Digitalization and Productivity: In Search of the Holy Grail – Firm-level Empirical Evidence from European Countries

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Abstract

This article assesses how the adoption of a range of digital technologies affects firm productivity. It combines cross-country firm-level data on productivity and industry-level data on digital technology adoption in an empirical framework that accounts for firm heterogeneity. The results provide robust evidence that digital adoption in an industry is associated to productivity gains at the firm level. Effects are relatively stronger in manufacturing and routine-intensive activities. They also tend to be stronger for more productive firms and weaker in the presence of skill shortages, which may relate to the complementarities between digital technologies and other forms of capital (e.g. skills, organisation, or other intangibles). As a result, digital technologies may have contributed to the growing dispersion in productivity performance across firms. Hence, policies to support digital adoption should go hand in hand with creating the conditions to enable the catch-up of lagging firms, notably by easing access to skills.

Why is innovation everywhere except in productivity statistics? This famous 1987 question by Robert Solow was recently revived and adapted to the digital era by Brynjolfsson *et al.* (2017). There are good reasons to believe that investment in digital technologies should have strong positive effects on productivity (Syverson, 2011;

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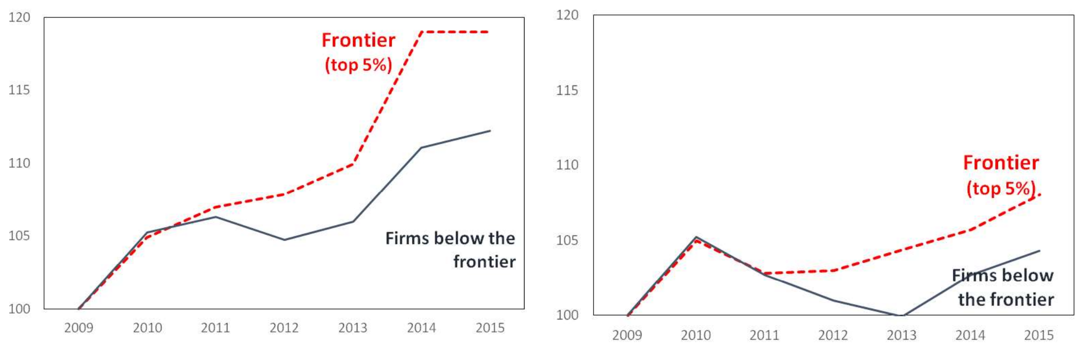
Chart 1: MFP at the Productivity Frontier and for the Average Non-frontier Firm, 2009-2015 (2009=100)

Panel A: High Digital Intensity Industries **Panel B: Low Digital Intensity Industries**



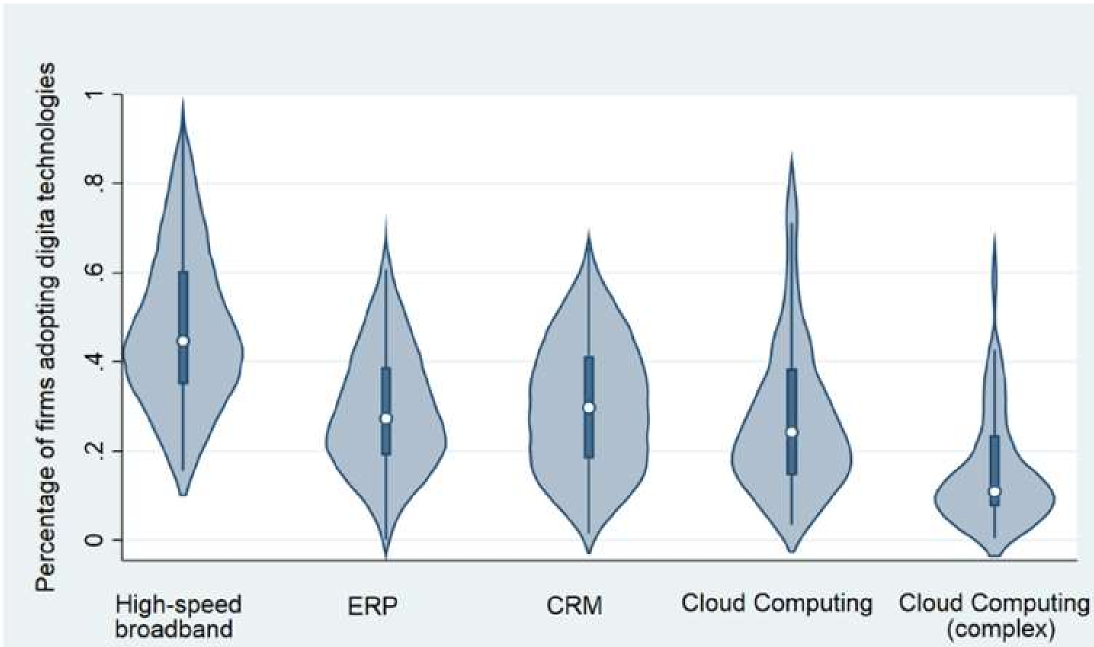
Note: The "frontier" is measured by the average of log multi-factor productivity, based on the Wooldridge (2009) methodology, for the top 5 per cent of companies with the highest productivity levels in each 2-digit industry and year, across 24 countries. The "firms below the frontier" lines capture the averages of the log-productivity distribution in each industry and year (excluding the top 5 per cent). The values obtained for the detailed 2-digit industries are averaged to industry groups that are classified either as having "high" or "low" digital intensities according to the methodology in Calvino *et al.* (2018). The series are normalized to 100 in the starting year (2009=100).
Source: Calculations using Orbis data of Bureau van Dijk, following the methodology in Andrews *et al.* (2016).

Brynjolfsson and McAfee, 2014). Yet, the empirical evidence at the industry and firm levels has been more nuanced (Acemoglu *et al.*, 2014; Bartelsman *et al.*, 2017; DeStefano *et al.*, 2018; Cette *et al.*, 2017), and aggregate productivity has generally been slowing down over the past decade, partly reflecting increasing dispersion in productivity performance across firms (Berlingieri *et al.*, 2017; Decker *et al.*, 2018). Notably, Andrews *et al.* (2016) and Berlingieri *et al.* (2018) have shown that aggregate patterns mask a widening productivity gap between a handful of frontier firms and a mass of laggard firms, especially in highly digitalized industries (Chart 1).

At the same time, cross-country data on firm-level adoption of digital technologies suggest that dispersion of adoption across firms is also wide and differs significantly across countries (Hagsten *et al.*, 2013; DeStefano, De Backer and Moussiegt, 2017), as shown in Chart 2. For instance, adoption of cloud computing is more than twice more common in large firms than in small firms in the average OECD country (OECD, 2017). Andrews *et al.* (2018) have related this dispersion to adoption obstacles that depend crucially on capabilities and incentives, whose strength differs across firms, industries and countries.

This article uses cross-country firm-level data to assess the productivity effects of industry-level digital adoption. We find strong evidence that operating in a digitalized environment benefits productivity, though not to the same extent across firms and industries, and explore some of the reasons why these benefits may have been disappointing at the aggregate level. We argue that the heterogeneity of adoption

Chart 2: Dispersion of Digital Technologies Across Countries, 2017 (Kernel densities based on the percentage of enterprises with at least 10 employees adopting digital technologies by country)



Note: This figure offers a visualisation of the distribution of digital adoption rates in 2017 across countries using a rotated kernel density plot (outer shape) and a boxplot (inner figure) indicating the median (white dot), the 25^{th} and the 75^{th} percentile of the distribution (top and bottom of the bar). The graph is based on country-year observations of the overall share of firms adopting a certain technology, where *high-speed broadband* refers to access to high-speed broadband (>30Mbits); *ERP* stands for the adoption of Enterprise resource planning systems, a software-based tool that can integrate the management of internal and external flows, from material and human resources to finance, accounting and customer relations; *CRM* stands for Customer Relationship Management software; *Cloud Computing* refers to ICT services used over the internet as a set of computing resources; and *Cloud Computing (complex)* is a subset of relatively more complex uses of Cloud Computing (e.g. accounting applications, CRM software, or computing power). See Annex D of Andrews *et al.* (2018) for a detailed description of each technology.
Source: Eurostat, Digital Economy and Society Statistics, comprehensive database

rates and adoption effects across firms and industries may contribute to explain why aggregate gains from digitalization have been disappointing and too weak to offset other factors contributing to the productivity slowdown. Econometrically, identifying causal effects of digital adoption on firm productivity poses multiple challenges. A first issue is reverse causality — does productivity increase due to adoption or is adoption just easier for high-productivity growth firms? Related to this, firm performance and adoption are likely to be driven by a number of common factors (e.g. skills or competitive pressures). Spillovers also pose identification issues: is productivity increasing due to within-firm adoption or due to the benefits of operating in a highly digitalized industry? Studies have shown that spillover effects across firms can be important (Syverson, 2011) and pure firm-level analysis obviously tends to miss them. Industry-level studies cover such spillovers, but they are by nature unable to account for the heterogeneous firm-level patterns that characterize adoption and its productivity effects.

In this article, we address some of these issues by combining industry-level cross-country data on adoption of a range of digital technologies with firm-level cross-country data on multifactor productivity in an empirical framework allowing for productivity heterogeneity across firms. Relying on adoption rates at industry rather than firm level is a way to mitigate endogeneity issues and to account for spillover effects from early adopters to other firms in the industry. This is because industry-level adoption rates will reflect both the adoption propensity (i) of the firm whose productivity is being assessed (direct effect), and (ii) of other firms in the same industry (spillover effect). As a result, industry-level adoption is less likely than firm-level adoption to be endogenous to firm-level productivity performance, though clearly other sources of endogeneity persist and need to be controlled for in estimates. Moreover, focusing on firm-level productivity performance helps identifying which categories of firms benefit most from adoption, for example depending on their size or productivity, and allows controlling for the effects of catching up to the technological frontier. Finally, looking at specific digital technologies instead of an aggregate ICT index accounts for the different effects they can have on productivity.

We rely on two main sources of data, the Eurostat Digital Economy and Society database for digital adoption and the Orbis database for firm-level productivity and other characteristics. We cover five major digital technologies (high-speed broadband internet, simple and complex cloud computing services, Enterprise Resource Planning and Customer Relationship Management softwares) in 19 EU countries and Turkey and 22 industries over 2010-15, which corresponds to the period sufficiently well covered by the Eurostat adoption rates and is also an important period for the adoption of these technologies (OECD, 2017). Both datasets are restricted to firms with at least 10 employees.

