree of codification of the knowledge required (which is also related to IP strategies), the degree of novelty of the technology, or its cumulativeness with respect to the prior related knowledge and the currently used vintages.

Different forms of learning may boost absorptive capacity, affecting the ability of businesses to realise returns to adoption. These include learning by doing, learning by using, learning from interaction or from inter-industry spillovers (see Malerba (1992[92])), which can even lead to improvements of the technology adopted (Hall, 2006[93]).

Absorptive capacity importantly mediates the extent to which firms can benefit from (external) knowledge spillovers, which in turn depend on geographical or social proximity, trade flows, interaction with suppliers or customers, or universities, as well as by specific local institutional features (Jaffe, Trajtenberg and Henderson, 1993[94]; Breschi and Lissoni, 2009[95]; Bloom, Draca and Van Reenen, 2016[96]; Belenzon and Schankerman, 2013[97]).

Research and development is an important determinant of absorptive capacity. Indeed, engaging in R&D activities does not only affect innovation outputs but also indirectly boost the ability of firms to assimilate and process knowledge, which can be relevant for the adoption of new technologies. This is the so-called second face of R&D (Cohen and Levinthal, 1989[98]; Griffith, Redding and Van Reenen, 2004[99]). Also in the case of Italy, empirical analyses have found that absorptive capacity enablers, such as internal and external R&D and employee expertise, are positively associated with technology adoption and innovation (Pereira and Leitão, 2016[100]). Yet, in Italy the "diffusion machine" seems not to work well (Andrews, Criscuolo and Gal, 2015[43]), as the distance between frontier firms and laggards is larger than in other countries.

Italy has been lagging behind relative to other OECD countries in terms of business R&D expenditure as a share of GDP, although significant improvements have been recorded since 2014, when public incentives to R&D have been reformed and strengthened. The poor performance of Italy relative to other developed countries reflects both a lower share of firms doing R&D, and lower intensity of R&D expenditures among innovating firms, and is present among small, medium, and large firms alike (Bugamelli et al., 2018[15]).

Several researchers have identified significant knowledge spillovers among Italian firms. Aiello and Cardamone (2008[101]) find that innovative activities generate positive spillovers on firms located nearby, and that these spillovers are particularly strong in Southern Italy, where firms are on average farther from the technological frontier. These findings have been confirmed by Sanso-Navarro and Vera-Cabello (2017[102]) who compare the strength of regional knowledge spillovers across France, Germany, Italy and Spain using regional data on patenting activities.

Local institutional features can foster knowledge spillovers across firms, and between firms and other actors (e.g. universities and research centres). Liberati, Marinucci and Tanzi (2014[103]) study the characteristics and the effects of 39 Science and Technology Parks (STPs) in Italy: geographical areas in which firms, R&D laboratories, universities and research centres are localised. They find that these institutions take time to generate significant effects, but in the long-term they are associated with better profitability and larger investments by firms. They also find that positive effects on sales and profitability are particularly relevant for firms participating in STPs located in Southern Italy. Relatedly, Corrocher, Lamperti and Mavilia (2019[104]) find a positive effect of Italian science parks on tenant firms' innovative performance, whose intensity depends on the strength of the research network within the park.

The above discussion points to a set of testable hypotheses regarding R&D, spillovers, and the role of local institutions:

a. R&D expenditures should be positively correlated with digital technology adoption, particularly with more advanced ones.

b. This correlation may significantly differ by firm size, although the sign of these cross-derivatives is ex-ante ambiguous. At one side, if returns to R&D are declining at the margin, the benefits of absorptive capacity may be larger for smaller firms. On the other side, if R&D expenditures, like other intangibles, feature economies of scale, then the complementarity between R&D and technologies may be stronger for large firms.

c. Knowledge spillovers may spur the adoption of technologies within markets. In our empirical analysis, we are going to gauge the relevance of these spillovers in markets defined by geographical area, industry, destination of products or origin of inputs.

d. Local institutions (such as innovation hubs, competence centres, etc.) may boost spillovers in digital technology adoption.

Technologies adopted: complementarity and hierarchies

The decision of adopting a new technology, especially in the case of digital technologies, may be significantly influenced by the use of previous vintages or by the use of older related technologies (Stoneman and Kwon, 1994[105]; Gomez and Vargas, 2009[54]). On the one hand, new technologies may build upon previous vintages, with different degrees of cumulativeness, or build upon the skills developed by using previous vintages (Colombo and Mosconi, 1995[106]). On the other hand, technologies may differ in the expected growth rate of their performance and this may influence the option value of waiting for the next vintage.

Digital technologies in particular are likely to require businesses to develop complementary assets and to adopt additional and complementary technologies. For instance, Internet-of-things technologies usually rely on advanced management software to collect and analyse the flow of data; big data analytics, particularly when performed with cloud solutions, may greatly benefit from broadband connectivity.

Technological hierarchies are likely to emerge, with more general digital technologies, hardware or powerful digital infrastructure enabling the adoption of more sophisticated or more specific technologies (Zolas et al., 2020[29]). In other words, existing technological sophistication and digital maturity of businesses may be linked to the adoption (or not) of new digital technologies.

The existence of technological complementarities has important implications for digitalisation policies. At one side, policies aimed at targeting one specific digital technology may have unintended positive effects on the adoption of other complementary technologies. On the other side, though, technological hierarchies may generate bottlenecks that reduce the effectiveness of digitalisation policies.

Evidence for Italy on technological complementarities are still quite scant. A recent contribution by ISTAT (2018[107]) shows that firms characterised by better educated workforce are more likely to adopt management software (ERP, CRM, etc.) and have a larger share of workers that use PCs. Evidence from the 2018 Census of Italian firms shows the emergence of clusters of technologies among more digital-savvy firms (ISTAT, 2020[108]).

In our empirical analysis, we build on these preliminary findings to provide novel evidence of technological complementarities and technological bundles among Italian firms. We study the existence of technological hierarchies, and the correlation between adoption of various digital technologies. Finally, we provide evidence of technological complementarities when evaluating a policy aimed at boosting the adoption of Industry 4.0 technologies.

External factors

Infrastructures and digital technologies

Digital infrastructures are key elements of the abovementioned technological hierarchies. Indeed, the digital transformation can only realise its full potential if access to high quality infrastructure, networks and related services are available and affordable to people and firms, especially at a time in which increasingly connected devices and machine learning applications require high amount of data to be transmitted. The needs for a strong digital infrastructure have been recently amplified by the COVID-19 outbreak, which has been accompanied by massive shifts to teleworking (OECD, 2020[109]).

Limited or unaffordable access to fast internet can be particularly harmful for firms, possibly preventing them from adopting digital technologies, effectively using them, or limiting their market potential.

In particular, a very large number of applications rely on broadband and many aspects of business are taking place over communication networks, including supply chain management, procurement, invoicing, recruitment, customer services, online payments, e-commerce or teleworking (OECD, 2008[110]).

However, although broadband is likely to enable adoption – and in such a way to be a pre-condition for the effective use of digital technologies – its direct effects on efficiency are still debated (see Bertschek et al. (2016[111]) for a survey).

This is partly because it is not easy to disentangle the role of the infrastructure enabling the use of ICTs from the role of ICTs themselves. Furthermore, broadband acts as enabler of a General Purpose Technology (ICTs) whose effects on productivity are not immediate but materialise with significant time lags and depend on complementary investments (Brynjolfsson and Hitt, 2000[112]; OECD, 2008[110]).

A recent study by Akerman, Gaarder and Mogstad (2015[113]) highlights, using Norwegian data, that broadband internet improves labour market outcomes and productivity of skilled workers, reducing those of the unskilled. Bertschek and Niebel (2016[114]) also find a positive role of mobile internet access for labour productivity in Germany.

Conversely other studies, such as the one by DeStefano, Kneller and Timmis (2014[115]) for the United Kingdom, find a limited effect of broadband on productivity outside major urban areas. Similar insights are also provided by Bertschek, Cerquera and Klein (2013[116]) for Germany, by Haller and Lyons (2015[117]) for the Irish manufacturing sector, and by Fabling and Grimes (2016[118]) for ultrafast broadband adoption in New Zealand.

This mixed evidence suggests that broadband and digital infrastructures are necessary conditions for the digital transformation but not sufficient for realising productivity gains at the firm level. These rather depend more closely on factors such as skills, management, absorptive capacity, which are however importantly complemented by fast broadband. In Italy, broadband connection is less diffused than in other developed economies: according to OECD data, in 2019 around 30% of inhabitants had a broadband subscription, while this share was above 40% in France, Germany and the United Kingdom, and around 33% for the average OECD country. Furthermore, Italy has one of the lowest internet speed among OECD countries, being just 9.2 Mbps, relative to an OECD average of 15.25 (Akamai, 2017[119]).

There is evidence that broadband speed has a significant effect for input accumulation and may boost productivity among Italian firms. Ciapanna and Colonna (2019[120]) exploit geographical variation in internet speed, which changes exogenously due to technical characteristics of the broadband network, and show that higher broadband capacity complements skilled workers in executing non-routine abstract tasks, while substituting unskilled workers in performing routine activities. A positive effect on total factor productivity is also identified. One crucial limitation of this study is that it does not observe whether the estimated effect is mediated by digital technology adoption, and if so, which of the various technologies is the effective channel of the effect. This clearly would have implications for the type of policies that could be bundled together with investments in broadband infrastructure in order to boost the digital transformation.

Our empirical analysis will try to overcome these limitations by matching local level data on broadband infrastructure with detailed information on digital technology adoption by Italian firms. We will focus, in particular, on the diffusion of ultra-fast broadband, the so-called Next Generation Access (NGA) which is needed to meet the EU Digital Agenda key objective of providing at least a 30 megabits per second connection to all EU citizens.

Finance and digital transformation

Funding constraints can limit digital transformation because new technologies may be costly to integrate into a firm’s production structure. Indeed, the large set of changes in firm activity, the acquisition of new skills, and the restructuring of the organisation required by the digital transformation importantly require investment in intangible assets. The sunkenness of the cost incurred, high uncertainties, very low or nihil pledgeability, and widespread spillovers are relevant challenges for financing intangibles (Haskel and Westlake, 2018[57]). For these reasons, equity financing, rather than debt, may seem a more effective way to finance digital technology adoption.

At the same time, the direct monetary fixed costs of the acquisition of new digital technologies is lowering. This does not simply reflect price reduction driven by obsolescence. Rather, it is the entire pricing structure that is changing. Indeed, the growing use of online software (cloud computing, online data analytics, CRMs and ERPs) is shifting the pricing strategies of technology providers: they no longer ask for a long-term upfront payment, but they rather increasingly charge subscription fees for a service. As a result, technological investments that were once capital expenditures may now be considered as operating expenditures (BMC, 2021[121]). This process has two opposing effects on firm financing: at one side, it lowers the need to demand credit, on the other, though, it further reduces (possibly annihilates) the pledgeability of purchased technologies, which are no longer assets owned by the firm.

A large body of research has studied how credit constraints affect innovation, as measured by patenting and R&D. These studies generally show that drops in credit supply tend to reduce innovative activities (Giebel and Kraft, 2020[122]; Manaresi and Pierri, 2019[17]), particularly for SMEs. Interestingly, the effect of credit on innovation may not be symmetric: exploiting matched firm-bank data for Italy both before and during the Great Financial Crisis, Manaresi and Pierri (2019[17]) show that a tightening of credit constraints reduces innovation and productivity growth in Italy, while a boost in credit supply does not have a positive effect.

A more developed financial intermediation increases access to credit and affects product or process innovation through its effect on the firm-level inputs in the innovation process, in addition to the effect of improved information acquisition and screening on the quality of the projects that are financed. For Italy, Benfratello, Schiantarelli and Sembenelli (2008[123]) show that local banking development affects the probability of process innovation, particularly in high-tech sectors, in sectors that are more dependent on external finance, and for small firms. Moreover, banking development may help stabilising technological adoption over the business cycle, as it reduces the cash-flow sensitivity of these investments.

Relationship lending is generally found to reduce information asymmetries between banks and firms, and to reduce the negative effect of lack of pledgeable assets, thus improving access to credit in particular for small firms (see Berger and Udell (1995[124]) for one of the earlier empirical findings). Herrera and Minetti (2007[125]), using data from a sample of Italian manufacturing firms, find that the duration of credit relationships has a positive effect for product innovations.

Conversely, empirical evidence on the impact of finance on technology adoption is currently scant. Bircan and De Haas (2020[126]) is one of the few recent contributions, showing how slacker credit constraints favours technological adoption, and this is reflected into productivity growth. The effect is stronger for industries farther from the world-level technological frontier, thus showing evidence of a role for the banking industry to sustain the catching-up with the frontier.

