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Digital technologies and productivity: A firm-level investigation☆

Francesco Nucci [a,*], Chiara Puccioni [b], Ottavio Ricchi [c]

[a] *Sapienza University, Italy*
[b] *Confindustria, Italy*
[c] *Italian Ministry of Economy and Finance, Treasury Department, Italy*

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ABSTRACT

We characterize the process of digital transformation of Italian firms and the impact on TFP. Using information of unusual breadth on different types of investments in digital technologies, we consider various dimensions of digital adoption such as whether firms invested in advanced domains (like AI) or bundles of more than one technology. We investigate the effects of digital technologies on productivity using alternative criteria to classify firms as digital adopters. With our baseline definition, the estimated effect on the percentage change in TFP between 2015 and 2018 is about one percentage point (0.97). With more restrictive definitions of digital adoption, the estimated impact is found to be larger, and it is largest when digital adoption is associated with investments in at least one AI-related technology. We also show that, in general, the effect of digital adoption is more sizeable in the service sector, in larger firms and in older firms.

1. Introduction

The rise of the New Digital Economy represents a major shift in the way firms operate. Digital technologies imply an overall reduction in firm's costs, such as those for information search and processing and for coordination and communications, and enable firms to substantially transform their production processes and business models (Goldfarb and Tucker 2019). Brynjolfsson et al. (2017) emphasize that economies have been experiencing a continuing progress of information technologies in many domains, from further technology advances in computer power to a large diffusion of investment in innovative technologies, like cloud infrastructure, and to advances in artificial intelligence and machine learning.

Yet, the rapid diffusion of digital technologies has coincided with a protracted slowdown of aggregate productivity growth since the mid-2000s (see, e.g., Cette et al., 2016). Indeed, despite the unprecedented pace of digital adoption in the business sector, the gains in terms of faster productivity growth at the economy level have not been visible. Among the explanations for this seeming productivity paradox, Van Ark (2016) argues that the new digital economy is still in its "installation phase", while Brynjolfsson et al. (2017, 2021) state that the measured productivity gains from digital investments do not materialize immediately and most of them are still to come. On the other hand, a wide dispersion has been documented in the extent to which firms are embracing the digital transformation (Andrews et al., 2018) and, according to Sorbe et al. (2019), this heterogeneity across firms and industries contributes to

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* Corresponding author.
E-mail address: francesco.nucci@uniroma1.it (F. Nucci).

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explain why aggregate productivity gains from digitalization are not so evident.

A variety of empirical studies, both at the industry and the firm level, have investigated the effects of investments in digital technologies on the productivity performance. In general, the existing evidence indicates a positive and statistically significant association between digital-technology adoption and productivity using different measures and different approaches (see Bloom et al., 2007; Draca et al., 2006; Syverson, 2011 for a review of the evidence).[1] However, there are several studies that reach a different conclusion. For example, Acemoglu et al. (2014) show that the intensity of information technologies does not affect labor productivity in the US manufacturing sector outside the computer producing sector. DeStefano et al. (2018) document no effects of ICT on productivity for UK firms and other existing studies on the impact of broadband adoption on productivity find no significant impact (see Haller and Lyons, 2015 and the references therein).

Against this background, this paper seeks to investigate how investments in digital technologies impinge on firms' productivity. Preliminary to this, we characterize the process of firm's digitalization in Italy and the multiple dimensions though which digital adoption can occur, shedding light on the heterogeneity across firms in the way they rely on new technologies. We document who invests in digital technologies and how by examining numerous firm characteristics. We then evaluate the effects of digital adoption on productivity focusing on different types of investment in digital technologies and considering that digital technologies are often used in bundles.

In our empirical investigation we use high-quality, firm-level on digital adoption of unusual breadth. Indeed, a Survey by the Italian Statistical Institute (Istat) in the 2019 Permanent census of enterprises has a detailed section on firms' use of digital technologies. Among numerous questions, the Survey has asked firms to report whether, in the period 2016–2018, they have invested in each of nine different types of digital technologies (Istat, 2020a). The types of digital technologies are grouped in three domains. The first (Internet-based technologies) comprises specific digital investments which refer to optic-fiber ultra-broadband connection, mobility connection (4G and 5G) and internet of things. The second domain (Areas of application of artificial intelligence, AI) encompasses investments in immersive technologies, big data, and automatization, robotics, and smart systems. The third domain (Other technological areas) includes investments in 3D printing, simulation of interconnected machines and cyber-security.

Based on firms' responses to these questions, we have first singled out the group of firms that did not invest in any digital technology in the period 2016–2018 and the group of those which have invested in at least one of the nine types of digital technologies. Then, to capture the different domains of digital adoption and the different ways in which the propensity to invest in digital technologies can be characterized, we have used various alternative classification criteria to allocate the firms into the group of digital adopters. Our first alternative to the baseline group identifies firms as 'digital' if they have invested in at least one new technology in the second and third domains, which are likely to comprise more advanced technologies (e.g., big data, advanced automation, 3D printing, augmented and virtual reality) compared to those included in the first domain. Other criteria to define digital adopters are based on whether firms have invested in a bundle of more than one digital technology. Thus, one group includes firms which have invested in a bundle of at least two types of new technologies, while another one includes firms that have invested in a bundle of at least three types. Finally, given the specificities of the second technological domain, we experiment with a definition of digital adopters that includes in this group only the firms with at least an investment in the areas of application of AI. In all cases, the reference group of the "non adopters" remains the same.

In estimating the effects of digital adoption on a measure of firm performance we focus on total factor productivity (TFP) and employ the propensity score matching (PSM) methodology combined with a difference-in-differences (DiD) analysis. This should allow us to mitigate the well-known problems of self-selection into treatment, endogeneity and reverse causation that may affect the estimation of the digitalization-productivity relationship. Thus, we focus first on numerous characteristics, evaluated before the treatment, that are likely to affect firms' adoption of digital technologies. Among firms with these characteristics, some have adopted digital technologies in the 2016–2018 period while some others have not. Second, we match firms that have invested in digital technologies with their corresponding "twins" that have not and then compare the variation in productivity over the period 2018–2015 between the two groups of firms.

We find that investments in digital technologies have discernible and statistically significant effects on firm productivity. Our estimation findings indicate that firms that have invested in at least one type of digital technology over the 2016–2018 period have a rate of variation of TFP, between 2015 and 2018, which is 0.97 percentage points higher, on average, than that of similar firms with no digital adoption. Not surprisingly, when we focus on the alternative definitions of treatment presented earlier, from those based on the adoption of more advanced technologies (e.g., AI) to those based on bundles of more than one technology, the estimated effects are larger in size and statistically significant. For all the criteria to classify firms as treated with digital adoption, we supplement our findings with several evidence on the quality of the matching, the existence of common trends before the treatment and the robustness of the results to alternative matching methods.

Moreover, we detect heterogeneity in the productivity gains from digital adoption not only regarding the way we measure the firm propensity to invest in digital technologies but also in reference to various firm characteristics. We show that the estimated effect of digital adoption on TFP varies in strength between different groups of firms and is, in general, stronger in firms operating in services, in larger firms and in older firms.

The remaining of the paper is organized as follows: in Section 2 we provide a background discussion of the relevant issues, with an overview of the related literature; Section 3 describes the data and especially the measures of digital adoption; Section 4 illustrates the empirical methodology; Section 5 presents the baseline econometric results, while Section 6 focuses on some extensions. Section 7 concludes.

2. Background and related literature

Significant advances in information technologies have taken place, ranging from further progress in computer power to adoption of innovative technologies like cloud infrastructure and those associated with artificial intelligence and machine learning (see, e.g., Brynjolfsson et al., 2017). The adoption of digital technologies induces a substantial decline of firms' costs along several domains and prompt innovation in their production processes and business models enhancing the flexibility of the firm organization (Goldfarb and Tucker, 2019). As shown by Bartel et al. (2007), the use of new computerized technologies can increase the customization of firms' products, induce faster machine setup times, and reduce the run time during production.

Parallel to this, however, measured productivity growth has shown a large deceleration over the 2005–2015 period and low productivity growth rates have been recorded in that period in almost all developed economies, especially in the euro area. Labor productivity growth rates in a broad group of developed countries declined in the mid-2000s and have remained low since then. As Van Ark (2016) reports, the slowdown in global total factor productivity growth has been even more dramatic, moving down from 1.3 per cent from 1999 to 2006 to 0.3 per cent from 2007 to 2014. This amounts to a "productivity paradox", that is the

[1] Previous contributions include, among others, Brynjolfsson and Hitt (2003), Bloom et al. (2012), Gal et al. (2019) and Anderton et al. (2023).

coexistence of advances in ICT with a protracted slowdown in productivity growth, and Brynjolfsson et al. (2017) reformulate the original Solow paradox as follows: "we see transformative new technologies everywhere but in the productivity statistics".[2]

Several empirical studies, both at the firm and the industry level, investigate the relationship between the adoption of digital technologies and productivity. In their survey, Draca et al. (2006) note that several studies at the industry level detect significant productivity gains from IT capital over the 1987–2000 period. As for firm-level investigations, Draca et al. (2006) state that most of them find a positive and significant association of IT with productivity. Similarly, if we focus on more recent surveys the empirical evidence points, in general, to a positive association between digital adoption and productivity (Syverson, 2011; Bloom et al., 2012) and this is confirmed in Gal et al. (2019), who provide an updated and comprehensive literature review. There are, however, contributions to the literature that reach a different conclusion. For example, Acemoglu et al. (2014) provide evidence for the US that, if the computer-producing industries are excluded from the sample, then the intensity of use of IT investments has no effect on productivity. Similarly, DeStefano et al. (2018) find no significant impact of ICT on productivity.[3] As for the impact of firms' broadband adoption on productivity, Haller and Lyons (2015), Bertschek et al. (2013) and Colombo et al. (2013) do not detect significant effects, contrary to other contributions, such as for example Akerman et al. (2015) and Grimes et al. (2012), who reach a different conclusion.