These technologies have been selected for their potential to improve firm productivity. For example, cloud computing gives firms flexibility to scale up or down their operations without incurring the cost of building and maintaining IT infrastructure, while also offering the possibility to access documents and software from anywhere in real time. Enterprise resource planning (ERP) software integrates and automates various functions, such as planning, purchasing, inventory, sales, marketing, finance and human resources into a single system, which can improve the speed and reliability of information exchanges within firms as well as with suppliers and customers. For more details, see Andrews *et al.*, (2018)

Our main result is that industry-level digital adoption is associated with significant productivity returns at the firm level. While the data do not permit to disentangle whether these are mainly driven by within-firm adoption or spillovers from other digitalized firms, our attempts to control for within-firm investment (in tangible or intangible assets) tentatively suggest that both channels may play a role. Our results are little affected by the inclusion of potential common drivers of adoption and productivity (such as skills and the regulatory environment), suggesting that they are not driven by the omission of these factors. Results are also robust to using adoption rates lagged by one year, or alternatively adoption rates at the beginning of the sample period, suggesting that they are not primarily driven by reverse causality.

Interestingly, we find that productivity gains are strongest for high productivity firms, suggesting that digital adoption in an industry has contributed to the increasing productivity dispersion across firms of this industry. This is in line with recent evidence showing that the catch-up of laggard firms is weaker in industries that rely more on ICT specialists (Berlingieri *et al.*, 2018). In contrast, productivity gains do not systematically depend on firm size. Different technologies have different effects in this respect. For example, Enterprise Resource Planning is more beneficial for larger firms and cloud computing for smaller ones, which is consistent with the idea that cloud computing is attractive for small firms as a means to avoid investing in a large IT infrastructure, in line with a recent finding by Bloom and Pierri (2018) for the United States. Further, we find that the productivity benefits of adoption are significantly thwarted by skill and occupational shortages, pointing to synergies between digitalization and other kinds of intangibles. Finally, we find that digitalization is on average more beneficial in manufacturing than service firms, and more broadly in industries involving a high share of routine tasks, which is consistent with previous findings (Akerman *et al.*, 2013; Dhyne *et al.*, 2018).

While further research is needed to identify the firm-level sources of the estimated productivity benefits, our evidence is consistent with three drivers. First, the fact that highly productive firms benefit most from digital technologies and that skill shortages reduce these benefits points to the existence of important complementarities between these technologies and other intangible investments that raise productivity, such as managerial competence or worker skills. This echoes earlier results by Andrews *et al.*, (2018), who found a strong association between the propensity to adopt digital technologies and access to such intangibles at the industry level. Second, interactions with digitalized firms (within an industry or more broadly in global value chains) can generate positive spillovers, for example thanks to back and front office digital integration with suppliers and customers. Third, a strong incidence of routine tasks may generate scope for taking advantage of digital technologies by streamlining production processes.

Our results point to both opportunities and challenges for policies aimed at enhancing aggregate productivity via wider technology adoption. The generally positive effects of digital adoption and the importance of complementarities suggest that broad-based policies that support the diffusion of digital technology, such as the roll out of high-speed broadband and the upgrade of the skill pool, can bring important aggregate productivity benefits (Sorbe *et al.*, 2019). However, an important characteristic of digitalization is that high-productivity firms have tended to benefit more from it than less productive ones. This probably reflects a combination of (i) a higher propensity to adopt digital technologies, (ii) greater productivity benefits from adoption thanks to higher endowment in skills and organizational capital, and (iii) more positive spillovers from interacting with digitalized peers (the empirical analysis in this article cannot disentangle these three factors). In turn, the higher productivity gains enjoyed by more productive firms may have compounded productivity dispersion across firms, a phenomenon that has been shown to underlie some of the productivity slowdown (Andrews *et al.*, 2016; Decker *et al.*, 2018). Moreover, to the extent that some of the benefits of digitalization depend on the ability of adopting firms to automate routine tasks (including by shedding labour), policies may also have to deal with the potential labour market implications of widespread adoption of digital technologies.

The article is organised as follows. In the first major section, we relate our work to previous research and highlight the issues involved in estimating the productivity effects of digitalization. The second section describes the empirical methodology and the data. We then present the results for the average firm and explore the heterogeneity of the digital-productivity link across industries and firms. We conclude discussing open research issues and policy implications.

Digitalization and Productivity: A Complex Link

A number of firm- and industry-level studies provide evidence of positive links between investment in digital technologies and productivity performance.[2] Digital technologies enable firms to innovate, for example by improving business processes, and to automate certain routine tasks; they also reduce the costs of interacting with suppliers and customers (Bartel *et al.*, 2007; Brynjolfsson *et al.*, 2008; Akerman *et al.*, 2013). However, three recent studies contrast with this literature. Acemoglu *et al.* (2014) find no effect of IT intensity on manufacturing productivity except in the computer-producing industry, using US firm-level data over 1977-2007. Bartelsman *et al.* (2017) find no significant effect of broadband access on within-firm productivity, but still a positive effect at the aggregate level, which may indicate positive effects from reallocation (i.e. more productive firms growing in size relatively to less productive firms), firm entry and exit, or spillovers across firms. Similarly, DeStefano *et al.* (2018) find that broadband ADSL positively affected firm size but not firm productivity, based on UK data for the early 2000s. In a context of slow global productivity growth, these papers have led to renewed discussions about Robert Solow's 1987 productivity paradox.

This overall puzzling picture reflects the fact that links between adoption of digital technology and productivity are complex and their empirical identification challenging. The key reason is that digital technologies typically support productivity in combination with other factors. Indeed, past studies have shown strong complementarities of digital technologies with organizational capital and management skills (Brynjolfsson and Hitt, 2000; Basu *et al.*, 2003; Bloom *et al.*, 2012; Aral

2 See for example reviews in Dedrick *et al.* (2003), Draca *et al.* (2009), Syverson (2011), Munch *et al.* (2018). Refer to the online Appendix C for an overview of the main studies and their results at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

et al., 2012), R&D and intangible investments (Corrado *et al.*, 2017; Mohnen *et al.*, 2018),[3] human capital and ICT-related skills (Bugamelli and Pagano, 2004) and a regulatory environment that enables the efficient reallocation of resources (Gust and Marquez, 2004; Conway *et al.*, 2006; Bartelsman, 2013). There are also complementarities between different digital technologies, for example between high-speed broadband and cloud computing (DeStefano *et al.*, 2019) or supply-chain management and customer-relationship software (Wieder *et al.*, 2006; Aral *et al.*, 2006; Engelstätter, 2009; Bartelsman *et al.*, 2017). Another complication is that productivity gains tend to materialize with a certain lag, as digital adoption can disrupt production processes in the short term and require organizational adjustments to fulfill their potential (Van Ark and Inklaar, 2006; Brynjolfsson, Rock and Syverson, 2017). This in turn can result in productivity mismeasurement that may lead to a productivity J-curve if complementary intangible investments are imperfectly measured (Brynjolfsson *et al.*, 2018).

Beyond these factors, a number of more technical reasons complicate the econometric identification of the productivity effects of digital technologies. A key one is endogeneity, which can result from both reverse causality and common factors influencing productivity and adoption. Reverse causality arises from the fact that digital adoption may be easier for high-productivity firms, because their high productivity can give them the financial means to invest in new digital technologies. In addition, certain potential drivers of digital adoption (e.g. managerial skills, organizational capital, favourable business and regulatory environment) can also support productivity directly, i.e. beyond their impact through digital adoption. If not properly addressed, this endogeneity can bias estimates upwards.

Another issue is the level of aggregation used in the analysis. Both the firm and the industry levels have advantages and downsides. Firm-level analyses are typically more subject to the endogeneity issues discussed above, although certain studies have developed original instrumentation techniques to overcome them (De Stefano *et al.*, 2014). In addition, firm-level studies can miss the positive spillovers generated by adoption by other firms, which past research has shown to be significant (Syverson, 2011). In contrast, industry-level studies take into account both within-firm and spillover effects (typically without being able to disentangle them), but they do not take into account the firm-level heterogeneity in productivity drivers and performance. This can lead to less accurate specifications and hinder the identification of heterogeneous effects of adoption across firms.

Finally, the way to measure digital adoption also opens a number of questions. A number of papers rely on broad measures of digital intensity (e.g. spending on ICT, number of computers per worker), while

3 In contrast, Hall *et al.* (2012) find no evidence of complementarity between ICT and R&D investment on firm-level Italian data over 1995-2006.

others focus on adoption of specific technologies, such as Enterprise Resource Planning software (Hunton *et al.*, 2003). Certain studies cover several specific technologies, but they tend to focus only on single countries (Aral *et al.*, 2006; Engelstätter, 2009). Overall, broad measures of digital intensity offer more general results, but may rely on less precise identification and cannot assess heterogeneous effects of technologies across firms (e.g. small firms may benefit relatively more from certain technologies, such as cloud computing) or complementarities between technologies.

This article aims to address some of these issues to provide robust cross-country evidence on the links between digital adoption and productivity. The combination of industry-level data on adoption and firm-level data on productivity is a way to mitigate endogeneity concerns, as discussed below, while it allows to cover both within-firm and spillover effects of adoption. In addition, it permits accounting for firm heterogeneity and assessing how different industries and types of firms (e.g. in terms of size or productivity) benefit from digital technologies — an area that has been relatively little explored, especially in a cross-country perspective. The joint focus on several specific digital technologies, which is relatively new for a cross-country analysis, allows for a more refined identification. Finally, complementarities between technologies are explored by testing the effect of the first principal component of the adoption variables considered.

Nevertheless, the approach in this article has a number of limitations, as further discussed below. While it covers both within-firm effects of adoption and within-industry spillovers, it leaves aside reallocation effects as well cross-industry spillovers, and in this respect probably underestimates productivity gains from adoption. In addition, it cannot directly disentangle within-firm and spillover effects, although it explores indirect ways to do so. Another limitation is that the measure of digital adoption used in this article is binary at the firm level (surveyed firms report using the technology or not) hence it does not take into account the changing firm-level intensity in the use of technologies.

Empirical Approach and Data

Model Specification

The empirical specification takes the neo-Schumpeterian growth approach to technology diffusion and innovation by Aghion and Howitt (1997) and Acemoglu *et al.* (2006), which has been implemented in a number of empirical studies at the firm (Griffith *et al.*, 2006; Arnold *et al.*, 2011; Andrews and Criscuolo, 2013; Andrews *et al.*, 2016; Adalet McGowan *et al.*, 2017) and industry levels (Nicoletti and Scarpetta, 2003; Bourlès *et al.*, 2013). Multi-factor productivity (MFP) is assumed to follow an error correction model of the form:[4]

4 See Bourlès *et al.* (2013) for a derivation of a similar specification from a co-integrating relationship in levels relating MFP to frontier MFP.

$$\Delta MFP_{f,s,c,t} = \alpha_1 \Delta MFP_{Frontier\ s,t} + \alpha_2 Gap_{f,s,c,t-1} + \beta\ Dig\_adopt_{s,c,\bar{t}} + \gamma X_{f,sc,t} + \delta_{c,t} + \delta_i + \varepsilon_{c,t} \quad (1)$$

$\Delta MFP_{f,sc,t}$ is the change in the logarithm of multi-factor productivity (MFP) of firm f, which operates in sector s and country c, in year t, estimated with the Wooldridge (2009) method. MFP growth of firm f is assumed to depend on MFP growth of the productivity frontier ($\Delta MFP_{Frontier\ s,t}$), which is defined as the average MFP among the 5 per cent most productive firms in sector *s* and year t across the countries in the sample,[5] and on the lagged distance to the frontier ($Gap_{f,sc,t-1} = MFP_{Frontie\ r\ s,t-1} - MFP_{f,s,t-1}$). Frontier firms are excluded from the sample to avoid endogeneity issues.