Bank credit may play a key role in financing technological adoption by Italian SMEs also because of a structural lack of alternative sources of external financing. Indeed, Italy has been historically characterised by the underdevelopment of its private equity and venture capital markets. Exploiting a unique database covering all private equity investments, Vacca (2013[127]) studies the structure of private equity and VC operations in Italy. The study highlights that VC investments are only partly devoted to young and innovative start-ups, that the investment duration is rather short (usually less than three years), and that (with few exceptions) VC funds do not specialise in specific sectors or types of firms. Moreover, there is no evidence of sequential financing, from venture capital to bank credit, nor of a significant effect of venture capital financing on the cost of credit, so that the signalling value of VC financing may be relatively poor. While these results paint a grim picture of the Italian private equity market, it must be noted that this analysis precedes the large set of reforms implemented over the last five years to bolster the Italian VC market.

In our analysis, we provide novel evidence on the link between finance and digital technology adoption. In particular, our database allows us to study how the financial structure of digital intensive firms differs from the one of less digitalised firms, thus casting light on the financial needs of digital intensive firms.

Moreover, we will match firm-level data with local level estimate of exogenous changes in credit supply, retrieved from matched firm-bank data using state-of-the-art econometric methodologies. The analysis allows to directly identify the effect of credit supply on digital technology adoption, to assess its significance and symmetry.

Public policies for Going Digital

Public policy significantly affects how the diffusion of new technologies translates into productivity gains, and the extent to which these gains are widespread in the economy.[3] Policy makers can affect many of the areas discussed in the previous sub-section, starting from skills, absorptive capacity, and access to finance.

Policies reducing skills mismatches, enhancing ICT competences, promoting life-long learning – through training of working adults or active labour market policies – and supporting business expenditures for R&D are key to boost absorptive capacity and to allow many firms to benefit from the digital transformation (Andrews, Nicoletti and Timiliotis, 2018[91]; Berlingieri et al., 2020[6]). Policy-makers have also room for intervention in reducing financial barriers to adoption, which are particularly challenging in a knowledge economy where intangibles lack collateral and require significant complementary investments, especially for SMEs (Berlingieri et al., 2020[6]).

Furthermore, competitive pressures, regulation and trade are other areas in which policy can have an important role. Competitive pressures have the potential to foster managerial quality and to induce higher returns to adoption (Andrews, Criscuolo and Gal, 2016[4]; Andrews, Nicoletti and Timiliotis, 2018[91]) (Andrews, Criscuolo and Gal, 2016[4]).

Workers' mobility affects technology diffusion given its important link with knowledge spillovers that can boost technology adoption. In this context, occupational licenses, non-compete clauses, or increases in barriers to skilled migration may reduce mobility and in turn slowdown diffusion (Marx, Strumsky and Fleming, 2009[128]; Marx and Fleming, 2012[129]; Kerr, 2018[130]; Hermansen, 2019[131]).

Data portability, inter-operability and regulations related to data also have the potential to affect competition and diffusion of digital technologies.

Trade openness is not only related to higher competitive pressures on incumbents, but also favours knowledge spillovers that arise among trading partners (Crespi, Criscuolo and Haskel, 2008[132]; Criscuolo, Haskel and Slaughter, 2010[133]; Bloom, Draca and Van Reenen, 2016[96]), as well as increases market size and the expected profits of adoption (Acemoglu and Linn, 2004[134]; OECD, 2015[1]). In this sense, reducing barriers to trade may boost technology diffusion.

Uncertainty may also challenge technology diffusion, deterring or delaying adoption of new technologies and making (especially laggards) firms more cautions in investing (Bloom, Bond and Van Reenen, 2007[135]). In this sense policy should oriented at reducing uncertainty and enabling experimentation.

A key take-away from this discussion is that not a single policy but a comprehensive policy mix affecting incentives and capabilities is required to boost technology diffusion and returns to adoption (Andrews, Criscuolo and Gal, 2016[4]; Nicoletti, von Rueden and Andrews, 2020[136]; Berlingieri et al., 2020[6]).This mix should include both demand-side measures, including those related to promoting the awareness of new technologies, developing absorptive capacity and reducing risks, together with supply-side measures ensuring competition, credit, addressing the regulatory challenges of the digital era, improving knowledge production and sharing, and fostering experimentation. These policies are likely to bring double dividends, as they not only affect technology adoption and productivity growth, but may also have positive implications for business dynamism and inclusiveness (OECD, 2015[1]; OECD, 2018[137]; Calvino, Criscuolo and Verlhac, 2020[138]).

In Italy, public policies for firm digitalisation have been significantly boosted and restructured since 2016, with the introduction of the National Industry 4.0 Plan. With it, and with its further developments named Firm 4.0 (2017) and Transition 4.0 (2019), the Italian government aimed at developing a coherent framework to collect various policy interventions involving financial incentives for digital adoption, support to innovation and R&D, and support to the diffusion of digital knowledge and skills among firms. Central to this plan was the provision of a significant tax incentive (the "hyper-depreciation") for investments in tangible advanced digital technologies (so-called Industry 4.0 technologies), that came into effect in 2017. This measure introduced a total tax depreciation of up to 250% of the cost of new "smart" and interconnected equipment. Since 2020, the tax depreciation has been substituted with a tax credit, in order to benefit also firms with zero or negative profits (which may be firms who have incurred substantial expenditures to grow).

Several other policies for innovation were included in the Plan. Most of them were into effect before 2016, but were strengthened and widened over time. An R&D tax credit was introduced in 2015. Over the years, several changes have involved the types of eligible expenditures and the credit rates. In its most recent version, the policy covers both R&D, expenditures incurred for process and product innovation, and expenditures for the development of industrial designs. Tax credit rates range from 10% to 20% of the volumes.

Since 2012, the Italian government had introduced a set of policies to support innovative start-ups. The "Start-up Act" encompassed a wide set of interventions to ease access to equity and credit markets, reduce red tape and administrative costs, provide a more flexible labour market legislation, and support brain gain. The Start-up Act has generated positive effects on asset accumulation (particularly of intangible assets) and value added of beneficiary firms, while relaxing their financial constraints on both equity and credit markets (Manaresi, Menon and Santoleri, 2021[139]). Since 2015, a similar though less generous policy was introduced to support innovative SMEs.

The Plan recognises also the importance of supporting the diffusion of digital knowledge, skills and capabilities among firms to allow them to fully benefit from digitalisation. For these purposes, it encompasses two interventions.

First, it established a network of local-level institutions aimed at orienting firms in the digitalisation process, improving their knowledge of existing technologies, and helping them understand their skills gaps and mismatches. The Industry 4.0 Network encompasses three types of institutions: the Digital Firm Points (*Punti Impresa Digitale* – PID), the Digital Innovation Hubs (DIH), and the Competence Centres (OECD, 2020[18]). In the view of the policy-maker, the PIDs active in all Italian regions should represent the first contact point for firms that are willing to strengthen their digitalisation. PIDs offer trainings on Industry 4.0 technologies, assess the digital readiness of the firm, provide mentoring, and information on financial support. Finally, they offer orientation towards more specialised structures, such as the DIH and the Competence Centres. The Digital Innovation Hubs are administered by the Italian Industrial Association and are aimed at raising awareness, providing training, and orienting the firm towards the Competence Centre that is most relevant for its business. The Competence Centres represent the most advanced stages of the Industry 4.0 Network: they are eight public-private partnerships aimed at supporting digitalisation in various fields (such as smart manufacturing, big data, advanced robotics, cybersecurity) and distributed over the Italian territory.

Second, since 2018, the Plan included a tax credit for expenditures incurred to train workers in advanced digital skills ("*Credito d'imposta Formazione* 4.0"), which covers 30-50% of all expenditures incurred (including employee wages during the hours of training). The policy was designed to favour mostly micro and small firms, which can benefit from a higher tax credit relative to larger firms.[4] Despite its generosity, the take-up of this measure in its first two years of adoption has been relatively low and the majority of financial resources allocated were not used. Aside from some complex bureaucratic steps that were initially required and some limitations on the eligibility of training expenditures that have been subsequently removed,[5] one key factor behind the low take-up of this and other digital policies is the lack of awareness of them by firms. According to a recent survey by ISTAT, in 2019 still more than 50% of Italian firms were unaware of the presence of the Industry 4.0 Plan (ISTAT, 2020[140]).

Our data allows us to study several of these policies. First, thanks to information on the localisation of each PIDs and DIH, we study whether the presence of these institutions is associated with stronger spillovers in digital technology adoption among firms. Second, we exploit the R&D survey to assess how the introduction of the R&D tax credit is associated with changes in the amount of R&D and in its distribution across firms. Finally, we perform a policy evaluation of the hyper-depreciation policy, with additional details presented in the many body of text.

Within-firm determinants of the digital transformation

The skills of the workforce

Digital technologies are not only complementary among themselves: the skills of the workforce are key factors that may favour technology adoption and its returns. Figure A C.4 precisely focuses on the complementarities between skills, technology adoption and returns to adoption.

In particular, panel A of Figure A C.4 plots adoption rates of different digital technologies focusing separately on firms that have a share of workers with at least a bachelor degree in the top-quintile (i.e., just about higher than 20%, this group of firms is labelled high-skilled), other firms (low-skilled).[6] The figure shows that firms with a high share of high-skilled workers are typically more likely to adopt digital technologies. This is true for most groups of digital technologies, but for enabling technologies, which are adopted more homogeneously among high- and low-skilled firms.

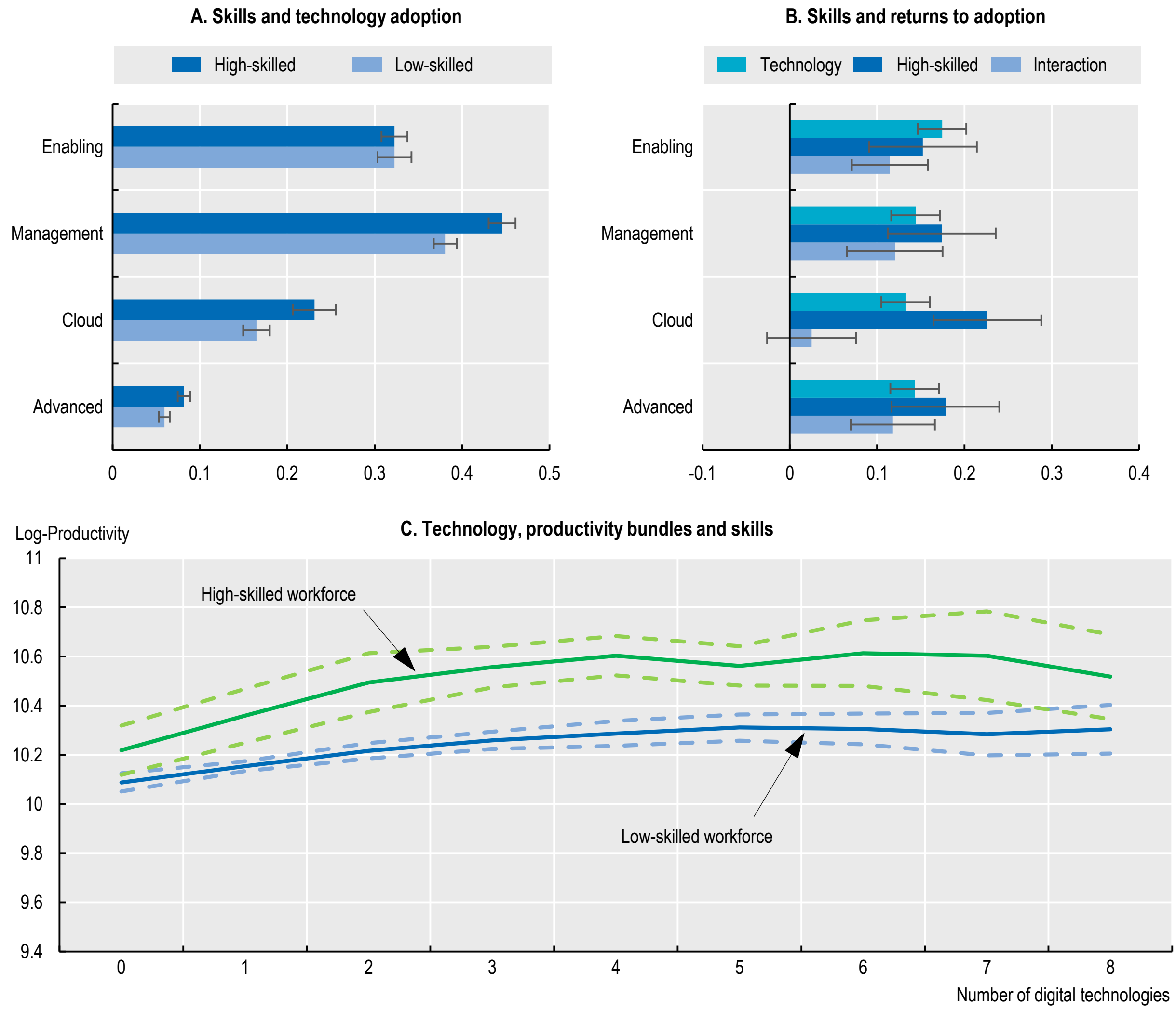
Panel B focuses instead on how labour productivity is correlated with technology adoption, skills, and their interaction. The top bar depicts the correlation between technology adoption and productivity, the middle bar the correlation between being a high-skilled firm and productivity, and the low bar the role of the interaction between the two. The figure suggests that both technology adoption and skills have positive returns in terms of productivity, and that there exist significant complementarities between technology and skills for enabling, management and advanced technologies.