Gal et al. (2019) use data on digital technology adoption at the industry level and estimate total factor productivity at the firm level using the control function approach to mitigate the endogeneity of input choices in the production function. They find that the impact of digital adoption on productivity increases can be sizeable, especially for firms that already enjoyed high level of productivity, and their results hold for various technologies (high-speed broadband access, simple and complex cloud computing, CRM, and ERP software). Moreover, they show that productivity gains from digital technologies are larger in manufacturing than in services and, in general, in industries with a high reliance on streamlined or automated routine tasks.

Using a panel of US establishments, Jin and McElheran (2019) provide evidence that recent dramatic increases in firms' ability to access information technologies as a service are conducive to positive effects on productivity of young establishments and that performance gains from new IT services are disproportionately detected among young firms. A firm-level study on the effects of computerization on productivity is due to Brynjolfsson and Hitt (2003), whose results indicate that, over short horizons (one year), computerization does not significantly affect productivity growth. Conversely, however, as the time horizon increases, computerization does impinge on productivity. They interpret this result by emphasizing the role of computers as a general-purpose technology (GPT), so that adoption of digital technologies is not simply about purchasing capital in the form of computers of other machinery. It also involves a host of complementary investments and innovations which may require time to implement (see Brynjolfsson et al., 2021).

Focusing on patterns before mid-2000s, Bloom et al. (2012) use microeconomic data on establishments in Europe owned by US multinationals vis-à-vis establishments in Europe owned by non-US multinationals or purely domestic establishments. IT related productivity is derived through the control function approach introduced by Olley and Pakes (1996) with several refinements. Specifically, they estimate an augmented Cobb-Douglas production function where both IT and non-IT capital inputs are separately considered, so that IT capital is taken as a state variable and its potential endogeneity is controlled for. They provide estimates for the productivity of IT capital and document differences across US and European firms in IT-related productivity. Their empirical results point to US people-management practices as a driver of the productivity premium, owing to a superior ability in IT exploitation.

Similarly, Caroli et al. (2001) show that information technologies induce productivity gains in firms characterized by decentralized architectures, higher levels of human capital and team-based production. At the same time, Tambe et al. (2012) argue that firms endowed with proper organizational structures, processes and skills can enjoy larger benefits from digital technologies, because the interplay of technological and organizational innovations can induce productivity enhancements through greater product customization and increased product variety. Garicano (2010) emphasizes the relevance of complementarities between information and communication technology (ICT) and organizational design. He shows that: a) the required adaptation and refocusing of firms' organizational practices differ depending on the type of ICT investments; b) the impact of ICT on productivity might be negligible without organizational changes because complementarities between organization and ICT are important.[4]

Other authors, such as Bloom et al. (2007), detect a positive effect of ICT on firm productivity in Europe at the macro level (average effect) but it is heterogeneous across firms and positively depends on factors such as the quality of practices in human resources management and the degree of decentralization in firms' organizational structure.

Anderton et al. (2023) use a large European panel dataset at the firm level and show that digitalization accelerates firms' TFP growth on average, although its impact is very heterogeneous. According to their findings, only firms operating in some sectors seem to benefit from digital adoption, only the 30% most productive laggard firms benefit from digitalization, and intangible assets act as a complement, as their presence amplifies the effect of digital adoption on firm's TFP growth.[5]

Cusolito et al. (2020) estimate the effects of adopting digital business solutions on TFP focusing on firm-level data for 82 developing economies over the period 2002–19 drawn from the World Bank's Enterprise Survey (WBES). The latter collects information on technology adoption

[2] There can be non-negligible lags between the implementation of digital technologies and their full operationalization, so that productivity enhancements can take time to materialize. Van Ark (2016) argues that the New Digital Economy is still in its installation phase and productivity gains are yet to come. According to Brynjolfsson et al., 2021, when new technologies are introduced, productivity growth is initially underestimated because capital and labor are used to accumulate unmeasured intangible assets but, eventually, as growing intangible stocks begin to contribute to production, measured productivity growth will rise. At the same time, there is a wide dispersion across firms in the diffusion of digital technologies and the obstacles to it provide another explanation of the slowdown of aggregate productivity (Andrews et al., 2016).

[3] Gordon (2000, 2003) challenges the view that ICT use played an important role in post-1995 productivity growth. He asserts that, if the IT-producing industry were leaving aside, then observed productivity growth in the US economy was simply a cyclical phenomenon.

[4] Brynjolfsson and Hitt (2003) also lend support to the view that the contribution of information technology to firm's productivity hinges crucially on organizational complements such as new business processes and work practices, new skills and new organizational and industry structures. These complementary investments on innovation, although often hard to measure, can be larger than the investments in digital technologies themselves. Draca et al. (2006) argue that measured ICT can be seen as only the tip of the iceberg, as a successful realization of an ICT project requires a reorganization of the firm around the new technology. These reorganization costs may be interpreted simply as adjustment costs, but they can be particularly substantial in the case of ICT.

[5] To measure digitalization, they rely on two variables at the country, sector, and year level. One of them is the ratio between the real investment in Computer Software and Databases, ICT and R&D as a share of total real investment. The second variable of digitalization uses information on prices of digital investment and measures the extent to which the digital investment intensity exceeds, or falls short of, what would be expected from the relative price of digital technologies. They estimate firm-level TFP using the method proposed by Gandhi et al. (2020), which has the benefit of imposing less restrictions on the functional form of gross output production functions.

as firms are asked whether they have a business website for carrying out their operations or use a business email to communicate with clients and suppliers. They estimate firms' TFP from a log-linearized Cobb-Douglas production function relying on the Olley and Pakes (1996) approach, with the extensions proposed by Levinsohn and Petrin (2003) and Ackerberg et al. (2015). Differently from them, however, Cusolito et al. (2020) endogenize TFP by setting it as a function of the adoption of digital business solutions in addition to other variables affecting performance. They find that the (probability adjusted) median TFP premium associated with the adoption of a business website for firm operations is 2.2 per cent and it is higher than the TFP premiums associated to other variables that affect performance.

Bugamelli and Pagano (2004) use firm-level data drawn from a large sample of Italian manufacturing firms and estimate a marginal product of ICT much higher than its user cost. Their empirical findings point to an increase in the share of skilled workers and an extensive reorganization of the workplace as preconditions for enjoying productivity gains from ICT adoption. Indeed, reorganization costs act as capital adjustment costs, with a sizeable fixed-cost component, and, therefore, small and medium firms have extra difficulties in paying them. They provide firm-level evidence on a lack of these complementary investments whose cost have acted as a barrier to investment in ICT. Calvino et al. (2022) discuss how the weak diffusion of digital technologies in Italy among smaller and less productive firms has dragged down Italian productivity growth. Their empirical analysis has highlighted three main determinants of the subdued digital diffusion among small firms: i) lack of complementary skills among workers, ii) low capabilities of managers, and iii) low investments rates in R&D and other intangible capital.

Hall et al. (2012) investigate the role of ICT investments and R&D jointly as an input to innovation rather than simply as an input of the production function. They also allow for measures of organizational innovation to take into account the interaction among all these factors. Using a complex model, estimated on a large sample of Italian manufacturing firms, they find that R&D and ICT both contribute to innovation, even though to a different extent. Importantly, ICT and R&D affect productivity both directly and indirectly through the innovation equation. Each of them individually, however, has large impacts on productivity and this suggests some firms' underinvestment in these activities.[6]

Whilst our paper relates to several contributions surveyed in this section, there are, however, three distinctive elements. First, we use firm-level, high-quality information of unusual breadth on digital adoption that allows us to characterize the process of digital transformation of Italian enterprises and the different dimensions of the firm propensity to invest in the new technologies. Second, we rely on a methodology that seeks to establish more directly the impact of digital adoption on productivity and, to tackle the complexity of digitalization, we use a variety of alternative criteria to allocate firms in the group of digital adopters. Third, we pay attention to the heterogeneity in the estimated effects and investigate whether they vary in strength depending on a variety of firm's characteristics. We now turn to our empirical investigation and first describe the data that we employ in the analysis.

[6] Pellegrino and Zingales (2017) find that TFP growth was faster in ICT-intensive sectors in those countries where firms have good practices in the selection and rewarding of managers. Schivardi and Schmitz (2018) calibrate a general equilibrium model with firm-level evidence and find that inefficient management practices limit the productivity gains of firms from their IT adoption.

3. The data

3.1. The firm-level databases

In our empirical study we use information from four different databases at the firm level. Three of them are maintained, and suitably integrated, by Italy's National statistical institute (Istat). The first database is the Permanent Census of enterprises, which gathers information about the Italian productive system on issues such as firms' organization and business development, competitiveness and environmental sustainability (see Istat, 2020; Monducci, 2020; Costa et al., 2020). We employ data from the first permanent census that took place in 2019 and covered the whole population of Italian enterprises with at least 20 employees, while the enterprises with the number of employees comprised between 3 and 19 have been properly sampled. The Permanent Census is a sample survey that mainly gathers qualitative information. The latter, however, can be suitably integrated with information from statistical registers of enterprises and employees. Thus, we combine information from the permanent census with data from the other sources. First, we rely on the Statistical register of active enterprises (ASIA - Enterprises), a business register developed at Istat covering all enterprises conducting economic activities in the fields of industry, commerce and services that contribute to gross domestic product. We use ASIA register of enterprises to obtain information on structural characteristics of the firms, such as, for example, the main economic activity (industry), size, legal form, age, and turnover. We also rely on the SBS Frame (Structural Business Statistics), a statistical register on the economic accounts of Italian enterprises. From the SBS Frame we obtain information on some firms' economic variables, such as, for example, the value of production, costs of different type and employment. Moreover, in estimating total factor productivity we also use data from Orbis, a well-known data source with longitudinal firm-level information drawn from annual balance sheets and income statements collected by Bureau van Dijk. The final database that is employed in the empirical analysis refers to about 68,000 firms.

3.2. The characterization of firms' digital adoption

The Survey of the 2019 Permanent census of enterprises has been conducted from May to October 2019, with 2018 as the reference year. Importantly for our purposes, that survey features a detailed section on firms' reliance on digital technologies. The survey focusing on this specific issue has been conducted among enterprises with at least ten employees in the year 2017. The Survey collects information on several aspects pertaining to digitalization (see Istat, 2020a) and we focus on investments made in different types of digital technologies. In section X.5.12, the Survey has asked firms to report whether, in the period 2016–2018, they have invested in each of the following nine types of digital technologies that Istat grouped in three different domains (Istat, 2020a).