Based on economic theory and previous estimations of this model, one should expect α_1 to be positive but below 1, indicating that innovation at the frontier benefits other firms but only partially so, and α_2 to be positive, indicating that firms below the frontier benefit from a catch-up effect. However, the speed of frontier growth, the variance of non-modelled productivity shocks and the nature of firm entry and exit (productivity enhancing or not) can either lead to productivity convergence or divergence across firms. In practice, divergence has generally been prevailing over recent years at the OECD level (Chart 1), although not necessarily within each country.

The main coefficient of interest is β, which captures the effect of industry-level digital adoption on firm-level productivity growth. $Dig\_adopt_{s,c,\bar{t}}$ represents the share of firms in sector s and country c that report using a specific digital technology (e.g. high-speed broadband internet connection, cloud computing) averaged over the period 2010-15. The effect of different digital technologies is assessed in separate identical regressions (i.e. one regression per technology). In addition, their combined effect is assessed using a composite indicator of adoption, which is constructed as the principal component of five variables representing the adoption of different digital technologies (high-speed broadband, simple and complex cloud computing, ERP and CRM software), in the spirit of Andrews *et al.* (2018).

As digital adoption is typically observed only for two or three years in the period of interest, the regression relies on the average of the digital adoption variable over the available years ($Dig\_adopt_{sc,\bar{t}}$), meaning that adoption does not vary over time in our regression framework. While this may hinder identification, it also mitigates potential endogeneity issues (e.g. if adoption and productivity in a specific year were driven by a common factor) and can help capturing lagged benefits of adoption. Since the digital adoption variable only varies at the country-industry level (and

5 In line with Andrews *et al.* (2016) and others, we define the frontier as the top 5 per cent percent of firms and use the global industry frontier as opposed to the national frontier. In theory, both can be relevant to productivity catch-up, but the global frontier is likely to be measured more consistently and with less noise in our dataset.

not across firms in an industry or over time) standard errors are clustered at the country-industry level to address potential correlation of residuals.

Longer time series are available in the data only for the adoption of ERP software. This allows the estimation of alternative specifications less subject to potential endogeneity issues. Two options are considered: using (i) adoption rates lagged by one year, or (ii) adoption rates in the first year of the sample period (2010).

The baseline specification also includes a vector of control variables ($X_{fsc,t}$), including firm size (measured as the log of employment[6]) and age, as well as industry and country-year fixed effects.[7] In alternative specifications, additional controls are included to account for potential common determinants of productivity and digital adoption at the industry level, such as skill shortage and regulatory environment indicators. In an attempt to disentangle the within-firm effect of digital adoption from spillovers resulting from digital adoption by other firms in the industry, we also control in a separate specification for firm-level investment (tangible or intangible) as a proxy for firm-level digital adoption. With this additional control capturing within-firm effects, the estimated β coefficient should only reflect spillover effects. However, these proxies are clearly imperfect (but the only ones available in our dataset) and corresponding results should be considered as illustrative.

Overall, this empirical framework offers the benefit of taking account of firm heterogeneities and firm-specific drivers of productivity, making it richer and more robust than an industry-level framework. In addition, the use of industry-level adoption as a determinant of firm-level adoption addresses certain endogeneity concerns since industry-level adoption is less likely than firm-level adoption to be influenced by firm-level productivity.

Still, one should keep in mind a number of caveats. First, it is possible that some endogeneity still persists despite the benefits of the general approach combining industry and firm-level data and the additional control variables introduced (and, in the case of ERP, the use of lagged and initial digital adoption rates). This would be the case if unobserved factors were affecting simultaneously adoption levels in an industry and productivity growth rates of the firms in this industry in a way that is not captured by industry and country-year fixed effects and by the additional control variables. Second, it is possible that the productivity catch-up of lagging firms is achieved via the adoption of digital technologies that more advanced firms have already adopted, in which case this effect may be captured (at least partially) by the productivity gap variable rather than the digital adoption variable. Results are robust to dropping the catch-up term in the regression, suggesting that this is not an

6 Regressions using turnover instead of employees as a measure of size yield quantitatively similar results as the baseline specification.

7 Results are also robust to including industry-year fixed effects.

issue.[8]

Third, another potential concern is that dropping the firms at the productivity frontier (i.e. the top 5 per cent in each industry) may lead to underestimating the effect of relatively new technologies that they may be the first ones to adopt (e.g. complex cloud computing services).[9] Fourth, in the absence of firm-level adoption rates coupled with information on firm entry/exit, estimations may fail to account for missed adoption opportunities and unsuccessful adoption processes forcing firms to exit the market, and symmetrically for successful entry of digital-natives highly productive firms. Finally, as shown by past research, reaping the benefits of digital adoption generally requires broader organizational changes, which are likely to be per se productivity-enhancing. Given that the estimates encompass a combination of the effect of adoption and such concomitant reorganisations, they reflect the productivity gains from digitalization in a broad sense (i.e. including the effect of these reorganisations).

In addition to the specifications described above, a number of refinements of the baseline specification are introduced to assess which industries and firms benefit most from digitalization and what are the potential complementarities with other factors:

- to assess which industries benefit more from digital adoption, we interact the digital adoption variable with (i) a categorical variable separating manufacturing and service industries, (ii) a variable capturing the average routine intensity of tasks in each industry, with the idea that industries with higher routine intensity may benefit more from digitalization through the automation of routine tasks;
- to assess which firms benefit more from the diffusion of digital technologies, the digital adoption variable is successively interacted with two categorical variables splitting the sample into (i) four size classes (from smallest to largest firms) and (ii) four productivity classes (from least to most productive). As a different way to test if productivity effects of digitalization vary according to productivity levels, the digital adoption variable is also interacted with lagged distance to the frontier; and
- to better understand complementarities of digital technologies with skills, we explore if skill shortages in ICT-related areas affect the adoption-productivity link by interacting industry and country level measures of skill shortages with the digital adoption variable.

8 That results are robust to omitting the productivity gap variable is also an indication that they are not subject to a potential bias that may result from including a transformation of the lagged level of the dependent variable as an explanatory variable.

9 Indeed, regressions including the top 5 per cent firms display slightly higher coefficient estimates for digital adoption rates than our baseline preferred specification.

Combining Firm and Industry-level Data

We combine various industry-level sources on digital adoption, routine intensity and occupational or skill shortages with firm-level information on productivity. Digital adoption data are drawn from the Eurostat "community survey on ICT usage and e-commerce in enterprises" and have country and industry dimensions and, for a subsample of technologies, also a time dimension. The survey provides a compilation of data on the use of various types of information and communication technologies in enterprises with at least 10 employees. To the best of our knowledge, this dataset is the only source of comparable cross-country data on digital adoption rates at the industry level.

Our analysis focuses on a subset of five indicators selected from a list of several hundred variables available in the Eurostat dataset. The selected indicators are the availability of high-speed broadband internet access, use of simple or complex cloud computing (CC, CC_HI), and the use of front or back office applications — customer relationship management (CRM), and enterprise resource planning (ERP). Technologies were selected based on their potential to improve productivity within the firm, but also via spillovers. These spillovers include potential network effects on other firms (e.g. ERP systems, the utility of which might increase with the number of clients and business partners working with it). These technologies also have possible complementarities between themselves (e.g. broadband access with other technologies, or Cloud Computing with ERP). An additional selection criterion was to maximize cross-country, cross-industry coverage.[10]

Since adoption rates of different technologies are positively correlated[11] and there could be complementarities from adopting them jointly, we also combine them into a single index using their first principal component (i.e. the linear combination of adoption rates that accounts for the largest fraction of their total variance). The first principal component explains a high fraction (more than 60 per cent) of the overall variation in the digital adoption indicators,[12] and the weights assigned to them are relatively close to each other,[13] implying that all technologies are important contributors to the first principal component. More broadly, this index may capture a general tendency of digital technology adoption in a given country-industry cell, in which case it is possible that it captures to some extent the adoption of other digital technologies not covered in this article.

10 For more details see a companion paper examining the drivers of digital adoption by Andrews *et al.* (2018) where the same set of indicators are used.

11 Refer to Table 4 in the online Appendix A for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

12 Refer to Panel A of Table 5 in the online Appendix A for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

13 Refer to Panel B of Table 5 in the online Appendix A for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Productivity and other firm-level variables come from Orbis, a widely used harmonized cross-country longitudinal firm-level database, building on the data construction steps described in Gal (2013), Andrews *et al.* (2016), and Gopinath *et al.* (2017).[14] The underlying data are sourced from annual balance sheet and income statements, collected by Bureau van Dijk (BvD) — an electronic publishing firm — using a variety of underlying sources ranging from credit rating agencies (e.g. Cerved in Italy) to national banks (e.g. National Bank of Belgium). It is the largest available cross-country firm-level database for economic and financial research, which contains not only publicly listed but also privately owned companies. However, important processing and cleaning work needs to be undertaken to transform the financial information to a database suited for economic analysis.

This involves three broad steps: (i) ensuring comparability of nominal variables across countries and over time (industry-level PPP conversion and deflation based on Inklaar and Timmer (2014) and the OECD STAN database, respectively); (ii) deriving new variables that are used in the analysis (real capital stock, productivity); and (iii) keeping only company accounts with valid and relevant information for our present purposes (filtering and cleaning).[15] We obtain productivity as a residual from estimating value-added based production functions, separately for each detailed industry, using the control function approach based on intermediate inputs to mitigate the endogeneity of input choices (Wooldridge, 2009).[16] We restrict the sample to firms that have an average of at least 10 employees (over our sample period) to match the reference group of the industry level digital adoption variable.

Concerning control variables at the industry level, we utilize a recently developed indicator for the routine content intensity of tasks in each industry (Marcolin *et al.*, 2016). This indicator provides a measure of the routine content of occupations, based on data from the OECD Survey of Adult Skills (PIAAC). It measures the degree of independence and freedom in planning and organizing the tasks to be performed on the job as a proxy for non-routine content. The occupation-level index is translated into an industry-level index by constructing the weighted average of the occupation-based index by industry,

14 The version used throughout this article was made available to the OECD by BvD in March 2017.

15 We prefer unconsolidated accounts in case a firm reports both unconsolidated and consolidated accounts so as to ensure that the covered economic activity refers to the local, domestic markets and does not reflect global activities in case of multinational firms. Further, we drop firms that report extreme growth rates in productivity and employment, i.e. which are in the top or bottom 1 per cent of the growth distribution within each country and industry. This step also serves to mitigate the risk of retaining company accounts that are affected by abrupt and large changes resulting from mergers, acquisitions or split-ups.