Besides increasing the returns of each different technology, skilled workers may help the firm manage the complexity of using technology bundles. This is explored in panel C of Figure A C.4, which plots the results of estimating the model:

$$y_{it} = \sum_{k=1}^{12} \beta_k NoTech_{it}^k + \sum_{k=1}^{12} \delta_k NoTech_{it}^k \times HighSkilled_{it} + \lambda_{rst} + Size_{it} \times Age_{it}\theta + \varepsilon_{it}$$

where the dependent variable is labour productivity of firm *i* measured in year *t*. For a given number k of digital technologies, the distance between the green and blue line in panel C of Figure A C.4, corresponding to the coefficient δ_k of the empirical model, can be considered a proxy of the productivity gains from having a high-skilled workforce. The figure shows that the relationship between the number of technologies adopted and labour productivity is stronger for firms having a high-skilled workforce. In particular, the green line is steadily increasing at least until bundlings of four different technologies, and then remains constant. Conversely, for low-skilled firms (blue line) the relationship appears generally flatter, if not decreasing – although less precisely measured – when the number of technologies measured is large enough.

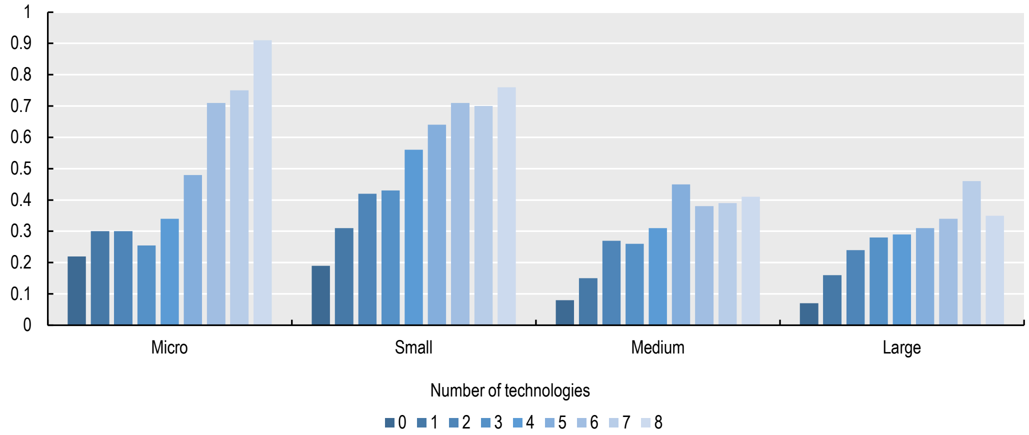
Figure A C.4. Adoption rates by skill-intensity of the workforce and labour productivity gains from technology adoption and skill-intensity of the workforce



Note: Results of panel A are obtained from a linear probability model of technology adoption on a high-skilled dummy variable. Results of panel B are obtained from a regression of log-labour productivity on a dummy equal to 1 if the firm adopts one specific technology, a dummy equal to 1 if the firm has a high-skilled workforce, and the interaction between the two. Results of panel C are obtained from a regression of log-labour productivity on the number of digital technologies adopted interacted with a dummy equal to 1 if the firm has a high-skilled workforce. All models control for sector-region and size-age unobserved heterogeneity. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT data.

Moving beyond average results, in Figure A C.5, we study whether these productivity gains change by firm size.

Figure A C.5. Productivity gains of a high-skilled workforce by firm size and number of digital technologies



Note: Results of a regression of log-labour productivity on the number of digital technologies adopted interacted with a dummy equal to 1 if the firm has a high-skilled workforce, estimated separately for micro, small, medium and large firms. All models control for sector-region and size-age unobserved heterogeneity. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors' elaboration on ISTAT data.

To provide a better understanding of the relationship between skills of the workforce and digital technology and obtain an estimate of the complementarity between the two, we need to move towards a more structural approach to firm production. We estimate a production function that features three types of labour input: workers with primary education, those with secondary education, and those with tertiary education (see Box A C.1 for a discussion of the production function estimation procedure). Importantly, the production function features complementarity between advanced digital technologies and each type of workers.

Box A C.1. Estimating complementarities between digital technologies and inputs: a production function approach

Production function estimation

Production function estimates are based on a model of firm optimal choice of inputs to maximise its profits. The model usually assumes that production uses inputs according to a function *f(.)* such as:

$$Y = f(X, \beta, \Omega)$$

where Y is output (usually measured either in revenues or value added), X is a set of inputs, β is the vector of input elasticities, and Ω represents Hicks-neutral productivity (usually referred to as multifactor productivity).

In order to estimate input elasticities and productivity, the researcher needs to assume (i) a functional form for *f(.)*, (ii) a law-of-motion for productivity, and (iii) the existence of at least one fully-flexible input (i.e., an input that can be freely adjusted period-by-period to cope with shocks to demand and/or productivity). More generally, for each input X, the researcher will have to assume whether it is flexible or subject to adjustment costs, and whether it is static or dynamic (i.e., whether its effect on production realises in a single period or is persistent).

With these sets of assumptions, the production function can be estimated using the control function approach (Wooldridge, 2009[23]; De Loecker and Warzynski, 2012[141]).

Production function estimation with digital technologies and heterogeneous inputs

In our workhorse estimate, we assume that the firm optimises a value-added production function with two types of capital (tangible and intangible capital), three types of labour input (workers with primary, secondary, tertiary education), and advanced digital technologies (as an additional inputs). The model assumes that Hicks-neutral productivity follows a first-order stochastic Markov process. Formally, if we define small letters to define the log of a variable, we estimate the model:

$$y = (\beta_T + \beta_{DT} * D)k^T + (\beta_I + \beta_{DI} * D)k^I + (\beta_L + \beta_{DL} * D)l^L + (\beta_M + \beta_{DM} * D)l^M + (\beta_H + \beta_{DH} * D)l^H + \beta_D D + \omega + \varepsilon$$

where D is a dummy = 1 if the firm has adopted advanced digital technologies; k^T and k^I are tangible and intangible capital; l^L, l^M, and l^H are primary, secondary, and tertiary workers; ω is Hick-neutral productivity and ε is an error term. To overcome the problem of zeros in capital and employment variables, we exploit the inverse-hyperbolic sine transformation to all continuous variables (Bellemare and Wichman, 2020[142]).[1] All results discussed in this paper are, nonetheless, robust to the use of a standard log-transformation.

We estimate the production function for year 2018, separately for each one-digit sector.

Production function with heterogeneous managerial quality

Following Schivardi and Schmitz (2018[89]), we posit that managerial quality may result in better ability to use digital technologies together with other inputs. Operationally, we distinguish firms in two groups: those whose CEO has a tertiary education and those whose CEO has at most a secondary education. We then estimate the above production function separately for the two types of firms.

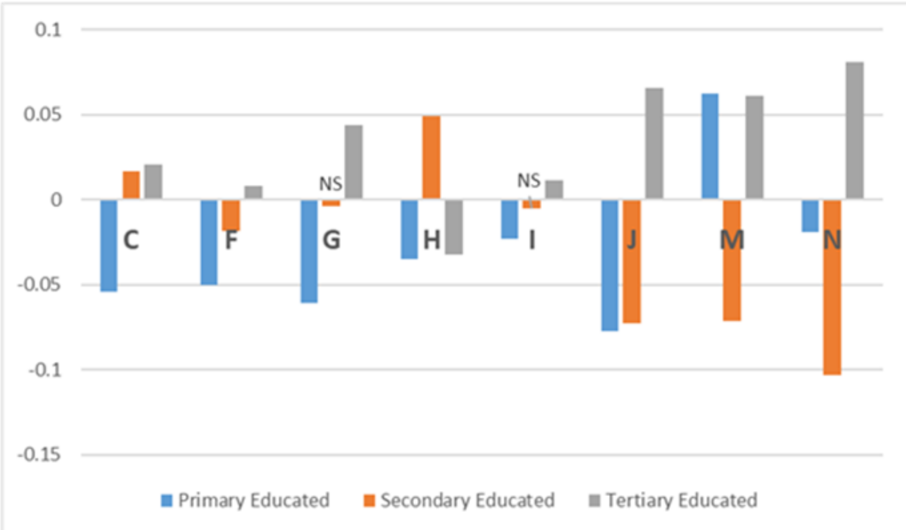
Note:
1: The inverse-hyperbolic sine (or area hyperbolic sine) of a variable x is defined as:

$$\operatorname{asinh}(x) = \log(x + \sqrt{x^2 + 1})$$

Assessment of complementarity and substitutability between labour and advanced digital technologies is based on the sign of the cross-derivative of the inputs in the production function. If returns to one type of employment increase when advanced technologies are adopted (cross-derivative higher than zero), the two inputs are considered as complements. The opposite holds for substitutability (cross-derivative lower than zero).

Based on the methodology outlined above, Figure A C.6 provides evidence of complementarity (positive bar) between tertiary-educated workers and advanced digital technologies, and of substitutability in most sectors (negative bar, except in Professional services, M) between primary-educated workers and those technologies. The evidence is more mixed for secondary-educated workers, with evidence supporting substitutability in most services sectors, with the relevant exception of Transportation and storage (H).

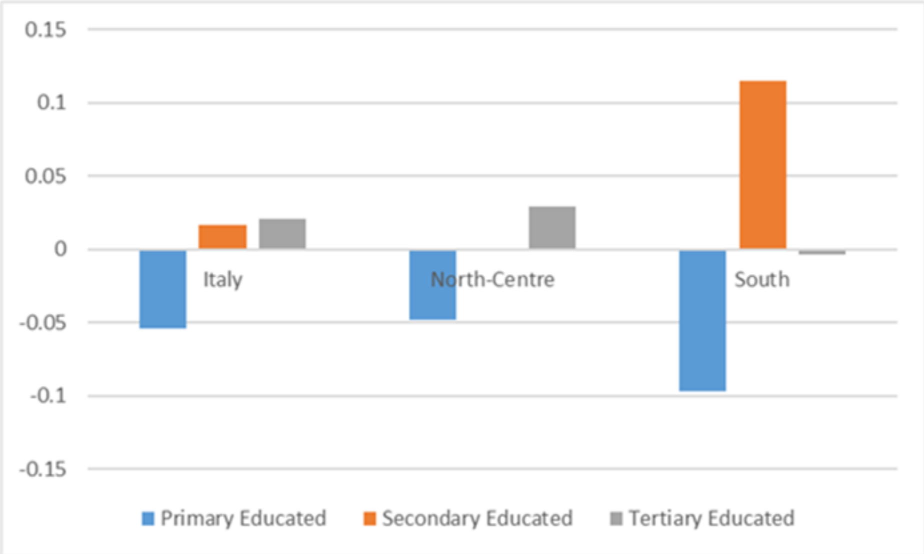
Figure A C.6. Estimated complementarity between advanced digital technologies and workers with different education



Note: Complementarities between advanced digital technologies and workers with different skills, estimated at the sector level exploiting the production function presented in Box A C.1. Sector C refers to Manufacturing; F Construction; G: Wholesale and retail trade; H: Transportation and storage; I: Accommodation and food services; J: Information and communication; M: Professional, scientific and technical activities; N: Administrative and support services.
Source: Authors' elaboration on ISTAT data.

As discussed in Annex B, the digital gap of Italian firms is strongly correlated with the geographical divide in firm's productivity. In particular, firms in the North are both more likely to adopt digital technologies and displaying higher productivity. Our structural framework allows to study whether lower digital technology adoption in the South may be related to geographic differences in complementarities with workforce education.