A) Internet-based technologies
   1) Optic-fiber ultra-broadband connection
   2) Mobility connection (4G and 5G)
   3) Internet of things
B) Areas of application of artificial intelligence (AI)
   4) Immersive technologies
   5) Elaboration and analysis of big data
   6) Advanced automatization, collaborative robots, and smart systems
C) Other technological areas
   7) 3D printing
   8) Simulation of interconnected machines
   9) Cyber-security.

In Fig. 1, for every single type of investments in digital technologies, we report the percentage of firms which have made these investments in

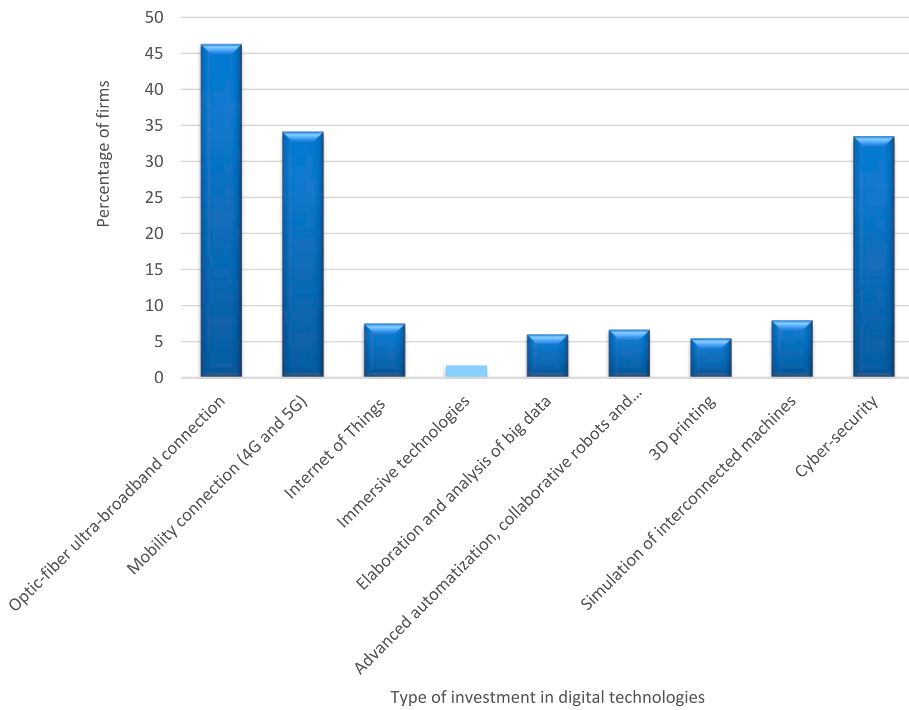

Fig. 1. Percentage of firms which made investments in digital technologies in the period 2016–2018 for every single type of investment
Legend: Our calculations on Istat data.

the period 2016–2018. Firms' purchases of Internet-based technologies that refer to connectivity, such as optic-fiber ultra-broadband connection and mobility connection (4G and 5G), have been made by a significant fraction of firms (respectively, 46 and 34 per cent). Investments in more advanced digital technologies are in general much less diffuse. For example, in the areas of application of AI, investments in immersive technologies have been made by slightly less than 2 per cent of firms, while those in big data and in automatization, robotics and smart systems are reported in, respectively, 6 and about 7 per cent of the firms. A roughly similar incidence characterizes firm investments in both 3D printing and simulation of interconnected machines (equal to about 5 and 8 per cent, respectively). One third of the firms in our sample have made investments in cyber-security. The overall picture from Fig. 1 points to a rather limited diffusion of digital adoption among firms, especially with reference to more advanced technologies.

In Fig. 2 we document other dimensions of digital adoption by reporting the distribution of firms per number of types of digital investments made in the 2016–2018 period. 32 per cent of firms in the sample have made no digital investments in any of the nine alternative types, while firms that made only one type of investments in digital technologies represent about 25 per cent of the sample. Hence, the firms that have invested in the 2016–2018 period in bundles of digital technologies are about 43 per cent, of which about 22 per cent have invested in two types of digital technologies and about 13, 5 and 2 per cent have invested, respectively, in three, four and five types. Only a handful of firms have invested in six or more types of digital technologies (1.7 per cent of the sample).

The group of firms with no investments in digital technologies is our control group. To assign firms to the group of those "treated" with digital adoption we rely on alternative criteria. Our baseline criterion is to define a firm as treated if it has invested in at least one of the nine types of digital technologies. The alternative criteria are the following. First, firms are defined as treated if they have invested in at least one digital technology in the second or third domain, which refer to the "Areas of application of artificial intelligence" and "Other technological areas", respectively, and typically encompass more advanced technologies compared to the first domain. Second, a firm enters the treatment group if it has invested in a bundle of two or more digital technologies, while the third alternative criterion establishes that a firm is considered as treated if it has invested in a bundle of at least three types of digital investments. Our fourth alternative criterion to define treatment with digital adoption is that the firm has made at least one investment in AI. In all five classification criteria to assign firms to the treatment group, the control group remains the same. This implies that, only for the baseline definition of treatment, the number of firms in the treated and untreated (control) groups amounts to the number of firms in the whole sample. Conversely, when the alternative ways to define treatment are used, the number of firms in both the treated and the control group is lower than the number of firms in the whole sample. In Table 1 we document the composition of the group of treated firms for all the alternative classification criteria we use. Firms in the baseline treatment group (group A) are 68 per cent of firms in the sample. The first alternative treatment group (group B) includes 40.2 per cent of firms, while the second (group C), third (group D) and fourth (group E) alternative treatment groups refer, respectively, to 43.4, 21.7 and 11.3 per cent of the firms in the sample.

Before turning to the empirical methodology and the results, let us provide information on the other variables, especially productivity, and present some descriptive statistics.

3.3. Productivity, other variables, and descriptive statistics

We use total factor productivity (TFP) as measure of firm performance in the empirical analysis. Firm-level TFP is obtained through the estimation of production functions separate for each macro-sector relying on the Levinsohn and Petrin (2003) methodology (LP) augmented with the Ackerberg et al. (2015) corrections (ACF). They are both semi-parametric algorithms building on the original method proposed by Olley and Pakes (OP; 1996) which controls for the correlation between the unobservable productivity shocks and the input levels using firm investments as a proxy variable for productivity. The LP method seeks to overcome the issue of a significant number of zero investment values in the data by using intermediate inputs, instead of investment, as a proxy variable. The Ackerberg et al. (2015) method puts into questions

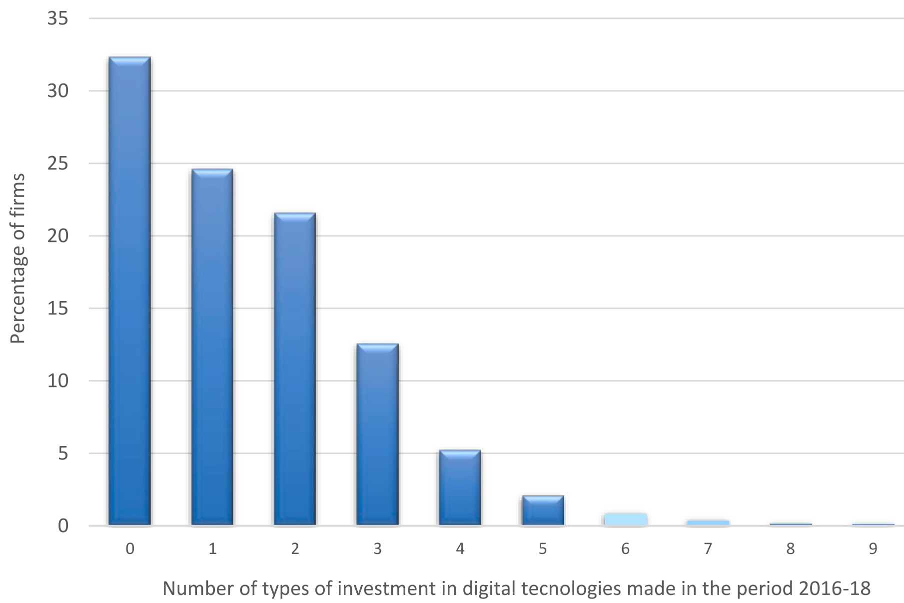

Fig. 2. Distribution of firms per number of types of investment in digital technologies made in the period 2016-2018
Legend: Calculations on Istat data.

Table 1
– Mean values of variables across different groups in terms of types of investment in digital technologies (*Values are in thousands of Euro*).

Year 2018	All sample	Control Group	Baseline treated Group A	Alternative treated Group B	Alternative treated Group C	Alternative treated Group D	Alternative treated Group E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Revenues	14610	8966	17270	21930	21010	28110	32740
Gross production	15230	9348	18010	22900	21930	29340	34380
Value added	3664	2337	4289	5398	5205	6872	8214
Number of workers	59.4	42.8	67.2	79.1	78.9	99.4	116.9
Purchases	7852	4764	9305	11890	11310	15300	17520
Labor costs	2391	1587	2769	3434	3344	4388	5258
Age (years)	24.1	23.4	24.5	25.6	24.8	25.2	25.7
Labor productivity	276.7	234.8	296.4	321.0	314.9	349.9	344.3
log (TFP)	5.242	5.228	5.249	5.253	5.256	5.264	5.259
Number of firms	67925	21740	46185	27333	29450	14736	7699
Incidence of firms (%)	100.0	32.0	68.0	40.2	43.4	21.7	11.3
Year 2015	All sample	Control Group	Baseline treated Group A	Alternative treated Group B	Alternative treated Group C	Alternative treated Group D	Alternative treated Group E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Revenues	12450	7930	14570	18550	17760	23650	27250
Gross production	13310	8233	15700	20240	19360	26430	32030
Value added	3057	2005	3552	4483	4303	5676	6706
Number of workers	50.72	38.0	56.7	66.9	66.2	82.5	95.9
Purchases	6966	4162	8286	10800	10280	14420	17720
Labor costs	1999	1370	2295	2856	2760	3613	4302
Age (years)	21.13	20.4	21.5	22.6	21.8	22.2	22.7
Labor productivity	285.7	239.7	307.3	339.4	330.5	385.1	414.2
log (TFP)	5.289	5.278	5.294	5.296	5.299	5.305	5.301
Number of firms	67925	21740	46185	27333	29450	14736	7699
Incidence of firms (%)	100.0	32.0	68.0	40.2	43.4	21.7	11.3

Legenda: Calculations on data drawn from Istat and Orbis's Bureau Van Dyck.

the hypothesis in both the OP and LP method that labor is a fully adjustable input. Rather, labor is seen as a state variable because of significant hiring and firing costs and it should therefore be an argument of the demand function for the proxy variable (for an insightful review of the state of the art in firm-level TFP estimation, see Bournakis and Mallick, 2018).[7]

As we elucidate below, our variable of interest is the log change in firm TFP between 2015 and 2018. In Table 1 we report the mean value for several firms' variables in both 2015 and 2018. We provide distinct figures for the whole sample (column 1), the control group (column 2), the baseline treatment group (column 3) and each of the other alternative treatment groups (column 4 through 7). The variables refer to gross production, revenues, value added, number of workers, purchases of intermediate goods and services, labor costs as well as labor productivity (gross output per employee) and the log of TFP. In Table 2 we provide information on the percentage distribution of firms by several

[7] We thank Federico Belotti for useful insights on these methodologies and for sharing his Stata code to estimate TFP through the LP and ACF algorithms.