16 A number of limitations that commonly affect productivity measurement should be noted. First, differences in the quality and utilisation of capital and labour inputs cannot be accounted for as the capital stock is measured in book values and labour input by the number of employees. Secondly, measuring outputs and inputs in internationally comparable price levels remains an important challenge. Finally, similar to most firm-level datasets, Orbis contains variables on outputs and inputs in nominal values and no additional separate information on firm-specific prices and quantities. For further details, see Andrews *et al.* (2016).

Table 1: Descriptive Statistics

	Mean	Median	Bottom decile	Top decile	Standard deviation**	Observations
Digital variables (percentage of firms)						
High-speed broadband	0.359	0.301	0.155	0.650	0.182	401
Enterprise Resource Planning	0.329	0.305	0.107	0.585	0.179	417
Customer Relationship Management	0.327	0.288	0.143	0.575	0.170	409
Cloud Computing (all uses)	0.244	0.198	0.075	0.482	0.162	391
Cloud Computing (complex)	0.138	0.105	0.034	0.286	0.114	380
First principal component	0.853	0.351	-1.637	4.341	2.381	349
Firm-level variables						
MFP growth per year all firms	0.010	0.010	-0.255	0.276	0.264	1,803,155
MPF Frontier growth	0.019	0.019	-0.032	0.075	0.045	2,449,946
Gap to frontier (lagged)	1.711	1.619	0.860	2.614	0.772	1,737,330
Age	21.967	18.000	43.000	4.000	17.809	3,318,977
Employees (log)	3.534	3.219	2.485	4.977	1.075	3,367,107
Capex (log)	11.275	11.225	8.437	14.200	2.332	809,083
Intangibles (log)	11.276	11.364	7.317	15.194	3.263	2,627,018
Other (industry-level)						
Routine intensity	-0.101	0.024	-0.730	0.315	0.369	22
Knowledge intensity	0.423	0.380	0.260	0.620	0.167	22
Skill shortages	-0.053	-0.037	-0.233	0.131	0.156	1577
Resource management skills	0.005	0.007	-0.028	0.040	0.029	1577
Management of personnel resources	0.006	0.007	-0.035	0.048	0.034	1577
Computer and electronics	0.017	0.010	-0.032	0.081	0.044	1577
Technical skills	-0.002	-0.001	-0.019	0.016	0.017	1577
Regulatory impact	0.119	0.072	0.027	0.337	0.113	339

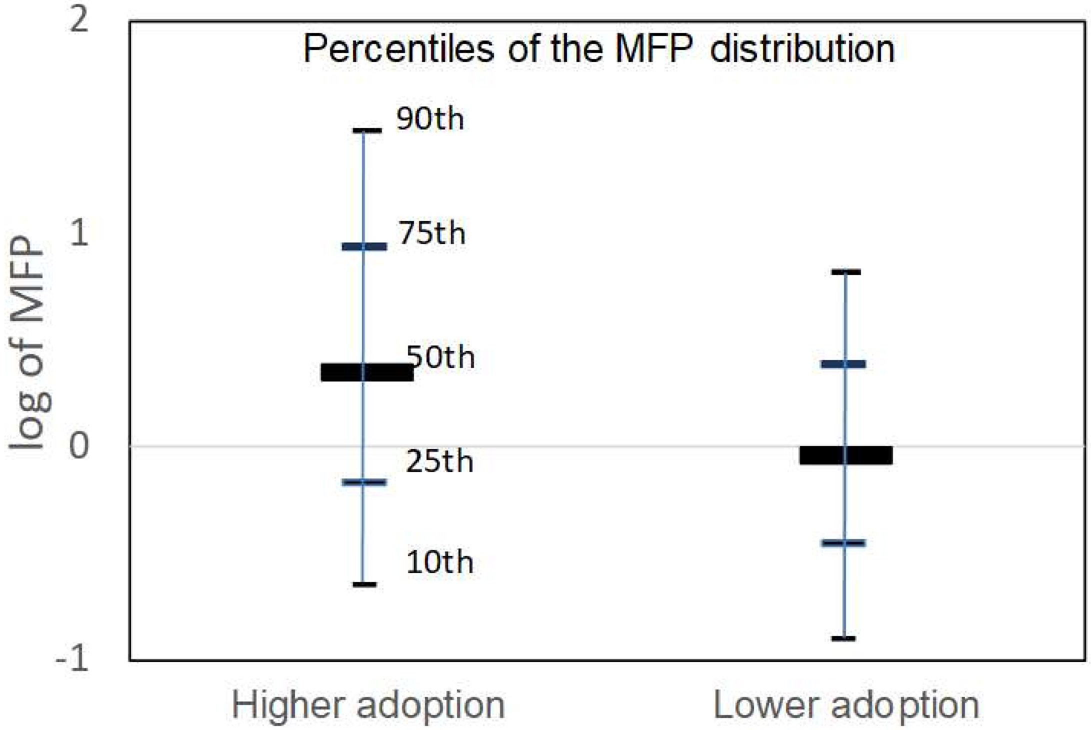
Note: MFP is measured in logarithms, based on the Wooldridge (2009) methodology. The top decile excludes firms in the top 5 per cent. The first principal component (i.e. the one associated with the largest eigenvalue) is obtained from the five digital adoption indicators. For a detailed description of each indicator, please refer to Table 1 in online Appendix A at http://www.csls.ca/ipm/37/OECD_appendix.pdf.
Source: OECD calculations.

with the occupational weights by industry obtained from the European Labour Force Survey (1995-2015).

Occupational and skill shortages rely on the OECD Skills for Jobs database, which uses labour market signals at the occupation level — in particular, relative wages, hours worked, employment and unemployment as well as qualification mismatches — to derive indicators of skill shortages in an industry (OECD, 2018). The indicators cover a rich set of skills, of which we use the following ones: *i)* resource management skills, which capture the ability to allocate resources efficiently; *ii)* management of personnel resources, which identifies how well managers motivate, develop and direct people as they work, and identify the best people for each job; *iii)* computer and electronics skills, which refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; and *iv)* technical skills, which are associated with workers' capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems.

Our combined dataset contains about 1.5 million firm-year observations in the baseline specification, spanning across 20 OECD countries (all from the European Union plus Turkey) and 22 industries over

Chart 3: MFP Distribution in Industries with High and Low Digital Adoption Rates



Note: "Higher adoption" and "lower adoption" denotes industries that are above and below, respectively, of the median industry in terms of the first principal component (i.e. the one associated with the largest eigenvalue) of the five digital adoption indicators. The percentiles are calculated within each industry and then averaged to the two industry groups, and are shown in relative terms to the median across firms with lower adoption.
Source: Orbis database of Bureau van Dijk; Eurostat, Digital Economy and Society Statistics, comprehensive database.

2010-2015 (Table 1).[17] A simple descriptive chart (Chart 3) suggests that firms tend to have higher productivity when they operate in industries where digital adoption rates are higher, but also that they exhibit higher dispersion in productivity, which is consistent with the evidence presented in Chart 1 that uses a broader classification of digital intensity following Calvino *et al.* (2018).

Results

Digital Adoption and Productivity in the Average Firm

Table 2 shows the results of estimating the baseline MFP model by ordinary least squares (OLS). All coefficients have the expected sign and significance. Roughly 20 percent of increases in frontier growth are passed to the average firm and 10 percent of the gap with frontier is filled each year

17 The set of countries are as follows: Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, the Netherlands, Poland, Portugal, Slovenia, Spain, Sweden, Turkey and the United Kingdom. The industries covered range from manufacturing to administrative and other support services, excluding the financial sector (i.e. 2-digit codes between 10 and 82, excluding 64-66).

Table 2: Baseline Results
Dependent Variable: MFP Growth

	Basic	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.218***	0.222***	0.212***	0.218***	0.215***	0.230***	0.236***
	(0.0353)	(0.0383)	(0.0374)	(0.0378)	(0.0377)	(0.0381)	(0.0394)
Gap to frontier	0.105***	0.104***	0.104***	0.105***	0.104***	0.107***	0.107***
(lagged	(0.0106)	(0.0118)	(0.0114)	(0.0117)	(0.0114)	(0.0118)	(0.0126)
Age	-0.0002***	-0.0003***	-0.0003***	-0.0002***	-0.0003***	-0.0003***	-0.0003***
	(5.19e-05)	(5.89e-05)	(5.53e-05)	(5.78e-05)	(5.67e-05)	(5.75e-05)	(6.24e-05)
Employees	0.0224***	0.0216***	0.0216***	0.0220***	0.0217***	0.0233***	0.0233***
(log)	(0.00252)	(0.00275)	(0.00266)	(0.00272)	(0.00268)	(0.00277)	(0.00295)
Digital		0.143***	0.101**	0.187***	0.0864**	0.0419	0.0161***
Technology		(0.0343)	(0.0402)	(0.0347)	(0.0437)	(0.0555)	(0.00391)
Observations	1,681,981	1,453,519	1,503,462	1,485,781	1,505,867	1,435,145	1,348,670
R-squared	0.063	0.062	0.062	0.063	0.062	0.064	0.064

Note: This table reports the estimates of the baseline equation where firm-level multifactor productivity (MFP) growth is regressed on average MFP growth of the 5 per cent firms with highest MFP in each sector-year cell, the firm's lagged gap to this productivity frontier, age and size (measured by the number of employees), and the average country-sector level adoption rates of individual digital technologies. The last column shows results for the 1^{st} principal component of the five technologies. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with more than 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

via catch-up (column 1). These are standard magnitudes at the firm level and consistent with an overall pattern of productivity dispersion (Andrews *et al.*, 2016). The main result is that an industry environment characterized by high digital adoption rates is associated with higher MFP growth in the average firm. With the exception of complex cloud computing, all digital technologies are positively and significantly associated with MFP growth. This is also the case for the first principal component of the five digital technologies (last column), which captures the simultaneous covariation and potential complementarities of several technologies.[18]

These results are robust to using (i) digital adoption rates lagged by one year, or (ii) adoption rates at the beginning of the sample period.[19]. While this could only be tested for ERP software (the only technology in our sample with sufficient time coverage in the data), it nevertheless suggests that results are not primarily driven by reverse causality.[20]

