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Digital Technologies and Productivity: a firm-level investigation for Italy

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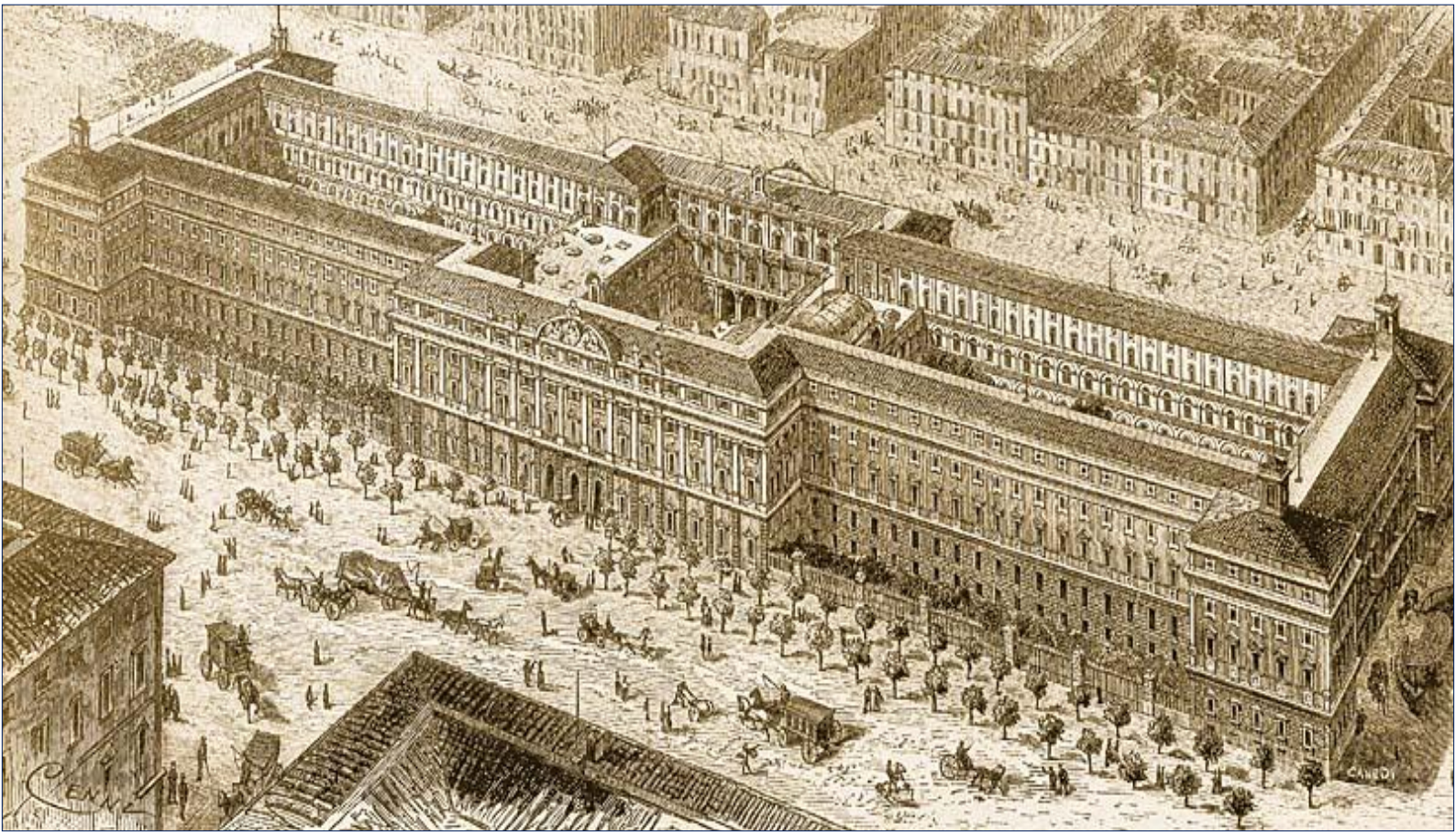

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Indice

Digital Technologies and Productivity: a firm-level investigation for Italy*

Francesco Nucci,[§] *Chiara Puccioni*[≠] *and Ottavio Ricchi* [#]

Abstract

We use three integrated firm-level databases maintained by the Italian Statistical Institute (Istat). In one of them, based on firms' responses to a detailed Survey on digital adoption, Istat has identified different groups of firms in terms of their pattern of use of digital technologies. Relying on this statistical work, we divide firms in two groups in our empirical investigation: the one with firms that extensively adopt digital technologies and the other with firms that do not. By considering digital adoption in the first group as a treatment, we employ the propensity score matching (PSM) approach combined with a difference-in-differences (DiD) analysis and establish more directly the causal impact of firm's use of digital technology on productivity. We find that firms with high digital adoption have a rate of variation of labor productivity, between 2015 and 2018, which is, on average, 2.7 percentage points higher than that of firms with low digital adoption. We also detect heterogeneity in this result as the estimated effect is found to be stronger in manufacturing firms, small firms and young firms.

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1. Introduction

The diffusion of digital technologies has represented a major shift in the way firms operate. As emphasized by Goldfarb and Tucker (2019), digital adoption implies an overall reduction in their costs, such as those for information search and processing and for coordination and communications. This has engendered a restructuring of the economy and has reshaped the market environment. Against this background, several contributions have analyzed the effects of digitalization on a number of key variables and a significant body of literature has focused on the relationship between digital adoption and productivity. In general, the adoption of digital technologies is found to be associated with higher productivity (see e.g. Gal et al. 2019 and references therein).

This paper seeks to investigate how digital technology usage impinges on firms' productivity and our goal is to identify causal effects establishing more directly the impact of firm's use of digital technology on its productivity. To tackle the well-known problems of self-selection into treatment, endogeneity and reverse causation that may well affect estimation of the relationship between digitalization and productivity, we employ the propensity score matching (PSM) methodology and combine it with a difference-in-differences (DiD) analysis. Thus, we focus first on a number of characteristics that are likely to affect firms' use of digital technologies. Among firms with these characteristics, some have substantially adopted digital technologies while some others have not. Second, we match firms that have extensively relied on digital technologies with their corresponding "twins" that have not and then compare the variation over time in productivity between the two groups of firms (see Angrist and Pischke, 2009 and Duhautois et al., 2020, for an analysis of the impact of product innovation on job quality).

In our empirical investigation we use three high-quality databases at the firm level all maintained and suitably integrated by Istat, the Italian Statistical Institute. They are the Permanent Census of enterprises, the Statistical register of active enterprises (ASIA - Enterprises) and the SBS Frame (Structural Business Statistics), a statistical register on economic accounts of Italian enterprises. Importantly for our purposes, a Survey 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 relied on each of 11 different digital technologies (Istat, 2020a). Based on firms' responses to these questions, Istat statisticians and economists have developed a simple latent class (LC) model without covariates and identified four groups of firms in terms of their pattern of use of digital technologies; accordingly, firm membership in one of the classes was assigned based on its responses (Istat, 2020a). Relying on the in-depth statistical analysis conducted by Istat, in our empirical investigation we divide firms in two groups: on the one side, a) firms with either a "non-systematic" or "encouraging" attitude towards digitalization (those in the first two latent classes identified by Istat) and, on the other, b) firms either "experimenting innovative IT solutions" or being "digitally mature" (those comprised in the other two classes). Firms in the latter group *extensively* adopt digital technologies, whilst those in the other group do not and we therefore consider digital adoption in group (b) as a treatment, so that firms in that group are the treated firms, while those in group (a) are the untreated firms.

Our first step in the empirical analysis is to estimate a probit model where the dependent variable is a dummy variable taking the value of one if a firm is "treated" and zero otherwise. We show that a marked digital adoption occurs more in large firms and that, compared to high-technology sectors in manufacturing, extensive digital adoption is less likely in all other industries, both in manufacturing and in services. The effect of age is also positive and firms operating in the North of Italy are more likely to rely on digital technologies. We also find that firms with a higher share of service purchases to the value of production are more likely to adopt digital technologies, similarly to firms with a lower share of labor costs to the value of production. Then, we proceed with the match of treated units to untreated units based on the estimated propensity score. Subsequently, we compare the variation in (the log of) productivity over the 2015-2018 period between firms with marked digital adoption (treated) in the post-2015 period and those without it (control).