Table 2
Incidence (%) of the treatment groups (vs. the control group) for different definitions of treatment with digital investments.

Incidence of groups:	Control Group	Baseline treated Group A	Alternative treated Group B	Alternative treated Group C	Alternative treated Group D	Alternative treated Group E	All sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
by Macro area (%)							
North	57.4	62.8	67.4	64.5	66.4	68.7	61.1
Center	20.9	18.8	17.4	18.3	17.9	16.3	19.5
South	21.7	18.4	15.2	17.3	15.7	14.9	19.4
Total:	100	100	100	100	100	100	100
by Size class (%)							
0-10 workers	6.2	4.8	3.9	4.4	3.9	3.4	1.9
11-20 workers	33.3	26.6	23.2	23.9	20.8	18.0	27.7
21-50 workers	43.9	43.8	43.4	43.2	41.5	40.3	46.2
51-100 workers	10.8	14.6	16.7	16.2	18.2	20.0	14.6
101-250 workers	4.5	7.2	8.9	8.5	10.4	12.2	7.0
>250 workers	1.3	2.9	3.9	3.8	5.2	6.2	2.7
Total:	100	100	100	100	100	100	100
by Sector (%)							
High-tech (Manufacturing)	0.9	1.6	2.1	1.9	2.4	2.6	1.4
Medium high-tech (Manufacturing)	9.2	11.3	13.9	12.1	14.3	16.5	10.6
Medium low-tech (Manufacturing)	14.3	14.2	16.8	14.7	15.5	19.3	14.3
Low-tech (Manufacturing)	16.4	13.9	14.8	13.2	12.8	13.6	14.7
Knowledge-intensive services	9.6	13.7	14.9	15.1	16.5	19.0	12.4
Less Knowledge-intensive services	37.3	35.2	29.5	33.7	30.6	24.5	35.8
Others	12.2	10.2	8.0	9.3	7.9	4.4	10.8
Total:	100	100	100	100	100	100	100

Legenda: Calculations on Istat data Column (1) provides the percentage distribution of firms by macro area, size class and sector of activity for the control group; columns (2)–(6) provide the same information for each of the treatment group. Column (7) refers to all sample.

characteristics: geographic macro-area, size, and sector of activity. In so doing, we consider not only the whole sample (column 7) but also focus separately on the control group (column 1), the baseline treatment group (column 2) and each of the alternative treatment groups (column 3 through 6). The evidence in the table indicates that, if the treatment group is characterized for investments in more advanced technologies, *i.e.* moving from the baseline treatment group (A) towards group (E), then the percentage incidence of firms located in the North of Italy, of larger size and operating in more technology-intensive sectors tends to increase. We now illustrate the estimation methodology that we employ on our data.

4. The empirical methodology

Our goal is to evaluate the impact of firm investments in digital technologies on its productivity. In so doing a proper methodology ought to be utilized. Firms that adopt digital technologies have characteristics that are likely to differ from those of firms that do not (self-selection into treatment). Hence, a difference in productivity outcome between firms that have invested in digital technologies and those that have not cannot be seen as the actual effect of digitalization. Firm productivity is affected by a variety of other factors beyond digital technologies, some of which are observed in the data, such as, for example, size, age, sector of activity and human capital, while some others are not. Moreover, we also face the endogeneity problems that may affect our empirical findings and try to distinguish between the effects of digitalization on productivity and the influence that the latter, in turn, may have on the adoption of digital technologies. Indeed, reverse causation may be at work in the relationship between digitalization and productivity as, for example, higher productivity may reduce firm's unit costs and thereby make digital investments more affordable for the enterprise. Moreover, idiosyncratic, and often unobservable, firms' features may impinge on both their use of digital technology and their productivity performance.

To partially deal with these issues, we employ the propensity score matching (PSM) approach and combine it with a difference-in-difference (DiD) analysis (see, among others, Heckman et al., 1997, 1998; Blundell and Costa Dias, 2009). We first identify (with alternative criteria) the firms that invested in digital technologies in the 2016–2018 period as those in the treated group ($T=1$) and then focus on numerous observable characteristics, evaluated before treatment, that may introduce heterogeneity across firms in their propensity to invest in digital technologies. Among firms exhibiting these characteristics, some have invested in digital technologies while some have not. Put it differently, the assignment of treatment (*i.e.* digitalization) is not random in our framework, as the latter is not based on experimental data. Second, we match firms that did invest in digital technologies with their corresponding "twins'' that, albeit showing similar characteristics, did not adopt these technologies and then compare the variation over time in productivity between the two groups of firms.

Establishing which individual units are similar conditioning on a vector of variables, $\mathbf{X}_i$, is a challenging task (curse of dimensionality). Rosenbaum and Rubin (1983) show that independence conditional to the set of control variables, $\mathbf{X}_i$, continues to hold if the latter are summarized by one single variable: the propensity score, $P(T_i = 1|\mathbf{X}_i)$. The propensity score for an individual firm is the estimated conditional probability that it is included in the treatment group, $P(T_i=1|\mathbf{X}_i)$. Thus, firms are matched according to their propensity to be treated, $P(T_i=1|\mathbf{X}_i)$, and the approach therefore requires that there be firms with similar propensity scores in both groups so that the matching occurs within a common support, i.e. within the range of propensity scores for which there are firms in both the treatment and control groups.

Our first step is then to estimate a probit model on our sample where the dependent variable is a binary variable, treatment (T_i), and the explanatory variables are the set of variables, $\mathbf{X}_i$, that are evaluated *before* treatment (in 2015) and are likely to influence the probability of being treated (in the period 2016–2018). Then, for each firm in the treated group (T=1) we construct a "counterfactual", by focusing on similar firms that are in the untreated group and compare the rate of change in productivity between the two groups of firms (Stuart and Rubin, 2008; see Duhautois et al., 2020 for an application on the impact of innovation on job quality). Propensity score matching creates equivalent (balanced) treatment and control groups in terms of confounding variables.

Several matching algorithms are available, such as, for example, the nearest-neighbor matching, the radius and caliper matching, the stratification and the kernel matching. Whilst they are all based on the distance between estimated propensity scores, they differ in how many units to match and how to do it. In our baseline analysis, we rely on radius matching, with which every treated unit is matched with the control units whose propensity scores fall in a predefined neighborhood (the caliper) of the propensity score of the treated unit. By employing all available comparison observations within a predefined distance around the propensity score of the respective treated, this method allows for the use of more untreated units when good matches are available and fewer units when they are not. Radius match is therefore a one-to-many matching algorithm. One possible drawback is the difficulty of knowing a priori what radius is reasonable. As in Duhautois et al. (2020), in our baseline estimations we rely on a caliper vaue of 0.00001, which is small and implies a precise matching between the treated and control firms. There is a trade-off between the size of the matching group and the reduction of the bias between the treated and untreated firms. A small value of the caliper implies that more firms drop out of the common support (i.e., "off-support'' firms), as their degree of specificity is too high for counterfactuals to be found. In our empirical analysis, the number of treated firms dropping out of the common support varies across the definition of treatment but is, in general, relatively low. However, we also check the robustness of our findings using other matching algorithms, such as the kernel matching and the radius matching with a different (larger) caliper value.

An important condition for the PSM approach to be valid is that no systematic differences should exist among firms in the treated and control groups in terms of unobserved characteristics that may affect the outcome variable. This assumption is unlikely to hold as several unobserved factors may well introduce heterogeneity across firms in the adoption of digital technologies. To tackle this issue, we use the time dimension of our data and resort to first difference for washing out unobserved sources of firms' heterogeneity in the outcome variable. This is the difference-in-difference (DiD) approach that computes the change in (the log of) TFP between two periods of time (the first difference) and compares this variation between treated and untreated firms (the second difference). In practice, our baseline estimate with the radius matching model of the average treatment effect on the treated (ATT) is[8]

$$ATT = 100*\frac{1}{N^{TR}}\sum_{i=1}^{N^{TR}}\left(\Delta\log\,(TFP)_i^T - \overline{\Delta\log\,(TFP)}_i^C\right), \quad (1)$$

where N^{TR} is the number of treated firms that have been matched, $\Delta\log\,(TFP)_i^T$ is the change between 2015 and 2018 in the log of TFP for the i-th treated firm and $\overline{\Delta\log\,(TFP)}_i^C$ is the average value of the change between 2015 and 2018 in the log of TFP for the untreated firms matched with the i-th firm.[9] In using the estimator in Eq. (1) we assume that, before treatment, the outcome variables in the treated and untreated firms are characterized by the same trend (the common-trend assumption). Using firm-level data over periods of observation prior to treatment, we verify that the common-trend assumption is satisfied as the effect of treatment on the outcome variable is not a figment of preexisting differences in the productivity performance.