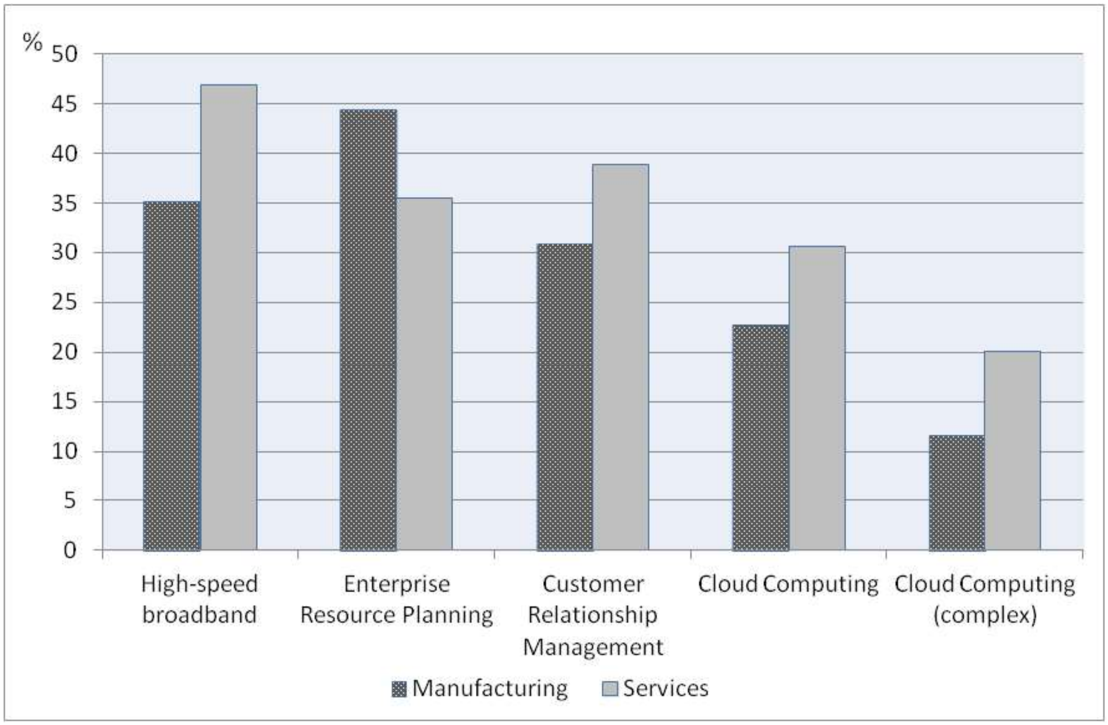
If one interprets the results as causal, they imply that a 10 percentage point increase in adoption of high-speed broadband (or cloud computing) would translate into an instantaneous increase in MFP growth by 1.4 percentage points (or 0.9 percentage point). After 5 years, this would im-

18 Refer to the online Appendix A for details http://www.csls.ca/ipm/37/OECD_appendix.pdf. An alternative approach would consist of including the adoption rates of different technologies separately in the same regression, but their individual coefficients could be difficult to interpret as the non-negligible correlation between the adoption of different technologies could give rise to multicollinearity.

19 Refer to Table 2 in the online Appendix B for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

20 Results are also robust to restricting the estimation period of the baseline regression to the years 2014-15, a period for which all digital technology variables are available (Refer to Table 1 in online Appendix B for details at http://www.csls.ca/ipm/37/OECD_appendix.pdf).

Chart 4: The Diffusion of Digital Technologies Across Sectors, Selected Technologies, 2016 (or latest available)



Note: This figure shows the average adoption rate of selected digital technologies in the manufacturing sector (NACE Rev.2 10-33) and the services sector (NACE Rev.2 45-82) of the 20 countries included in this analysis.
Source: OECD calculations based on Eurostat, Digital Economy and Society Statistics, comprehensive database.
Source: OECD calculations based on Eurostat, Digital Economy and Society Statistics, comprehensive database.

ply a 5.8 per cent (or 3.5 per cent) higher MFP level for the average firm.[21] Effects found for other technologies are of the same order of magnitude, but as shown below exhibit different patterns across industries and firms, underlining the importance of distinguishing their respective association with productivity rather than bundling all technologies in a single ICT aggregate. Overall, results suggest that at least on average there is no apparent productivity paradox at the firm level: the digitalization of an industry is indeed linked to better productivity performance of its firms.

Sectoral Differences and Routine Tasks

Economy-wide coefficient estimates may nonetheless mask differences in the co-variation of productivity and adoption in different parts of the economy. Indeed, the take-up of digital technologies varies significantly across industries (Chart 4 and Table

21 The effect after 5 years results from cumulated annual increases in MFP growth combined with weaker catch-up due to progressively higher MFP levels.

22 Appendix A is available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

3 of online Appendix A)[22] and is generally higher in services than in manufacturing.[23] However, the association of digital adoption with higher firm-level productivity is much stronger in manufacturing than services for most technologies, with the notable exception of high-speed broadband (Table 3).

One relevant factor for the effect of digital adoption is the intensity in routine tasks, which digital technologies can presumably replace or streamline (Akerman *et al.*, 2013). We therefore augment our baseline specification with the interaction between digital technology adoption and the indicator of sectoral routine task intensity proposed by Marcolin *et al.* (2016).[24] Results (Table 4), consistent with Chevalier and Luciani (2018), show that digital adoption is more closely associated with productivity gains in sectors highly intensive in routine tasks than elsewhere, perhaps reflecting a wider scope for substitution between technology and labour in these sectors. If one assumes that these effects are causal, Chart 5 shows for instance that the productivity benefits of raising adoption in a high routine-intensive sector are significantly higher than in other industries.

Channels and Robustness to Omitted Variable Bias

While our estimates are suggestive of a positive link between digital adoption and productivity performance, they suffer from a number of limitations already mentioned. Here, we attempt to identify the channels underlying the links (within-firm adoption versus spillovers from other firms) and the potential role of omitted variables.

To try disentangling the effects of the spillovers versus within firm, we run regressions including total firm-level capital expenditure or expenditure on intangible assets, which are available in the Orbis database (Table B.5, Panels A and B).[25] Coefficient estimates barely change for most of the digital technologies, save for cloud computing whose coefficient either declines (when including intangible investment) or loses significance (when including total capital expenditure). It would seem, therefore, that for most technologies the effects captured reflect either mainly sector-wide spillovers or benefits from within-firm adoption that cannot be controlled for using the available set of information from company accounts.

A potential source of concern is that sector-level adoption rates may capture the effects of other sectoral drivers of productivity that are correlated with adoption. For instance, Andrews *et al.* (2018) find

23 This is consistent with findings in previous research, such as Dhyne *et al.* (2018).

24 We use the indicator for the United States, under the assumption that it reflects structural sectoral features in a relatively frictionless economy, which would be common in all countries. This also avoids possible endogeneity issues between adoption rates and routine intensity. Results are also robust to replacing the Marcolin *et al.*'s indicator of sectoral routine intensity with the indicator of sectoral knowledge intensity used in Andrews *et al.*, (2018). Table 3 of Appendix B is available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

25 Refer to Panels A and B in Table 5 of online Appendix B at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Table 3: Differentiating Between Manufacturing and Services
Dependent variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.184***	0.170***	0.178***	0.179***	0.182***	0.189***
	(0.0413)	(0.0400)	(0.0410)	(0.0409)	(0.0421)	(0.0443)
Gap to frontier	0.127***	0.125***	0.126***	0.126***	0.128***	0.129***
(lagged)	(0.00540)	(0.00508)	(0.00512)	(0.00522)	(0.00523)	(0.00561)
Age	-0.000204***	-0.000215***	-0.000203***	-0.000219***	-0.000282***	-0.000270***
	(5.38e-05)	(5.04e-05)	(5.31e-05)	(5.17e-05)	(4.97e-05)	(5.30e-05)
Employees (log)	0.0256***	0.0254***	0.0257***	0.0258***	0.0271***	0.0273***
	(0.00201)	(0.00194)	(0.00195)	(0.00199)	(0.00207)	(0.00217)
Digital technology	0.119**	0.113***	0.211***	0.189***	0.359***	0.0264***
(Manufacturing)	(0.0535)	(0.0419)	(0.0481)	(0.0524)	(0.115)	(0.00517)
Digital technology	0.173***	0.0526	0.158***	0.0589	0.0644	0.0140***
(Services)	(0.0329)	(0.0578)	(0.0384)	(0.0509)	(0.0574)	(0.00395)
Observations	1,223,625	1,273,088	1,256,137	1,275,982	1,221,521	1,135,046
R-squared	0.073	0.073	0.073	0.073	0.074	0.074

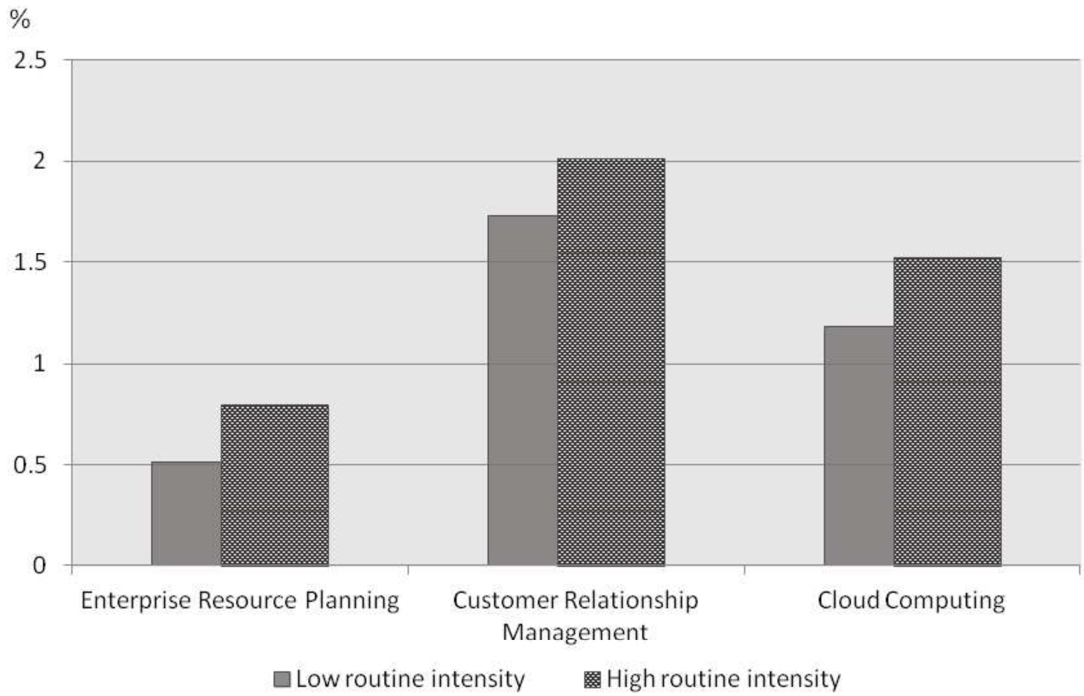
Note: Colum 1-6 of this table show the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 percent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), and the interaction between digital technology adoption rates and a dummy for the sector. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the first principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 20 manufacturing and market services sectors (NACE Rev 2, 10-82, excl. sectors 35-43) over the period 2010-15 for firms with at least 10 employees. To maximize coverage, unweighted averages of each digital technology variable are used over the period. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Table 4: Differentiating According to Sector Routine Intensity
Dependent variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.236***	0.235***	0.239***	0.234***	0.267***	0.264***
	(0.0483)	(0.0480)	(0.0478)	(0.0481)	(0.0472)	(0.0474)
Gap to frontier	0.101***	0.101***	0.102***	0.101***	0.105***	0.107***
(lagged)	(0.0152)	(0.0150)	(0.0154)	(0.0153)	(0.0161)	(0.0166)
Age	-0.000286***	-0.000286***	-0.000284***	-0.000278***	-0.000319***	-0.000323***
	(6.28e-05)	(6.28e-05)	(6.33e-05)	(6.29e-05)	(7.21e-05)	(7.47e-05)
Employees (log)	0.0195***	0.0194***	0.0200***	0.0194***	0.0206***	0.0213***
	(0.00317)	(0.00314)	(0.00323)	(0.00318)	(0.00332)	(0.00345)
Digital technology	0.168***	0.0551	0.177***	0.123**	0.185*	0.0229***
	(0.0580)	(0.0517)	(0.0470)	(0.0593)	(0.101)	(0.00564)
Digital technology	0.0177	0.136**	0.133*	0.162**	0.286**	0.0222***
X routine intensity	(0.0658)	(0.0617)	(0.0777)	(0.0653)	(0.128)	(0.00569)
Observations	1,137,711	1,142,895	1,138,659	1,138,021	1,070,569	1,052,191
R-squared	0.063	0.062	0.063	0.063	0.065	0.065