Figure A C.7. Estimated complementarity between advanced digital technologies and workers with different education by geographic area



Note: Complementarities between advanced digital technologies and workers with different skills, estimated separately in North-Centre and Southern Italy exploiting the production function presented in Box A C.1. Sector-level estimates are aggregated exploiting sector-level value-added shares computed for the entire Italian economy (to avoid sector composition to affect the geographical comparison).
Source: Authors' elaboration on ISTAT data.

A similar analysis to the one carried out in Figure A C.6 is therefore done separately focusing on firms located in different regions, and distinguishing overall dynamics in Italy from the one observed in the North-Centre and South. Figure A C.7 shows indeed the geographical heterogeneity in complementarity and substitutability patterns between labour and advanced digital technologies, focusing on the manufacturing sector. In the North-Centre advanced digital technologies are complementary to tertiary-educated workers, while in the South, somehow surprisingly, there is evidence of complementarity only with secondary-educated workers.

This could possibly be explained by the fact that the technologies adopted may be different in the South and in the North-Centre, or that narrower defined sectoral specialisation differs. It could also be that the relationship between skills and education is different (for instance, tertiary-educated workers in the South might be less likely to have a STEM major). Finally, other factors may reduce the returns to tertiary education in the South, such as possibly lower managerial skills. The richness of the data will be exploited to dig this further.

Management skills

Section 1 in this Annex has discussed the increasing evidence on the role of managerial skills and practices in the adoption and effective use of more advanced digital technologies.

Over the course of the last ten years, several researches have highlighted a gap in the managerial capabilities of Italian firms relative to other OECD countries. For instance, Bloom, Sadun and Van Reenen (2008[30]) highlight that Italian firms, particularly those owned by families, exhibit a significant gap vis-à-vis US companies (see also Bugamelli et al. (2012[143])).

It is, thus, crucial to assess whether and the extent to which this gap explains low technology adoption rates, particularly among SMEs.

This section provides new insights on the role of management skills and practices for the digital transformation. It first analyses both descriptively and through the lenses of a structural model of firm production how the skills of top-managers affect the propensity of firms to adopt advanced digital technologies, and the returns and complementarities of inputs in the firm's production function. The analysis then turns to the role of middle-managers. Due to the lack of data, existing research has largely overlooked their role in shaping firm's productivity, focusing almost exclusively on top-executives.

Data

Data on managers are available from 2012 to 2016 from the registries administered by the Italian Chambers of Commerce (Unioncamere). We identify the top-executives as CEOs, single owners, etc.

Middle managers are identified as those individuals that have a managerial role (reported to the Chamber of Commerce) and are not member of the executive board (we exclude roles that are external to the firm, such as auditors).

Management skills varies widely across firms, by sector, size, geographical area, and they are positively correlated with firm productivity

A first step to better understand the role of management skills and practices for the digital transformation of Italian firms consists in investigating the distribution of managerial skills across different sectors, regions, and groups of firms.

Figure A C.8 focuses on the management skills distribution, proxied by the educational attainment of top executives, across different sectors of the Italian economy. While the overall economy appears characterised by the prevalence of secondary-educated top executives, significant sectoral heterogeneity emerges.

Sectors like Construction (F), Transportation and storage (H), or Other services (S, which includes a number of personal service activities) exhibit the highest shares of primary-educated top executives, while sectors like Professional, scientific and technical services (M) or Information and communication (J) exhibit the highest shares of tertiary-educated top management.

The distribution of managerial skills is also highly heterogeneous across Italian macro-regions, even after accounting for differences in sectoral specialisation. This is evident from Figure A C.9: the blue bars indicate the extent to which shares of firms with high-skilled top executives in the North-West, Centre and South of Italy are different from the same share in the reference macro-region, North-East, with confidence bands reflecting the precision of these point estimates.

High-skilled managers are more prevalent among firms in the North-East, with increasingly lower shares of firms with high-skilled top executives in the North-West, Centre and South.

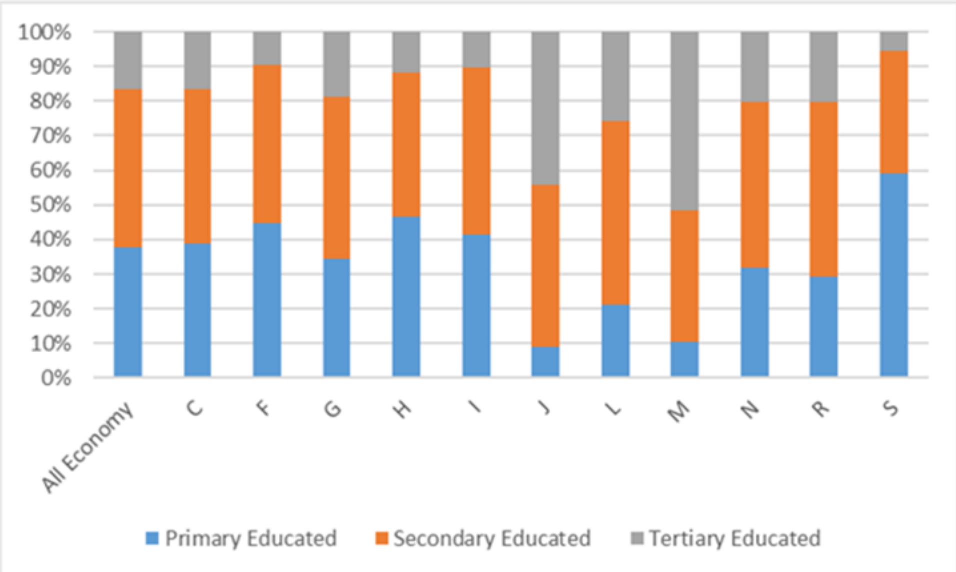
Firm size also appears to be correlated to management skills. This is investigated in Figure A C.10, which shows the extent to which high-skilled managers are distributed across firms with different size classes. The blue bars indicate differences with respect to the baseline category (micro firms), with confidence bands reflecting the precision of these point estimates.

The presence of high-skilled managers is notably higher in larger firms, with a significant gap between micro-small firms and large ones that cannot be explained by sectoral or geographical characteristics.

Differences in management skills across firms with different age appear instead less clear-cut, once other confounding factors (i.e., sector, geography, firm size) are accounted for. This is shown in Figure A C.11, which suggests that firms less than 5 years old (reference category), 6-10 years old, or more than 10 years old have similar shares of high-skilled management.

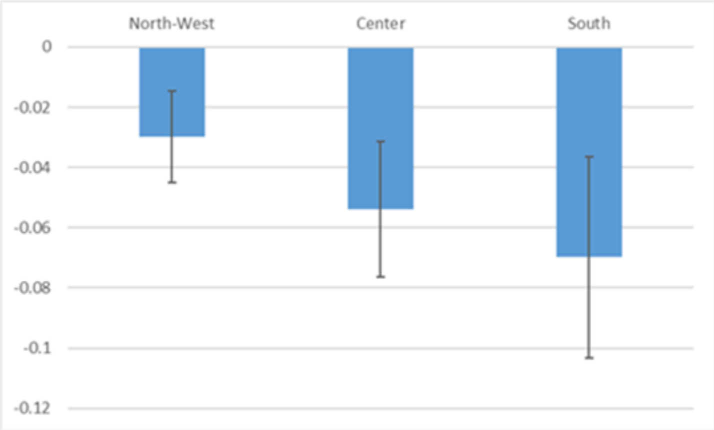
Looking at the share of high-skilled management across the productivity distribution provides instead additional interesting insights. These are shown in Figure A C.12, which highlights that – holding sectoral and geographical characteristics, as well as firm age and size effects fixed – leading firms, i.e., those in the top 10% of the productivity distribution, have significantly higher shares of high-skilled managers than all other firms (the slightly higher share among firms at the bottom 10% with respect to those in deciles 2-9 are driven by young firms).

Figure A C.8. Share of firms by skill of top-executive, all economy, sectors



Note: Sector C refers to Manufacturing; F Construction; G: Wholesale and retail trade; H: Transportation and storage; I: Accommodation and food services; J: Information and communication; L: Real estate; M: Professional, scientific and technical activities; N: Administrative and support services, R: Arts, entertainment and recreation; S: Other services.
Source: Authors' elaboration on ISTAT data.

Figure A C.9. Share of firms with HS top executive, by geographic area, holding fixed firm's sector

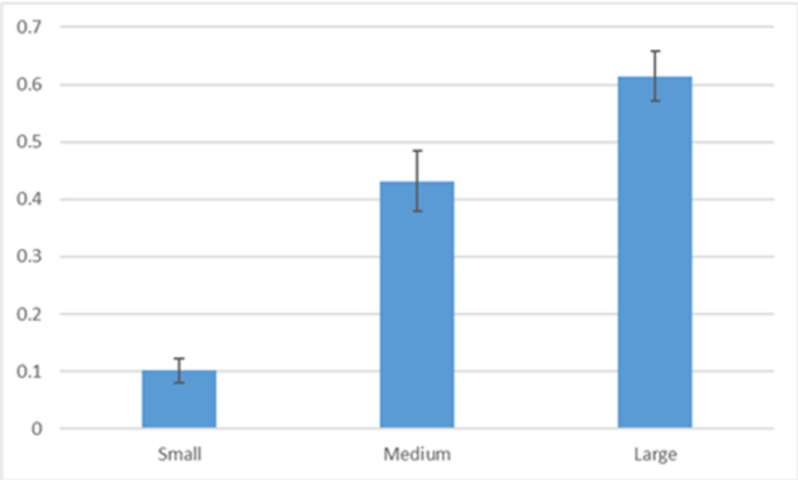


Note: Results of a estimating the following model:

$$HSM_{is} = \beta_1 NW_i + \beta_2 C_i + \beta_3 S_i + \gamma_s + \varepsilon_i$$

where *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *NW*, *C*, *S*, are dummies equal to 1 if the firm is located in the North-West, Centre or South of Italy, respectively; γ_s is a sector fixed-effect, and the error term is allowed to display serial correlation at the sector level.
Source: Authors' elaborations on ISTAT data.

Figure A C.10. Share of firms with HS top executive, by size, holding fixed firm's sector and area

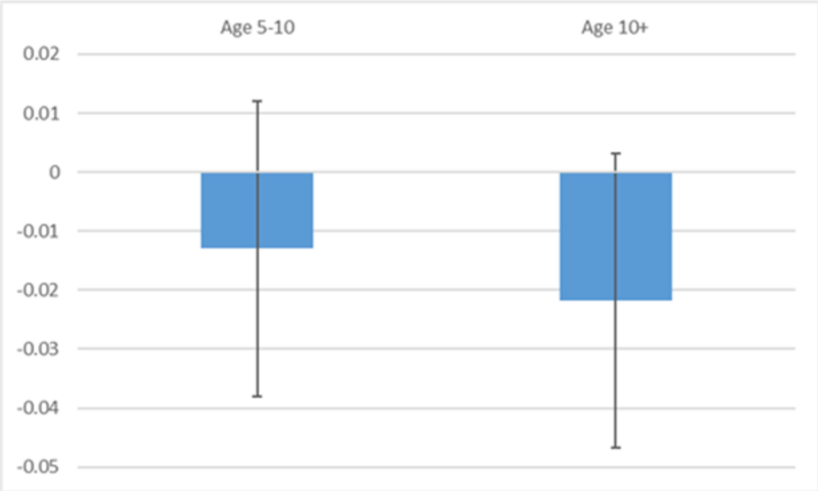


Note: Results of a estimating the following model:

$$HSM_{isr} = \beta Size_i + \gamma_s + \lambda_r + \varepsilon_i$$

where *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *Size* are dummies for the firm's size class; γ_s, λ_r are sector and region fixed-effect, and the error term is allowed to display serial correlation at the sector level.
Source: Authors' elaborations on ISTAT data.

Figure A C.11. Share of firms with HS top executive, by age, holding fixed firm's sector, area and size

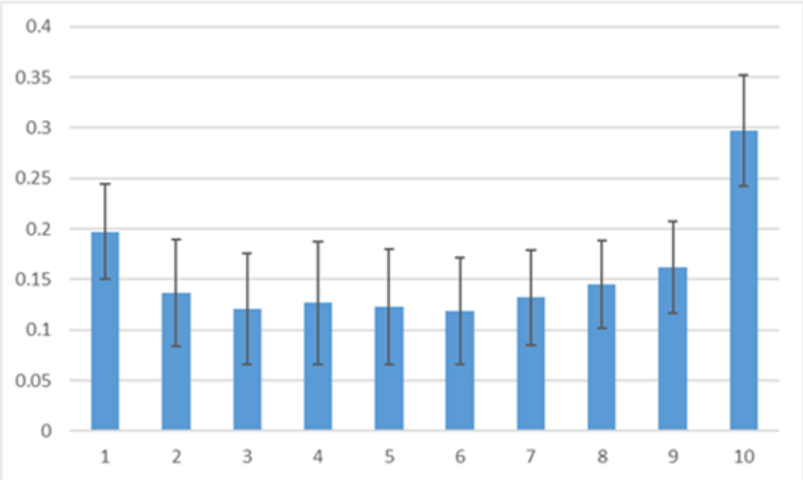


Note: Results of a estimating the following model:

$$HSM_{isr} = \delta Age_i + \beta Size_i + \gamma_s + \lambda_r + \varepsilon_i$$

where *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *Age* are firm's age dummies; *Size* are dummies for the firm's size class; γ_s, λ_r are sector and region fixed-effect, and the error term is allowed to display serial correlation at the sector level.
Source: Authors' elaborations on ISTAT data.