In the empirical analysis, we rely on several criteria for assessing the quality of the match. Indeed, since we condition on the propensity score, rather than on the set of covariates, $\mathbf{X}_i$, one needs to verify whether the matching can balance the distribution of the relevant covariates in the treatment and the control group, and we do so by providing corroborative evidence of this. Let us now turn to the empirical findings.

5. The results

The first step in our modelling approach is that of estimating the probability of being digital adopter. In our probit model the dependent variable is a dummy variable taking the value of one if the firm is "treated" with digital adoption and zero otherwise. As discussed earlier, we consider a baseline criterion to define treatment plus various alternative criteria. Conversely, the group of untreated firms is univocally defined as the set of firms that made no investments in any digital technology. We estimate a probit model for each alternative definition of the treatment variable, and the set of covariates refer to observable characteristics that may introduce a degree a difference among firms in their propensity to invest in digital technologies. These variables deal with the following aspects: size, industry, geographical location, age, the share of firm expenditure in services to the value of its production and the share of labor costs to the value of production. For industry classification, we use Eurostat indicators on high-tech industry and knowledge–intensive services (High-tech aggregation by NACE Rev.2). In particular, the classification of manufacturing industries according to technological intensity distinguishes between high-technology, medium-high-technology, medium-low-technology and low-technology. Following a similar approach, Eurostat classifies service sectors as

Table 3
Determinants of Firm Digital Adoption: the results of a probit model with the baseline definition of treatment (A).

Dependent variable: Digital adoption (Baseline treatment A)	Estimated Coefficients		Marginal effects dy/dx	
Size (ref. under 10 employees)				
10–19	0.059***	(0.019)	0.021***	(0.007)
20–49	0.179***	(0.019)	0.063***	(0.007)
50–99	0.339***	(0.023)	0.118***	(0.008)
100–249	0.446***	(0.029)	0.156***	(0.010)
250 and over	0.655***	(0.042)	0.229***	(0.015)
Age (ref. lowest quartile)				
2nd quartile	0.048***	(0.014)	0.017***	(0.005)
3rd quartile	0.043***	(0.014)	0.015***	(0.005)
Top quartile	0.035**	(0.015)	0.012**	(0.005)
Labor cost per unit of output (ref. lowest quartile)				
2nd quartile	−0.102***	(0.015)	−0.036***	(0.005)
3rd quartile	−0.187***	(0.015)	−0.065***	(0.005)
Top quartile	−0.336***	(0.016)	−0.117***	(0.005)
Sector by level of technology (ref. high-tech manuf.)				
Medium high-tech (Manufacturing)	−0.203***	(0.049)	−0.071***	(0.017)
Medium low-tech (Manufacturing)	−0.289***	(0.049)	−0.101***	(0.017)
Low-tech (Manufacturing)	−0.405***	(0.049)	−0.141***	(0.017)
Knowledge- intensive services	−0.005	(0.050)	−0.002	(0.017)
Less Knowledge- intensive services	−0.280***	(0.048)	−0.098***	(0.017)
Others	−0.351***	(0.049)	−0.122***	(0.017)
Geographical area (ref. North)				
Center	−0.084***	(0.013)	−0.029***	(0.005)
South	−0.089***	(0.013)	−0.031***	(0.005))
Service costs per unit of output (ref. lowest quartile)				
2nd quartile	0.096***	(0.015)	0.033***	(0.005))
3rd quartile	0.158***	(0.015)	0.055***	(0.005))
Top quartile	0.187***	(0.015)	0.065***	(0.005))
Constant	0.611***	(0.052)		
Number of observations	67925			
Wald test χ^2	1811.5			
(with p-value)	0.000			
Pseudo R^2	0.022			
Log likelihood	−41648.1			

Robust standard errors in parentheses.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

[8] In our empirical work, we have employed, among others, the user-written Stata command psmatch2, developed by Leuven and Sianesi (2003).

[9] See Lechner (2002) on how the identification of ATT can be affected under heterogeneous treatments and Zhou and Xie (2020) for treatment effect heterogeneity with selection bias.

knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS).

In Table 3 we report the estimation results of the probit model with reference to the baseline definition (A) of treatment with digital adoption. We report both the estimated coefficients and the marginal effects. Our estimation findings suggest that a marked digital adoption occurs more in larger firms. We consider six size classes and find that, compared to the lowest size class (the reference category), the magnitude of the estimated coefficients progressively increases for higher size classes, as expected. As for the sector of economic activity, compared to high-technology sectors in manufacturing (the reference category), digital adoption is found to be less likely in all other industries, both in manufacturing and in services, as highlighted in previous literature. In line with other scholars' findings, even in knowledge-intensive services, an extensive digital usage is less likely than in high-tech industries. The effect of age is also positive as, compared to firms with age that lies in the lowest quartile (up to ten years in 2015 since firm establishment), older firms are more likely to rely extensively on digital technologies. Not surprisingly, compared to firms in the North of Italy, the other firms are, *ceteris paribus*, less likely to adopt digital technologies, with the divergence being larger with respect to the South than to the Centre. We also find that firms with a higher share of service purchases to the value of production are more likely to adopt digital technologies. Arguably, this expenditure may include services that are complementary to technology, such as, for example, training, consulting, testing and process engineering and this would contribute to explain our empirical result. Finally, the estimation findings reported in Table 3 indicate that firms with a higher share of labor costs to the value of production are, *ceteris paribus*, less likely to adopt digital technologies. A possible explanation is that this covariate somehow approximates the degree of labor intensity in the firm production structure and therefore, perhaps not surprisingly, more labor-intensive firms are less likely to rely markedly on digital technologies. It is important to emphasize that all variables included in the probit model refer to the year 2015 and are therefore evaluated *before* the possible participation into treatment, *i.e.*, before the 2016–2018 period during which firms have (or have not) invested in digital technologies.

In Tables 4a and 4b we report the results from estimating the probit model using each of the four alternative definitions of treatment with digital technologies (definition (B) through (E)). We report only the estimated marginal effects and their standard errors. The picture that emerges from the estimation with the baseline treatment definition (Table 3) is broadly confirmed in all cases. Not surprisingly, however, the estimated effect of each covariate on the probability of treatment varies from one definition of treatment to another. For example, operating in a large firm (with at least 250 workers) has a marginal effect on the likelihood of treatment which is larger if the definition of treatment is having invested in AI (definition (E)) and not simply in at least one of

Table 4a
Determinants of Firm Digital Adoption: the results of a probit model with alternative ways to define treatment: definitions of treatment (B) and (C).

Dependent variable: Digital adoption Alternative treatment (B) & (C)	Marginal effects dy/dx (B)		Marginal effects dy/dx (C)	
Size (ref. under 10 employees)				
10–19	0.035***	(0.009)	0.025***	(0.008)
20–49	0.102***	(0.009)	0.093***	(0.008)
50–99	0.191***	(0.010)	0.176***	(0.010)
100–249	0.252***	(0.012)	0.234***	(0.012)
250 and over	0.357***	(0.017)	0.339***	(0.017)
Age (ref. lowest quartile)				
2nd quartile	0.034***	(0.006)	0.021***	(0.006)
3rd quartile	0.035***	(0.006)	0.017***	(0.006)
Top quartile	0.030***	(0.006)	0.012**	(0.006)
Labor cost per unit of output (ref. lowest quartile)				
2nd quartile	−0.054***	(0.006)	−0.048***	(0.006)
3rd quartile	−0.101***	(0.006)	−0.092***	(0.006)
Top quartile	−0.178***	(0.007)	−0.162***	(0.006)
Sector by level of technology (ref. high-tech manuf.)				
Medium high-tech (Manufacturing)	−0.099***	(0.020)	−0.105***	(0.020)
Medium low-tech (Manufacturing)	−0.134***	(0.019)	−0.142***	(0.020)
Low-tech (Manufacturing)	−0.207***	(0.019)	−0.211***	(0.020)
Knowledge- intensive services	−0.030	(0.020)	−0.011	(0.020)
Less Knowledge- intensive services	−0.203***	(0.019)	−0.153***	(0.019)
Others	−0.244***	(0.020)	−0.190***	(0.020)
Geographical area (ref. North)				
Center	−0.054***	(0.006)	−0.039***	(0.006)
South	−0.071***	(0.006)	−0.043***	(0.006)
Service costs per unit of output (ref. lowest quartile)				
2nd quartile	0.053***	(0.006)	0.047***	(0.006)
3rd quartile	0.082***	(0.007)	0.077***	(0.006)
Top quartile	0.099***	(0.007)	0.097***	(0.006)
Number of observations	49073		51190	
Wald test χ^2	3443.6		2693.1	
(with p-value)	0.000		0.000	
Pseudo R^2	0.055		0.041	
Log likelihood	−31851.9		−33470.2	

Robust standard errors in parentheses.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 4b
Determinants of Firm Digital Adoption: the results of a probit model with alternative ways to define treatment: definitions of treatment (D) and (E).

Dependent variable: Digital adoption Alternative treatment (D) & (E)	Marginal effects dy/dx (D)		Marginal effects dy/dx (E)	
Size (ref. under 10 employees)				
10–19	0.026***	(0.010)	0.011	(0.010)
20–49	0.109***	(0.010)	0.095***	(0.010)
50–99	0.222***	(0.011)	0.202***	(0.011)
100–249	0.295***	(0.013)	0.265***	(0.012)
250 and over	0.428***	(0.018)	0.388***	(0.016)
Age (ref. lowest quartile)				
2nd quartile	0.027***	(0.007)	0.021***	(0.007)
3rd quartile	0.017**	(0.007)	0.008	(0.007)
Top quartile	0.007	(0.007)	−0.001	(0.007)
Labor cost per unit of output (ref. lowest quartile)				
2nd quartile	−0.052***	(0.007)	−0.054***	(0.007)
3rd quartile	−0.108***	(0.007)	−0.100***	(0.007)
Top quartile	−0.198***	(0.007)	−0.182***	(0.007)
Sector by level of technology (ref. high-tech manuf.)				
Medium high-tech (Manufacturing)	−0.119***	(0.021)	−0.088***	(0.020)
Medium low-tech (Manufacturing)	−0.177***	(0.021)	−0.115***	(0.020)
Low-tech (Manufacturing)	−0.262***	(0.021)	−0.209***	(0.020)
Knowledge- intensive services	−0.031	(0.022)	−0.011	(0.020)
Less Knowledge- intensive services	−0.213***	(0.021)	−0.222***	(0.019)
Others	−0.263***	(0.022)	−0.310***	(0.021)
Geographical area (ref. North)				
Center	−0.041***	(0.006)	−0.047***	(0.006)
South	−0.053***	(0.007)	−0.039***	(0.007)
Service costs per unit of output (ref. lowest quartile)				
2nd quartile	0.056***	(0.007)	0.057***	(0.007)
3rd quartile	0.090***	(0.008)	0.073***	(0.007)
Top quartile	0.110***	(0.008)	0.090***	(0.008)
Number of observations	36476	29439		
Wald test χ^2	3269.8	3322.6		
(with p-value)	0.000	0.000		
Pseudo R^2	0.073	0.114		
Log likelihood	−22806.1	−14988.7		

Robust standard errors in parentheses.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 5
The effect of adoption of digital technologies on productivity (*Effects on percentage variation of TFP*).