We find digital adoption has discernable and statistically significant effects on firm productivity. If gross production per worker is used, then our estimation findings indicate that firms with high digital adoption have a rate of variation of productivity, between 2015 and 2018, which is 2.7 percentage points higher, on average, than that of similar firms with low digital adoption. We supplement our findings with several

evidence on the quality of the matching and also show that our findings are robust to alternative measures of labor productivity.

Moreover, we detect heterogeneity in our main finding, as the estimated effect of digital adoption on productivity varies in strength between different groups of firms. In particular, it is stronger in manufacturing firms, small firms and young firms. To account for the fact that some firms enjoy large productivity gains from digital technology usage while others do not, several contributions have emphasized that investments in digital technologies are complementary to skilled and specialized labor and require an intense reorganization and managerial capital as pre-conditions for enjoying productivity gains from their adoption (see e.g. Caroli and Van Reenen, 2002 and Tambe, Hitt and Brynjolfsson, 2012). Albeit indirectly, our empirical findings lend support to this view.

The remaining of the paper is organized as follows: in Section 2 we provide a background discussion of the relevant issues and 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

A key feature of digital technologies is that they induce a substantial decline of costs along several domains. As elucidated by Goldfarb and Tucker (2019), search costs, that is expenses for gathering information, significantly drop when economies become more digital and this tends to reduce prices and increase variety. Moreover, these reduced search costs facilitate exchanges of goods and services, for example, through a higher reliance on platform-based transactions, and affect the firm organization and structure. As for the costs of transporting information through the internet and distributing digital goods, they are virtually nihil and, by the same token, long-distance communication

with digital technologies becomes as unexpensive as short-distance one (Goldfarb and Tucker, 2019).[1]

As discussed in Calvino and Criscuolo (2019), this major and multi-dimensional costs reduction associated with digital diffusion should facilitate entry, upscaling and creative destruction and, in general, it should pave the way for a more dynamic business environment. In their analysis, they show that digital intensive sectors tend to be more dynamic than other sectors, consistently with their lower barriers to entry and higher degree of resource reallocation. However, they also document that business dynamism (entry, exit and job reallocation) has declined in digital intensive sectors over the last 20 years, even faster compared to other sectors of the economy. Whilst this would be broadly in line with the typical life-cycle pattern of innovative industries (Klepper, 1996), Calvino and Criscuolo (2019) detect significant cross-country differences in the evolution of digital intensive sectors.

Against this backdrop, our chief focus is on the effects of digitalization on productivity. Anderton et al. (2020) argue that the impact of digitalization in the economy is, in general, expected to resemble those of other technology and supply-side shocks and their contribution provides an interesting review of the effects of digitalization on other key variables in addition to productivity. For the link between digital adoption and productivity, a starting point might be the highly cited remark by Solow (1987), who argues that "you can see the computer age everywhere but in the productivity statistics". This amounts to the "productivity paradox", *i.e.* the coexistence of advances in ICT with a protracted slowdown in productivity growth. Jorgenson, Ho and Stiroh (2008) and Bloom et al. (2010) show that there was a post-1995 rise in

[1] Goldfarb and Tucker (2019) also emphasize that, with digital products, replication costs are often close to zero as these products have zero marginal costs (and are non-rival) and this may create incentives for firms to supply digital products at zero price (e.g. open sourcing software that are complementary to other services). They also draw attention on the reduction in both tracking and verification costs in coincidence with the shift towards a digital economy. These costs are those associated with connecting an individual person or firm with information about them and a drop of these costs has effects on the possibility of practicing price discrimination and advertisement targeting. The verification costs are those for appraising identity, reputation, product quality and trustworthiness of a firm or an individual.

productivity, which was largely driven by investments in information technologies in IT-using sectors, but it lasted until the middle of 2004. Indeed, as stressed by Brynjolfsson, Rock and Syverson (2017), measured productivity growth over the past decade has shown a large deceleration and low productivity growth rates have been recorded 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. At the same time, however, Brynjolfsson, Rock and Syverson (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, in particular. Thus, they reformulate the Solow paradox as follows: "we see transformative new technologies everywhere but in the productivity statistics".

The available evidence suggests that, in coincidence with the widespread productivity slowdown, other stylized facts have emerged. First, an increasing productivity dispersion between frontier and laggard firms (Andrews, Criscuolo, and Gal, 2016), lower business dynamism and a high degree of resource misallocation (Gopinath et al., 2017). Apart from traditional explanations such as bottlenecks and frictions that may indeed constrain firm decisions, there are interpretations of the weak productivity performance in the digital era that are linked to specificities of ICT and digital technologies themselves. Several contributions, in particular, have emphasized that these factors of production are typically complementary to skilled and specialized labor and require new production processes and managerial capital as well as adaptation and in-depth refocusing of firms' organizational practices, which are often difficult to undertake.

Caroli and Van Reenen (2002) show that information technologies induce productivity gains in firms characterized by decentralized architectures, higher levels of human capital and team-based production. Similarly, Tambe, Hitt and Brynjolfsson (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. They show that

important dimensions of firm's organizational improvements deal, not only with internal workplace factors, such as decentralization (Bresnahan, Brynjolfsson, and Hitt, 2002), but also with external factors, *i.e.* the existence of a network of external information relationships and practices (with customers, suppliers, partners, or employees). Garicano (2010) emphasizes the relevance of complementarities between information and communication technology (ICT) and organizational design. He shows that the required changes in organizational design do differ depending on the type of ICT investments and, more importantly, that complementarities between organization and ICT are so important that, without organizational changes, the impact of ICT on productivity might be negligible.

Brynjolfsson and Hitt (2002) draw attention to the finding in the literature that the contribution of information technology to firm's productivity and performance 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. The two authors define these types of complementary innovation as computer-enabled organizational investments, which affect productivity by both reducing costs and enhancing output quality in several dimensions (new innovative products and improvements in existing ones).[2] Draca, Sadun and Van Reenen (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.

Goldfarb and Tucker (2019) argue that, while the growth accounting literature has suggested a link between technology investments and productivity growth at the country level, establishing a causal link is more challenging at the macro level.[3] The

[2] As noted by Brynjolfsson and Saunders (2009), it is also important to consider complementary investments to technology, such as, for example, training, consulting, testing and process engineering.

[3] In their 2006 survey, Draca, Sadun and Van Reenen point to some facts from the growth accounting literature: productivity growth has accelerated in the US since 1995

paradox of a weak aggregate productivity growth in association with a growing digital dimension in the economy is accompanied by a rising heterogeneity across firms in productivity growth, with the frontier firms expanding faster than other firms. Moreover, there may be non-negligible lags between the implementation of digital technologies and their full operationalization, so that productivity enhancements can take time to materialize.

Obstacles to diffusion across firms of advanced digital tools and technology applications, with increasing distance between the best practice and laggard firms, are often seen as an explanation of the widespread weak productivity pattern. It is therefore very important to investigate the main drivers of technology adoption as Andrews, Nicoletti and Timiliotis (2018) do in their analysis on cross-industry, cross-country data. Using proper proxies, they provide evidence that capabilities to the complementary intangible investments, such as organizational capital, up-to-date managerial practices, innovative working arrangements, workers skills and an efficient allocation of human resources do affect adoption of digital technologies and their diffusion. Different models of ICT adoption, with a focus on its determinants, are illustrated in Bloom et al. (2007). Along similar lines, Brynjolfsson and McElheran (2016) explore the determinants of what they call data-driven decision-making (DDD) and analyze the types of firms that adopt it and the factors underlying its diffusion. They find that adoption of DDD is asymmetrical, as it is detected in firms with higher size (in accordance with economies of scale), higher intensity of complementary innovations, such as information technology and talented workforce, and higher ability to learn about new practices. Moreover, in a companion paper, Brynjolfsson and McElheran (2016a) show that DDD adopters enjoy higher productivity.