Figure A C.12. Share of firms with HS top executive, by productivity decile, holding fixed firm's sector, area, size and age



Note: Results of a estimating the following model:

$$HSM_{isr} = \theta PD_i + \delta Age_i \times Size_i + \gamma_s + \lambda_r + \varepsilon_i$$

where *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *PD* are firm's productivity decile dummies; *Age* are firm's age dummies; *Size* are dummies for the firm's size class; γ_s, λ_r are sector and region fixed-effect, and the error term is allowed to display serial correlation at the sector level.
Source: Authors' elaborations on ISTAT data.

Firms with more skilled top-executives are more likely to adopt technologies, and have higher returns to technology bundles

After having explored the distribution of management skills and in particular the relative presence of high-skilled management across different dimensions, this sub-section focuses on the extent to which skills of top executives are related to digital technology adoption and returns to adoption in Italian firms. This builds upon and complements the discussions and findings related to the skills of the workforce presented in the previous section.

In this context, Figure A C.13 focuses on the extent to which technology adoption is related to the skills of top executives, highlighting differences in adoption rates of different digital technologies in two different groups of firms: those guided by high-skilled managers and those by low- or middle-skilled ones.

As evident when comparing the orange and blue bar in Figure A C.13, for all technologies considered adoption rates are higher in firms with high-skilled management, and this is not driven by other confounding factors that have been accounted for (i.e., sector, macro-region and size-age unobserved heterogeneity). The gap in adoption rates appears particularly significant for management software and enabling technologies, which have been also shown to have significant complementarities with other advanced digital technologies.

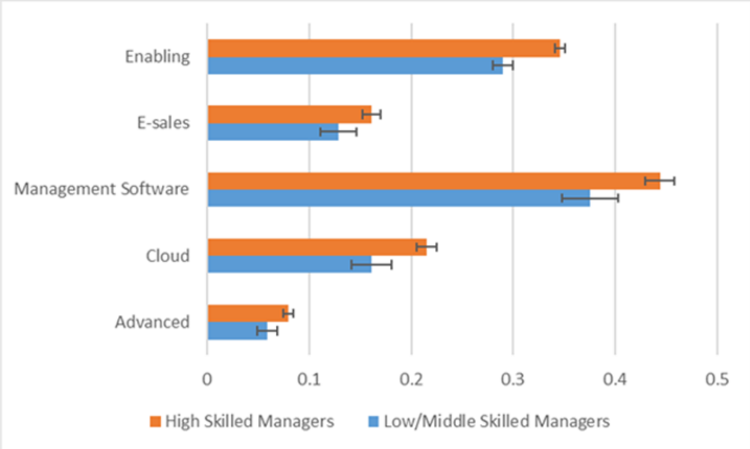
Indeed, management skills appear also related to the digital sophistication of firms, as proxied by the number of different digital technologies adopted. This is shown in Figure A C.14, which focuses on the share of firms with high- or low-skilled top executives separating out businesses that are increasingly digitally sophisticated, i.e., that have adopted an increasing number (from zero to twelve) of different digital technologies.

Figure A C.14 shows that having a high-skilled management tends to be more likely in more digitally sophisticated firms, and this is particularly true when considering firms that have adopted up to nine different digital technologies.[7]

Taking a perspective similar to the one outlined in the previous section focused on the skills of the workforce (see the discussion about Figure A C.3), we explore the returns to digital technology adoption by skills of the top executives, focusing on firms adopting an increasing number of digital technologies.

Figure A C.15 shows that firms led by high-skilled managers have higher levels of labour productivity for any given number of technology adopted. Furthermore, it shows that the relationship between the number of technologies adopted and labour productivity tends to be stronger in firms managed by high-skilled top executives. Overall, this evidence confirms the relevance of management skills for firm performance and suggests that these may allow to better deal with the complexities that arise when combining different digital technologies.

Figure A C.13. Share of firms adopting technologies by skill of top-executives

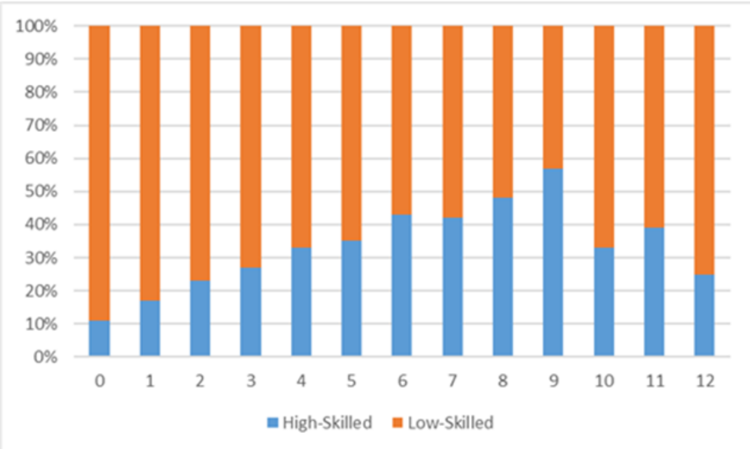


Note: Results of a estimating the following model:

$$Tech_i^k = \alpha HSM_{isr} + \delta Age_i \times Size_i + \gamma_{sr} + \varepsilon_i$$

for each digital technology *k*, where *Tech* is a dummy equal to 1 if the firm *i* has adopted the technology *k* in 2018; *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *Age* are firm's age dummies; *Size* are dummies for the firm's size class; γ_{sr} are sector-region fixed-effects, and the error term is allowed to display serial correlation at the sector level.
Source: Authors' elaborations on ISTAT data.

Figure A C.14. Share of firms with HS top-executive by number of technology adopted

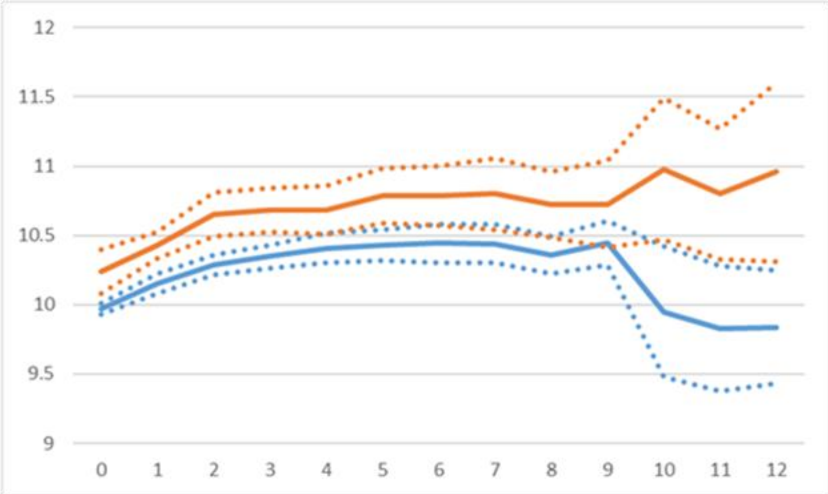


Note: Results of a estimating the following model:

$$HSM_{isr} = \sum_k \beta_k NoTech_i^k + \delta Age_i \times Size_i + \gamma_{sr} + \varepsilon_i$$

where *NoTech* is a dummy equal to 1 if the firm *i* has adopted *k* technologies in 2018; *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *Age* are firm's age dummies; *Size* are dummies for the firm's size class; γ_{sr} are sector-region fixed-effects, and the error term is allowed to display serial correlation at the sector level.
Source: Authors' elaborations on ISTAT data.

Figure A C.15. Labour productivity by number of technologies adopted and skill of the top-executive



Note: Results of a estimating the following model:

$$\log y_i = \sum_k \beta_k NoTech_i^k + HSM_{isr} + \sum_k \theta_k NoTech_i^k \times HSM_{isr} + \delta Age_i \times Size_i + \gamma_{sr} + \varepsilon_i$$

where *y* is labour productivity, *NoTech* is a dummy equal to 1 if the firm *i* has adopted *k* technologies in 2018; *HSM* is a dummy equal to 1 if the manager of firm *i* has a tertiary education; *Age* are firm's age dummies; *Size* are dummies for the firm's size class; γ_{sr} are sector-region fixed-effects, and the error term is allowed to display serial correlation at the sector level.

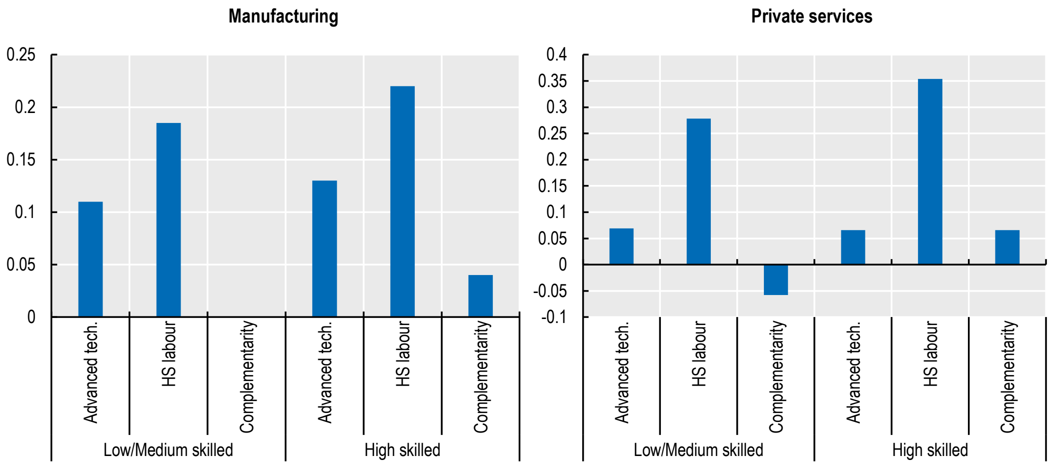
Source: Authors' elaborations on ISTAT data.

Management skills boost the returns of worker skills, advanced digital technologies, and their complementarity

While the previous sub-section has focused on the role of management skills alone or in relation with technology adoption, this one addresses another key related issue: the extent to which management skills are able to boost returns to worker skills, advanced digital technologies, and their complementarity.

This is explored using the structural framework discussed in Box A C.1, with results summarised graphically in Figure A C.16. The figure highlights not only that returns to advanced technologies and high-skilled labour tend to be higher in firms managed by high-skilled top management, but also that those are more complementary. This suggests that management skills plays a key role enabling firms to leverage the complementarities between other labour inputs and advanced technologies, which are crucial to boost firm productivity.

Figure A C.16. Returns to advanced technology, high-skilled labour, and their complementarity

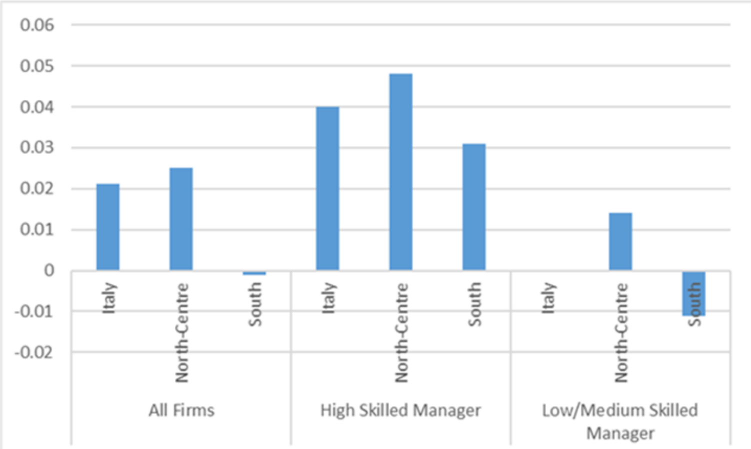


Note: The figure plots the estimated elasticities of output to advanced digital technologies, high-skilled labour, and their interaction, following the production function methodology discussed in Box A C.1, separately for high and low/medium skilled managers.
Source: Authors' elaborations on ISTAT data.