Baseline (A) and alternative definitions of treatment with digital adoption (B), (C), (D) and (E)	Baseline Treatment Group (A)	Alternative Treatment Group (B)	Alternative Treatment Group (C)	Alternative Treatment Group (D)	Alternative Treatment Group (E)
Outcome variable:					
Percentage variation of TFP between 2015 and 2018	0.97*** (0.376)	1.59*** (0.428)	1.60*** (0.421)	2.13*** (0.515)	2.20*** (0.64)
Number of "on-support" ("off-support") untreated firms	21,371 (369)	20,838 (902)	20,860 (880)	19,425 (2,315)	16,755 (4,985)
Number of "on-support" ("off-support") treated firms	43,446 (2,739)	25,365 (1,968)	27,275 (2,175)	13,331 (1,405)	6,910 (789)

Notes: The coefficients represent the estimated difference in the 2015 to 2018 log-change in TFP between treated and control firms. Robust standard errors in parentheses. For each definition of treatment, we report in each column the number of "on-support" untreated and "on-support" treated firms. The number in parenthesis below it is the corresponding number of "off-support" untreated and treated firms (*i.e.* those that drop out of the common support).
As illustrated in the text, treatment group (A) comprises firms that invested in at least one type of digital technologies; Group (B) comprises firms that invested in at least one type of digital technologies in the of "Areas of application of artificial intelligence" or "Other technological areas"; Group (C) comprises firms that invested in a bundle of at least two types of digital technologies; Group (D) comprises firms that invested in a bundle of at least three types of digital technologies; Group (E) comprises firms that invested in at least one AI technology.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

the nine types of digital technologies (baseline definition (A)): the marginal effects are 0.339 and 0.229, respectively (and are both statistically significant).

After estimating the probability that a firm adopts digital technologies conditional on observed characteristics, we proceed with the match of treated to untreated units based on the estimated propensity score. In the third step, we compare variation over the 2015–2018 period in the log of TFP between firms with digital adoption (treated) and those without it (control). In Table 5, we report the estimation results for the baseline (A) definition of treatment as well as for the alternative definitions ((B) through (E)). We find a positive and statistically significant impact of digital adoption on firm productivity. The positive effects reported in the table amount to the percentage difference in the variation over time of the log of TFP between digital and non-digital firms. Our estimation findings indicate that firms that invested in at least one type of digital technologies (baseline definition (A) of treatment) have a rate of change of productivity, between 2015 and 2018, which is 0.97 percentage points higher, on average, than that of firms with no investments in new technologies. When we define treatment with investment in at least one more advanced type of digital technologies (definition (B)), the estimated effect is larger and equal to 1.59 percentage points. A similar effect (1.60) is uncovered when we consider as treated the firms that invested in a bundle of at least two types of digital technologies (definition (C)). The estimated effect is larger (2.13 percentage points) if the treated firms are considered those that invested in a bundle of at least three types of digital technologies (definition (D)). Finally, if we restrict the definition of treatment only to firms that have invested in at least one technology related to artificial intelligence, then the effect of treatment is the largest one (2.20 percentage points). In all cases, the estimated effect is statistically significant at the one per cent level.[10]

We now assess the quality of the matching. Put it simply, we need to compare the picture before and after the matching and verify if there remain any differences once we condition on the propensity score. To do this, we first use a two-sample *t*-test to verify if there are statistically significant divergences in the means of covariates of the two groups.

Table 6
The extent of balancing between the two groups (treated and control) after matching: the case of the baseline treatment group (A).

Matched variables:	Mean			
	Treated	Control	% bias	t-stat
Size (ref. under 10 employees)				
10–19	0.292	0.292	0.1	0.11
20–49	0.434	0.433	0.1	0.15
50–99	0.128	0.128	−0.1	−0.17
100–249	0.052	0.052	0.3	0.38
250 and over	0.015	0.015	0.1	0.08
Age (ref. lowest quartile)				
2nd quartile	0.263	0.263	0	−0.04
3rd quartile	0.229	0.230	−0.1	−0.18
Top quartile	0.229	0.229	−0.1	−0.1
Labor cost per unit of output (ref. lowest quartile)				
2nd quartile	0.258	0.258	−0.1	−0.12
3rd quartile	0.251	0.252	−0.2	−0.25
Top quartile	0.215	0.216	−0.2	−0.28
Service costs per unit of output (ref. lowest quartile)				
2nd quartile	0.244	0.243	0.2	0.24
3rd quartile	0.254	0.255	−0.2	−0.35
Top quartile	0.268	0.268	−0.1	−0.08
Sector by level of technology (ref. high-tech manuf.)				
Medium high-tech (Manufacturing)	0.108	0.109	−0.2	−0.3
Medium low-tech (Manufacturing)	0.142	0.142	−0.1	−0.12
Low-tech (Manufacturing)	0.140	0.139	0.3	0.53
Knowledge- intensive services	0.133	0.135	−0.4	−0.54
Less Knowledge- intensive services	0.369	0.368	0.1	0.19
Others	0.100	0.099	0.1	0.1
Geographical area (ref. North)				
Center	0.179	0.178	0.1	0.2
South	0.181	0.181	−0.1	−0.11
Pseudo R^2	0.000			
LR test χ^2 (with p-value)	1.89 (0.99)			
Rubin's B statistic	0.9			
Rubin's R statistic	1.01			

While significant differences are expected before the matching, after it the covariates should be balanced in the two groups and no significant differences should therefore be detected. In Table 6, we focus on the baseline definition of treatment (A) and report the mean in the treated and control groups for each of the covariates. The two groups seem to be very similar for all the observables and the assumption of the equality of means is always satisfied in some cases.[11] Since the *t*-test requires controversial assumptions, such as normal distribution of covariates,

[10] In Table 5, for each definition of treatment, we report the number of "on-support" untreated and "on-support" treated firms. We also report (in parenthesis) the corresponding number of "off-support" untreated and treated firms, *i.e.* those that drop out of the common support. Reassuringly, although we use a small caliper value to ensure a precise matching between treated and control firms, the number of treated firms dropping out of the common support is rather low: for the baseline definition of treatment, the "off-support" units are 369 untreated and 2739 treated firms, while the "on-support" units are, respectively, 21,371 and 43,446.

[11] As reported in the table, the pseudo-R^2 after matching is estimated to be rather low, Rubin's B statistic is far less than 25 and Rubin's R statistic lies between 0.5 and 2.

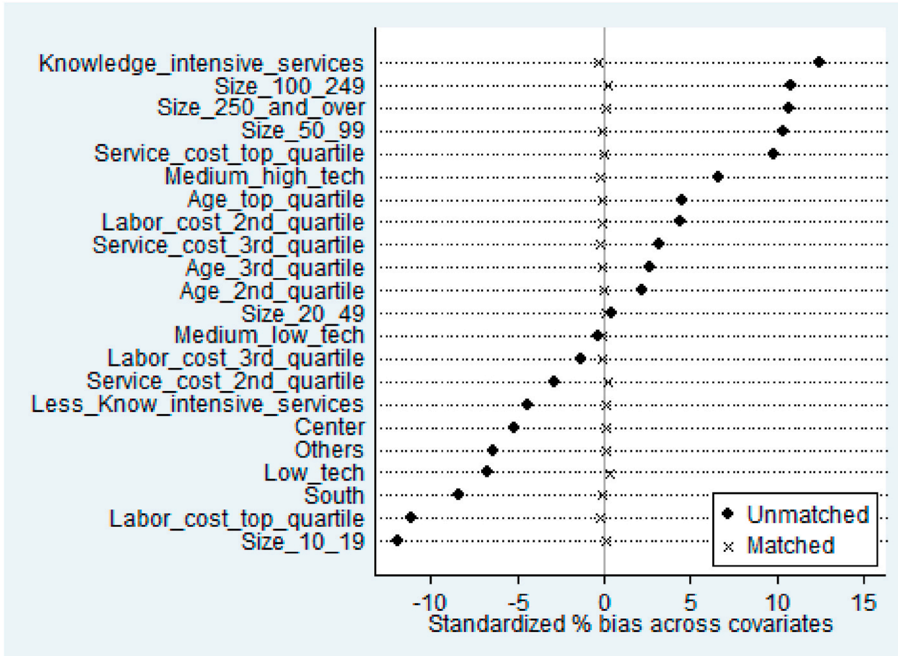

Fig. 3. Assessing balancing properties after matching: % standardised bias (*Treatment group with the baseline definition (A) of treated firms*).