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and this pattern is linked to ICT. By contrast, there has been no acceleration of productivity growth in the EU, mostly due to the performance of the ICT-using industries. They also recall that, in a growth accounting set-up, there has been fast technological progress in the IT-producing industries and, thereby, fast TFP growth in these sectors and IT capital deepening in other sectors. A parallel factor accompanying these patterns is the rapid fall of IT prices. Jorgenson, Ho and Stiroh (2008) document that, since 2000, the sources of productivity growth have shifted as much of TFP growth originated in the industries with the highest intensity of use of information technology.

At microeconomic level, a large literature has established that adoption of digital technologies is associated with higher productivity. However, there is heterogeneity underlying this finding, as only some types of firms may benefit from these productivity gains. The heterogeneity and asymmetry in the distribution of firm productivity reflects a number of factors, including differences in the intensity of complementary intangible assets that we have discussed earlier.[4] As Bloom et al. (2007) show, a positive effect of ICT on firm productivity is detected in Europe at the macro level (average effect) but it is actually 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. Focusing on patterns before mid-2000s, Bloom, Sadun and Van Reenen (2012) seek to provide an explanation for the diverging path of US and European productivity growth in the 1995–2006 period, with US productivity accelerating and European productivity slowing down compared to the previous decade. By using 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, not only do they estimate differences across them in IT-related productivity, but their results point to US people-management practices as a driver of the productivity premium, owing to a superior ability in IT exploitation. Using a panel of US establishments, Jin and McElheran (2017) provide evidence that recent dramatic increases in firms' ability to access information technologies as a service are conducive to positive effect on the survival and 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

[4] An in-depth analysis on intangible assets and their role for resource reallocation and economic growth has been developed by Andrews and de Serres (2012).

complementary investments and innovations, such as those discussed earlier, which may require time to implement.[5] Moreover, as Draca, Sadun and Van Reenen (2006) put it, an implication of ICT being a general-purpose technology is that its adoption entails experimentation that may lead to innovation by the firm.

Several empirical studies both at firm and industry level estimate a positive relationship between adoption of digital technologies and productivity. In their survey, Draca, Sadun and Van Reenen (2006) note that, while early studies at the industry level found no significant relationship between IT and productivity, those relying on more recent data did detect significant productivity gains from IT capital over the 1987-2000 period. As for firm-level studies, Draca, Sadun and Van Reenen (2006) state that most of them find a positive and significant association of IT with productivity. While there is, in general, a consensus in the literature on a positive relationship between digital adoption and productivity (see Gal et al., 2019, for an updated and comprehensive literature review), there are, however, some papers that reach a different conclusion. For example, Acemoglu et al. (2014) argue that the Solow's paradox is far from being resolved, as they 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, as described in Gal et al. (2019), Bartelsman, van Leeuwen and Polder (2017) and DeStefano, Kneller and Timmis (2018) find no significant impact of firms' broadband access on their productivity.[6]

In their recent, in-depth analysis of digitalization and productivity, Gal et al. (2019) rely on data at the firm level on productivity and data at the industry level on digital technology adoption. They find that the impact of digital adoption on productivity

[5] In an insightful discussion, Davis (2010) argues that the development and exploitation of digital information, similarly to previous major historical shifts based on new general-purpose technologies, involve a complicated "techno-economic regime transition" whose favorable outcome is conditional to a variety of complementary changes in methods of production, work modes, business organization, and institutional support.

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

increases can be sizeable, especially for firms that already enjoyed high level of productivity. 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. Another finding is that digitalization, while increasing productivity on average, has also contributed to widen productivity dispersion across firms, as about half of the productivity divergence between the top and bottom quartiles of firms in each industry may result from digitalization. Indeed, less productive firms are likely to have shortages of managerial and digital-related technical skills and a lower ability to adapt business practices and automate their routine tasks and this contributes to reduce their productivity gains from digital technologies. With their industry-level data on digital adoption, Gal et al. (2019) cannot fully disentangle whether the firm-level productivity gains from digital technologies are driven by within-firm adoption or, conversely, by spillovers from higher digitalization of other firms in the same industry. Yet, they provide some indirect evidence suggesting that both channels may be actually relevant. Based on these results and those by Andrews, Nicoletti and Timiliotis, (2018), Sorbe et al. (2019) argue convincingly that the heterogeneity across firms and industries in both adoption rates and adoption effects contributes to explain why aggregate productivity gains from digitalization are not so evident.[7]

Since our paper focuses on the Italian economy, in investigating the link between firm productivity and digitalization, it is useful to survey the contributions based on Italian data. Bugamelli and Pagano (2004) 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. As we have seen before, reorganization costs act as capital adjustment costs with a sizeable fixed cost component. As such, small and medium firms, whose incidence is particularly high in Italy, have extra difficulties in paying them. They provide firm-level evidence on a lack of these complementary investments whose cost may have acted as barriers to investment in ICT. Castiglione

[7] See Pilat and Criscuolo (2018) for an insightful discussion and a useful summary of the main findings obtained within the OECD's Going Digital project on the link between digital transformation and productivity.
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(2012) uses a stochastic production frontier approach to study the contribution of ICT investments to firm productivity. She analyzes whether ICT investments impinge on firm's technical efficiency, approximated through the firm's distance of its actual output from the optimal production frontier. Relying on panel data on Italian manufacturing firms, she finds that ICT investments have a positive effect on firms' technical efficiency.

Hall, Lotti and Mairesse (2012) ask themselves why European firms do not invest much in ICT and even more so Italy, which has been a laggard in Europe in ICT as a share of all investment. They investigate the role of R&D and ICT investments 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 estimation 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 underinvestment in these activities by Italian firms. Finally, Pellegrino and Zingales (2017) investigate the drop of TFP in Italy observed since mid-90s and 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. They provide evidence that Italian firms are unable to take advantage of the productivity gains from the ICT revolution because they tend to select and reward their managers based on considerations unrelated to performance and merit. Schivardi and Schmitz (2018) calibrate a general equilibrium model with firm-level evidence and find that inefficient management practices limit the productivity gains of Italian firms from their IT adoption.

Whilst our paper relates to many contributions surveyed in this section, there are, however, three distinctive elements. First, to identify causal effects we rely on a methodology that is aimed at establishing more directly the impact of digital adoption on productivity. Second, we use a large integrated database of firm-level information that are of unusually high quality. Third, we pay attention to heterogeneity in the estimated effects and investigate whether they vary in strength depending on a number of firm's characteristics. We now turn to our own empirical investigation, describing first the data on Italian firms that we employ in the analysis.

3. The Data

3.a Three Firm-Level Integrated Databases

The information we use in our empirical study is drawn from three different databases at the firm level that are all maintained, and suitably integrated, by Istat, Italy's National statistical institute. The first data source 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 and Costa et al., 2020). We employ data from the first permanent census that took place in 2019 and involved a sample of about 280,000 enterprises employing more than three workers. The census covers the whole population of Italian enterprises with at least 20 employees, while enterprises with a number of employees comprised between 3 and 19 have been properly sampled. The whole sample represents about 24 per cent of Italian enterprises, employing 76.7 per cent of workers in Italy (12.7 million) and 91.3 per cent of employees and accounting for 84.4 per cent of Italian added value. 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. In particular, we combine information from the permanent census with data from two 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, 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 firms' economic variables, such as, for example, the value of production and sales, costs of different type and employment.

3.b Granular Information on Digital Technology and Innovation

The Survey of the 2019 Permanent census of enterprises has been conducted from May to October 2019 with 2018 as the reference year. Its actual outcome is a dataset referring to 201,465 enterprises. Importantly for our purposes, that survey features a detailed section on firms' digitalization and 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. Thus, our dataset refers to 108,682 enterprises, of which 90,159 reported to use at least one type of digital technology in the 2016-2018 period, while the other 18,523 firms reported to have not (see Istat, 2020a and Monducci, 2020).