Note: This table reports estimates of the baseline equation augmented with an interaction between digital technologies and the intensity of routine tasks (see Marcolin et al., 2016, for a description of the indicator). All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the 1st principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with at least 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15 and routine intensity refers to the average over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

Chart 5: Multifactor Productivity Gains for the Average Firm Associated with a 10 Percentage Point Increase in Industry-level Adoption



Note: Estimates are derived from the baseline equation augmented with an interaction between digital technologies and the country-sector-level intensity of routine tasks (Marcolin *et al.*, 2016) (Table 4). High (low) routine intensity represents the 75^{th} (25^{th}) percentile of the distribution in this classification.

that digital adoption rates are influenced by a number of sector-level structural and policy factors affecting firm-level capabilities and incentives to adopt. A number of these factors, such as the regulatory environment and the availability of skills may also directly affect firm-level productivity growth (Arnold *et al.*, 2011; Andrews *et al.*, 2016).

Omitting these factors could artificially inflate the estimated effects of sector-level digital adoption rates. To control for this possibility, we extend the model with two additional control variables: (i) the OECD indicator of the impact of upstream anti-competitive regulations in each sector (Conway and Nicoletti, 2006; Égert and Wanner, 2016), and (ii) a new indicator of sectoral occupational shortages recently published in the OECD Skills for Jobs Database (2018). Reassuringly, while both regulatory burdens and lack of skills have the expected negative association with productivity performance,[26] the finding that higher digital adoption rates are associated with higher MFP growth remains largely unaffected when we account for the direct influence of these variables.[27]

26 The lack of significance of the regulatory impact indicator is most likely related to the relatively short time period spanned, as most of the variation in this indicator is within country-industry in the sample of relatively homogeneous EU countries mostly covered by our analysis.

27 Refer to Panel in C Table 5 of online Appendix B at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

The Role of Skills

The likely complementarity between digital technologies and other intangible investments suggests that skill shortages in a sector could impede digital adoption from yielding its full productivity benefits. We test this conjecture by further extending the baseline model to include the interaction between digital adoption and skill shortages. One concern with this approach could be that industries in which adoption is high (or low) may cause (or suffer from) skill shortages, and this endogeneity could bias estimates in unpredictable ways. However, there appears to be no systematic correlation between adoption and shortages in the data.[28] Since the OECD Skills for Jobs database includes a large number of skills (captured through occupations), we concentrate first on general shortages and subsequently focus more specifically on skills that are likely to be most complementary to digital adoption (managerial, computer and electronics, and technical).[29]

Consistent with the idea that digital technologies are complementary to organizational and human capital, we find that general occupational shortages in an industry curb the linkage between adoption rates and productivity performance (Table 5) for specific technologies (such as high-speed broadband, CRM and cloud computing) and for all technologies combined (first principal component).[30]

Since a lack of skill shortages are found to be correlated with a higher automation risk (OECD, 2018) we implement a further test to rule out that our results on skill shortages are merely a reflection of a greater capacity for productivity-enhancing automation in industries with low skill shortages. In particular, we include interactions of digital technologies not only with skill shortages but also with routine intensity — to capture automation risk — in the same regressions. As shown in Table 4 of online Appendix B, the results on both channels remain robust to this specification.

Digging deeper (Table B.6), shortages in managerial, electronic and technical skills all inhibit the ability of firms to reap the productivity benefits of higher sector-level adoption rates.[31] The damaging effects of skill shortages on the productivity gains from adoption are substantive (Chart 6, Panel A). For instance, moving from rel-

28 Refer to Table 6 of online Appendix A at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

29 "Occupational shortages" pools shortages in all occupational categories covered by the OECD dataset; managerial shortages covers "Resource management skills" (ability to allocate resources efficiently) and "Management of personnel resources" (how well managers motivate, develop and direct people and identify best people for each job); "Computer and electronics" refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; "Technical skills" are associated with workers' capacity to design, set up, operate and correct malfunctions, involving application of machines or technological systems. See OECD (2018) for details.

30 Since skill shortages are constructed by relying among other factors on differences in wage dynamics across occupations, they could also capture to some extent differences in industry productivity, which in turn are related to average firm productivity. However, this is mitigated by the fact that wages enter only with a small weight (20 per cent) into the skill shortage indicator (see subsection Combining Firm and Industry-level Data and OECD (2018)).

31 Refer to Table 6 of online Appendix B athttp://www.csls.ca/ipm/37/OECD_appendix.pdf.

Table 5: Assessing the Effects of Skill Shortages, Dependent Variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component
Frontier growth	0.154***	0.128***	0.141***	0.133***	0.133***	0.145***
	(0.0372)	(0.0378)	(0.0373)	(0.0374)	(0.0374)	(0.0375)
Gap to frontier	0.105***	0.104***	0.106***	0.104***	0.105***	0.106***
(lagged)	(0.0133)	(0.0126)	(0.0130)	(0.0126)	(0.0126)	(0.0136)
Age	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0004***
	(6.30e-05)	(6.13e-05)	(6.25e-05)	(6.12e-05)	(6.15e-05)	(6.67e-05)
Employees (log)	0.0228***	0.0224***	0.0230***	0.0225***	0.0228***	0.0231***
	(0.00303)	(0.00290)	(0.00298)	(0.00290)	(0.00291)	(0.00311)
Occupational	-0.0363***	-0.0264*	-0.0316***	-0.0232	-0.0232	-0.0309**
shortage	(0.0128)	(0.0140)	(0.0110)	(0.0142)	(0.0141)	(0.0124)
Digital technology	0.170***	0.0465	0.201***	0.0957**	0.0247	0.0163***
	(0.0420)	(0.0468)	(0.0408)	(0.0478)	(0.0664)	(0.00411)
Occupational shortage	-0.287***	-0.121	-0.274***	-0.0411	-0.170**	-0.0186***
X digital technology	(0.0851)	(0.105)	(0.0935)	(0.0649)	(0.0802)	(0.00534)
Observations	1,106,487	1,142,249	1,128,495	1,149,976	1,151,662	1,080,849
R-squared	0.062	0.061	0.062	0.062	0.062	0.062

Note: This table reports the estimates of the baseline equation where firm-level multifactor productivity growth is regressed on growth of the top 5 per cent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), average country-sector level adoption rates of individual digital technologies, an index capturing sector-level general occupational shortages, and their interaction with the digital adoption variable. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. The last column shows results for the first principal component of the five technologies. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2011-15 for firms with at least 10 employees. To maximize coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent $p<0.01$, $p<0.05$ and $p<0.1$ respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

atively low to high shortages would reduce the estimated firm-level productivity growth gains from an increase in high-speed broadband internet diffusion by more than a quarter; a similar reduction in productivity gains due to shortages is estimated for CRM. Focusing on specific skills, the strongest downward effects of shortages on productivity gains from wider sector-level adoption rates (of all technologies combined) are found for electronic and technical skills (Chart 6, Panel B).

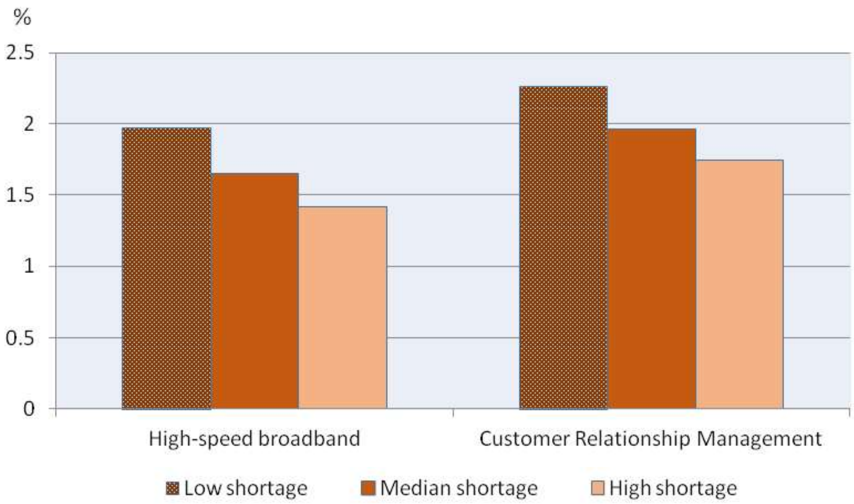
Which Firms Benefit Most from Adoption?