As highlighted in Figure A C.17, complementarities between skills and advanced digital technology are markedly different in the North-Centre and the South. In the North-Centre, advanced digital technologies are complementary to high-skilled (tertiary-educated) workers, while in the South, these appear more as substitutes. Figure A C.17 further focuses on the extent to which patterns of complementarity and substitutability between high-skilled workers and advanced digital technologies differ among firms managed by high-skilled or low-skilled top executives.

Interestingly, Figure A C.17 shows that, when firms are managed by high-skilled top executives, the complementarity between high-skilled labour and advanced digital technology adoption is positive also in the South of Italy. This points to the importance of fostering management skills to enable firms, especially in the South of Italy, to fully realise the potential arising from a complementary use of labour and technology.

Figure A C.17. Complementarity between advanced technology and high-skilled labour by geographic area



Note: The figure plots the estimated elasticities of output to advanced digital technologies, high-skilled labour, and their interaction, following the production function methodology discussed in Box A C.1, separately for high and low/medium skilled managers and for geographic area.
Source: Authors' elaborations on ISTAT data.

Besides top executives, middle managers matter

Beyond the key role of top executives, examined in depth in the previous sub-section, the following paragraphs take a different perspective focusing more closely on the managerial skills of a specific group of executives: middle managers.

Focusing on middle managers represents a novel contribution into the exploration of the role of organisational practices and firm structure for technology adoption and business performance.

This is particularly original considering the key role of different organisational layers, especially beyond top management, in affecting information flows and decision making, respond to technological change or to challenges possibly due to the use of a new technology, and the limited number of existing studies focusing directly on middle managers.

A first descriptive analysis in this context consists in exploring the determinants of the probability of having at least one middle manager, especially focusing on the role of firm size and education of top executives.

This is shown in Figure A C.18, which highlights that middle managers are more common among larger firms and that more skilled top executives are more likely to make use of middle managers. This is true when holding fixed age-size-sector-region-specific confounding factors.

Given the important role of top executives' education highlighted in the previous sub-section, Figure A C.19 further explores the extent to which management skills affect the probability of having a high-skilled (highly educated) middle manager.

The figure shows that high-skilled top executives hire significantly more high-skilled middle managers than low-skilled top managers. This difference is particularly pronounced among micro and small firms.

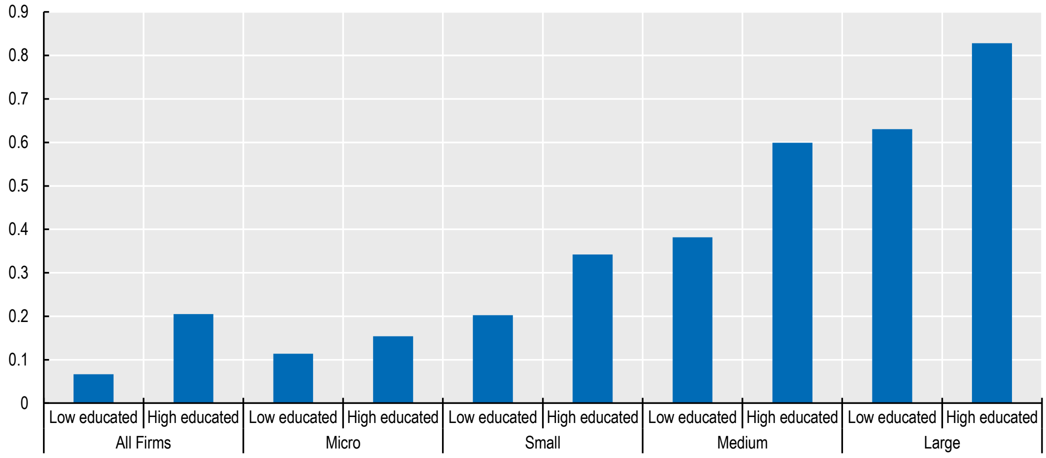
Figure A C.20 further explores the extent to which technology adoption is related to the existence and skills of middle managers, beyond the role of the top management skills explored in Figure A C.13.

The figure suggests that the presence of middle managers is associated with higher adoption rates of most advanced digital technologies considered. This is particularly true for enabling technologies and management software, while is less true for online sales. The presence of high-skilled middle managers, instead, is associated with higher use of all digital technologies analysed, exhibiting an incremental effect likely related to the skills of those middle managers.

Furthermore, as shown in Figure A C.21, middle managers – and especially high-skilled ones – seem to play an important role in dealing with technological complexities arising in digitally sophisticated firms (i.e., those adopting a significant number of different digital technologies).

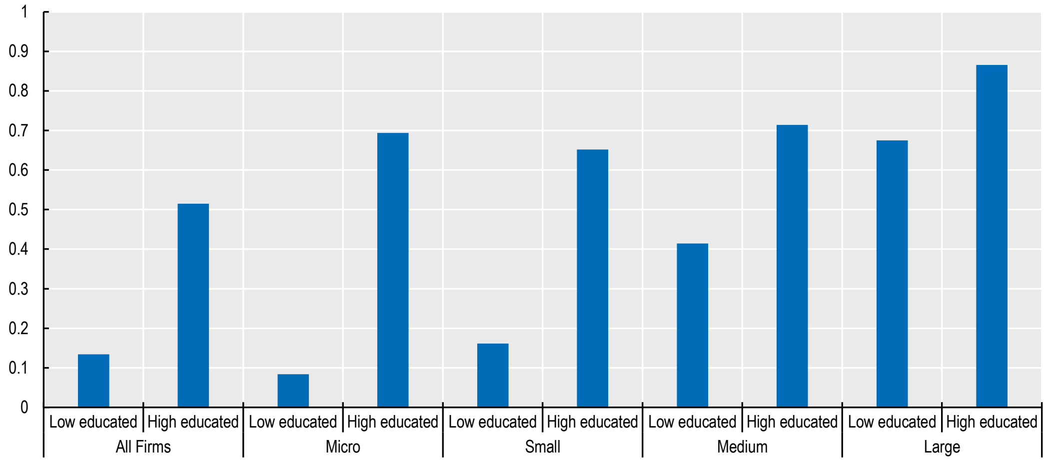
This evidence taken together suggests that existence of assortative matching: high-skilled top executives tend to hire more (high-skilled) middle managers, and overall this is related to higher digital technology adoption. This also suggest that higher adoption rates shown in Figure A C.13 are not only related to the skills of top managers alone, but more likely to a combination of the skills of different layers of management.

Figure A C.18. Probability of having at least one middle manager – by education of the top executives and firm size



Note: The figure reports the results of estimating a linear probability model of the probability of having at least one middle manager on the education of the top-executive, by size of the firm and holding fixed the firm's age and sector-region unobserved heterogeneity.
Source: Authors' elaboration on ISTAT data.

Figure A C.19. Probability of having middle managers with high education – by education of top executive and firm size

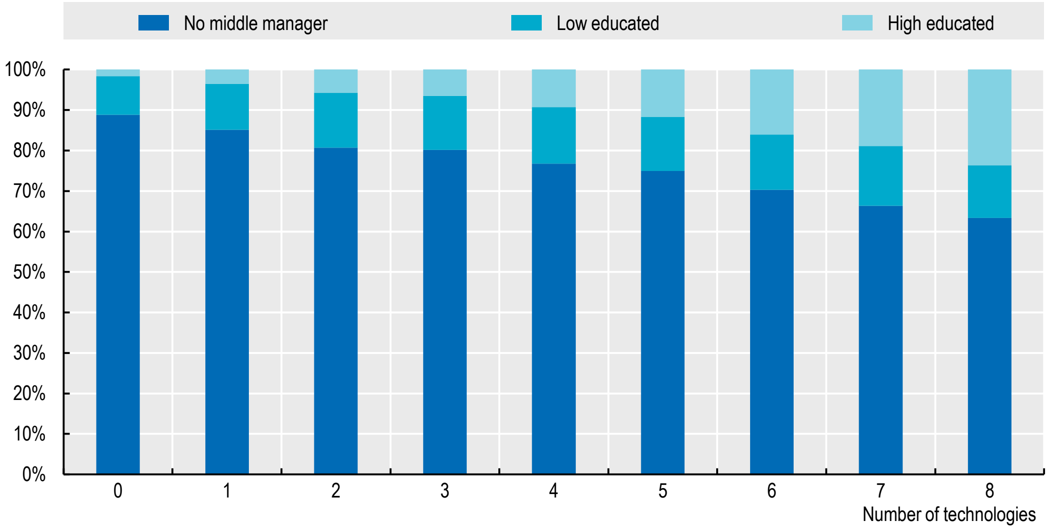


Note: The figure reports the results of estimating a linear probability model of the likelihood of having at least one middle manager with tertiary education (conditional on having at least one middle manager) on the education of the top-executive, by size of the firm and holding fixed the firm's age and sector-region unobserved heterogeneity.
Source: Authors' elaboration on ISTAT data.

Figure A C.20. Technology adoption by existence and education of middle managers – conditional on education of top-executives

Note: The figure reports the conditional probability of having adopted a technology among firms with no middle manager, low/middle skilled middle managers or at least one middle manager with tertiary education, holding fixed sector-region and age-size unobserved heterogeneity.
Source: Authors' elaboration on ISTAT data.

Figure A C.21. Share of firms with no, low-skilled, and high-skilled middle managers, by number of technologies adopted



Note: The figure reports the share of firms with no, low/middle-educated and high-educated middle managers among firms by number of digital technologies adopted.
Source: Authors' elaboration on ISTAT data.

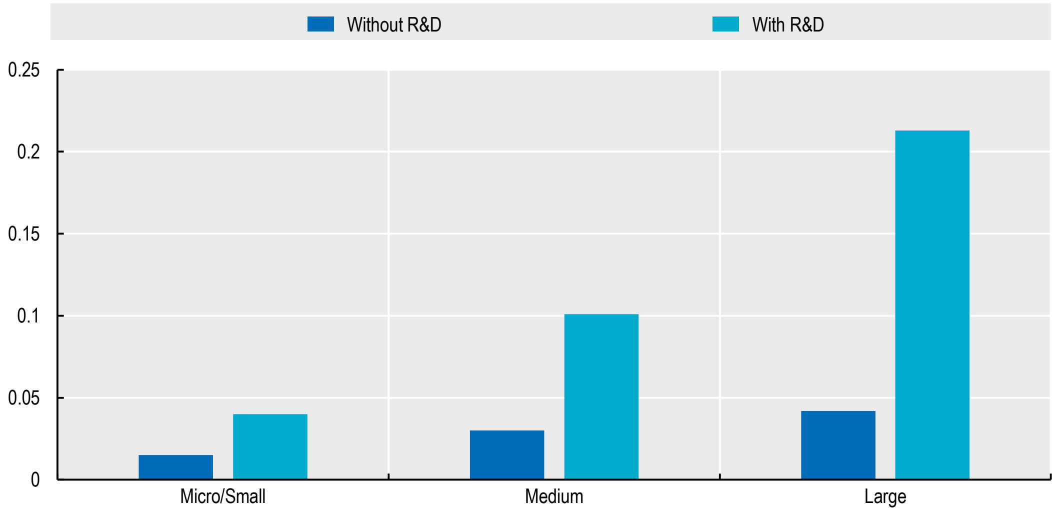
R&D and intellectual property products

This section investigates the relationship between technology adoption and R&D expenditures and intellectual property products such as patents, trademarks, and designs.

R&D boosts firm absorptive capacity

A regression analysis[8] shows that R&D is positively associated with digital technology adoption. Firms which invest in R&D are, indeed, on average 7% more likely to adopt an advanced technology than firms which do not perform R&D. As highlighted in Figure A C.22, this difference in technological adoption rates between R&D and non-R&D firms is increasing in firm size: the probability of technological adoption for R&D performers, compared to non-investors, is twice as high for micro/small enterprises (the likelihood increases from 2% to 4%), more than three times as high for medium-sized enterprises (from 3% to 10%), and more than five times as high for large enterprises (from 4% to more than 20%).

Figure A C.22. Advanced technology adoption by firm size and R&D status



Note: Results of a regression of a dummy equal to 1 if the firm adopts any advanced digital technology on a dummy equal to 1 if the firm has performed any R&D activity, interacted with size dummies, controlling for sector-region and age fixed effects.
Source: Authors' elaboration on ISTAT data.