The Survey collects extremely granular information on a wide range of aspects, which can be summarized as follows (Istat, 2020a):

a) The specific activities undertaken by the firm within its own innovation projects (if any) in the period 2016-2018: eleven types of non-mutually exclusive activities were proposed in the questionnaire, ranging from software and database development to acquisition of hardware, network and telecommunication equipment. Firms were also asked to indicate the amount of expenditure in all these activities as a percentage of sales.

b) The digital platforms used in 2018 by the firm for selling its goods and providing services (if any): ten types of digital platforms were proposed, some of which are industry specific. Moreover, firms were asked to report the share of their sales obtained through digital platforms.

c) The adoption of digital technologies by the firm in the 2016-2018 period (see below).

d) The effects of digitalization on a number of aspects of firm' performance.

e) The firm training activities for employees in the 2016-2018 period to cope with new digital technologies and to learn how to carry out digital processes for specific purposes.

f) The relevance of specific digital skills in the workforce as well as the actual availability of them within the firm (in 2018); ten different (non-mutually exclusive) types of digital skills are listed in the questionnaire.

g) The firm's future prospects (over the 2019-2021 period) on employees' skills distribution and human resource management in light of the digitalization process.

In this paper, we focus in more detail on the adoption of digital technologies (point c of the above list). In particular, the Survey has asked firms to report whether, in the period 2016-2018, they have relied or not on each of the following digital technologies (Istat, 2020a):

1) Business software for enterprise accounting, management and planning (such as for example, ERP and CRM)
2) Cloud services, providing firms with access to software applications, infrastructure and business processes via the internet
3) Internet connection through ultra-broadband networks based on fiber optic cables
4) Internet connection through Mobile Networks (4G-5G)
5) Internet of Things
6) Immersive technologies, merging the physical world with a digital or simulated reality (e.g., Augmented reality and virtual reality)
7) Big data processing and analysis
8) Advanced automation functions, Collaborative robots and Intelligent systems
9) 3D printing
10) Obtaining simulated, virtual outcomes through interconnected devices
11) Cyber security

Based on firms' dichotomous responses to these eleven questions, Istat statisticians and economists have developed and tested a simple latent class (LC) model without covariates (Istat, 2020a). The latter is a statistical model through which firms are classified into mutually exclusive and exhaustive types (latent classes), based on their categorical responses. The LC analysis allowed Istat to identify four groups of firms in terms of their pattern of use of digital technologies and a firm's membership in one of the four classes was assigned probabilistically based on its responses.
Istat has excluded from the LC model those firms that did respond to the questionnaire and reported no adoption at all of digital technologies (18,523 firms). The number of firms assigned to one of the four latent classes and considered in our analysis is therefore 90,159.

The first group comprises firms whose use of digital technologies is defined by Istat as "non systematic" (about 29% of total firms with more than 10 employees). They have

adopted at least a business software in the 2016-2018 period as well as simple IT infrastructures, such as cloud or Fiber-optic internet connection (see Istat, 2020a). The second group (about 45% of the total) includes firms that, according to Istat, exhibit a "constructive" attitude towards adopting a coherent digital strategy. They use high-speed Mobile Internet connection and make an integrated use of other technologies, such as Internet of things and/or remote sensing. Firms in this group consider investments in cyber security as crucial. The third group comprises firms that, according to Istat, are on the threshold of digital maturity and "experiment" innovative IT solutions, which are sometimes in combination among them (22% of the total). This group features firms investing in big data, simulation activities and robotics. Finally, the fourth group includes what Istat defines "digitally mature" firms, characterized by an integrated use of the available digital technologies (about 4% of all firms with more than 10 employees; see Istat, 2020a).

Based on the in-depth statistical analysis conducted by Istat, we create two groups of firms in our empirical investigation: (a) the first group comprises those belonging to the first two latent classes identified by Istat: firms with a "non-systematic" or "constructive" attitude towards digitalization and (b) the second group, that comprises firms in the other two classes: firms "experimenting innovative IT solutions" and those that are "digitally mature". Firms in the latter group (Group b) are those that *substantially* rely on digital technologies while firms in the other group (Group a) are those that do not. We consider exposure to digitalization by firms in the first group as a treatment, so that those in that group are the treated firms while those in the other group are the untreated (control) firms. We then use a quasi-experimental approach that allows us to establish a causal link between firm's digitalization and productivity. A critic might argue that our distinction between intensive adopters (treated) and non-intensive adopters (control) is seen as arbitrary given that the latent class model developed by Istat returned four, rather than two, groups. Reassuringly, however, the four groups identified by Istat have a clear ordering pattern in terms of intensity of use of digital technologies. Thus, although some degree of specificity is washed out in the aggregation process, the information loss from focusing on two groups (as our econometric methodology requires) should not be severe. Nevertheless, however, we tackle this issue further in the empirical analysis. Before turning to that section, let us

first provide some information on the other variables used in our investigation and present some descriptive statistics.

3.c Other variables and Descriptive Statistics

We approximate firm's productivity using labor productivity, which is measured as the ratio of gross production to the number of workers. We consider changes in firm's labor productivity between 2015 and 2018. As for workers in each firm, we have separate information for employees and self-employed every year. In addition to gross production in each year, we have annual information on firm's current revenues, other revenues, purchases of intermediate goods and services, value added, labor costs and wages and salaries. We also have information on the geographical area (at the province level), the industry (Ateco classification), the year of firm's establishment (age) and the occurrence of major legal transformation or corporate operations.[8]

In Table 1 we report the median value for a number of variables in both 2015 and 2018. We focus on the whole sample of 108,682 firms that have responded to the Survey questions in the 2019 Census of enterprises on the use of digital technologies in the 2016-2018 period. In other words, we also include in the descriptive statistics the 18,523 firms that, in that Survey, have reported no use of digital technologies. Given our focus on the treated and untreated firms in terms of adoption of digital technologies, in the table we also report the median values of the variables in 2015 and 2018 separately for the untreated (Group a) and treated firms (Group b). We also include the median values for the set of firms that have not entered that model as they reported no use of digital technologies (no_DT). In the table we indicate the number of firms in each group and the percentage incidence of each of them.

[8] In particular, they are the following: a) sale of the firm and transformation in a new firm; b) firm closure and transformation in a new firm; c) sale of the firm and transformation in an existing firm; d) firm closure and transformation in an existing firm; e) firm's birth from the transformation of a firm that sells its assets; f) firm's birth from the transformation of a firm that closes its activities; g) acquisition after a transformation of a firm that sells its assets ad h) acquisition after a transformation of a firm that closes its activities.

In Table 2 we provide information on the distribution of firms across the two groups as well as on the distribution of firms across the groups conditional on a variety of specific dimensions: geographic macro-area, firm's size and sector of activity. Finally, in Table 3 we provide some information on the firms' use of digital platforms for selling their products and on the incidence of revenues obtained through the intermediation of digital platforms.

4. The Empirical Methodology

Our goal is to ascertain the direct impact of firm's use of digital technology on its productivity. To identify causal effects a proper methodology ought to be utilized. Firms that rely extensively on 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 used digital technologies and those that have not should not 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, industry and human capital, while some others are not. Moreover, we have also to tackle 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 deal with these issues, we employ the propensity score matching (PSM) approach and combine it with a difference-in-difference (DiD) analysis (see Heckman, Ichimura and Todd, 1997; 1998 and Blundell and Costa Dias, 2009). In particular, we focus first on a number of characteristics that may introduce heterogeneity across firms in their propensity to use digital technologies. Among firms exhibiting these characteristics, some have relied extensively on digital technologies while some have not. Put it

differently, the assignment of treatment (*i.e.* extensive digitalization) is not random in our framework, as the latter is not based on experimental data. Second, we match firms that did rely extensively on digital technologies with their corresponding "twins" that, albeit showing similar characteristics, did not adopt these technologies and then compare changes in productivity between the two groups of firms (Angrist and Pischke, 2009).