To study the link between digitalization and productivity growth across the firm productivity distribution, we test two approaches (Table 6). First, we introduce dummy variables that divide the sample according to productivity quartiles in each industry, from lowest to highest initial productivity levels (columns 1 to 6).[32] Second, we interact digital adoption rates with the gap to the productivity frontier variable (column 7). The results of both approaches are consistent and strongly suggest that the positive association between

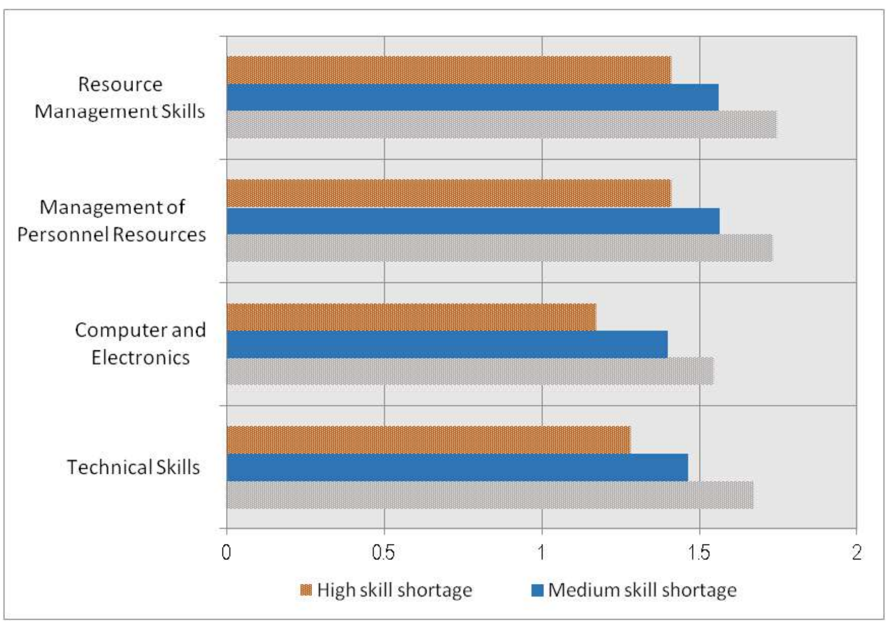
32 Given that these dummies could duplicate the information conveyed by the gap to frontier variable, we also ran the same regression omitting the gap. The results remained unchanged. See Table 8 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Chart 6: Skill Shortages and the Returns from Digitalization

Panel A: Increase in MFP Growth Associated with a Ten Percentage Point Increase in the Diffusion of Digital Technologies in the Presence of General Occupational Shortages



Panel B: Increase in MFP Growth Associated with a Ten Percentage Point Increase in the Diffusion of High-speed Broadband, for Specific Skill Shortages



Note: These figures show the ceteris paribus impact of a ten percentage point increase in the diffusion of high-speed broadband or customer relationship management in a labour market environment characterized by a low (25th percentile of the distribution), medium (median of the distribution) or high (75th percentile of the distribution) shortage in occupations (Panel A) or specific skills Appendix Table B.5 (Panel B). Calculations are based on estimates from Table 5 (Panel A) and Table B5 (Panel B). Resource management skills capture the ability to allocate resources efficiently; management of personnel resources identifies how well managers motivate, develop and direct people as they work, and identify the best people for each job; computer and electronics refers to the knowledge of circuit boards, processors, chips, electronic equipment, computer hardware and software, including application and programming; and technical skills are associated with worker's capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems. See OECD (2018) for more information.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, OECD (2018).

Table 6: The Heterogeneous Effects of Digitalization Across Productivity Quartiles Dependent variable: MFP growth

	High-speed broadband	Enterprise Resource Planning	Customer Relationship Management	Cloud Computing	Cloud Computing (complex)	First principal component	First principal component
Frontier growth	0.206*** (0.0388)	0.197*** (0.0377)	0.203*** (0.0382)	0.201*** (0.0382)	0.216*** (0.0387)	0.220*** (0.0399)	0.235*** (0.0394)
Gap to frontier (lagged)	0.0741*** (0.0197)	0.0760*** (0.0191)	0.0762*** (0.0195)	0.0758*** (0.0193)	0.0807*** (0.0205)	0.0780*** (0.0208)	0.108*** (0.0120)
Age	-0.000*** (4.96e-05)	-0.000*** (4.75e-05)	-0.000*** (4.86e-05)	-0.000*** (4.84e-05)	-0.000*** (4.89e-05)	-0.000*** (5.16e-05)	-0.000*** (5.94e-05)
Employees (log)	0.0198*** (0.00185)	0.0197*** (0.00178)	0.0202*** (0.00183)	0.0198*** (0.00183)	0.0212*** (0.00193)	0.0216*** (0.00202)	0.0235*** (0.00288)
Quartile 2 (dummy)	-0.0636*** (0.0124)	-0.0662*** (0.0134)	-0.0577*** (0.0148)	-0.0312** (0.0140)	-0.0331** (0.0135)	-0.0392*** (0.0119)	
Quartile 3 (dummy)	-0.0704*** (0.0183)	-0.0710*** (0.0199)	-0.0672*** (0.0215)	-0.0358* (0.0208)	-0.0363* (0.0207)	-0.0437** (0.0194)	
Quartile 4 (dummy)	-0.0852*** (0.0263)	-0.0859*** (0.0290)	-0.0841*** (0.0304)	-0.0457 (0.0298)	-0.0459 (0.0298)	-0.0554* (0.0287)	
Digital technology (Quartile 1)	0.0845*** (0.0326)	-0.00483 (0.0452)	0.100** (0.0444)	0.122** (0.0590)	0.0668 (0.0741)	0.0107** (0.00425)	
Digital technology (Quartile 2)	0.170*** (0.0332)	0.0898** (0.0395)	0.166*** (0.0330)	0.0862* (0.0449)	0.0373 (0.0606)	0.0150*** (0.00382)	
Digital technology (Quartile 3)	0.179*** (0.0358)	0.0933** (0.0390)	0.182*** (0.0315)	0.0905** (0.0410)	0.0478 (0.0555)	0.0156*** (0.00347)	
Digital technology (Quartile 4)	0.191*** (0.0424)	0.109*** (0.0386)	0.202*** (0.0347)	0.0888** (0.0422)	0.0473 (0.0523)	0.0164*** (0.00365)	
Digital technology							0.0139*** (0.00394)
Digital technology X gap to frontier (lagged)							-0.00763** (0.00323)
Observations	1,403,093	1,451,507	1,434,364	1,453,557	1,383,623	1,299,953	1,348,670
R-squared	0.062	0.062	0.062	0.061	0.062	0.063	0.065

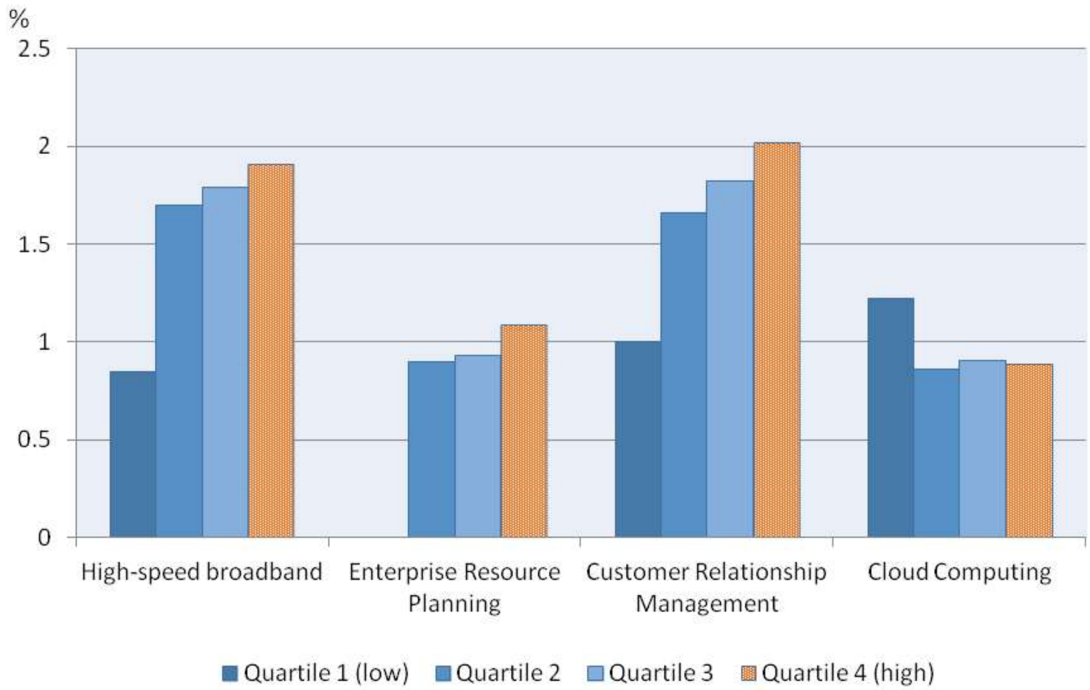
Note: Colum 1-6 of this table show the results of the equation where firm-level multifactor productivity growth is regressed on growth of the top 5 per cent frontier firms in each sector-year cell, the firm's gap to this frontier, age and size (measured by the number of employees), a dummy for each productivity quartile (omitting the first quartile for reference), and the interaction between digital technology adoption rates and a dummy for each productivity quartile. Quartile 1 refers to the bottom of the distribution (i.e. low productive firms), quartile 4 to the top. Alternatively, the last column displays results of the baseline equation augmented by an interaction term between digital technologies and the lagged gap to the frontier. All regressions include sector and country-year fixed effects and are clustered at the country-sector level. In all cases, the coefficient estimates of quartile 1 and 4 are statistically different. The 1st principal component refers to the five technologies of column 1-5. Firms at the sector-year frontier are excluded from the regressions. Regressions are based on firm-level data from 20 countries and 22 sectors (NACE Rev 2, 10-82) over the period 2010-15 for firms with at least 10 employees. To maximise coverage, unweighted averages of each digital technology variable are used over the period 2010-15. ***, ** and * represent p<0.01, p<0.05 and p<0.1 respectively.
Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

sector-level diffusion of digital technologies and productivity growth is strongest for high productivity firms (or firms close to the frontier).[33]

For instance, if one assumes that the results are causal, the estimated productivity gains from raising adoption rates by 10 percentage points are more than doubled for high productivity relative to low productivity firms in the case of high-speed broadband and CRM (Chart 7). Interestingly, cloud computing is the only technology for which low-productivity firms tend to benefit more, consistent with the idea that it may be less demanding than other technologies (e.g. ERP and CRM) in terms

33 For brevity, we only report results for the 1st principal component in the case of interaction with distance to the frontier. More detailed results can be found in Table B.7. Results by productivity quartile for ERP are also robust to using lagged or initial adoption rates, suggesting that they are not primarily driven by reverse causality. See Table 2 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Chart 7: Multifactor Productivity Gains from a 10 Percentage Point Increase in the Industry-level Diffusion of Specific Technologies, by Productivity Quartiles, after 1 year



This chart shows the ceteris paribus increase in multifactor productivity growth from increasing the diffusion of digital technologies by ten percentage points across different productivity quartiles. Quartile 1 refers to the bottom of the distribution (i.e. low productive firms), quartile 4 to the top of the distribution (i.e. high productive firms). Results for ERP for the least productive firms are not statistically significant. Calculations are based on estimates from Table 6, column 1-4. Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