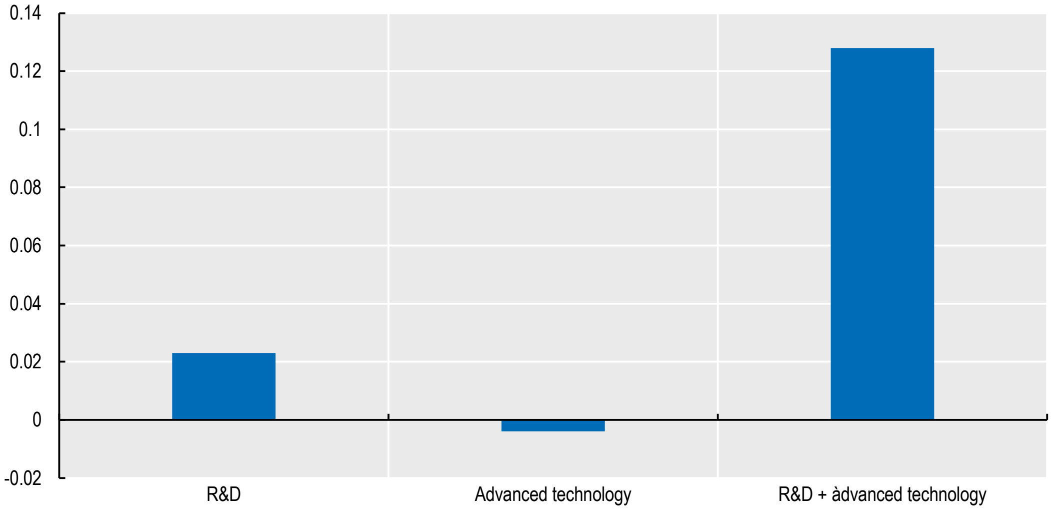
The same type of analysis has been conducted looking at the ownership of intellectual property products (patents, trademarks, and designs). Firms that applied for a patent are more likely to adopt advanced technology than firms that did not: this gap remains quite constant for micro/small and medium-sized enterprises (2 percentage points difference), and it only increases for large enterprises (7 percentage points difference).

Data shows that R&D investments and ownership of IP products are positively correlated. When both are taken into account, only R&D remains significantly correlated with the probability of adopting each type of technology (cloud, enabling, e-sales, management and advanced technologies).

What should be remembered is that patents, trademarks and designs are realisations of, respectively, an innovation, and perceived qualities of the product or the firm. R&D, though, differs from the other intangible assets considered, in that it is an expenditure performed to generate an innovation. A regression analysis[9] shows, in fact, that the likelihood of applying for a patent is higher for firms investing in R&D (Figure A C.23).

More interestingly, the same regression proves also that performing R&D together with adopting an advanced technology increases the probability of applying for a patent by 13 percentage points (Figure A C.23). This complementarity between R&D and advanced technology can be explained by the fact that R&D activities are technology intensive and digitalisation increase firms' capacity to generate innovations.

Figure A C.23. Probability of applying for a patent



Note: Results of a regression of a dummy equal to 1 if the firm has applied for a patent on dummies for R&D activity and advanced digital technology adoption, controlling for sector-region and age fixed effects.
Source: Authors' elaboration on ISTAT data.

Factors outside the firm affecting the digital gap of Italian firms

Spillovers in technology adoption

While the existence of spillovers in innovative activities (such as R&D and patenting) have well been identified in the literature (Bloom, Schankerman and Van Reenen, 2013[144]), the role of spillovers in technology adoption has received much less attention.

Yet, whether they exist or not represents a crucial question both from a scientific and a policy point of view. Spillovers have important implications for growth and welfare. If spillovers are positive, they can strength growth by boosting diffusion. If, instead, they are negative, they could generate long-term equilibria characterised by persistent slow growth. Generally, the existence of spillover may affect the social welfare attainable by a laissez-fair equilibrium. For this reason, their existence represents one important rationale for government intervention.

Our unique data infrastructure allows us to apply, to technology adoption, established methodologies developed to identify spillovers in R&D and patenting (Bloom, Schankerman and Van Reenen, 2013[144]). We define spillovers in the adoption of a digital technology as the correlation between the probability of adoption by one firm and the adoption rates of other firms active in the same market. Crucially, we cannot aim at identifying causal parameters, so we emphasize that we look at correlations, which may be driven by causal effects and/or by correlated shocks to technology opportunities, as exemplified below. To capture the extent of this spillover correlation, we consider the share of revenues generated by adopters in the market.

Formally, for each firm i active in market K in 2018, we compute the variable:

$$SO_{iK}^{-i} = \sum_{j}^{-i} \frac{Y_{jK} \times 1(Tech_{jK} = 1)}{\sum_j Y_{jK}}$$

The share is computed after excluding firm i from the market (to limit the reflection bias, (Manski, 1993[145]; Angrist, 2014[146])). We consider four types of markets K in our analysis:

the three-digit sector *S*, the province *P*, the destination-sector market of exports *X*, and the origin-sector market of imports *M*.[10]

We estimate the effect of spillovers on technology adoption using the following linear probability model:

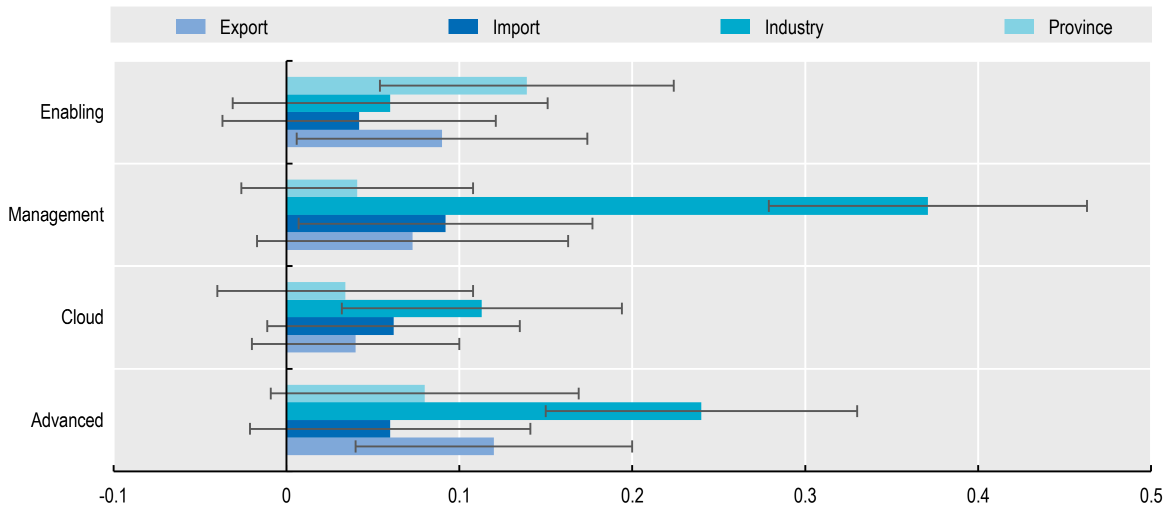
$$1(Tech_i = 1) = \beta_P * SO_{iP}^{-i} + \beta_S * SO_{iS}^{-i} + \beta_X * SO_{iX}^{-i} + \beta_M * SO_{iM}^{-i} + \gamma_s + \lambda_r + \theta_h + \iota_a + \varepsilon_i \qquad (1)$$

where $\gamma_s, \lambda_r, \theta_h, \iota_a$ are a set of two-digit sector, region, size class, and age class fixed effects, and the error-term ε_i is allowed to display serial correlation at the sector level. Our coefficient of interest are the set of β_K that identify how the probability of adopting a technology is affected by the rate of adoption in each market *K*.

The sign (as well as the existence) of spillover effects is ex-ante ambiguous. At one side, knowledge spillovers among firms and the existence of preferences for technology in downstream demand may positively affect β_K. On the other side, the adoption by leader firms of the technology may generate winner-takes-most dynamics that may deter technology adoption by other firms. We may expect this negative channel to be stronger the more the digital market is concentrated, as the benefits of a technology may accrue to a more limited number of firms.

Figure A C.24 displays the results of estimating (1) in our sample, using different technologies as dependent variables.

Figure A C.24. Spillover effects by reference market and by type of technology



Note: Results of estimating model (1) on different technologies.
Source: Authors' elaboration on ISTAT data.

Province-level spillovers are generally not statistically different from zero. The only exception is for enabling technologies, where they are mostly related to contextual effects, such as the diffusion of broadband infrastructure.[11] In that case, we find that a 1% increase in the share of revenues generated by adopters in one province increases the likelihood of adopting by other firms by around 0.13%.

We identify strong and significantly positive sector-level spillovers on management software, cloud computing, and advanced technology adoption. In the case of management software and advanced technologies, the result is particularly striking: a 1% increase in the share of revenues generated by adopters increases the likelihood that another firm adopts by 0.36% and 0.25%, respectively.

Import spillovers are generally not significant. One notable exception is in the case of management software, which are crucial to streamline information flows with upstream suppliers.

Importantly, we find evidence of positive spillovers in export markets for both enabling and advanced technologies.

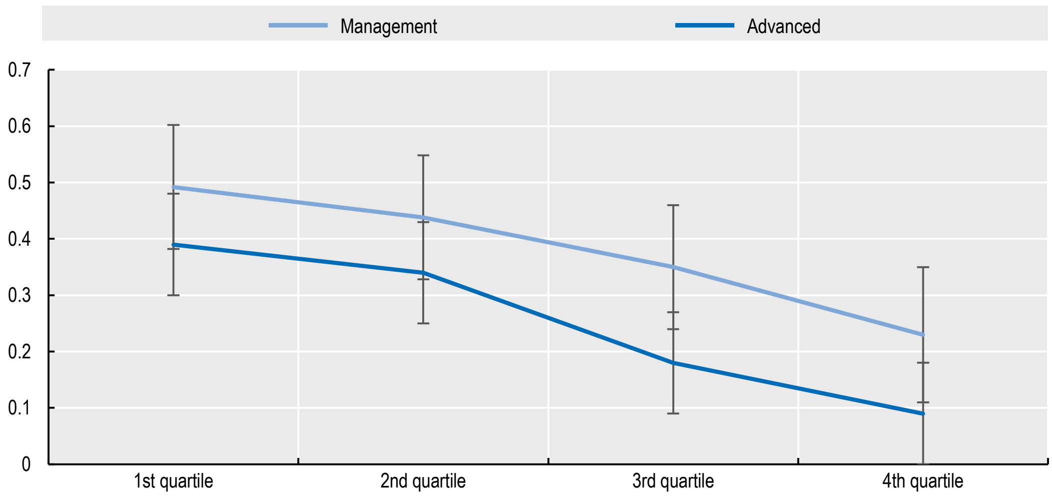
Finally, we try to test whether winner-takes-most effects, which on average seem not to dominate positive spillover effects, are indeed present. For this purpose, we focus on sectoral spillovers and we look at how they are affected by the degree of sector concentration. We then estimate the following model:

$$1(Tech_i = 1) = \sum_Q \beta_{SQ} * QuartHHI_{sQ} * SO_{iS}^{-i} + X\delta + \gamma_s + \lambda_r + \theta_h + \iota_a + \varepsilon_i \qquad (2)$$

where $QuartHHI_{sQ}$ is a dummy = 1 if the sector belongs to the quartile Q of the sectoral distribution of the Herfindhal-Hirschmann Index. The vector X includes province, export, and import spillovers, interacted with the quartile dummies of the corresponding HHI distribution.[12]

We provide results for management software and advanced technologies in Figure A C.25. We find that industry concentration significantly dampens spillover effects. In particular, moving from the first to the fourth quartile of the HHI distribution, is associated with a drop in 0.3 in the positive spillover effect (the difference is significant at p<0.05).

Figure A C.25. Spillover effects by quartiles of the distribution of sector-province level, Herfindhal-Hirschmann index



Note: Results of estimating model (2).
Source: Authors' elaboration on ISTAT data.