The PSM model was proposed by Rosenbaum and Rubin (1983) for the effects of medical treatments. In our framework it allows us to compare productivity outcomes in firms with similar characteristics. The outcome variable is labor productivity. Firms that extensively adopted digital technologies in the 2016-2018 period are those in the treated group ($T=1$) and for each of them we construct a "counterfactual" by focusing on similar firms that are in the untreated group as they did not use digital technologies extensively. The goal is to match firms with maximal similarity. Propensity score matching creates equivalent (balanced) treatment and control groups in terms of confounding variables which allow to identify the impact of the treatment (digitalization in our case) on the outcome variable, Y (productivity).

The true causal effect of T for firm i would be $Y_i(T=1) - Y_i(T=0)$, which is impossible to estimate since each firm has either the value of $Y_i(T=1)$ or $Y_i(T=0)$. Let $E[Y(T=1)]$ define the average of possible outcomes on the treated and $E[Y(T=0)]$ the average of possible outcomes on the untreated. The average treatment effect (ATE) of $T=1$ is defined as $ATE = E[Y(T=1)] - E[Y(T=0)]$. The average treatment effect on the treated (ATT) is $ATT = E[Y(T=1) \mid T = 1] - E[Y(T=0) \mid T = 1]$. Since the second term on the right-hand side is not observed, to identify this effect we assume that – conditioning on a given set of observable covariates, X, which are not affected by treatment – the average of potential outcomes, say in the $T=0$ situation, is independent of treatment assignment. That is,

$$E[Y(T=0) \mid X, T=1] = E[Y(T=0) \mid X, T=0]. \qquad (1)$$

This equality reflects the conditional independence assumption (CIA), dictating that – once we condition on some observable characteristics, X – assignment of a unit i to

treatment can be taken as if it were random, i.e. $[Y_i(T=1), Y_i(T=0)] \perp [(T=1, T=0) \mid X.]$. The previous expression for ATT can, therefore, be rewritten as

$$\text{ATT} \mid X = \text{E}[Y(T=1) \mid X, T=1] - \text{E}[Y(T=0) \mid X, T=0], \qquad (2)$$

where a control group is constructed so that the distribution of a set of observable characteristics, X, is similar to the corresponding distribution of the treated firms.

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

Our first step is then to estimate a probit model on our sample where the dependent variable is a binary variable, treatment (T), and the explanatory variables are the variables, X, that are evaluated *before* treatment (in 2015) and are likely to influence the probability of being treated. From this model we estimate the propensity score and use it for matching treated and untreated firms.

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. We rely on the kernel-based matching, which associates to the outcome variable, Y_i, of a treated firm, i, a matched outcome given by a kernel-weighted average of it for all untreated firms, where the weight given to each untreated firm j is inversely proportional to the distance in the propensity scores of firms i and j. Differently from other methods (such as the caliper matching), with kernel-based matching *all* untreated firms are used in the match, although with different weights. Thus, an advantage of this method is that it exploits

all available information, as every firm is included in the estimation. The effect on the outcome variable estimated with the kernel matching model is the following:

$$\text{ATT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(Y_i^T - \sum_{j=1}^{N^C} w_{ij}Y_j^C\right), \tag{3}$$

where N^T and N^C are the number of, respectively, treated and control (untreated) firms, Y_i^T is the value of the outcome variables for the i-th treated firm and Y_j^C is the value of the outcome variables for the j-th control (untreated) firm. The term, $\sum_{j=1}^{N^C} w_{ij}Y_j^C$, represents the weighted average of outcome variables for all untreated firms, with weights proportionally decreasing as the distance of the propensity score from the treated firm increases. The expression for the weight, w_{ij}, is the following:

$$w_{ij} = \frac{K\left(\frac{p_i-\pi_j}{h}\right)}{\sum_{j=1}^{N^C} K\left(\frac{p_i-\pi_j}{h}\right)}, \tag{4}$$

where the K function is the kernel function and a widely used one is the gaussian function:

$$K\left(\frac{p_i-\pi_j}{h}\right) = e^{-\frac{1}{2}\left(\frac{p_i-\pi_j}{h}\right)^2}, \tag{5}$$

with K reaching its highest value of one when the untreated firm, j, has the same propensity score of the treated firm, i; that is, $p_i = \pi_j$. In the function, h is the bandwidth (or smoothing parameter) that governs the pace at which weights decline as distance increases (the higher is h, the lower is the pace). In our analysis, we also use the Epanechnikov kernel, which was shown to be efficient in the class of kernel functions.

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 approach that computes the change in (the log of) labor productivity (*LP*) between two periods of time (the first difference) and compares this variation between treated and untreated firms (the second difference). In practice, the effect in expression (3) is calculated as follows:[9]

$$ATT = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(\Delta lp_i^T - \sum_{j=1}^{N^C} w_{ij}\Delta lp_j^C\right), \qquad (6)$$

where Δlp is the change in the log of labor productivity between 2015 and 2018. It is important to note that validity of the estimator in Eq. (6) rests on the assumption of a parallel trend before the treatment in the level of the outcome variable for (matched) treated and untreated firms. Unfortunately, we do not have firm-level data for the pre-2015 period and, admittedly, a proper test of this assumption would not be obvious in our case, as adoption of digital technologies can be repeated and firms in the two groups may have already relied extensively on digital adoption before our observation period (see Duhautois et al., 2020, for an application of the same approach in investigating the impact of innovation on job quality).

In the empirical analysis, we also rely on some criterion for assessing the quality of the match. Indeed, since we condition on the propensity score rather than on the set of covariates, *X*, one needs to verify whether the matching is able to balance the distribution of the relevant covariates in the treatment and the control group. 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 an extensive vs. non-extensive digital adoption. In our probit model the dependent variable is a dummy variable taking the value of one if the firm is "treated" and zero otherwise.

[9] In our empirical work, we have employed the user-written Stata command "diff", developed by Villa (2016) and the user-written Stata command psmatch2, developed by Edwin and Sianesi (2003).

The set of covariates in the model refer to observable characteristics that may introduce a degree a difference among firms in their use of digital technologies. These variables deal with the following aspects: size, industry, geographical location, age, share of expenditure in services to the value of production and 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 knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS).

In Tab. 4 we report the estimation results of the probit model. We do not report marginal effects but focus on the sign of the estimated coefficients, their statistical significance and their relative size within each group of dummy variables. 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 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. 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 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 Tab. 4 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 considered *before* participation into treatment, *i.e.* before firms' engagement into extensive digitalization (in 2016-2018).

After estimating the probability that a firm adopts extensive digitalization based on observed characteristics, we proceed with the match of treated units to untreated units based on the estimated propensity score.

In the third step, we compare variation in the log of productivity over the 2015-2018 period between firms with marked digital adoption (treated) and those without it (control). We consider two alternative measures of labor productivity: gross production per worker and value added per worker. In Tab. 5, we report the estimation results. No matter which measure of labor productivity is used, we find a positive and statistically significant impact of digital adoption on firm productivity. The positive effects reported in the table amount to the difference in the change over time of the log of productivity between digital and non-digital firms.[10] If gross production per worker is used, then our estimation findings indicate that firms with high digital adoption have a rate of change of productivity, between 2015 and 2018, which is 2.7 percentage points higher, on average, than that of firms with low digital adoption. The two columns differ with respect to the kernel function used. In column (1) we use the Epanechnikov kernel function while in column (2) we use the gaussian function. In the former case, the estimated effect is 0.03. When we use value added per worker, the estimated impact of digital adoption ranges between 0.01 and 0.007 (see Tab. 5). In all cases, the estimated effect is statistically significant at the one per cent level; in the estimation, we have used

[10] Relying on total factor productivity (TFP) may provide useful insights in our analysis in addition to labor productivity, as digital adoption is likely to also make capital more productive, not only labor. Arguably, the use of labor productivity may thus underestimate the gains from digital technologies. Unfortunately, we cannot delve into this issue as we do not have data on TFP.

robust standard errors and we have also clustered them to tackle the possible problem with grouped error terms.[11]

We now address the issue of assessing 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 divergence in the means of covariates of the two groups. 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 report the mean for the treated and control groups for each of the covariates. The two groups seem to be very similar for most observables, although the assumption of the equality of means is not satisfied in some cases (in 7 cases out of 22).[12] Since *t*-test requires controversial assumptions, such as normal distribution of covariates, and is sensitive to sample size, several studies dissuade comparisons after PSM that are based on *t*-tests (see e.g. Ho, Imai, King and Stuart, 2007, and reference therein). We also use another approach for assessing the difference in marginal distributions of the covariates, which is 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. 1, we report the standardised bias for each covariate and, in all cases, it is below 3 per cent in the matched samples, which is considered as a satisfactory outcome in most empirical studies (see Caliendo and Kopering, 2008). Finally, we also present in Fig. 2 a visual inspection of the density distribution of the propensity score in both groups, providing evidence that the region of common support between treated and untreated firms is adequate.