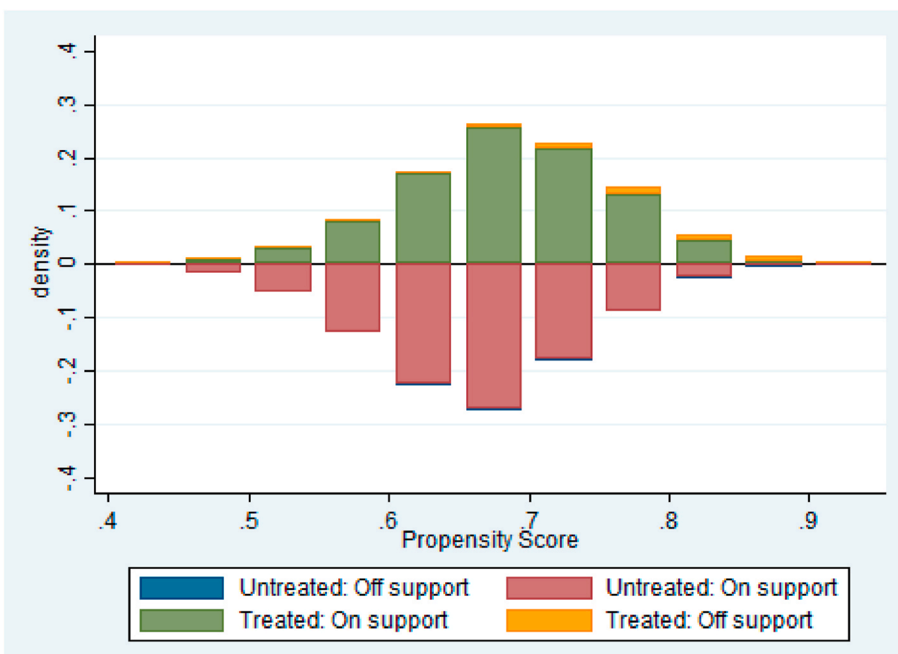

Fig. 4. Matching Share by Propensity Score (*Treatment group with the baseline definition (A) of treated firms*).

and is sensitive to sample size, several studies cast doubt on comparisons after PSM that are based on *t*-tests (see e.g. Ho et al., 2007, and reference therein). Thus, we also use another approach for assessing the difference in marginal distributions of the covariates: the standardised bias. The latter is the difference of sample means in the treated and matched control groups as a ratio to the square root of the simple average of the sample variances in the two groups. In Fig. 3, we focus again on the baseline definition of treatment and report the % standardised bias for each covariate, and, in all cases, it is far below 3 per cent in the matched samples, which is considered as a satisfactory outcome in most empirical studies (see Caliendo and Kopeinig, 2008). Finally, from a visual inspection of Fig. 4 we assess the extent to which the distributions of propensity scores in treatment and control groups overlap, providing evidence that, in our analysis, the range of common support between treated and untreated firms is adequate.[12]

We also verified that the significant effect on productivity of the treatment with digital adoption is not simply a figment of diverging

[12] All these balancing tests have been conducted also for each of the alternative definitions of treatment and they confirm the picture emerging from the inspection made for the baseline definition of treatment.

Table 7
Testing for common trends before the treatment (*Effects on percentage variation of TFP over the period 2013–2015*).

Baseline (A) and alternative definitions of treatment with digital adoption (B), (C), (D) and (E)		Baseline Treatment Group (A)	Alternative Treatment Group (B)	Alternative Treatment Group (C)	Alternative Treatment Group (D)	Alternative Treatment Group (E)
		I) First test				
Dependent variable:	Regressors:					
Percentage variation of TFP between 2013 and 2015	1) Treatment dummy variable	−0.16	−0.27	−0.24	0.59	0.24
		(0.331)	(0.364)	(0.360)	(0.589)	(0.537)
	2) Other controls (size, age, labor and services cost per unit of output, sector, area)	Yes	Yes	Yes	Yes	Yes
Number of observations		64,069	46,508	48,279	25,927	27,739
	II) Second test					
Outcome variable:						
Percentage variation of TFP between 2013 and 2015		−0.30	−0.53	−0.62	0.34	−0.33
		(0.375)	(0.424)	(0.414)	(0.705)	(0.635)
Number of "on-support"		60,793	43,566	45,180	19,207	22,366
("off-support") untreated and treated firms		(3,276)	(2,942)	(3,099)	(6,720)	(5,373)

Notes: The two tests are described in the text. Robust standard errors are reported in parentheses. For test II, we report, for each definition of treatment, the number of "on-support" and (in parenthesis) "off-support" firms (*i.e.* those that drop out of the common support). As illustrated in the text, treatment group (A) comprises firms that invested in at least one type of digital technologies; Group (B) comprises firms that invested in at least one type of digital technologies in the of "Areas of application of artificial intelligence" or "Other technological areas"; Group (C) comprises firms that invested in a bundle of at least two types of digital technologies; Group (D) comprises firms that invested in a bundle of at least three types of digital technologies; Group (E) comprises firms that invested in at least one AI technology.

patterns in productivity dating back before the treatment. To test for these common trends before the treatment we could use information back to 2013 and performed the following two tests. First, we regressed the log variation in TFP between 2013 and 2015 on the treatment dummy variable as well as on all the covariates used earlier for the probit analysis but evaluated in 2013. In the second approach for testing common trends before treatment, we replicated the PSM analysis combined with DiD as follows: first, in the probit analysis the treatment dummy variable was regressed on all covariates documented before for the main analysis but referred to 2013. Then we matched treated and untreated firms using the propensity score from this estimation and computed the ATT using the log variation in TFP between 2013 and 2015 as the outcome variable. In Table 7 we first report the estimated coefficient of the dummy variable for the 'fake' treatment using the baseline and all the alternative definitions of 'fake' treatment. In all cases, the estimated coefficient is not statistically significant, and this lends support to the hypothesis of common trends before the treatment. Moreover, in the same table we document the estimated ATT using the PSM analysis described earlier. Again, no matter what the definition of treated firms are, no statistically significant effects of being in the treatment group are detected in the TFP (log) variation between 2013 and 2015. We now turn to a robustness analysis and some extensions.

6. Robustness and extensions

6.1. Other matching methods

In our baseline analysis we have used the radius matching method with a caliper value of 0.00001. Here we replicate the analysis using different approaches. First, we continue to use radius matching but with a larger caliper value (0.001) and second, we employ the kernel-based matching. As for radius matching, a larger value of the caliper value implies that less firms drop out of the common support, as the requirements for counterfactuals to be found become less stringent than in the case with a smaller caliper value. The kernel matching associates to the outcome variable of a treated firm, i, a matched outcome given by a kernel-weighted average of it for all untreated firms, where the weights are inversely proportional to the distance in the propensity scores of firms i and j. With kernel-based matching all untreated firms are used in the match, although with different weights; thus, all available information is exploited, as every firm is included in the estimation. The effect on the outcome variable estimated with the kernel matching model is the following:

$$\text{ATT} = 100^{*}\frac{1}{N^T}\sum_{i=1}^{N^T}\left(\Delta\log\,(TFP)_i^T - \sum_{j=1}^{N^C} w_{ij}\Delta\log\,(TFP)_j^C\right), \tag{2}$$

where N^T and N^C are the number of, respectively, treated and control firms, and $\Delta\log\,(TFP)_i^T$ and $\Delta\log\,(TFP)_j^C$ are the values of the outcome variables for the i-th treated and the j-th control (untreated) firm, respectively. The term, $\sum_{j=1}^{N^C} w_{ij}\Delta\log\,(TFP)_j^C$, is the weighted average of the outcome variables for all untreated firms.[13]

In Table 8 we report the estimated effect of treatment on the difference in the log variation of TFP over the 2015–2018 period between treated and control firms. For each matching method, we separately consider each definition of treatment. When the larger caliper value is used with radius matching, the estimated effects continue to be positive and statistically significant as those reported in Table 5. With the baseline definition of treatment, the estimated effect is almost identical to the corresponding one reported in Table 5 (0.92 vs. 0.97 per cent). For the alternative definitions of treatment, the estimated effects are a little bit smaller in size compared the those documented in Table 5 but their profile across measures of treatment is qualitatively very similar. When the kernel-based matching method is used, the estimated effects are statistically significant and larger in size than those obtained with the radius matching. In general, however, their distribution across different measures of treatment is like the one obtained with the other methods: the smallest effect is found with the baseline definition of treatment and

[13] The expression for the weight, w_{ij}, is the following: $w_{ij} = \frac{K\left(\frac{p_i - \pi_j}{h}\right)}{\sum_{j=1}^{N^C} K\left(\frac{p_i - \pi_j}{h}\right)}$, where $K(\cdot)$ is the kernel function (widely used kernels are the gaussian and the Epancehnikov), with K reaching its highest value of one when the untreated firm, j, has the same propensity score of the treated firm, i ($p_i = \pi_j$). h is the bandwidth (or smoothing parameter) that governs the pace at which the weights decline as distance increases (the higher is h, the lower is the pace).

Table 8
The effect of digital adoption on productivity using other matching methods (*Effects on percentage variation of TFP*).

	Baseline Treatment Group (A)	Alternative Treatment Group (B)	Alternative Treatment Group (C)	Alternative Treatment Group (D)	Alternative Treatment Group (E)
	Baseline (A) and alternative definitions of treatment with digital adoption (B), (C), (D) and (E)				
	I) Radius matching with a caliper value of 0.001				
Outcome variable:					
Percentage variation of TFP between 2015 and 2018	0.92***	1.22***	1.28***	1.48***	1.40**
	(0.350)	(0.407)	(0.392)	(0.483)	(0.602)
Number of "on-support" ("off-support") untreated and treated firms	67,881	48,987	51,113	36,379	29,281
	(44)	(86)	(77)	(97)	(158)
	II) kernel-based matching				
Percentage variation of TFP between 2015 and 2018	2.22*	2.81**	2.76**	3.20***	3.32**
	(1.189)	(1.211)	(1.200)	(1.237)	(1.373)
Number of untreated and treated firms	67,925	49,073	51,190	36,476	29,439

Notes: The coefficients represent the estimated difference in the 2015 to 2018 log-change in TFP between treated and control firms. Robust standard errors in parentheses. For the Radius matching (I), we report, for each definition of treatment, the number of "on-support" and (in parenthesis) "off-support" firms (*i.e.* those that drop out of the common support).
As illustrated in the text, treatment group (A) comprises firms that invested in at least one type of digital technologies; Group (B) comprises firms that invested in at least one type of digital technologies in the of "Areas of application of artificial intelligence" or "Other technological areas"; Group (C) comprises firms that invested in a bundle of at least two types of digital technologies; Group (D) comprises firms that invested in a bundle of at least three types of digital technologies; Group (E) comprises firms that invested in at least one AI technology.
***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table 9
Heterogeneity across Firms in the Effect of Digital adoption on Productivity *Sample splitting analysis – Outcome variable: percentage variation of TFP between 2015 and 2018*.