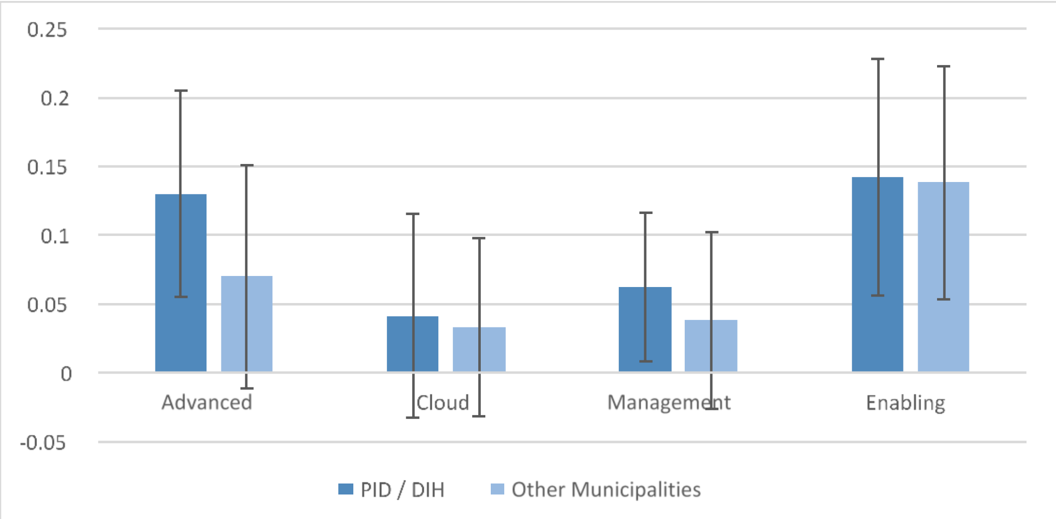
In order to boost knowledge diffusion among Italian firms, the Italian government launched the "National Network Firm 4.0" to support firms in their process of digitalisation. In our analysis, we test whether the presence of an institution of the Network within the municipality affects the spillover at the province level. In particular, we estimate model (1) by interacting each spillover variable with a dummy equal to 1 if the municipality in which the firm is active has one Digital Firm Spot (or *Punto Impresa Digitale* – PID) and/or a

Digital Innovation Hub. The goal is to understand whether the network reinforces knowledge flows and interlinkages between firms that support the diffusion of digital technologies.

In Figure A C.26, we focus on the results for provincial spillovers, as other types of spillovers do not yield any significant differences between firms active in municipalities with and without PID and DIH. Results show that areas where PID or DIH are located are also characterised by significant province-level spillovers in advanced digital technologies and managerial software.

Notice that, in the current analysis, it is not possible to disentangle whether stronger provincial spillovers are *caused* by PID and DIH presence, or that some factors that increases the measured spillover predicts also the location choice of PID and DIH institutions. This is just a first, suggestive result that points to the importance to study in depth the process of technology diffusion through spillovers to bring additional evidence on this crucial topic for policy-makers.

Figure A C.26. Provincial spillovers for firms active in areas where there is or there is not a PID/DIH institution



Note: Results of estimating model (1) separately for municipalities where PID/DIH have been implemented and have not been so.
Source: Authors' elaboration on Unioncamere and ISTAT data.

Finance and the digital transformation

Funding constraints can limit the digital transformation, as this may require sizable up-front costs for the acquisition of the new technologies and for their integration into the firm's production and organisational structure.

The adoption and implementation costs of the new technologies entails investments in intangible assets whose returns might be hard to quantify and predict (the positive association between adoption ad intangible assets has been discussed in Annex B). As such, equity and internal resources, rather than debt, should be the preferable source of financing.

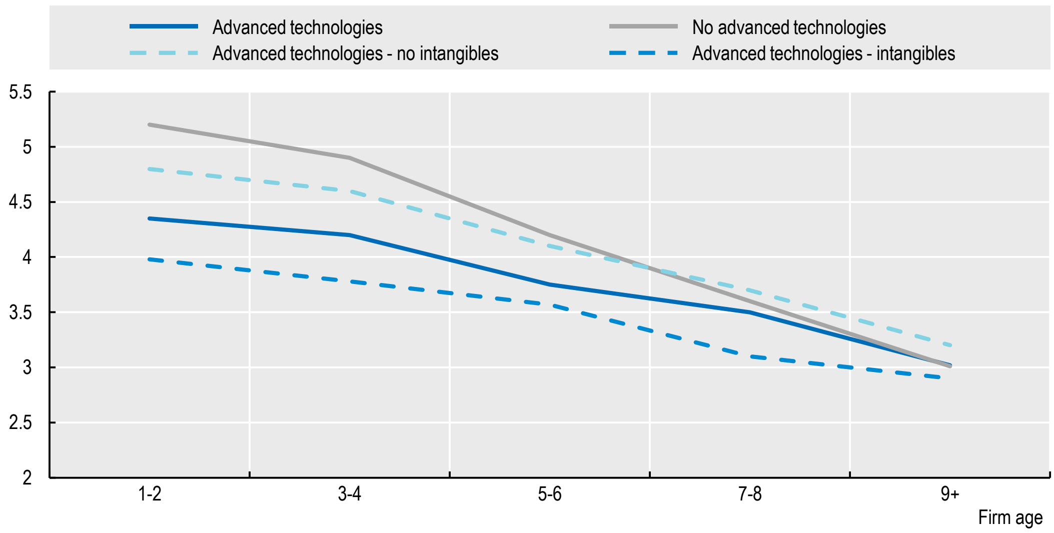
Our data are in line with this prediction: Figure A C.27 shows the average equity multiplier, defined as the ratio between a firm's total assets and is net worth, for firms of different age. The multiplier is a measure of leverage, as a high multiplier indicates that a significant portion of a firm's assets are financed by debt.[13] Leverage tends to be lower for firms adopting advanced technologies (blue solid line) than for firms that do not (grey solid line). This is true in the first years on the firm's life, when lower reputational and tangible capital accumulation makes access to external debt more difficult.

The dotted lines distinguish between adopters with and without investments in intangibles, according to balance sheets data. The lower leverage of adopters is mainly driven by the second group of firms, especially for younger firms. Gonzalez-Torres, Manaresi and Scoccianti (2020[25]), using a model of firm dynamics with heterogeneous agents and financial frictions, and testing it with 2005-17 data for Italian limited liability companies, show that intangible goods make firms more efficient and profitable, reducing their demand of total capital and, crucially, their leverage at entry.

Of course, other confounding factors may drive the above differences: adopters of advanced technologies in the early years of their life might in fact be innovative startups that are more attractive to VC, business angles and other similar investors.

Nevertheless, the prominence that bank debt has in the financial structure of Italian firms, in particular of SMEs, suggests that the access to this type of credit might as well affect the adoption of digital technologies.

Figure A C.27. Leverage and adoption over the life cycle



Note: Results of a regression of the leverage indicator (the ratio between total assets and net income) on a set of age dummies, controlling for size-age and region-sector fixed effects.
Source: Authors' elaboration on ISTAT data.

We used bank credit supply shocks, estimated as in Amiti and Weinstein (2018[45]) from bank-firm level data of the credit registers of the Bank of Italy (see Manaresi and Pierri (2019[17])), to assess the relationship between finance and technology adoption.

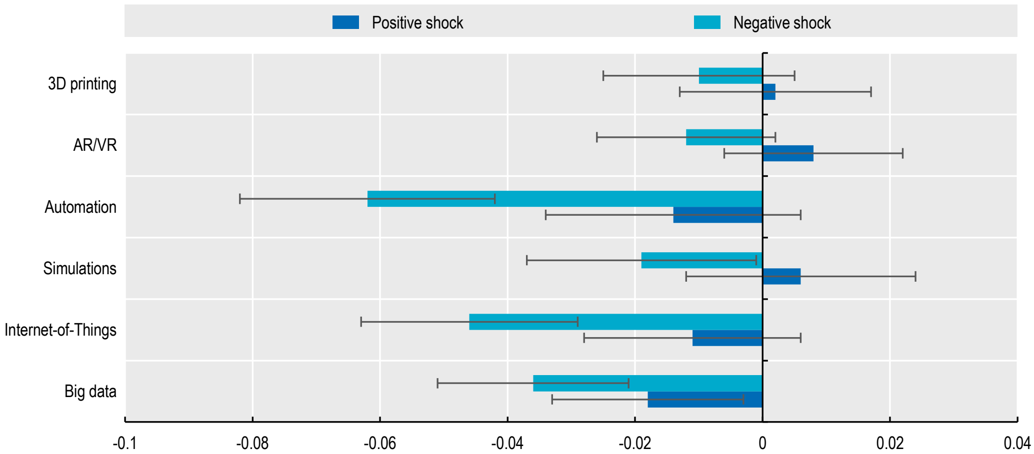
Figure A C.28 depicts the coefficients of the cross section regressions between the dummies capturing the adoption over the period 2016-18 of each of the different technologies and the average yearly shock measured over the same period aggregated at the municipality-two-digit sector. The specifications also include sector, municipality, age and size fixed effects as further controls.

Interestingly the effect of credit supply shocks is not symmetric: in case of a negative shock, it is negative and significant for the adoption of automation, simulation, internet of things and big data technologies. On the contrary, positive shocks tend to have no effects on the adoption of any of the technologies considered.

In other words, the probability of having adopted a certain digital technology is lower for firms operating in a sector-municipality that was hit by a negative supply shock than for firms with similar characteristics but active in a sector-municipality pair characterised by a shock of a smaller magnitude. Positive supply shocks, instead, do not affect the probability of adoption, suggesting, for instance, that relaxing credit constraint is not a sufficient condition for the adoption of advanced digital technologies, as the skills of the labor force, the competences of the management and the other complementary intangibles discussed above are also needed.

The negative response is particularly strong for automation and internet-of-things technologies, which is not surprising given the more tangible nature of this type of investment.

Figure A C.28. Effect of credit supply shocks on advanced technology adoption



Note: Results of a regression of a dummy equal to 1 if the firm adopts the technology listed in the vertical axis on positive and negative supply shifters, controlling for size-age and sector and municipality dummies. Standard errors are allowed to display serial correlation at the sector level.
Source: Authors’ elaborations on Bank of Italy and ISTAT data.

Endnotes to Annex C

[1] Available cross-country data allow to disaggregate National Accounts at best at the STAN36 level. In principle, this may be problematic, as specialisation in more narrowly-defined industries may matter. We discuss below how this is unlikely to be a relevant concern in our case.

[2] Almost 30% of Italians under 35 completed a tertiary degree, against 45% of the OECD average, and almost 50% and 35% of Germany and France, respectively. Very similar results are obtained for the age class 35-44.

[3] Calvino and Criscuolo (Calvino and Criscuolo, 2022[152]) review some of the recent literature on the role of public policy for technological adoption and diffusion across businesses in the digital era, especially focusing on recent OECD studies. For previous and complementary discussions, see for instance Stoneman and David (1986[149]); Stoneman and Diederen (1994[150]); Stoneman and Battisti (2010[151]).

[4] Micro and small firms can receive credit for 50% of the eligible expenditures incurred, up to a total amount of benefit of EUR 300 000. For medium-sized firms these values are 40% and EUR 250 000, respectively; for large firms, they are 30% and EUR 250 000.

[5] Up to the year 2020, the firm needed to sign an ad hoc agreement with trade unions to benefit from the tax credit. Moreover, in the initial formulation of the Law, expenditures for trainers were generally not eligible for the tax credit.

[6] The bars are based on a regression of adoption rates on a high-skilled dummy variable, controlling for sector and size-age unobserved heterogeneity.

[7] The findings for firms adopting more than nine digital technologies may be less precise due to the limited number of underlying data points. Still, the share of high-skilled managers in those firms is never lower than the one in less digitally sophisticated firms (especially those adopting less than three different digital technologies).

[8] Performed keeping fixed sector-region and size-age heterogeneity.

[9] The analysis is carried out performing a regression controlling for heterogeneity in size, age, sector and geographic area.

[10] In the case of exports, spillovers for firm i are first computed at the destination-country level, and then averaged at the firm-level using the share of each of destination in total firm's export as weight. Formally, first we compute, for each firm *i*, active in sector *s*, and exporting to destination country *d*, we compute:

$$SO_{isdX}^{-i} = \sum_{j}^{-i} \frac{Y_{jsdX} \times 1(Tech_{jsdX} = 1)}{\sum_j Y_{jsdX}}$$

where Y_{jsdk} is firm *j*'s revenue from export to country *d*. We then average across products at the firm level:

$$SO_{isdX}^{-i} = \sum_{j}^{-i} \frac{Y_{jsdX} \times 1(Tech_{jsdX} = 1)}{\sum_j Y_{jsdX}}$$

In the case of imports, we follow the same logic, though clearly in this case we consider expenditures on imports (rather than revenues from exports) as weights.

[11] Indeed, the positive provincial spillover effects on enabling technologies are significantly dampened when we control for the increase in broadband supply. Results are available upon request.

[12] We do not report results for province, export and import spillovers because they are generally found not to be significantly affected by concentration. In particular, in the case of province, HHI is measured using province-level revenue shares; in the case of export using sector-destination export shares (weighted at the firm-level using the firm-level share of export by destination); in the case of import using sector-origin import shares (weighted at the firm-level using the firm-level share of import by destination).

[13] Relative to the standard leverage measure (1- Net worth/Total assets), it allows better exploiting the variation among highly leveraged firms. Thus, it better fits the case of Italy, where advantage is generally high among firms.