[11] In our difference-in-difference (DiD) application, the identification of the treatment effect is based on variations across firms and years. Thus, the regressor of primary interest is correlated within firms. The cluster-robust variance estimator (CRVE) is a simple way to deal with correlation within-groups.

[12] The analysis is conducted on the estimation results obtained with gross production per worker as a measure of productivity and using the Epanechnikov kernel function. Moreover, as reported in the table, the pseudo-R-squared 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.

6. Some extensions

We have also considered some extensions in our analysis. The first one deals with an enlargement in the group of firms in the untreated group. In particular, in previous sections we have illustrated the approach of Istat for assigning firms to each of the four groups in terms of intensity of use of digital technologies. The economists and statisticians of Istat decided not to include in any group those firms that reported no use at all of digital technologies. While in the analysis so far we have maintained this hypothesis, we now depart from it and include in the group of untreated firms also those that reported no use of digital technologies. In Table 7, we report first the estimation results from the probit model, while in Tab. 8 we report the impact on the rate of variation of productivity. Not surprisingly, the estimated effect is in general larger than in the baseline case and it is still statistically significant. This suggests that including in the control group also those firms that have not relied at all on digital technologies magnifies the differential effect on productivity of being intensive vs. non-intensive digital adopters.[13]

An important extension deals with an investigation of whether there is a degree of difference in the effect of digital adoption on productivity variation that depends on structural characteristics, such as the macro-sector of the firm, age and size. We address this issue by applying our methodology on different sub-samples of data. The results are reported in Table 9. First, we distinguish between manufacturing firms and firms in the service sector. The estimated effect of digital adoption on productivity variation is found to be stronger in firms in the manufacturing sector than in those in the service sector. The effects are, respectively, 0.031 and 0.028, and are statistically significant at the one per cent level in both cases. Second, we focus on size and distinguish between smaller and larger firms. The splitting criterion is based on the median of the number of workers

[13] For completeness, we have also experimented with a simple OLS model, where firm productivity variation is regressed on dummy variables representing firm's membership in one of the four groups identified by Istat. The estimated results, that are not reported here for space constraints but are available upon request, albeit different in size from those reported in the text, suggest that firms in the groups of more intensive digital adopters exhibit a higher productivity change than that of firms in the other groups.

and the threshold number is 26 workers. The impact of digital technologies on productivity change is estimated to be stronger in smaller firms (0.044) than in larger firms (0.023) and in both cases the effect is statistically significant at the one per cent level. Third, we consider firm age and distinguish between younger and older firms. The criterion for splitting the sample is the median of the number of years since establishment and the threshold age is 20 years. The effect on productivity of adopting digital technologies is found to be larger in younger than in older firms: the estimated effects are, respectively, 0.051 and 0.020 and they are both statistically significant at the one per cent level. While these findings unveil a discernable and significant degree of heterogeneity in the estimated effects, we are aware of the fact that a split of the sample to zoom in on particular classes of firms, by reducing the number of observations, may reduce the ability of the PSM methodology to find good matches.

7. Concluding remarks

Using a quasi-experimental methodology on high-quality microeconomic data, we have established at the firm level a positive and statistically significant effect of digital adoption on productivity variation. This holds true for more than one measure of labor productivity (gross production per worker and value added per worker). In applying the methodology, we have also uncovered some interesting evidence on the characteristics of firms that adopt digital technologies. We have also shown that there is heterogeneity across firms in the effect of digital technologies on productivity, as the latter is estimated to be larger in manufacturing firms, small firms and young firms.

A natural step forward in our future analysis is to shed light on the degree of complementarity between digital technologies and other firms' tangible and intangible assets and on the role that this complementarity plays in shaping the impact of digital adoption on productivity. Thus, our goal now is to delve into this alternative source of heterogeneity and identify its contribution to the substantial dispersion across firms that is typically detected in their productivity improvements from digital adoption. In doing so, we seek to pay attention to the role of firm's ability to have access to finance,

which is likely to introduce a further degree of specificity across firms in the productivity-digitalization link.

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Annex

Tab 1 – Median values of variables across different groups in terms of use of digital technologies
(*Values are in euro*)

Year 2015	All sample	Group a (untreated)	Group b (treated)	No_DT
Gross production	3334545	3064834	6534984	1772001
Number of workers	22	21	32	18
Labor productivity	142368	137333	189100	97478
Revenues	3313311	3044034	6486624	1761466
Purchases of goods and services	1835010	1676155	3893469	841448
Value added	1068713	987541	1899158	662891
Labor costs	733930	677170	1249902	484867
Wages and salaries	532066	491246	901438	352241
Age (years)	18	18	20	15
Number of firms	103313	59089	27079	17145
Incidence of firms (%)	100	57	26	17

Year 2018	All sample	Group a (untreated)	Group b (treated)	No_DT
Gross production	3785018	3472219	7689533	1914021
Number of workers	26	25	37	21
Labor productivity	141713	136586	193168	93856
Revenues	3765844	3452858	7613091	1908809
Purchases of goods and services	2034577	1852792	4523753	880896
Value added	1234916	1142908	2298099	747844
Labor costs	877487	811389	1514391	553711
Wages and salaries	633400	586618	1093424	400589
Age (years)	21	21	23	18
Number of firms	103313	59089	27079	17145
Incidence of firms (%)	100	57	26	17

Legenda: calculations on the Istat merged firm-level databases. Group 0 is the class of the untreated firms in terms of adoption of digital technologies; Group 1 is the group of treated firms. No_DT is the group of firms that reported no adoption of digital technologies.

Tab 2 – Incidence of the groups for different use of digital technologies conditional on several dimensions (*Percentages*)

	Group 0 (Untreated)	Group 1 (Treated)	Total
Incidence of groups by macro area (%)			
North-West	70.5	29.5	100
North-East	72.4	27.6	100
Center	77.4	22.6	100
South	78.9	21.1	100
Incidence of groups by size class (%)			
0-10 workers	78.6	21.4	100
11-20 workers	77.1	22.9	100
21-50 workers	70.1	29.9	100
51-100 workers	58.5	41.5	100
101-250 workers	49.5	50.5	100
251-500 workers	39.9	60.1	100
more than 500 workers	27.6	72.4	100
Incidence of groups by industry (%)			
Manufacturing, mining and quarrying and other industrial activities	65.4	34.6	100
Construction	78.7	21.3	100
Wholesale and retail trade, transportation and storage, accommodation and food service	73.1	26.9	100
Information and communication	48.9	51.1	100
Financial and insurance activities	53.0	47.0	100
Real estate activities	75.0	25.0	100
Professional, scientific, technical, administrative and support service	68.6	31.4	100
Public administration and defence, education, human health and social work activities	67.4	32.6	100
Other service activities	77.9	22.1	100
Total	68.6	31.4	100

Legenda: calculations on the Istat merged firm-level databases.