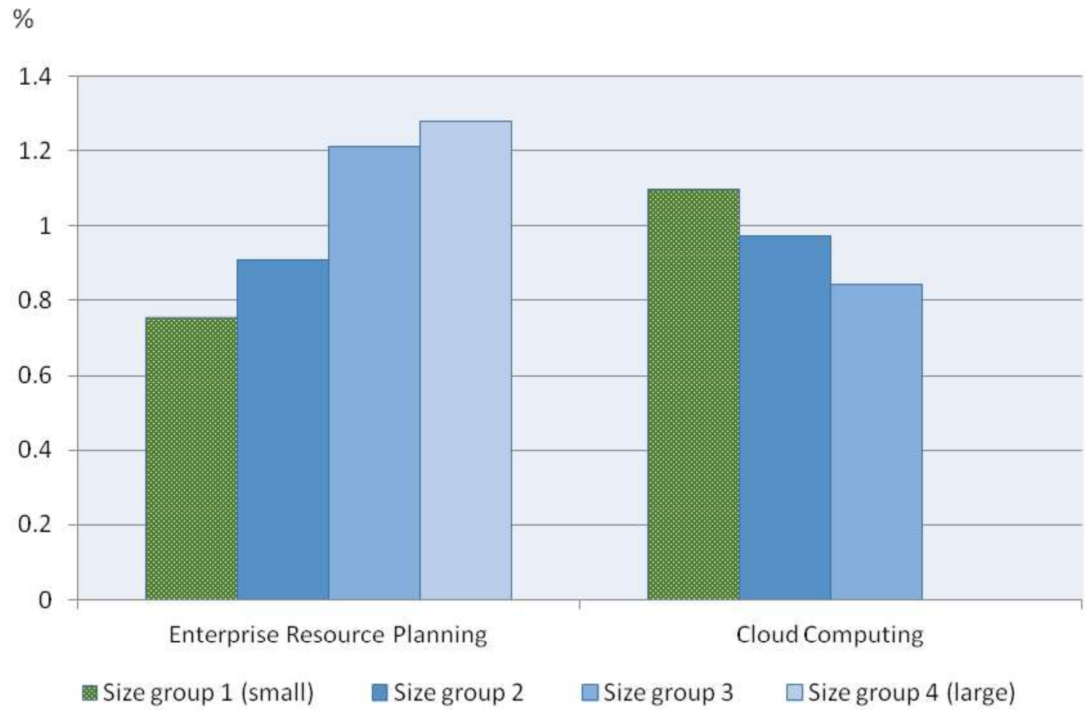
of complementary investments in organizational capital.

Regressions that differentiate firms by size suggest that size matters less than productivity in terms of gains from digital adoption (Chart 8 and Table 9 in online Appendix B).[34] Interestingly, the effect of size depends on the technology. As expected, cloud computing has the strongest positive association with productivity performance for the smallest firms, which are for instance able to avoid the fixed costs of investing in data storage and processing facilities, which is a way to acquire "scale without mass" (Bloom and Pierri, 2018). The opposite is found for Enterprise Resource Planning, which is most strongly associated with productivity improvements in the largest firms, due to the well-known economies of scope and scale characterizing this technology. Confirming that productivity is the key determinant, crossing the size and productivity criteria shows that, independent of the technology, it is always

34 Appendix B is available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

35 Refer to Table 10 from online Appendix B at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

Chart 8: Multifactor Productivity Gains from a 10 Percentage Point Increase in Diffusion of Digital Technologies, by Firm Size, after 1 year



This graph shows the ceteris paribus increase in multifactor productivity growth from increasing the diffusion of digital technologies by ten percentage points across different size groups. Size group 1 captures firms with 10-20 employees, size group 2 firms with 21-50 employees, size group 3 firms with 51-250 employees, and size group 4 capture very large firms with more than 250 employees. Results for cloud computing for the largest firms are not significant. Calculations are based on estimates from Table 9 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf. // Source: OECD calculations based on ORBIS and Eurostat, Digital Economy and Society Statistics, comprehensive database.

the highest productivity firms that benefit most.[35]

The finding that sector-level digital adoption is most closely associated with productivity increases in the best performing firms would point to an inherent tendency of digitalization to increase productivity dispersion as digital technologies spread out. This is consistent with evidence pointing to a rising dispersion in productivity within narrowly-defined sectors (Syverson, 2011) and a rising gap between productivity growth in the best firms and the rest, especially in highly digitalized sectors (Andrews *et al.*, 2016; Berlingieri *et al.*, 2017). It is also in line with recent findings on the speed of catch-up of laggard firms, which is shown to be weaker in industries that rely more on ICT specialists (Berlingieri *et al.*, 2018).

A simple back-of-the-envelope calculation suggests that the simultaneous increase in the take-up of all five digital technologies considered in this article could explain about 0.28-0.35 log point per year out of the 0.64 log point annual observed divergence in productivity between the top and bottom quartiles over 2010-15, i.e. about half of the total divergence.[36]

One potential explanation for the higher gains of high-productivity firms is that adopting digital technologies and exploiting them efficiently requires other endowments, such as managerial ability, know-how or technical skills. It is likely that these endowments are more present in high productivity firms than elsewhere. Consistent with this, additional regressions suggest that skills shortages at the industry level reduce the gains from digitalization relatively more in less productive firms than in more productive ones, suggesting that it is relatively more difficult for less productive firms to attract workers with relevant skills.[37]

Conclusion

Our findings support the idea that the adoption of digital technologies is generally associated with substantially higher firm-level productivity. These results hold for a range of different technologies (high-speed broadband access, simple and complex cloud computing, CRM and ERP software). This association is stronger in manufacturing industries and more generally in industries that are intensive in routine tasks, suggesting that digital adoption can streamline production processes and to some extent act as a substitute for routine labour input.

The association between the adoption of digital technologies and productivity is also stronger for firms that are already highly productive, hence likely to benefit from complementary organizational and technical skills. This evidence is consistent with a potential for digitalization to exacerbate dispersion in firm-level performance outcomes (Brynjolfsson and McAfee, 2011). Compared to past innovation waves, gains from digital technologies may have been less easy to reap for less productive firms, because these gains depend crucially on firm-specific intangible assets and skills (e.g. data, tacit knowledge, organizational capital) and complementary additional investments in these factors, which are harder to implement in these firms. This is in line with recent evidence at the macroeconomic level that shows a slower penetration of the latest technologies within countries — even though their initial diffusion across countries is now faster than in the past (Comin and Mestieri, 2018).

This sheds some light on the so-called "modern productivity paradox". Overall gains from digitalization may appear disappointing compared to past innovation waves or to the potential offered by these technologies since this potential, albeit important, is fully realised only by the most

36 These results are obtained by using the estimated coefficients on the first principal component from Table 6 (last column) and combining average changes in adoption with the weight of each technology in the first principal component. The average adoption rates in 2010 (2015) are the following: for ERP, 25 per cent (35 per cent), for CRM, 31 per cent (34 per cent). For the other two variables where no data are available in 2010 — cloud computing and high speed broadband — we assumed zero prevalence, with 2015 values being 24 per cent (cloud computing simple), 13 per cent (cloud computing complex) and 35 per cent (high speed broadband). For high-speed broadband, as alternative, we also assumed 20 per cent in the initial year, leading to the two values that define the interval of the final result.

37 Refer to Table 11 in online Appendix B available at http://www.csls.ca/ipm/37/OECD_appendix.pdf.

productive firms. A key question is the counterfactual scenario to which one compares current trends. Overall, our results suggest that current productivity growth is clearly stronger (especially among the more productive firms) than in a hypothetical scenario without digitalization, but weaker than in a scenario where all firms would reap the full benefits from digital technologies.

While this finding contributes to explaining disappointing productivity growth, it does not explain by itself the broad-based productivity slowdown observed since the mid-2000s in OECD countries. This suggests either that a first, more significant wave of ICT adoption — leading to productivity gains in manufacturing and certain services such as distribution or finance, especially in the United States (Cette *et al.*, 2016; Van Ark *et al.*, 2008) — has run its course, or that other negative factors may have masked the productivity gains from digitalization. For example, weakening business dynamism (Decker *et al.*, 2016; Calvino *et al.*, 2018) and legacies of the global financial crisis (Adler *et al.*, 2017) have been drags on overall productivity growth.

More broadly, the ability of less productive firms to catch up has apparently diminished, resulting in an increasing dispersion in productivity outcomes (Andrews *et al.*, 2016; Berlingieri *et al.*, 2017; Berlingieri *et al.*, 2018). As discussed in this article, digitalization is a factor that has contributed to this divergence — a back-of-the-envelope calculation suggests that it could have contributed to about half of the observed divergence between the top and bottom productivity quartiles in each industry over 2010-15. Our findings suggest that shortages in technical and managerial skills in an industry tend to amplify this divergence, since they affect predominantly less productive firms.

Looking ahead, there is a risk that a wide and enduring productivity gap across firms is not only a reflection of weaker diffusion of innovation, business dynamism and potentially competition, but may in itself fuel a further weakening of these factors. For example, the most productive firms may become more difficult for other firms to challenge because they benefit from firm-specific intangible assets and can attract the most skilled workers. Andrews *et al.* (2016) find that industries where productivity dispersion widens more also tend to have weaker aggregate productivity growth. Mounting evidence of rising mark-ups — especially in digitally intensive industries — and sector concentration (Calligaris *et al.*, 2018; Bajgar *et al.*, 2019), as well as declining firm entry and exit rates (Calvino *et al.*, 2015; Adalet McGowan *et al.*, 2017) — again, especially in highly digitalized sectors (Calvino and Criscuolo, 2018) — are consistent with this picture.

These findings raise challenges and opportunities for policies aimed at making the best of digital technologies. Policies encouraging digital adoption are warranted given the intrinsic potential of these technologies to support productivity, but should be accompanied by efforts to create the conditions enabling the catch-up of productivity laggards and the efficient reallocation of resources in the economy (Sorbe *et al.*, 2019). This includes smoothing the costs of the digital transition for displaced workers and maximising their reemployment potential.

As shown by Andrews *et al.* (2018), both capabilities (e.g. enhancing managerial and digital-friendly skills) and incentives (e.g. reducing entry and exit barriers) are relevant to stimulate digital adoption. Moreover, certain drivers of digital adoption identified by Andrews *et al.* (2018) are also likely to support the performance of lagging firms (e.g. widening the skill pool, improving access to financing, reducing entry barriers to certain markets). Enhancing skills is particularly important in this respect, as lagging firms are more affected by skill shortages than more productive firms. In addition, further efforts may be needed to ensure that large incumbents do not create barriers to the entry and growth of competitors and the diffusion of innovation in the economy (Berlingieri *et al.*, 2018).

Further research is needed to improve our understanding of the links between digital adoption and productivity. More specifically, two issues that were not covered in this article due to data limitations would deserve further attention. First, better disentangling the benefits of within-firm digital adoption from the positive spillovers via adoption in other firms (a question this article could only explore tentatively) would be useful. Second, it would be interesting to broaden the perspective to account for reallocation effects (does digital adoption enable more productive firms to grow faster than less productive ones?) as well as the propensity for entry and exit of firms in a more digitalized environment.

More broadly, the benefits of digitalization could be assessed beyond the scope of firm productivity. Indeed, households and governments also likely benefit from the use of digital technologies, and from a more digitalized environment in general. There are probably important complementarities to be explored between digital adoption in firms, households and governments, as joint increases in adoption can facilitate interactions between them as well as skill upgrades.

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