	Manufacturing Firms	Service firms	Younger firms	Older firms	Smaller firms	Larger firms
Baseline Treatment Group (A)	0.99* (0.527)	1.42** (0.586)	0.79 (0.615)	2.13*** (0.493)	0.86* (0.523)	1.63*** (0.554)
N. obs.	27,777	32,798	32,695	35,230	33,571	34,354
Alternative Treatment Group (B)	1.54*** (0.571)	1.83*** (0.648)	1.00 (0.729)	2.12*** (0.543)	0.93 (0.615)	2.09*** (0.613)
N. obs.	21,895	22,160	22,902	26,171	23,298	25,775
Alternative Treatment Group (C)	1.38** (0.584)	1.85*** (0.657)	2.16** (1.255)	1.91*** (0.497)	1.38** (0.598)	1.89*** (0.602)
N. obs.	21,212	24,582	24,586	26,604	24,640	26,550
Alternative Treatment Group (D)	1.48** (0.684)	2.34*** (0.809)	1.20 (0.779)	2.05*** (0.604)	1.58** (0.778)	2.22*** (0.703)
N. obs.	15,498	17,156	17,596	18,880	17,706	18,770
Alternative Treatment Group (E)	2.03** (0.804)	1.83** (1.062)	2.81*** (0.964)	0.95 (0.760)	2.24** (1.018)	2.02** (0.868)
N. obs.	12,880	13,565	14,361	15,078	14,665	14,774

Notes: In splitting the sample according to firm age, the threshold was the median across firms, calculated in 2015, in their years of activity since establishment. When size is considered, the threshold was the median across firms in 2015 in their number of employees. The coefficients represent the estimated difference in the 2015 to 2018 log-changes in TFP between treated and control firms.
Robust and clustered standard errors in parentheses. For each definition of treatment and each sub-sample, the number of observations refers to both "on-support" and "off-support" firms. As illustrated in the text, treatment group (A) comprises firms that invested in at least one type of digital technologies; Group (B) comprises firms that invested in at least one type of digital technologies in the of "Areas of application of artificial intelligence" or "Other technological areas"; Group (C) comprises firms that invested in a bundle of at least two types of digital technologies; Group (D) comprises firms that invested in a bundle of at least three types of digital technologies; Group (E) comprises firms that invested in at least one AI technology. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

the effects increase when the definitions of treatment refer to more advanced technologies or to bundles of at least two investments. We now investigate whether and how the estimated effect of digital adoption varies across firm characteristics.

6.2. heterogeneous effects across firms

The adoption of digital technologies can have idiosyncratic effects on firms due to their characteristics, which can lead to different opportunities and challenges when digital investments are made. In terms of firm size and age, for example, as pointed out by many scholars, enterprises often need to supplement digital technologies, especially in the Industry 4.0 area, with complementary investments to effectively embrace digital transformation and enjoy productivity gains (Brynjolfsson et al., 2017). These complementary investments often imply significant upfront fixed costs, so that small firms, that are also more likely to be financially constrained than larger firms, may face serious obstacles in accumulating these assets and this may prevent them from reaping the benefits of digital transformation.

On the other hand, because smaller and younger firms may have a

Table 10
The Effect of Digital adoption on other firm variables (*Effects on percentage variation of the firm variable over the period 2015–2018*).

	Baseline Treatment Group (A)	Alternative Treatment Group (B)	Alternative Treatment Group (C)	Alternative Treatment Group (D)	Alternative Treatment Group (E)
	I) Employment				
Outcome variable					
Percentage variation of employment between 2015 and 2018	4.79*** (0.418)	5.79*** (0.474)	6.10*** (0.470)	7.57*** (0.568)	9.90*** (0.708)
Number of "on-support" ("off-support") firms	69,596 (3,178)	49,369 (3,168)	51,774 (3,091)	35,352 (3,813)	25,627 (6,020)
II) Revenues					
Outcome variable:					
Percentage variation of revenues between 2015 and 2018	5.97*** (0.435)	7.44*** (0.501)	7.51*** (0.488)	9.64*** (0.608)	11.47*** (0.742)
Number of "on-support" ("off-support") firms	69,660 (3,058)	49,325 (3,171)	51,859 (2,960)	35,359 (3,770)	25,673 (5,945)

Notes: The two tests are described in the text. Robust standard errors are reported in parentheses. For each definition of treatment, we report the number of "on-support" and (in parenthesis) "off-support" firms (i.e. those that drop out of the common support).
As illustrated in the text, treatment group (A) comprises firms that invested in at least one type of digital technologies; Group (B) comprises firms that invested in at least one type of digital technologies in the of "Areas of application of artificial intelligence" or "Other technological areas"; Group (C) comprises firms that invested in a bundle of at least two types of digital technologies; Group (D) comprises firms that invested in a bundle of at least three types of digital technologies; Group (E) comprises firms that invested in at least one AI technology.
***p < 0.01; **p < 0.05; *p < 0.10.

very low level of digital adoption and some technologies significantly reduce the costs of transporting and transmitting data (Goldfarb and Tucker, 2019), we might also expect digital adoption to increase value creation in these firms more than in the others.

For all these reasons, in an extension of the analysis, we investigate the degree of difference (if any) in the estimated effect of digital adoption on productivity that depends on specific firms' structural characteristics. We address this issue by applying our methodology on different sub-samples of data that separate firms according to their sector, the age and the size. The results are reported in Table 9. First, we split the whole sample based on whether a firm operates in the manufacturing or the service sector.[14] The estimated effect of digital adoption on productivity variation is found to be slightly stronger in firms in the service sector than in manufacturing firms. This holds true using the baseline definition (A) of treatment as well as the alternative definitions, with one exception only. With definition (A) of treatment, the effect in services is 1.42 per cent vs. 0.99 in manufacturing. However, when we turn to investments made in AI technologies, the effect is much stronger in manufacturing than in services (2.03 vs. 1.83 per cent, respectively). In all cases the estimated effects are statistically significant whilst with different confidence level. Second, we consider firm age and distinguish between younger and older firms. The criterion for splitting the sample is the median, in 2015, of the number of years since establishment and the threshold age is 18 years. The effect on productivity of adopting digital technologies is found to be larger in older than in younger firms when the baseline definition of treatment is used and in three cases out of five. The case of treatment with investments made in AI is one of the two exceptions for which the effect is stronger in younger than in older firms. Third, we focus on size and distinguish between smaller and larger firms. The splitting criterion is based on the median of the number of workers in 2015 and the threshold number is 26.1 workers.[15] In general, the impact of digital technologies on productivity change is estimated to be stronger in larger than in smaller firms and the effect is statistically significant for all definitions of treatment. Interestingly, the only exception of a stronger effect for smaller, rather than larger, firms is again the case in which digital treatment is defined through investments made in AI technologies.[16]

6.3. *Digitalization and other firm variables*

Whilst this paper focuses more on productivity, it might also be important to shed some light on how other dimensions of firm's behavior are affected by the digital transformation. Therefore, we investigated how the adoption of digital technologies affects other firm variables in addition to productivity. In so doing, we rely on the same methodology used thus far, and conduct this further analysis with reference again to all our five measures of the firm propensity to invest in digital technologies. The other firm variables we focus on are employment and revenues. In Table 10, we document the effect of the treatment with digital technologies on the percentage variation of each of these variables over the period 2015–2018.

We detect a positive and statistically significant impact of digital adoption on the percentage change between 2015 and 2018 of both employment and revenues and this holds true across all measures of treatment. The estimated effect tends to be larger as we consider more stringent definitions of the treatment with digital adoption that involve investing in more advanced technologies (like AI) or in bundles of more than one technology.

7. Concluding remarks

Using firm-level information of high quality drawn from differences sources we first characterize the process of digital transformation of Italian firms using information of unusual breadth. We focused on numerous types of investments in digital technologies that firms have (or have not) made in the period 2016–2018 and we identified differences across firms in the propensity to adopt digital technologies. We did so by considering various dimensions of digital adoption, such as whether investments in technologies have been made in more advanced domains (like AI) or in bundles of more than one type of new technologies. We therefore used a variety of alternative criteria to classify firms

[14] The number of observations in these two sub-samples is lower than the corresponding number of observations in the whole sample considered so far for each distinct definition of treatment. The reason is that in our sample split we have distinguished between manufacturing vs. service firms and have therefore excluded firms operating in the following sectors: Electricity, Gas, Steam and Air Conditioning supply; Water supply, Sewerage, Waste Management and Remediation Activities; Construction.

[15] In the Istat registers, the number of workers reported for each firm in a given year is the yearly average. Hence, the information on the number of workers in a firm can well be a non-integer number.

[16] While these findings unveil a discernible and significant degree of heterogeneity in the estimated effects, we are aware that a split of the sample to zoom in on specific classes of firms, by reducing the number of observations, may reduce the ability of the PSM methodology to find good matches.

as digital adopters and investigated the effects of digital adoption on productivity. We have established at the firm level a positive and statistically significant effect of digital adoption on total factor productivity variation. With our baseline definition of digital adoption (having invested in at least one of the digital technologies envisaged in the Istat Survey), the estimated effect of it on the percentage change in TFP between 2015 and 2018 is about one percentage point (0.97). When we consider the alternative, more restrictive, definitions of "treatment" with digital adoption, with focus on investments made in more advanced technologies or in bundles of more than one technology, then the estimated effect is larger in size. Perhaps not surprising, we find that the largest effect on productivity is uncovered when the criterion for classifying firms as digital adopters is that they have invested in at least one AI-related new technology. We have also shown that there is heterogeneity across firms in the estimated effect of digital adoption on productivity, as the latter is, in general, found to be more sizeable in the service sector, in larger firms and in older firms.

A step forward in our future research is to shed light on whether the complementarity between digital technologies and other firms' tangible and intangible assets contributes to shape the impact of digital adoption on productivity. Thus, our goal now is to delve into this alternative source of heterogeneity across firms. In so doing, we will also consider obstacles in the firm's ability to have access to finance, which may provide serious impediments to build the necessary intangible assets, introducing a further degree of specificity across firms in the productivity-digitalization link.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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