Tab 3 – Incidence of expenditure on innovation projects and of digital platforms in revenues (*Percentages*)

	Median	Mean	St. dev	N. obs
Share of expenditure on innovation projects to sales	4.0	7.6	11.0	68744
Share of sales obtained through the intermediation of digital platforms to total sales	5.0	16.5	22.7	15897

Tab 4 – Determinants of Firm Digital Adoption: the results of a probit model

	Dep. variable: treatment	
	coeff.	se
Size (ref. under 10 employees)		
10-19	0.062***	(0.012)
20-49	0.262***	(0.012)
50-99	0.529***	(0.014)
100-249	0.748***	(0.016)
250 and more	1.148***	(0.021)
Age (ref. lowest quartile)		
2nd quartile	0.047***	(0.009)
3rd quartile	0.046***	(0.009)
Top quartile	0.043***	(0.010)
Labour cost per output unit (ref. lowest quartile)		
2nd quartile	-0.144***	(0.009)
3rd quartile	-0.275***	(0.010)
Top quartile	-0.438***	(0.010)
Service cost per output unit (ref. lowest quartile)		
2nd quartile	0.113***	(0.010)
3rd quartile	0.176***	(0.010)
Top quartile	0.245***	(0.010)
Sector by level of technology (ref. High-tech (Manufacturing))		
Medium high-tech (Manufacturing)	-0.284***	(0.029)
Medium low-tech (Manufacturing)	-0.359***	(0.029)
Low tech (Manufacturing)	-0.539***	(0.028)
Knowledge- intensive services	-0.140***	(0.029)
Less knowledge- intensive services	-0.521***	(0.028)
Other	-0.614***	(0.029)
Geographical Area (ref. North)		
Center	-0.130***	(0.009)
South	-0.165***	(0.009)
Constant	-0.256***	(0.031)
Pseudo R2	0.0643	
Nr. of obs.	166,988	

Table 5: Impact of Digital Technologies adoption on Labor Productivity

	(1)	(2)
Dependent variables:		
1) Labor productivity $ln\left(\frac{Gross\ production}{Number\ of\ workers}\right)$	0.030*** (0.004)	0.027*** (0.004)
Number of observations	166,982	166,982
2) Labor productivity $ln\left(\frac{Value\ added}{Number\ of\ workers}\right)$	0.007*** (0.003)	0.010*** (0.004)
Number of observations	163,712	163,768

Legenda: Both variables represent the variation in the log of the variable between 2015 and 2018. In both columns we use the kernel-matching algorithm. In column (1) the Epanechnikov kernel function is used, while, in column (2), it is the gaussian kernel function. Robust standard errors in parentheses. Standard errors are clustered.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Balancing properties for the baseline sample

	Mean		%bias	t-test	
	Treated	Control		t	p-value >t
Size (ref. under 10 employees)					
10-19	0.2256	0.23111	-1.2	-2.12	0.034**
20-49	0.3654	0.36526	0	0.05	0.964
50-99	0.15375	0.14913	1.4	2.08	0.037**
100-249	0.10651	0.10496	0.6	0.82	0.414
250 and more	0.07089	0.06906	0.9	1.16	0.245
Age (ref. lowest quartile)					
2nd quartile	0.24788	0.24922	-0.3	-0.5	0.616
3rd quartile	0.24708	0.24647	0.1	0.23	0.82
Top quartile	0.25548	0.24994	1.3	2.06	0.039**
Labour cost per unit (ref. lowest quartile)					
2nd quartile	0.27528	0.27183	0.8	1.25	0.21
3rd quartile	0.23821	0.23599	0.5	0.84	0.399
Top quartile	0.19411	0.19896	-1.2	-1.97	0.048**
Service cost per output unit (ref. lowest quartile)					
2nd quartile	0.23909	0.23875	0.1	0.13	0.896
3rd quartile	0.26756	0.26593	0.4	0.6	0.55
Top quartile	0.2958	0.29473	0.2	0.38	0.702
Sector by level of technology (ref. High-tech (Manufacturing))					
Medium high-tech (Manufacturing)	0.13288	0.1278	1.6	2.44	0.015**
Medium low-tech (Manufacturing)	0.14301	0.14224	0.2	0.35	0.723
Low tech (Manufacturing)	0.13227	0.12932	0.9	1.41	0.157
Knowledge- intensive services	0.17492	0.17679	-0.5	-0.8	0.426
Less knowledge- intensive service	0.32068	0.32773	-1.5	-2.44	0.015**
Other	0.07349	0.07377	-0.1	-0.17	0.862
Geographical Area (ref. North)					
Center	0.16873	0.17031	-0.4	-0.68	0.497
South	0.14771	0.15294	-1.4	-2.36	0.018**
Pseudo R2	0.000				
p > chi2	0.168				
B	3.3				
R	1.09				

Fig. 1: Assessing balancing properties after Matching: % standardised bias

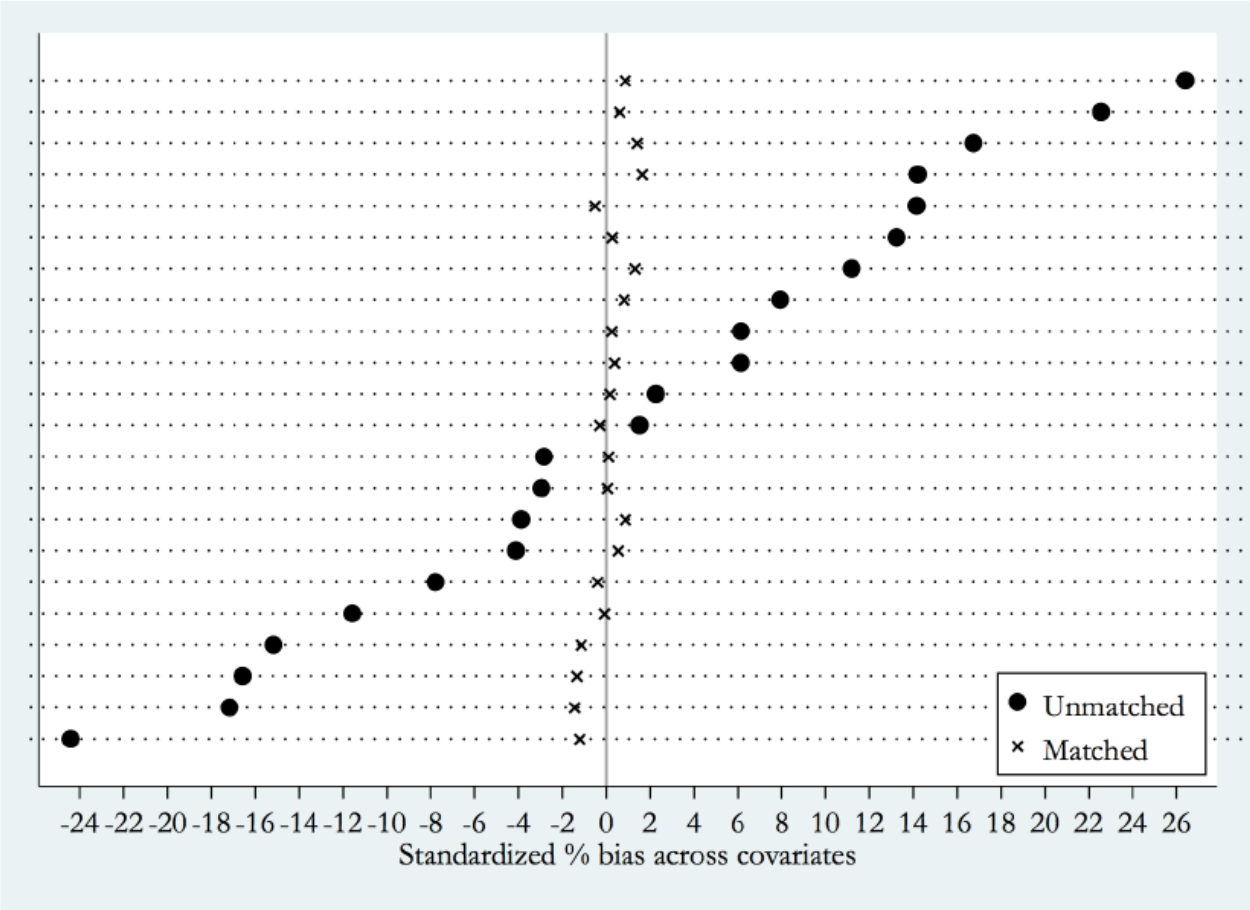
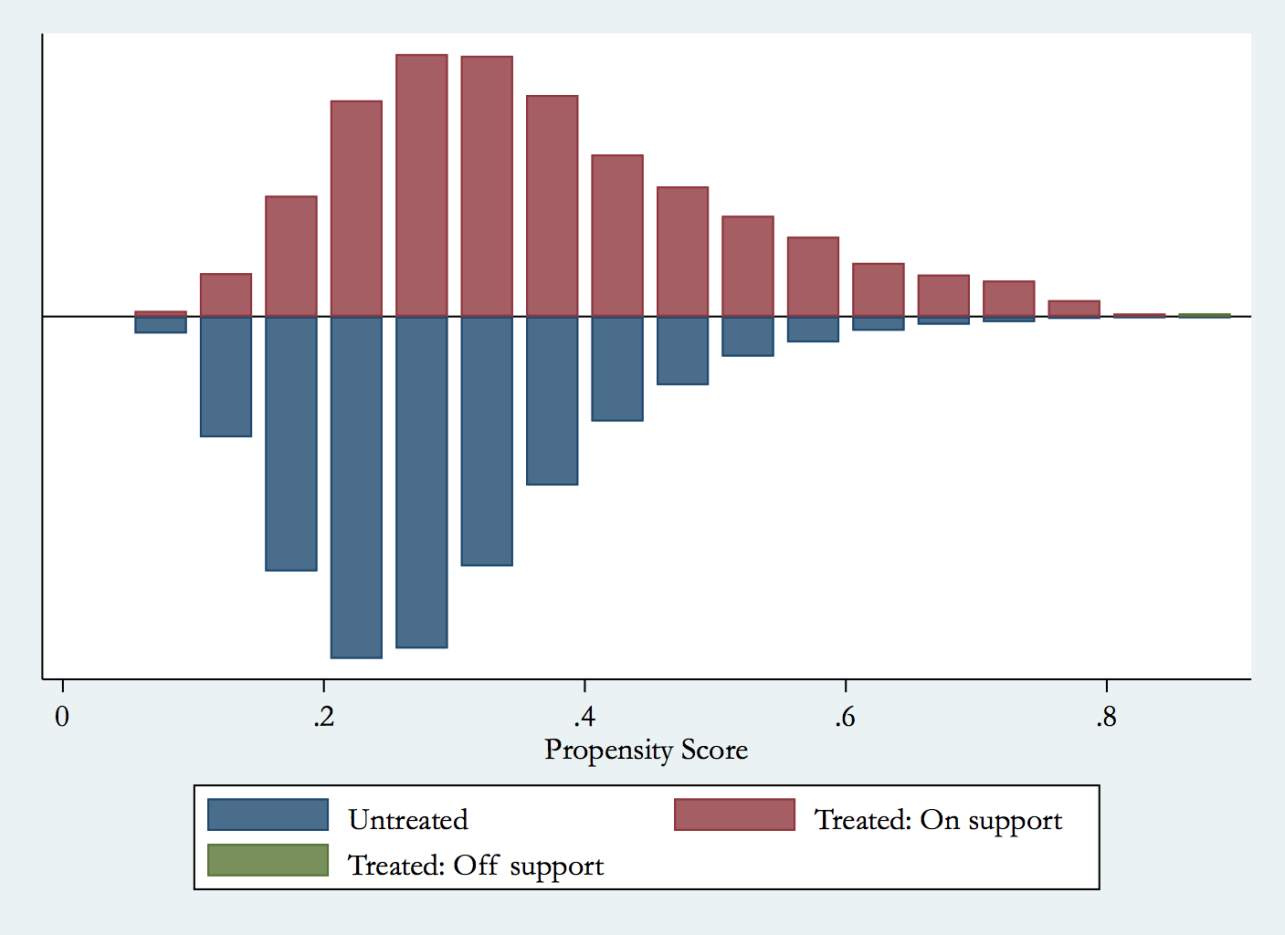


Fig. 2 Matching Share by Propensity Score



Tab 7 – Determinants of Firm Digital Adoption: the results from a probit model under a different hypothesis on the group of untreated

	Dep. variable: treatment	
	coeff.	se
Size (ref. under 10 employees)		
10-19	0.076***	(0.012)
20-49	0.304***	(0.011)
50-99	0.597***	(0.014)
100-249	0.831***	(0.016)
250 and more	1.252***	(0.020)
Age (ref. lowest quartile)		
2nd quartile	0.062***	(0.009)
3rd quartile	0.051***	(0.009)
Top quartile	0.053***	(0.009)
Labour cost per output unit (ref. lowest quartile)		
2nd quartile	-0.182***	(0.009)
3rd quartile	-0.329***	(0.009)
Top quartile	-0.528***	(0.010)
Service cost per output unit (ref. lowest quartile)		
2nd quartile	0.135***	(0.010)
3rd quartile	0.223***	(0.010)
Top quartile	0.287***	(0.010)
Sector by level of technology (ref. High-tech (Manufacturing))		
Medium high-tech (Manufacturing)	-0.299***	(0.028)
Medium low-tech (Manufacturing)	-0.399***	(0.028)
Low tech (Manufacturing)	-0.599***	(0.028)
Knowledge- intensive services	-0.147***	(0.028)
Less knowledge- intensive services	-0.560***	(0.027)
Other	-0.666***	(0.028)
Geographical Area (ref. North)		
Center	-0.147***	(0.008)
South	-0.191***	(0.009)
Constant	-0.387***	(0.030)
Pseudo R2	0.081	
Nr. of obs.	200,096	

Table 8: Impact of Digital adoption on Productivity: alternative hypothesis on the untreated

	(1)	(2)
Dependent variables:		
Labor productivity $ln\left(\frac{Gross\ production}{Number\ of\ workers}\right)$	0.037** (0.004)	0.032*** (0.003)
Number of observations	200,074	200,074
1) Labor productivity $ln\left(\frac{Value\ added}{Number\ of\ workers}\right)$	0.009** (0.004)	0.011*** (0.003)
Number of observations	196,092	196,012

Legenda: Both variables represent the variation in the log of the variable between 2015 and 2018. In both columns we use the kernel-matching algorithm. In column (1) the Epanechnikov kernel function is used, while, in column (2), it is the gaussian kernel function. Robust standard errors in parentheses. Standard errors are clustered.

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Heterogeneity in the Effect of Digital adoption on Productivity

(a) Manufacturing vs Service firms

	Manufacturing Firms	Service firms
Dependent variables:		
Labor productivity $ln\left(\frac{Gross\ production}{Number\ of\ workers}\right)$	0.031*** (0.0005)	0.028*** (0.007)
Number of observations	64,472	86,380

(b) Smaller vs Larger firms

	Smaller firms	Larger firms
Dependent variables:		
Labor productivity $ln\left(\frac{Gross\ production}{Number\ of\ workers}\right)$	0.044*** (0.009)	0.023*** (0.007)
Number of observations	83,465	83,498

(c) Younger vs Older firms

	Younger firms	Older firms
Dependent variables:		
Labor productivity $ln\left(\frac{Gross\ production}{Number\ of\ workers}\right)$	0.051*** (0.009)	0.020*** (0.006)
Number of observations	80,755	86,216

Legenda: We consider the variation in the log of the labor productivity between 2015 and 2018. We use the Epanechnikov kernel function as matching algorithm. Robust standard errors in parentheses. Standard errors are clustered.

*** p<0.01, ** p<0.05, * p<0.1

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